A Sensor-Based Empirical Framework to Measure Construction Labor Productivity

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ABSTRACT

Measurement of construction labor productivity involves various subjective factors (e.g., motivation, stress, fatigue). Most measurement approaches for subjective factors in productivity applications require manual data collection (e.g., questionnaires, interviews, observations); therefore, research gaps exist regarding how to (a) directly measure subjective factors using data that reflect workers' real performance at single points in time and (b) integrate these factors into existing or new models in labor productivity applications. This paper proposes an empirical framework for integrating real-time data from multiple sensors for directly measuring subjective factors affecting labor productivity. The proposed framework, which was designed, built, and evaluated using design science research methodology, contributes to the body of knowledge as part of a longer-term study proposing an empirical framework for triangulating data from a multi-sensor system to simultaneously measure multiple subjective factors affecting labor productivity. Study outcomes will complement existing artificial intelligence, simulation, and statistical models for construction productivity applications.

INTRODUCTION

Labor productivity is one of the determining factors contributing to the success of any construction project. Although monitoring labor productivity is vital in terms of construction project management, the current literature finds that it is challenging to accurately measure and manage construction productivity (Yi and Chan 2014). McKinsey Global Institute (2017) found that the labor-productivity growth for the construction industry averaged only 1% in the last 10 years. Therefore, the construction industry needs innovative techniques and advanced technologies to more objectively, effectively, and accurately measure labor productivity.

Measurement of construction labor productivity includes a combination of objective and subjective factors (Hwang et al. 2018). Objective factors, such as completeness of construction tasks, availability of materials and equipment, rework frequency, and change orders, can be measured numerically by using historical databases and data collected in the field (Yi and Chan 2017). Subjective factors in construction labor productivity applications often involve various human-related factors, such as motivation, emotion, cognitive load, fatigue, and stress (Aryal et al. 2017; Johari et al. 2020). Subjective factors can be determined using linguistic variables to report opinions and judgements, which often require the use of survey questionnaires and interviews (Hasan et al. 2018). Each subjective factor is a function of numerous variables within individuals, who may behave based on an attitude that they are unaware of or cannot express, which makes it difficult to measure their implicit attitude with direct questions. Most measurement approaches for subjective factors in productivity applications rely on indirect measures, such as surveys and observations, or secondary data such as data that have already been collected by others and are readily available from public sources, such as online libraries, internet searches, and databases. To support direct measurements of subjective factors that affect labor productivity, researchers are using sensors to collect timely data that reflect the real performance of construction workers at a single point in time (Ahn et al. 2019; Nwaogu and Chan 2021). However, current sensor-based measurement approaches in productivity applications only examine one or two subjective factors at a time (Choi et al. 2019; Jebelli et al. 2019). Therefore, research gaps exist regarding how to (a) simultaneously, measure multiple subjective factors and (b) integrate these factors into existing or new models that previously used indirect measures or secondary data for such factors.

To address the existing research gaps, this paper proposes an empirical framework that utilizes a multi-sensor system to simultaneously measure various subjective factors (e.g., motivation, stress, fatigue) that affect construction labor productivity. The subjective factors derived from the proposed framework will be used to replace those that were measured using indirect measures and also add new factors (e.g., improvisation) to existing predictive and simulation models in labor productivity applications. The proposed framework demonstrates a practical automated means for collecting and measuring multiple subjective factors that affect construction labor productivity in terms of human physiological (e.g., stress, fatigue, cognitive load) and biological (e.g., brainwaves, heart rate, skin temperature) responses. A longer-term study is planned that will use the proposed framework to analyze sensor-based data.

