Impact of Robot Autonomy on Workers’ Stress: Evidence from Virtual Reality and Physiological Measures

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Abstract

With the rapid development of robotics technology, collaborative robots have been widely used in manufacturing, construction, assembly, and logistics. While collaborative robots can improve productivity and reduce worker workload, their increased autonomy may make it difficult for workers to predict their behavior, thus causing psychological stress. However, existing research still provides a limited understanding of how different autonomy gradients affect workers' physiological stress. This study employed a between-subjects experimental design, recruiting 14 participants to complete a virtual prefabricated drywall installation task under three conditions of robot autonomy: low, medium, and full. The stress levels of the workers were assessed using the skin conductance response. The results showed that as the level of autonomy increased, the cumulative rate and magnitude of workers' stress responses both significantly increased. The sustained stress level (ΔSCL) under full autonomy conditions was significantly higher than that under low and medium autonomy conditions. The overall differences among the three groups were significant ($p < 0.05$), with the medium autonomy showing a stress pattern between the two. The study revealed the dynamic characteristics of worker stress under different autonomy situations and confirmed the key influence of autonomy level on stress response. Furthermore, this study provides empirical evidence for the automated design of collaborative robots, highlighting the importance of addressing occupational mental health risks that may arise from excessive autonomy in pursuit of production efficiency.

Keywords –

Robot autonomy; Stress; Electrodermal activity; Human-robot collaboration; Virtual reality; Industrial robot

1 Introduction

Human-robot collaboration (HRC) refers to a work model in which human operators and robots share a workplace and work together to complete tasks [1]. With the rapid development of robotics technologies and strong industry demands, an increasing number of collaborative robots are deployed in manufacturing, construction, assembly and logistics. While HRC can significantly improve productivity and reduce costs, it also exposes workers to a more complex and dynamic interactive environment, raising concerns about their mental health and safety [2].

Stress is psychologically defined as the emotional and physiological reactions triggered by tension, anxiety, or uncertainty [3]. Compared to human counterparts, high-speed, high-power collaborative robots may induce tension, anxiety, and stress in workers when operating in proximity [4]. If stress remains high and is not effectively managed, it can lead to decreased attention, operational or decision-making errors, thereby increasing the risk of accidents and adversely affecting the long-term health of workers [5]. Therefore, from the perspective of occupational health and safety, it is of great significance to identify and assess changes in stress in HRC.

The existing methods for assessing stress are divided into two categories: subjective and objective. Subjective methods typically rely on self-report questionnaires, such as the Perceived Stress Scale (PSS), which are easy to use but cannot provide real-time monitoring during the task and may be affected by emotions, memory biases, or social expectancy effects [6]. In contrast, objective methods based on physiological signals can record continuous dynamic changes in stress, such as galvanic skin response (GSR), electromyography (EMG), electroencephalography (EEG), and heart rate variability (HRV). Among them, GSR is particularly sensitive to short-term changes in psychological stress, as it reflects the activity level of the sympathetic nervous system, and skin conductance increases rapidly when stress rises [7].

Compared to EEG and HRV, GSR devices are easier to wear and more tolerant of body motion artifacts, making them particularly suitable for HRC scenarios where operators move frequently. Therefore, GSR is now widely used to analyze the effects of robot physical properties such as speed, distance, approach direction, and motion trajectory on worker stress [8-9]. VR can reproduce difficult or unsafe task scenarios in the real world under safe and controllable conditions, and existing reviews and empirical studies have shown that the combination of VR and physiological signals (such as GSR) is an effective and feasible research method [10-13].

In addition to robot physical parameters, with the development of automation and intelligent decision-making systems, the level of robot autonomy (LORA) has gradually become a research focus in recent years. Autonomy refers to a robot's ability to perceive, make decisions, and perform tasks without human input, and is a key variable in HRC system design [14]. According to the classic demand-control model [15], when individuals perform tasks under conditions of high task demands but a low sense of control, their stress levels tend to increase significantly. In the HRC context, higher robot autonomy often means that workers have less direct control over the task process and robot behavior, thereby weakening their predictability and sense of control, and may trigger stronger stress or tension responses [16].

