

Towards Human-Centric Smart Manufacturing: A Digital Twin Enabled Affective Ergonomic Framework For Adaptive Human Robot Collaboration

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Abstract

The advent of Industry 4.0 has ushered in an era of Smart Manufacturing, where Human-Robot Collaboration (HRC) is pivotal for enhancing productivity and flexibility. However, existing HRC paradigms often overlook the dynamic internal states of human operators, focusing primarily on task efficiency and physical safety. This oversight can lead to suboptimal performance, increased stress, ergonomic risks, and reduced job satisfaction. This paper proposes a novel Digital Twin (DT) enabled Affective-Ergonomic Framework designed to foster truly human-centric adaptive HRC. Our framework integrates real-time multi-modal sensing to continuously monitor human operators' affective (e.g., stress, fatigue) and ergonomic (e.g., posture, physical load) states. These data feed into a sophisticated Human Digital Twin (HDT), which leverages machine learning models to infer and predict human states. An adaptive decision-making engine then utilizes this HDT data, alongside Robot and Environment Digital Twins, to dynamically adjust robot behavior (e.g., speed, task allocation, assistance level) in real-time. We present the architectural design, illustrative mathematical models for state inference, and a conceptual case study demonstrating the framework's potential to significantly improve human well-being, mitigate ergonomic risks, enhance safety, and ultimately boost overall system performance in smart manufacturing environments. This approach paves the way for intelligent HRC systems that proactively respond to human needs,

Keywords: Human-Robot Collaboration, Digital Twin, Affective Computing, Ergonomics, Smart Manufacturing, Adaptive Control, Human-Centric AI.

1. Introduction

The fourth industrial revolution, or Industry 4.0, is transforming manufacturing landscapes worldwide, characterized by cyber-physical systems, the Internet of Things (IoT), and advanced analytics. A cornerstone of this transformation is the increasing prevalence of Human-Robot Collaboration (HRC), where humans and robots share a common workspace and cooperate on tasks. Unlike traditional automation, HRC aims to leverage the strengths of both human (flexibility, problem-solving, cognitive abilities) and robotic (precision, strength, endurance, repeatability) agents, promising enhanced productivity, improved product quality, and greater operational flexibility. However, the realization of HRC's full potential is intrinsically linked to its ability to be truly "human-centric." While significant advancements have been made in ensuring physical safety through collaborative robot design and safety standards (e.g., ISO/TS 15066), current HRC systems often treat human operators as static entities or focus solely on their physical presence. They largely neglect the dynamic and complex internal states of humans, including their cognitive load, emotional well-being (affective state), and

physical comfort (ergonomic state). Ignoring these crucial human factors can lead to a range of detrimental outcomes: increased stress and fatigue, higher risk of musculoskeletal disorders, reduced job satisfaction, and ultimately, suboptimal HRC performance and even safety incidents.

The fundamental problem addressed in this paper is the lack of a comprehensive, real-time, and adaptive framework for HRC that proactively considers and responds to the evolving affective and ergonomic states of human operators. Current HRC systems suffer from several limitations: **Static Human Models:** Most systems assume a constant human capability and state, failing to account for variations due to fatigue, stress, or discomfort throughout a work shift or across different tasks. **Reactive Safety:** Safety measures are often reactive (e.g., stopping upon collision) or based on pre-defined zones, rather than proactive adjustments based on human vulnerability or cognitive state. **Fragmented Human Factor Integration:** Affective computing and ergonomic assessment are often studied in isolation or applied post-hoc, without real-time integration into the HRC control loop. **Suboptimal Collaboration:** Without awareness of the human's internal state, robots cannot optimally adapt their behavior, leading to situations where the robot might exacerbate human discomfort, increase stress, or reduce efficiency, thereby undermining the very benefits of collaboration. Therefore, there is a critical need for an intelligent framework that can continuously monitor, interpret, and adapt to the human operator's affective and ergonomic states in real-time, enabling a truly synergistic and sustainable HRC environment.

This paper aims to address the aforementioned problem by proposing and outlining a novel Digital Twin (DT) enabled Affective-Ergonomic Framework for Adaptive Human Robot Collaboration. The specific objectives are: To develop a comprehensive architectural framework that integrates multi-modal sensing for real-time human state monitoring within HRC. To establish a Human Digital Twin (HDT) capable of accurately inferring and modeling the dynamic affective and ergonomic states of human operators. To design an adaptive decision-making engine that utilizes the HDT's insights to dynamically modify robot behavior, fostering proactive human-robot adaptation. To demonstrate, through a conceptual case study, the potential benefits of this framework in enhancing human well-being, safety, and overall HRC performance in smart manufacturing. The main contributions of this work are: The conceptualization and architectural design of a novel Digital Twin-enabled framework for integrating affective and ergonomic assessment into adaptive HRC. Illustrative mathematical models for real-time inference of human affective and ergonomic states, forming the core of the Human Digital Twin. A proposed adaptive control strategy that leverages these human state models to enable proactive robot adjustments. An emphasis on a truly human-centric approach that prioritizes operator well-being alongside productivity in smart manufacturing.