SENSOR APPLICATIONS IN MEASURING LABOR PRODUCTIVITY

Direct measurements of human emotions, fatigue, stress, and other physiological factors that affect construction labor productivity have been made in construction with real-time data collected using sensors (Johari et al. 2020). Sensors provide opportunity to collect physiological and biological signals that can be used to derive information on human attitudes and emotions (Aryal et al. 2017; Sun et al. 2020). To analyze sensing signal data, machine learning approaches have recently been used, including support vector machine, artificial neural networks, k-nearest neighbors algorithm, random forest, decision tree, discriminant analyses, fuzzy logic, bidirectional long short-term memory algorithm, and ensemble classifiers (Al Jassmi et al. 2019; Alberdi et al. 2016; Arpaia et al. 2020; Bangaru et al. 2021; Khowaja et al. 2020; Umer et al. 2020). For example, Jebelli et al. (2019) used workers' physiological signals from a wristband-type biosensor (i.e., PPG, EDA, ST) to develop a model that could recognize construction workers' physical-demand levels during construction activities. A machine learning model using a supervised-learning algorithm (i.e., Gaussian kernel support vector machine) was developed to allow the prediction of the construction activities' demand levels (i.e., low physical intensity, high physical intensity) based on physiological signals collected from workers. The model allowed automated and noninvasive assessment of workers' physical demands in the field by using wearable biosensors. The model enables the early detection of highly physically demanding tasks on construction sites, which will improve construction workers' productivity, safety, and general well-being. Ryu et al. (2020) noted that the use of sensors has gained attention in terms of their potential to replace human observers with automated monitoring technologies for data collection on construction activities. In the same study, they explored the use of wrist-worn accelerometer-embedded activity trackers for automated action recognition of masonry workers. They used machine learning with the collected data to classify workers' actions into four masonry tasks. They note that automated worker action recognition can be used for more effective management of work performance in terms of productivity.

Further, sensors provide opportunity to directly collect and derive information regarding human neural mechanisms, physiological responses (e.g., fatigue), biological responses (e.g., heart rates), and other subjective factors that affect construction labor productivity. Six types of sensors are commonly used in construction productivity, including inertial measurement unit (IMU), electrocardiography (ECG/EKG), photoplethysmography (PPG), electrodermal activity (EDA) / galvanic skin response (GSR), electromyography (EMG), eye trackers, and electroencephalography (EEG) (Ahn et al. 2019). Some biological responses, including heart rate, skin temperature, and brain waves, are frequently used to measure common subjective factors, such as stress, fatigue, and emotion. Table 1 summarizes six common subjective factors (mental and physical fatigue, mental and physical stress, heat stress, emotion, cognitive load, and situational awareness) that can be measured using sensors in construction productivity applications along with their associated physiological and/or biological sensor signal(s). The subjective factors and their associated sensors are used to design the proposed empirical framework for measuring construction labor productivity in the next section.

EMPIRICAL FRAMEWORK FOR MEASURING LABOR PRODUCTIVITY USING A MULTI-SENSOR SYSTEM

Design Science Methodology for Proposing a Sensor-based Framework. This study follows a design science research methodology approach, which is a scientific method for introducing a new artefact, such as a model or framework, that brings a new solution to a practical problem (Da Rocha et al. 2012). The artefact in this study is the sensor-based empirical framework for directly measuring subjective factors affecting construction labor productivity. Design science methodology was used to design, build, and evaluate the artefact including four components: constructs (i.e., concepts of the artefact), models (i.e., mechanisms of the artefact), methods (i.e., establishment of the artefact), and instantiations (i.e., implementation of the artefact) (Weber 2018). The design science methodology was applied in designing this framework as follows.

