Partial Personalization for Worker-robot Trust Prediction in the Future Construction Environment

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Abstract

Establishing proper trust between human workers and robots is crucial for ensuring safe and effective human-robot interaction in various industries, including construction. An accurate trust prediction facilitates timely feedback and interventions, helping workers calibrate their trust levels. While machine-learning modeling personalization (i.e., tailoring models to individual characteristics) has garnered attention in the literature, the conventional approach of developing a personalized model for each individual is impractical in labor-intensive industries like construction. Such an approach compromises efficiency and leads to an accuracy-efficiency tradeoff. To address this gap, this study aims to investigate the tradeoff inherent in model personalization and identify a cost-effective solution to enhance trust prediction accuracy without compromising efficiency. The results suggested that a partial model personalization method can effectively balance this tradeoff. Moreover, the proposed feature-based partial personalization approach enables a cost-effective trust prediction model development for the construction industry, demonstrating its broader applicability to other worker-related predictions in other settings. This study provides insights into the strategies to improve trust prediction accuracy while maintaining the efficiency of model development by considering the distinctiveness of the future construction industry.

Keywords –

Worker-robot trust; future construction; feature-based partial personalization; psychophysiology.

1 Introduction

As robots become more prevalent in the construction industry to improve automation in construction, how workers build their trust in robots during the interaction has drawn increasing interest [1]. Trust has been identified as an essential element in any successful relationship, and its importance should be further highlighted in such dynamic and hazard-rich workplaces as construction sites to ensure occupational safety [2–6]. Because robots' perfect performance cannot be guaranteed to date in construction, an appropriate level of trust (neither excessive nor inadequate) represents a prerequisite to a secure and effective worker-robot interaction. Trust has been discerned as a dynamic concept where workers continuously update their trust levels based on human-related (e.g., gender), robot-related (e.g., transparency), and workplace-related factors (e.g., time pressure) [4,7]. To understand varying human trust and acknowledge the implicit nature of trust, there has been a growing interest in using real-time psychophysiological responses rather than self-report subjective measures [8].

The literature has identified the latent safety issue in the construction domain accompanied by workers' inappropriate trust levels in robots [9,10]. For example, in the study investigating workers' situational awareness of robots, Chang and his colleagues found that scheduling pressure in construction projects provoked workers' overtrust in a faulty robot, leading to their ignorance of the robot as a dynamic hazard [2]. To address the trust dynamics and the challenges of appropriate trust-building on the job site, a recent review study suggested developing trust prediction models trained by psychophysiological responses to better monitor and understand workers' real-time trust in robots [4]. Such predictive models are envisioned to facilitate early feedback and interventions to reduce accidents and enhance the safety of worker-robot interactions.

Given the pivotal role of prediction accuracy, researchers have deployed various techniques across domains, e.g., data augmentation (i.e., increase the diversity of a training dataset) [11], ensemble methods (i.e., combining the predictions of multiple individual models) [12], and personalization (i.e., tailor a model to individual characteristics) [13]. Personalization, aiming to tailor the predictive model to the specific preferences, characteristics, or behavior of an individual user, has been prevailingly deployed in sensor-based human activity recognition [13]. Considering worker variability in construction, personalizing a trust prediction model for individuals holds the potential to enhance accuracy. However, discussions in the literature also highlight several efficiency and privacy-related concerns associated with model personalization [14,15]. These tradeoffs might potentially impede the acceptance and deployment of personalized models. There is a paucity of research regarding the accuracy-efficiency tradeoff associated with model personalization, especially within labor-intensive sectors like construction. Given the criticality of trust in worker-robot interaction, this study aims to (1) explore the trust prediction model personalization in the future construction industry and (2) provide insights into cost-effective personalization strategies for worker-robot trust.