This mechanism has been preliminarily demonstrated in other areas of automation. For example, in studies on automated driving, Heikoop et al [17] found that drivers experience higher stress under partially automated driving conditions. In the HRC study, Pollak et al [18] reported that workers' heart rates increased significantly when robots were in autonomous mode. Furthermore, research by Ulfert, Antoni, and Ellwart [19] also indicates that the higher the autonomy of the agent, the greater the level of technical stress on the user. These studies collectively suggest that increased system autonomy may, at the physiological level, even enhance human stress responses.

However, compared to the physical properties of robots, research on the impact of autonomy on stress is still significantly insufficient. Existing studies typically only compare manual and automatic modes, lacking a systematic exploration of how different levels of autonomy affect worker stress. Most studies focus only on average stress levels, neglecting the dynamic patterns of physiological stress changes over time. Therefore, the mechanism by which robot autonomy affects stress has not yet been fully revealed.

Based on this background, this study aims to systematically explore the effects of three different robot autonomy levels (low, medium, and full) on workers' stress. Specific objectives include: (1) revealing the dynamic patterns and response characteristics of worker stress under different levels of autonomy; (2) clarifying whether robot autonomy is a key driver of stress changes. This study not only provides empirical data for the dynamic assessment of psychological stress in HRC but also provides a scientific basis for the autonomous design of a humanistic and adaptive HRC system.

2 Method

2.1 Experimental Design

This study employed a between-subjects experimental design, randomly assigning participants to one of three experimental groups, each corresponding to a different level of robot autonomy. In the low-autonomy condition (Group A), the participants act as operators, possessing full decision-making power, and the robot only performs operations after receiving explicit instructions. Under medium autonomy (Group B), participants act as collaborators, and the robot can independently complete some sub-tasks, but key operations still require human confirmation, with humans and robots jointly leading the task process. Under the full autonomy condition (Group C), the participants act as supervisors, the robot has full decision-making power and can complete all operations independently, and the participants are mainly responsible for monitoring and intervening when necessary.

The experimental task is based on the drywall installation process in a virtual prefabrication factory scenario. Drywall installation is one of the most common and labor-intensive operations in prefabrication plants, involving the handling of heavy objects and repetitive tasks, and is therefore considered a typical HRC application scenario. In the virtual environment, participants need to collaborate with two robots to complete the installation of six plasterboard panels on a wall. Robot A is responsible for grabbing and transporting the plasterboard panels to the designated location, while Robot B is responsible for driving in the screws to secure the plasterboard panels. The participants' operational authority and decision-making responsibility in the task varied depending on their experimental group. The experimental environment was built on Unity 2022.3.38f1, forming a highly immersive virtual prefab factory that allows participants to move freely and interact with virtual objects in real time (see Figure 1). The task flow references industry standards [20-21], including key steps such as plasterboard handling, manual drilling, and bolt fixing, and is implemented in a virtual environment.

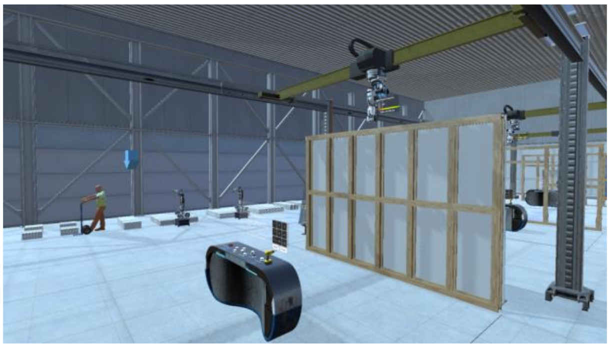

Figure 1. Overview of the immersive virtual reality scenario

To simulate real-world HRC risk scenarios, this study combines robot accident cases published by the Occupational Safety and Health Administration (OSHA) [22] with a systematic analysis of human-robot interaction (HRI) accidents by Zuo et al. [23]. Twelve dynamic hazards were embedded in the task, covering typical scenarios such as mechanical collisions, sudden energy releases, and intrusions into collaborative spaces. All hazards were kept consistent in type and triggering timing across the three sets of experiments to ensure comparability of experimental conditions.