To design the proposed framework, a literature review was conducted to summarize and study the subjective factors that affect construction labor productivity. This step involved investigating the root causes of the subjective factors based on human responses in order to form the constructs in designing the artefact. The constructs in the design process included human physiological (e.g., emotions, fatigue, cognitive load) and biological (e.g., brainwaves, heart rate, skin temperature) responses that govern the subjective factors affecting labor productivity. To build the proposed framework, a series of lab experiments using multiple sensors were prepared for collecting the constructs and deriving the subjective factors that affect labor productivity. The constructs and their associations can provide understandings regarding human neural mechanisms, physiological responses, and biological responses that govern the subjective factors affecting labor productivity. Eventually, the subjective factors will be integrated into existing and new artificial intelligence (AI) (e.g., machine learning, optimization, fuzzy logic), simulation (of construction processes, agents, and systems), and statistical models that previously used indirect measures for such factors. To evaluate the proposed framework, the longer-term study will use surveys and perform interviews with an expert panel concentrating on applications of sensor technologies in construction. The evaluation plan will focus on applicability, scalability, and completeness of the proposed framework. The results are expected to advise construction practitioners on how to guide workers' productivity and behaviors on real-world projects and predict their impact on construction performance. The proposed sensor-based framework is described in detail in the following section.

Table 1. Sensors used to measure subjective factors affecting labor productivity

Subjective Factor	Reference	Physiological and Biological Signal(s)	Sensor(s)
Mental and physical fatigue	Aryal et al. (2017)	Skin temperature, electroencephalogram waves	EDA and EEG
	Umer et al. (2020)	Heart rate, heart rate variability, skin temperatures, respiration rate, perceived exertion monitoring, mental effort	PPG and GSR
	Maman et al. (2017)	Heart rate, accelerations and inclination angles, movement variability, movement durations and repetitions	ECG/EKG and IMU
	Jebelli et al. (2018)	Electrodermal, skin temperature, photoplethysmogram, brain waves	EDA, PPG, and EEG
	Hwang et al. (2018)	Photoplethysmogram, skin temperature, brain waves	PPG, GSR, EEG
Heat stress	Yi and Chan (2017)	Heart rate, skin temperature	ECG/EKG, EDA
	Ojha et al. (2020)	Heart rate, electrodermal activity, electrodermal response, skin temperature	PPG, EDA
Mental and physical stress	Arpaia et al. (2020)	Cortisol concentration in blood or saliva, galvanic skin response, heart rate, brain activity	GSR, ECG/EKG
	Alberdi et al. (2016)	Heart rate, blood pressure, respiration rate, galvanic skin response, electrocardiogram	PPG, GSR, ECG/EKG
	Jung and Yoon (2017)	Blood pressure, respiration rate, galvanic skin response	PPG, GSR
	Lee et al. (2017)	heart rate variability, galvanic skin response, electrocardiogram	ECG/EKG, GSR
	Khowaja et al. (2020)	Galvanic skin response, heart rate variability	PPG, GSR
	Jebelli et al. (2019)	Electroencephalogram	EEG
Emotion	Al Jassmi et al. (2019)	Heart rate, galvanic skin response, electrocardiogram, skin temperature, respiration pattern	ECG/EKG, GSR
	Liu et al. (2016)	Electroencephalography, blood volume pressure, electromyogram	EEG, EMG
Cognitive load	Chen et al. (2016)	Electroencephalography	EEG
	Wang et al. (2017)	Brain waves	ECG/EKG, PPG
Situational awareness	Choi et al. (2019)	Electrodermal activity, heart rate, skin temperature	EDA, PPG

Sensor-based Framework Development. The proposed empirical framework is designed to investigate human neurological mechanisms, physiological responses (e.g., emotions, fatigue, cognitive load), and biological responses (e.g., brainwaves, heart rate, skin temperature) that govern the subjective factors affecting construction labor productivity by using a multi-sensor system in a laboratory setting. The collected sensory signals are then translated into the subjective factors to use in new data-driven predictive and simulation models for construction labor productivity. The framework involves five steps: (1) baseline setting, (2) data collection, (3) data sampling, (4) data analysis, and (5) predictive and simulation modeling, as shown in Figure 1.

Feedback from the cross-validation step will provide any necessary adjustments to the first and second steps.