2 Background

2.1 The Review on Human-robot Trust Prediction

As robots become seamlessly integrated with workplaces across industries, the understanding and prediction of human trust have created considerable value for ensuring the efficiency and safety of human-robot interaction. In the existing literature, the fusion of machine learning (ML) with psychophysiological measurements has emerged as a powerful tool for trust prediction [16–19]. For example, Ayoub and his colleagues designed a simulation task where participants needed to drive an autonomous vehicle in a simulator while collecting their heart rate, eye-tracking, and galvanic skin response (GSR) during the experiment [16]. Multiple ML models (e.g., Decision Tree and Naïve Bayesian) were trained with the collected data to predict their trust levels in the vehicle. In the study investigating users' trust in an AI assistant, the authors developed a predictive model using an electroencephalography (EEG) sensor [18] The proposed models in the literature have attained over 70% accuracy of trust prediction in a static setting where the participants did not necessarily exhibit physical movements. However, when dealing with dynamic and physically demanding work environments, the inherent challenge arises characterized by inevitable worker movements. These movements may inadvertently introduce motion artifacts and signal noises to psychophysiological data in such dynamic and physically demanding work environments, thereby impacting prediction accuracy. To tackle this challenge, recent research has implemented trust prediction strategies by (i) leveraging deep learning (DL) techniques, (ii) incorporating diverse types of psychophysiological responses as training datasets, and (iii) employing DL auto-encoders to automatically extract important features and remove noises from the raw data [20]. The results showed an accuracy level comparable to what the existing literature attains in static environments. Model personalization may hold significant potential in tailoring models to individuals' specific demands to further enhance the current prediction performance [21].

2.2 Model Personalization

Model personalization refers to customizing models to individual preferences, characteristics, or behaviors [22]. However, the conventional model takes a generalized approach to train a one-size-fits-all model for all individuals. The personalization approach primarily aims to improve the model's performance by considering each user's unique features and patterns, thereby providing more accurate predictions. While model personalization has been advocated as an effective strategy for enhancing accuracy, previous studies have underscored latent privacy and efficiency issues associated with this approach [14,16]. For instance, in the study examining the relationship between personalization and privacy, the findings indicated that personalized model creation would trigger users' privacy concerns [15]. Moreover, there is an intuitive inference that the development of personalized models requires a significant investment of time and computational resources [17]. Notably, the construction industry presents a unique challenge because of the substantial workforce and frequent changes. This characteristic of the construction industry might lead to the inefficiency of personalizing models for individual workers. To address the accuracy-efficiency tradeoff in model personalization, researchers have proposed "partial model personalization" as a potential solution [14]. Partial personalization uses specific features (e.g., layers and parameters) for individuals to develop a tailored model for a particular group [23,24]. In the construction context, workers can be categorized into groups based on their specific features, accommodating the variability among workers, and alleviating the demands of training personalized models. Therefore, the partial model personalization facilitates achieving a balanced tradeoff between accuracy and efficiency in construction. In summary, this research strives to investigate an effective model personalization strategy for optimizing trust prediction in future construction.

3 Methodology

3.1 Experimental Design and Procedure

This study developed a human-robot collaborative bricklaying experiment in which workers must complete the bricklaying tasks with a bricklaying co-bot (i.e., MULE) and different types of drones. While MULE was designed to automatically lift and drop heavy concrete blocks for workers, human interventions were still needed (i.e., applying mortar and moving MULE to correct positions). Moreover, drones assisted with (i) monitoring the environment for safety, (ii) delivering new materials to workers in an elevated platform for efficiency, and (iii) inspecting workers' behaviors to examine work progress.

This study designed two modules to manipulate workers' trust levels in drones: (i) Baseline and (ii) Error modules. The Baseline module refers to the scenario where all types of drones exhibit error-free performance. On the contrary, the Error module includes various drone-related system failures and errors (e.g., workers were struck by drones) to assess how the workers' trust in drones might change. Noteworthy, workers might decrease their trust in the Baseline module due to personal preferences even though the drones performed flawlessly. Similarly, workers might increase their trust in the Error module because they did not identify or perceive the drone failures as not risky [8].