Table 1. Dynamic hazards in the experimental scenario

ID	Hazard description
H1	Sawdust exposure from robotic cutting
H2	Tripping over ground obstacles
H3	Sparks from robot cable end
H4	Collision with Robot A
H5	Collision with the robotic arm
H6	Impact from released gypsum board
H7	Collision with autonomous mobile robot
H8	Collision with robotic drone
H9	Robot B’s end effector pressure overload
H10	Collision with automated guided vehicle
H11	Secondary robot intrusion into workspace
H12	Collision with drone carrying gypsum board

Before the formal experiment began, all participants received standardized operation and safety training to familiarize themselves with the VR device, task procedures, and potential hazards. Subsequently, the GSR device was calibrated, and one minute of resting-state GSR data was recorded as a baseline. After completing the above steps, participants entered a designated autonomous environment to conduct the formal experiment, completing the drywall installation task while continuously recording GSR signals. The entire experiment lasted approximately 15-30 minutes.

2.2 Participants

Participants were recruited through poster advertising, face-to-face recruitment, and snowball sampling, with a total of 14 healthy individuals signing up to participate in the experiment. Based on the pre-experiment background questionnaire, none of the retained participants in any autonomy group had prior experience with collaborative construction robots or drywall installation. Some participants reported broader experience with robots in real or virtual settings and/or construction-related work. These experiences were distributed across all three autonomy conditions rather than concentrated in one group. Nevertheless, given the small between-subjects sample, the potential influence of individual background differences cannot be fully excluded. During the data preprocessing stage, physiological data are screened for quality control based on data integrity and signal quality. Specifically, data were excluded only when the original GSR records could not support reliable skin conductance analysis. Exclusion criteria include: (1) prolonged signal interruption or data loss during the task; (2) persistent non-physiological oscillations consistent with unstable sensor contact or device connection problems; and (3) premature termination of the experiment due to subject discomfort, resulting in insufficient available task phase data. Under the above criteria, data from three participants were excluded. The even distribution of these exclusions under different autonomy conditions indicates that the data screening process did not systematically affect any experimental condition. It is important to emphasize that all data exclusions were based on quality control during the pretreatment phase and the completion of the experiment, rather than on the intensity of physiological responses or differences between groups. After the above screening, data from 11 participants were ultimately included for analysis. All participants had normal or adjusted-to-normal vision and no history of neurological disorders, cognitive impairment, or substance abuse. This study has been approved by the University of Canterbury Human Research Ethics Committee (HREC 2025/11/LR-PS), and all participants signed written informed consent forms before the experiment.

2.3 Apparatus

Participants wore the Meta Quest Pro Standalone VR headset to complete tasks during the experiment. The device is equipped with dual QLED displays, with a resolution of 1800x1920 pixels per eye, a refresh rate of 90Hz, and a field of view of 106° horizontally and 96° vertically. The experimental scenario runs in real time using the Unity 3D engine and is presented from a first-person perspective. GSR data were acquired using a Shimmer3R GSR+ Unit with a measurement range of 10 kΩ-4.7 MΩ (corresponding to 0.2-100 μS), an accuracy of ±10%, and a sampling rate of 248 Hz to capture subtle physiological pressure fluctuations during the task. The two electrode pads of the GSR device are worn on the inside of the index and middle fingers of the participant's non-dominant hand, respectively.

2.4 Data Analysis

The GSR signal processing was performed using the Ledalab V3.4.9 toolbox within the MATLAB R2024b environment. First, the raw signal is preprocessed, including artifact correction, filtering, and smoothing, to obtain a clean and reliable electrodermal activity (EDA) signal. Subsequently, the EDA signal was decomposed using Continuous Decomposition Analysis (CDA) implemented in Ledalab, separating it into skin conductance level (SCL) and skin conductance response (SCR). SCL represents the tonic component of skin electrical activity, reflecting the slow change in sympathetic arousal level over time, while SCR represents the phasic component related to external stimuli or task events, reflecting transient responses [24]. Existing research [25] has shown that SCL is closely related to an individual's overall arousal level and persistent cognitive and emotional stress. Compared to non-specific SCR, SCL is better suited to reflect the overall activation state of the sympathetic nervous system over a longer continuous period [26]. Due to significant individual differences in EDA data, baseline measurement methods are typically employed to minimize the influence of absolute SCL differences between individuals [27]. Therefore, this study selected the change in mean SCL relative to baseline (ΔSCL) as the main indicator for quantifying the sustained stress level during the task phase.

In terms of statistical analysis, the GSR data exhibited a non-normal distribution and heterogeneity of variance. Therefore, the Kruskal–Wallis nonparametric test was used to compare the stress levels across three autonomy conditions, followed by Dunn's post-hoc test for pairwise comparisons. Meanwhile, the Bonferroni correction was used to control the Type I error rate resulting from multiple comparisons, and the statistical significance threshold was set at $p<0.05$.