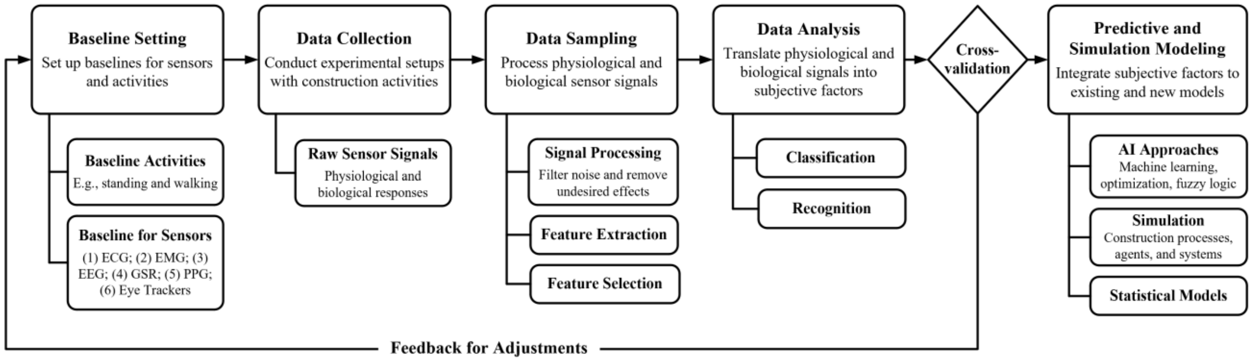

Figure 1. Sensor-based empirical framework for measuring subjective factors affecting construction labor productivity

First, baseline settings are established with (a) a series of baseline activities (e.g., standing, walking, lifting lightweight objects) and (b) a baseline for each sensor used in each baseline activity. This step prepares a baseline for comparison with any changes in a worker's physiological and biological responses between at-rest or basic-level activity (i.e., light-intensity activities of daily life) and working conditions. Outcomes of this step include a set of sensor signal constructs for several baseline activities that is then used as a yardstick to compare with any changes that occur in the signals during working activities. For example, the level of physical fatigue of a worker at rest before installing drywall can be measured using ECG, EEG, and PPG sensor signals and used as a baseline to compare with the same kinds of measurements made when the worker is installing drywall. Six types of sensors commonly used in the construction labor productivity domain, including (1) ECG; (2) EMG; (3) EEG; (4) GSR; (5) PPG; and (6) eye trackers, will be used in a series of lab experiments in this study. This multisensory system can help establish baselines for various states of construction workers during work-related activities set up in subsequent lab experiments. Using multiple sensors enables the collected physiological and biological signal data to be triangulated and facilitates better and more comprehensive measurement of specific subjective factors (e.g., motivation, stress, fatigue, cognitive load, physical ability).

Second, human physiological and biological response data in terms of sensor signals during certain construction activities will be collected via a series of experimental setups for comparing with the baseline established in the first step. These responses can be detected using single sensors and/or a multi-sensor system (i.e., a combination of multiple sensors that have interchangeable measurement features). Experimental setups mimicking real-world construction activities will be simulated in a lab environment, where data will be collected from the sensors connected to human subjects, consisting of researchers and actual construction workers. The setup of relative measurements will be incorporated along with randomized control experiments, which will be developed in order to discern any change when a new intervention is introduced. For example, a control experiment can be developed to measure changes in heart rate and blood pressure of a testing human subject when they are mimicking one activity and are interrupted by having to do another activity. The raw sensor signals are sampled and processed in the next step.

Third, data sampling includes signal processing to filter noise and remove undesired effects (i.e., any variations in the recorded sensor signals that does not originate from the signal source of interests) for all relevant physiological and biological sensor signals. Desired signals are processed with feature extraction in terms of time and frequency domains. The time domain includes a set of features, such as mean, median, and standard deviation, while the frequency domain includes a set of peak data in collected sensors' signals. Then, feature selection is conducted to reduce the dimension of the signal data and derive the physiological and biological signals. The product of this step is a set of physiological and biological signals used for subsequent data analysis.