Participants were presented with an introduction to the experiment and the functionalities of the bricklaying co-bot and drones. Training was provided to familiarize participants with the designated bricklaying task. Participants were equipped with a HTC VIVE headset, two controllers, three motion trackers, and psychophysiological wearable sensors (e.g., a Functional Near-Infrared Spectroscopy (fNIRS) and Empatica E4 wristband) and were asked to finish the Baseline and Error modules. Furthermore, A widely used 5-point Likert-scale trust questionnaire [25] was administered to collect their self-report trust levels in drones before and after each module, denoted by t_i (*initial trust before the Baseline module*), t_b (*trust after completing the Baseline module*), and t_t (*trust after completing the Error module*). All the procedures were approved by the Purdue Institutional Review Board (IRB). Figure 1 illustrates the experimental design and procedure of this study.

3.2 Participants

Eighty-nine participants (60 males and 29 females) were recruited to participate in this experiment. All the participants were from the departments of Civil Engineering and Construction Engineering and Management majors at Purdue University, representing the next generation of the workforce. The age range of participants was between 19 and 36 years (M= 22.54, STD= 3.32), with 64% of them having more than one year of experience in the construction industry.

3.3 Apparatus

The selected VR device was the HTC Vive Pro Eye

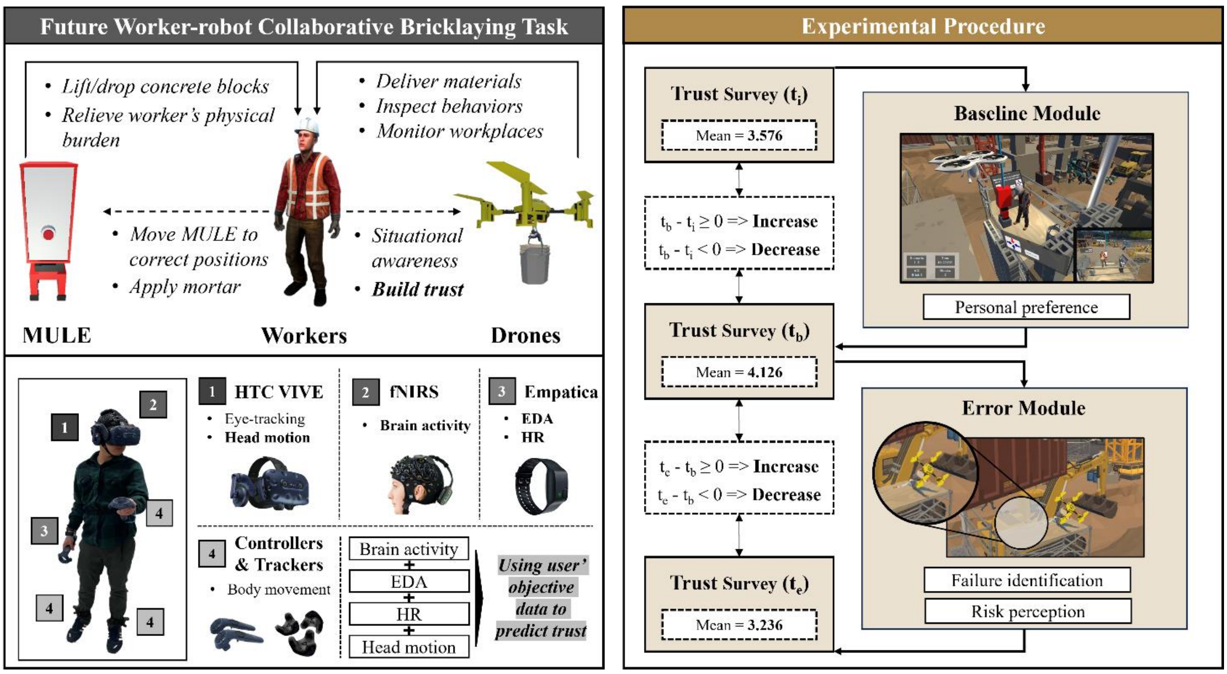

Figure 1. The experimental design and procedure of the bricklaying task.