3 Results

3.1 GSR Time-Series Pattern

Figure 2 shows the group-level patterns of GSR changes over time under three robot autonomy conditions, and there are significant differences between the groups. The GSR under the low autonomy condition (Group A) changed very gradually throughout the task, remaining almost at the baseline level. This indicates that, under this condition, collaborative tasks in manual operation mode did not trigger a significant physiological stress response. Under medium autonomy conditions (Group B), GSR showed a gradual accumulation and steady increase, indicating that participants' physiological stress gradually increased as the task progressed. In stark contrast, full autonomy (Group C) exhibited the most significant physiological response. Its GSR rapidly climbed to a high level in the early stages of the task and remained thereafter, indicating that participants quickly entered a high-stress state under conditions of full autonomy.

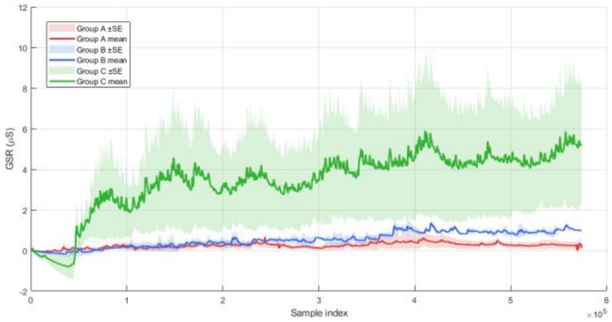

Figure 2. Group-level comparisons of GSR time series across three autonomy conditions

Furthermore, under full autonomy conditions, GSR signals fluctuate more frequently, with a significant increase in transient events with high amplitude, reflecting an enhancement of the short-term transient phasic component. In contrast, fluctuations were relatively less under low and medium autonomy conditions, and the overall signal was more stable.

3.2 ΔSCL Response

To further examine the effects of different levels of autonomy on sustained skin conductance response, statistical analysis was performed on the changes in skin conductance level (ΔSCL) in the three groups, and the results are shown in Figure 3. The mean of ΔSCL shows a consistent step-increasing pattern across the three groups. Specifically, low autonomy (Group A) was 0.293 μS, medium autonomy (Group B) rose to 0.903 μS, and complete autonomy (Group C) was significantly higher at 3.119 μS. This monotonic trend suggests that the intensity of the tonic component of the skin conductance response is closely related to the enhancement of robot autonomy, reflecting that participants' sustained stress levels are significantly higher under full autonomy conditions than under other conditions.

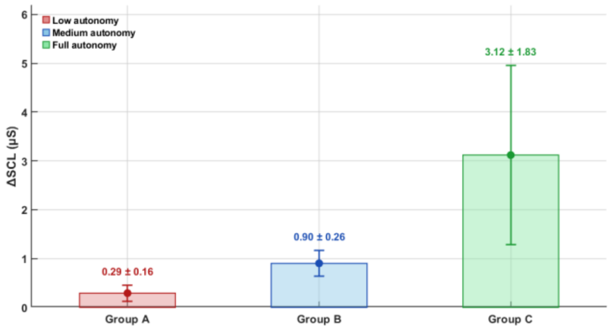

Figure 3. Statistical analysis results of ΔSCL across three autonomy conditions

It is worth noting that the standard deviation of ΔSCL in the fully autonomous group was significantly increased, and the data distribution was more dispersed, indicating that the differences in physiological responses among individuals were significantly increased. Some participants exhibited extremely high ΔSCL values under the full autonomy condition, significantly broadening the overall range, while the distribution under the low autonomy and medium autonomy conditions was more concentrated with smaller individual differences.

The Kruskal–Wallis nonparametric test results showed that the differences in ΔSCL among the three groups were statistically significant ($H=7.045$, $p = 0.0295$) with a large effect size ($\varepsilon^2 = 0.631$), indicating that stress levels differed substantially across robot autonomy conditions. Post-hoc Dunn tests showed that ΔSCL was significantly higher under the full autonomy condition (Group C) than under the low autonomy condition (Group A) ($p < 0.05$). Although the numerical trend of the medium autonomy group (Group B) was between the two groups, it did not reach a statistically significant difference compared with the high and low autonomy groups.