Fourth, data analysis includes classifying and translating the physiological and biological signals (e.g., brainwaves, heart rate, skin temperature) into the subjective factors (e.g., fatigue, stress, cognitive load) affecting construction labor productivity. This translation utilizes AI-based classification techniques including support vector machines and clustering. For example, heart rate and blood pressure signals can be extracted to infer the subject's levels of physical demand (Arpaia et al. 2020). Brainwaves, skin temperature, and heart rate signals can be used to infer the subject's levels of fatigue (Aryal et al. 2017). The levels of mental stress and cognitive load can be studied by using brainwave and heart rate signals (Alberdi et al. 2016). Cross-validation techniques are used to demonstrate how well the collected physiological and biological signals are classified and translated as indications of subjective factors to be used in predictive and simulation models. Validation results provide feedback to inform any necessary adjustments to the experimental setups. Any negative classification results (i.e., signals that do not belong to the group representing the subjective factor) help with further modification of randomized control experiments, activities, and interventions set up to produce and record the physiological and biological signals.

Finally, subjective factors derived from the classification step replace those produced by indirect measures (e.g., survey questionnaires and interviews) and add new subjective factors (e.g., improvisation) to existing predictive and simulation models in labor productivity applications.

Outcomes and Discussion of the Sensor-based Framework. The use of a combination of kinematic and physiological sensors in advanced construction labs around the world is still novel and limited in the number of available sensors for specific research purposes. The results of the proposed framework can benefit a wide range of AI (e.g., machine learning, optimization, fuzzy logic), simulation (of construction processes, agents, and systems), and statistical (e.g., analysis of variance [ANOVA] and regression) models in the productivity literature, as shown in Table 2.

Subjective factors that are directly measured using sensors can be used to replace those that are measured using indirect means (e.g., surveys, observations) or secondary data (e.g., online libraries, internet searches, databases). In addition, new subjective factors, such as improvisation, feeling of safety, and proactive work behaviors, can be added to extend the knowledge base of factors currently considered in existing models and to complement other modeling efforts in using fuzzy machine learning and hybrid techniques to predict labor productivity. For instance, current literature shows no evidence of directly measuring motivation of workers, which is one of the most difficult factors to measure, yet it is one of the most significant factors affecting construction productivity (Gerami Seresht and Fayek 2018). Motivation is a function of numerous variables that are difficult to directly measure and highly variable in individuals (Raoufi and Fayek 2018). The motivation of workers can be derived using a combination of some subjective factors/variables measured using sensors (e.g., factors that either represent or affect motivation). The proposed sensor-based framework utilizes a multi-sensor system, which will enable the collected physiological and biological signal data to be triangulated and facilitate better and more comprehensive measurement of challenging subjective factors like motivation. For example, usingthe framework proposed here, the subjectively measured crew motivation factors (e.g., efficacy, commitment/engagement, identification, cohesion) in the fuzzy system dynamics model for labor productivity presented by Gerami Seresht and Fayek (2018) will be measured directly using sensors. New predictive and simulation models will be developed using directly measured subjective factors as considered in future work.

Table 2. Selected predictive and simulation models for construction labor productivity