with a refresh rate of 90 Hz and a field of view of 110o (manufactured by HTC Corporation, Taoyuan, Taiwan). The experiment was run on an Alienware PC with an AMD Ryzen 9 5950X 16-Core processor and an NVIDIA GeForce RTX 3090 graphics card. To capture participants' psychophysiological responses, (i) Empatica E4 wristband (manufactured by Empatica, Boston, United States) was to collect electrodermal activity (EDA) with a sampling frequency of 64 Hz and heart rate (HR) with a sampling frequency of 1 Hz and (ii) fNIRS (Brite 23, Artinis, Netherlands) was used to collect brain activation and cognitive processing with a sampling frequency of 10 Hz.

3.4 Data Collection and Pre-Processing

Various types of objective data were collected from participants during the experiment and used to train a trust prediction model. The data included (i) fNIRS, (ii) EDA, (iii) HR, and (iv) head motion captured by the headset. Due to the heterogeneous data sources, pre-processing approaches were used to ensure consistent sampling frequencies and compliance with model training requirements. Specifically, raw fNIRS signals were processed by Homer3 packages to output the hemodynamic response function (HRF). Then, the HRF data was divided into segments by considering a 10-second time window due to sequential dependencies and hemodynamic delayed activation [26,27]. Each 10s segment was converted into a 2D image because this transformation offers an enhanced representation of the high spatial resolution in fNIRS data. Furthermore, this study conducted max-min normalization, re-sampling, and 10s time-window segmentation for the EDA, HR, and head motion data. Figure 2 presents a schematic overview of the pre-processing in this study.

Participants were requested to subjectively report their trust levels in drones three times (i.e., $t_{i\text{-}Mean}$: 3.576; $t_{b\text{-}Mean}$: 4.126; $t_{e\text{-}Mean}$: 3.236). While the data indicated the trust increased during the Baseline module and decreased during the Error module, this labeling method would not consider the variance among participants (e.g., some participants decreased their trust in Baseline module). As highlighted above, the drone system failures did not necessarily lower human trust, and its perfection did not guarantee increased trust. To address this issue, this study deployed customized labeling for each individual (i.e., the module in which each participant increased their trust was labeled as "increase" and the same logic for the "decrease"), as shown in Figure 1.

3.5 Model Development

The model development comprises two phases (Figure 2): (i) feature extraction and (ii) trust prediction. Compared to the traditional approach of manual feature extraction, this study considered automated extraction by applying the autoencoder (AE) technique. This technique has been proven to effectively reduce the dimension of the data with high representativeness of the extracted features. Due to the dissimilarity between the image (i.e., fNIRS) and time series (i.e., EDA, HR, and head motion) data, two types of AEs were implemented in this study. Specifically, convolution neural network (CNN)-based AE was developed for the fNIRS data, while the essential features of time-series data were extracted by long short-term memory (LSTM)-based AEs. All extracted features were then aggregated as the final trust prediction model input, which is a CNN model, to predict whether workers increase or decrease participants' trust during the interaction with robots in the future construction environment. Due to the page limit here, the details of the model structures and parameters were discussed in [20], and the personalization results and discussions are covered in this paper.

3.6 Partial Model Personalization

Multiple trust prediction models were developed for different groups of participants to investigate the performance of partial model personalization. Unlike full personalization, where an individual model is trained with one participant's data, this study employed a randomized grouping approach to achieve partial model personalization. The randomization process was repeated ten times, which refers to 10-fold cross-validation, to mitigate the potential bias introduced by the one-time randomized grouping. Each repetition involved the random distribution of participants into groups of 1 (generalization model), 2, 4, 8, and 16. Subsequently,