This result also indicates that the trend of changes in sustained physiological stress is not linearly increasing. Although the value of ΔSCL increases continuously, statistically speaking, the medium autonomy condition may constitute a "transition interval" for changes in physiological stress. Its sustained physiological response is not yet distinguishable from low autonomy conditions, but it is significantly lower than the high-stress physiological fluctuations of full autonomy conditions.

4 Discussion and Conclusion

The results of this study clearly demonstrate that the level of robot autonomy is a key factor influencing workers' physiological stress. Combining the dynamic model of GSR and the statistical analysis of ΔSCL, as autonomy gradually increases from low to high, workers' stress response not only increases significantly in magnitude, but also exhibits a faster cumulative rate and a stronger sustained physiological response.

The working environments of construction and prefabrication plants are inherently highly complex and uncertain, while industrial robots typically possess strength and speed far exceeding those of humans. However, with current technology, collaborative robots still cannot reach the level of human companions in terms of perception, judgment, and communication abilities. When robots complete complex tasks independently under full autonomy conditions, workers experience a significant decrease in the unpredictability and sense of control over their behavior. This "low sense of control" and "unpredictable behavior" often weakens the trust between humans and robots, thereby triggering stronger physiological stress responses. The results of this study confirm this. Under full autonomy conditions, workers' GSR signals rise rapidly at the beginning of the task and remain at a high level throughout the task phase, reflecting a sustained state of high stress.

In contrast, the medium autonomy condition provides a more balanced model for HRC. Under this condition, workers retain decision-making power over critical operations (especially steps involving design safety risks), while robots undertake some repetitive or highly predictable subtasks. This "shared control" model not only maintains workers' trust but also avoids the psychological discomfort and stress associated with complete autonomy. The experimental results show that the stress under medium autonomy conditions increases gradually, but the overall level is moderate and does not significantly burden the workers' continuous stress. Moderate stress can also promote concentration and task engagement. Therefore, "medium autonomy" may be the optimal balance between efficiency, safety, and occupational health for future HRC systems.

The main contributions of this study are reflected in two aspects. First, it reveals the dynamic changes in worker stress under different autonomy situations, confirms the decisive role of autonomy level in stress changes, and makes up for the shortcomings of previous studies in these aspects. Second, it provides empirical reference for the automated design of collaborative robots, emphasizing that while pursuing high efficiency, we should avoid the occupational psychological risks brought about by excessive autonomy.

Nevertheless, this study still has certain limitations. First, since the outcome variables of this study are task-level SCL and its variation (ΔSCL), the current analysis cannot distinguish the independent effects of different hazard categories or robot-specific hazards on workers' physiological responses. Nevertheless, this study standardized the control of all types of hazards and their triggering times under different autonomy conditions, thereby ensuring the consistency of hazard exposure in inter-group comparisons and making the observed differences mainly reflect the influence of the robot's autonomy level. Future research could introduce event-locked physiological indicators (such as SCR) and combine them with time-stamping of each hazardous event to conduct a more refined analysis of the instantaneous physiological responses triggered by different types of hazards. Second, a relatively small sample size may limit statistical power and reduce the robustness of the results. Furthermore, although no systematic bias was observed in participants' experience with robotics and their architectural backgrounds across different autonomy groups, the limited sample size between groups still made it impossible to completely rule out the potential confounding effects of individual background differences. Therefore, future research should expand the sample size and combine stratified allocation or covariate-based statistical analysis methods to more effectively control for individual differences, thereby improving the reliability and generalizability of research conclusions. Finally, this study was conducted in a VR environment. Although VR technology can simulate physical scenes and collaborative processes, its immersion, sensory load, and novelty may still affect the physiological arousal of participants, thus introducing potential confounding effects [28-29]. Although this study controlled these factors by standardizing VR devices, experimental environments, and task processes, the related effects could not be eliminated. Therefore, the results of this study should be understood as the relative physiological differences corresponding to different levels of robot autonomy in a constant VR human-robot collaborative environment, rather than the absolute effects completely detached from the experimental environment. Furthermore, VR environments may still differ from real HRC scenarios in terms of immersion, risk perception, and bodily feedback, thus affecting the external validity of the research results. Future research could validate the findings in real-world scenarios and incorporate quantitative measurements of VR-related experiences (such as immersion or discomfort) to further enhance the robustness and external validity of the research conclusions.

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