Author(s)/year	Model	Measurement method	Existing subjective factors
Artificial intelligence techniques (i.e., machine learning, optimization, and fuzzy logic)			
Jebelli et al. (2019)	Gaussian kernel support vector Machine	Physiological sensory data	Workers' physical-demand levels
Gerami Seresht and Fayek (2018)	Fuzzy system dynamics	Survey questionnaires	Crew motivation, site restrictions, soil moisture, material quality, material preinstallation requirements
Jebelli et al. (2018)	Online multi-task learning algorithms	Physiological sensory data	Workers' stress patterns
Tsehayae and Fayek (2016)	Context-specific fuzzy inference system	Survey questionnaires	Craftsperson motivation, team spirit of crew, treatment of foremen by superintendent and project manager, craftsperson trust in foreman, level of interruption and disruption
Simulations of Construction Processes, Agents, and Systems			
Kedir et al. (2020)	Fuzzy agent-based multicriteria decision-making model	Field data (i.e., interview surveys, observations, project documents, external databases)	Susceptibility, zealot percentage, noninteractive motivation variability, initial motivation states of crews.
Raoufi and Fayek, (2020)	Fuzzy Monte Carlo agent-based simulation	Field data (i.e., interviews, observations, project documents, external databases)	Crew motivational factors, situational/ contextual factors, crew performance metrics
Raoufi and Fayek (2018)	Fuzzy agent-based simulation	Survey questionnaires	Motivation, visibility of outcome of task design, communication, working relationship, building trust
Gerami Seresht and Fayek (2018)	Fuzzy system dynamics	Survey questionnaires	Crew motivation, site restrictions, soil moisture, material quality, material preinstallation requirements
Statistical Models			
Choi et al. (2019)	Hierarchical linear modeling	Physiological sensory data	Workers' perceived risk, electrodermal response
Sun et al. (2020)	Spearman correlation	Movement sensory data	Workers' safety behavior (i.e., individuals' gait adaptations, personality traits)
Ryu et al. (2020)	ANOVA	Accelerometer, gyroscope, magnetometer sensory data	Body loads, work experience, work methods, productivity of masons
Hamzeh et al. (2018)	ANOVA and Kruskal–Wallis H test	Survey data	Antecedents, behaviors, consequences of improvisation

CONCLUSIONS AND FUTURE WORK

This study proposes an empirical framework using a multi-sensor system to bridge the existing research gaps regarding how to simultaneously measure multiple subjective factors and integrate these data into existing or new models that previously used indirect measures for such factors. The proposed framework is designed to collect and translate human physiological and biological responses into subjective factors that affect labor productivity via a series of lab experiments using multiple sensors. The directly measured subjective factors will be integrated into existing and new predictive and simulation models to complement the efforts in measuring construction labor productivity. This study is in line with previous research in construction productivity applications in recognizing the effectiveness of using sensors in collecting and measuring subjective factors that affect labor productivity. The findings of this study are expected to help project managers better control construction planning practices by directly measuring the subjective factors (e.g., motivation, fatigue, stress) that affect construction productivity.

The study makes several contributions. First, the proposed sensor-based empirical framework improves researchers' ability to more objectively, effectively, and accurately measure subjective factors (e.g., stress, motivation, fatigue) that have previously only been measured subjectively or using indirect measures. The result is achieved by utilizing various sources of evidence from a multi-sensor system to triangulate sensing signal data and directly derive these factors. Accordingly, the outcomes of this study provide a holistic approach that will augment existing modeling efforts, including AI, simulation, and statistical models, and other sensor-based research for construction labor productivity applications around the world. Second, the proposed sensor-based framework assists construction practitioners in identifying several methods to improve their productivity, advise planning practices, and better workplaces by deepening understanding of how these factors impact workers on a neurological level. For instance, construction activities with a high potential for stress and fatigue can be identified and adjusted, resulting in higher productivity as well as increased well-being of workers.

Future work goals are to develop a longer-term study, including new data-driven predictive and simulation models for construction labor productivity applications that incorporate subjective factors measured using the proposed framework for driving strategic management decision-making. The proposed framework will be validated with empirical data, consisting of physiological and biological signals collected following a series of developed lab experiments. Several AI (e.g., machine learning, optimization, fuzzy logic, hybrid fuzzy techniques), simulation, and statistical modeling approaches will be considered. For example, support vector machines can derive subjective factors from raw sensor signals by identifying the boundary line that separates two or more groupings of signals. Fuzzy cluster analysis and pattern recognition can be used to partition sensor signals into meaningful clusters and then develop an inference system to recognize the patterns of the sensor signals and ultimately derive relevant subjective factors. Properly exploiting outcomes from predictive modeling and dynamic simulation approaches using a multi-sensor system will help construction practitioners develop more adequate productivity improvement strategies and inform strategic management decision making for construction activities.

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