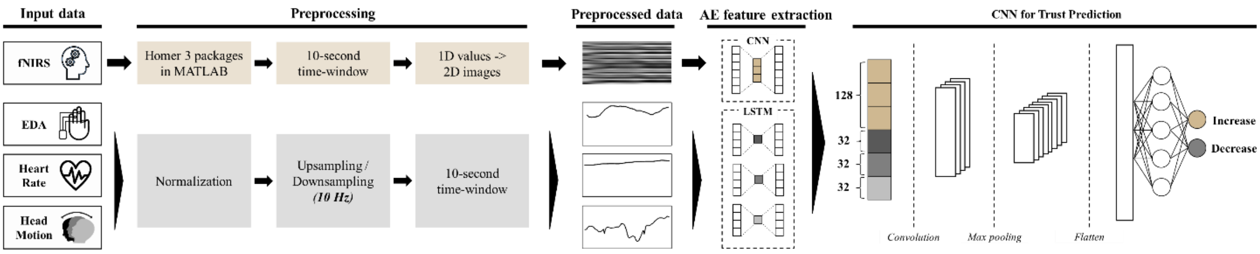

Figure 2. A schematic overview of the data preprocessing approaches and model development.

models were independently trained for each group within each repetition. The results were then averaged across the ten replications to provide a more robust and unbiased assessment of the model's performance. Lastly, the accuracy and efficiency values were normalized between 0 and 1 to examine the balance within the accuracy-efficiency tradeoff.

4 Results

Table 1 shows the average accuracy, training time, and efficiency of models across different levels of personalization. The accuracy of training and testing data from the generalized trust prediction model (i.e., only training one generalized model with no personalization) indicated 79.3% and 71.8%, respectively. As can be seen in Table 1, the testing accuracy increased as participants were divided into more groups *(#1*: 71.8%; *#2*: 71.3%; *#4*: 72.7%; *#8*: 77.1%; *#16*: 77.5%). However, higher level of personalization led to an increase in training time (*(#1*: 183.57s; *#2*: 181.67s; *#4*: 185.89s; *#8*: 192.26s; *#16*: 216.40s) and a decrease in efficiency (*#1*: 5.44e-3; *#2*: 5.50e-3; *#4*: 5.38e-3; *#8*: 5.20e-3; *#16*: 4.62e-3). These results demonstrate a trade-off between accuracy and efficiency within model personalization.

Table 1 Overview of the changes in accuracy and efficiency in partial model personalization.

# of groups	Testing accuracy	Training time	Efficiency (1/time)
1	71.8%	183.57s	5.44e-3
2	71.3%	181.67s	5.50e-3
4	72.7%	185.89s	5.38e-3
8	77.1%	192.26s	5.20e-3
16	77.5%	216.40s	4.62e-3

Figure 3 provides a visual representation of changes in the accuracy and efficiency variations based on a normalized scale. The two lines intersect approximately when the participants were divided into seven groups. These findings suggest an intermediate level of model personalization to better balance the model's accuracy and efficiency.

5 Discussion

An accurate understanding and prediction of workers' trust are paramount for ensuring the safety of human-robot interaction in such dynamic and hazardous workplaces as construction environments [28]. Although an acceptable prediction accuracy has been achieved by combining varied sources of workers' objective data and employing the AE technique, the various individual characteristics of workers present an opportunity for further enhancement, particularly through the integration

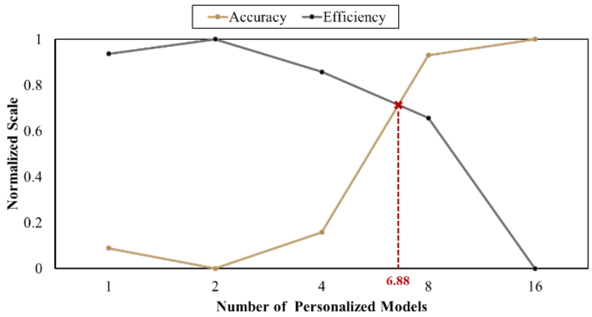

Figure 3. A graphical representation of the trade-off between model accuracy and efficiency.

of model personalization. The results of this study align with the construction literature, suggesting the effectiveness of model personalization to improve accuracy. For example, in the analysis focusing on cognitive load classification using fNIRS responses, Zhu and his colleagues found that the fully personalized models outperformed the generalized model [21]. However, the previous literature has not extensively addressed the efficiency issue, which is presumed to be very critical in the construction industry. This suggests an avenue for research in this paper to explore the efficiency implications of model personalization in the construction context.

The findings showed a decline in efficiency accompanied by a higher degree of personalization, which poses challenges in a labor-intensive industry where tasks require the presence of many workers on jobsites. Even though model personalization enhances trust prediction accuracy, full model personalization is impractical due to the complexity and time-consuming nature of training a personalized model for each worker, coupled with the dynamic crew-based nature of the industry. In recent research that aimed to develop DL models to recognize construction workers' postures in manual construction tasks, Zhao and Obonyo argued that the full model personalization is infeasible and proposed an improved model (i.e., integrating one CNN layer with two LSTM layers) with high generalizability to accommodate the variation among workers [29]. However, their proposed model was limited to the posture-related data of four participants, highlighting the need for an alternative approach to tackle the accuracy-efficiency tradeoff.

According to the results of this study, the balance between accuracy and efficiency was achieved when training seven partially personalized models to accurately predict workers' trust without compromising efficiency. That is, grouping workers into a limited number of groups and training a model for each group are suggested to achieve a better balance of efficiency and accuracy. While employing a randomized grouping method to categorize workers, this study proposes using feature-based model personalization as an optimal grouping strategy to enhance cost-effectiveness. Specifically, this feature-based approach necessitates an initial grouping based on workers' unique characteristics affecting trust-building. For example, prior studies have suggested the effects of human factors on trust, such as gender [30,31], personality [32,33], experience [34,35], and self-confidence [36] which can be considered as features for grouping. Understanding how worker-related characteristics will impact their trust in robots is a prerequisite to implementing this approach. This proposed featured-based model personalization could enhance the generalizability, scalability, and inclusivity of the proposed model because new workers can be classified into one of the existing groups without allocating extra resources to train another model [37]. More importantly, this approach extends its applicability beyond trust prediction to other worker-related classifications and predictions in construction. Ultimately, human-centered construction can be established in the foreseeable future [38].

While this study offers considerable value to the body of knowledge, there are some limitations worth mentioning. First, the recruited participants in this experiment represent the next generation of the construction workforce, whereas it is worthwhile to replicate the study with the current workforce and incorporate a larger group of participants with varied backgrounds. Second, the literature has mentioned the privacy concern associated with the full level of model personalization. While this issue is assumed to be mitigated by deploying the proposed feature-based personalization approach, future research is recommended to explore the accuracy-privacy trade-off within model personalization.

6 Conclusion

While existing literature underscores the benefit of model personalization in enhancing accuracy, its inherent inefficiency poses challenges, particularly within the construction context. Therefore, this study addresses this challenge by identifying the nuanced balance within the accuracy-efficiency tradeoff of model personalization and proposing a cost-effective (i.e., achieving high accuracy without consuming excessive time by regarding time as cost) solution to predict workers' trust. The proposed feature-based partial personalization approach addresses the unique labor-intensive and crew-based nature of the construction sector. This approach suggests classifying workers into groups based on a specific influential trust feature and training partial personalized models for each group. The proposed approach ensures an accurate prediction of models while maintaining the efficiency of the training process.

This research contributes to the body of knowledge by (i) introducing the concept of partial model personalization to the construction industry, recognizing the inefficiency of full personalization, (ii) navigating the balance within the accuracy-efficiency tradeoff, and (iii) proposing a cost-effective feature-based personalization strategy for conducting trust-related and other worker-related predictions in the construction domain. This research calls for further research initiatives to refine and expand the application of cost-effective model personalization strategies to foster safer and more efficient human-robot collaborations in construction environments.

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