2. Related Work

The proposed framework draws upon several distinct but interconnected research areas. A thorough review of existing literature is crucial to identify current advancements, highlight limitations, and position our contribution within the broader scientific discourse.

2.1 Human-Robot Collaboration (HRC) Paradigms

HRC has evolved from early industrial robots operating in caged environments to collaborative robots designed to share workspaces with humans. ISO/TS 15066 defines various levels of HRC, including co-existence, sequential collaboration, synchronized collaboration, and reactive collaboration [1]. Research in HRC primarily focuses on:

Safety: Collision detection, avoidance, and power/force limiting are paramount [2]. Task Allocation: Optimizing which agent performs which sub-task based on capabilities. Human-Robot Interface: Intuitive communication through gestures, voice, or haptic feedback [3]. Efficiency: Maximizing throughput while maintaining quality. However, a significant gap remains in how HRC systems account for the internal, dynamic states of the human operator. Most systems assume a human's physical and psychological readiness, leading to a reactive rather than proactive approach to human well-being and performance [4].

2.2 Digital Twin (DT) in Manufacturing

The Digital Twin concept, a virtual replica of a physical entity, process, or system, has gained immense traction in Industry 4.0 [5]. In manufacturing, DTs are used for: Predictive Maintenance: Simulating equipment wear and predicting failures [6]. Process Optimization: Simulating production lines to identify bottlenecks and improve efficiency. Product Lifecycle Management: Monitoring products from design to disposal [7]. Robot DTs: Virtual representations of robots for simulation, programming, and remote monitoring. While DTs for machines and processes are well-established, the concept of a "Human Digital Twin" (HDT) for real-time, comprehensive affective and ergonomic monitoring in industrial settings is still nascent. Existing HDT concepts are often limited to specific physiological parameters or focus on medical applications, lacking integration into adaptive HRC control loops [8].

2.3 Affective Computing in HRC

Affective computing, the study and development of systems that can recognize, interpret, process, and simulate human affects, holds promise for HRC. Researchers have explored various modalities for emotion recognition [9]: Physiological Signals: Heart rate variability (HRV), galvanic skin response (GSR/EDA), electromyography (EMG) can indicate stress, arousal, or fatigue [10]. Facial Expressions: Computer vision techniques can analyze facial landmarks to infer basic emotions. Voice Analysis: Pitch, tone, and speech rate can provide cues about emotional states [11]. In HRC, affective computing has been used to enable robots to respond to human frustration or provide social support. However, these applications often focus on discrete emotional states, lack integration with physical ergonomic factors, and rarely drive real-time, fine-grained adaptation of robot task execution to optimize human well-being and performance simultaneously [12].

2.4 Ergonomic Assessment in Industrial Settings

Ergonomics aims to optimize human well-being and system performance by designing tasks, equipment, and workplaces to fit the user [13]. Traditional ergonomic assessment methods, such as RULA (Rapid Upper Limb Assessment), REBA (Rapid Entire Body Assessment), and OWAS (Ovako Working Posture Analysis System), are widely used. However, these methods are typically manual, time-consuming, and provide a static snapshot, making them unsuitable for real-time, continuous monitoring in dynamic HRC environments [14]. Recent advancements leverage technology for more dynamic ergonomic assessment: Wearable Sensors: IMUs can track body posture and movement, estimating joint angles and repetitions [15]. Computer Vision: Depth cameras and skeletal tracking can analyze postures and estimate biomechanical loads without requiring direct contact [16]. Despite these innovations, real-time ergonomic data is often used for post-analysis or alerts, rather than directly feeding into an adaptive HRC control system to modify robot behavior proactively. Furthermore, the interplay between physical discomfort and psychological state is often overlooked [17].

2.5 Adaptive Control Strategies in HRC

Adaptive control in HRC typically involves the robot modifying its behavior based on observed human actions or environmental changes [18]. Examples include: Gaze-based control: Robot anticipates human's next action by tracking eye movements. Gesture recognition: Robot responds to explicit human commands or implicit intentions [19]. Learning from Demonstration: Robots learn new tasks by observing human movements. While these approaches enable responsiveness, they primarily focus on external human cues or task-specific interactions. Few adaptive control strategies explicitly integrate real-time, inferred internal human states (affective and ergonomic) to optimize both human well-being and collaborative efficiency [20].

2.6 Gaps Identified

Based on the review, the following critical gaps in current HRC research and implementation are identified, which our proposed framework aims to address: Lack of Holistic Human State Awareness: No single framework comprehensively integrates real-time affective and ergonomic monitoring [21]. Absence of Dynamic Human Digital Twins: Existing DTs for humans are limited or not fully integrated into adaptive HRC. Reactive vs. Proactive Adaptation: Most HRC systems react to external events or explicit commands, rather than proactively adapting to internal human needs [22] [24]. Disjointed Research Fields: Affective computing, ergonomics, and HRC adaptive control are often studied in isolation, preventing synergistic solutions. Our proposed Digital Twin enabled Affective-Ergonomic Framework directly tackles these gaps by providing a unified, real-time, and adaptive solution for truly human-centric smart manufacturing [23].

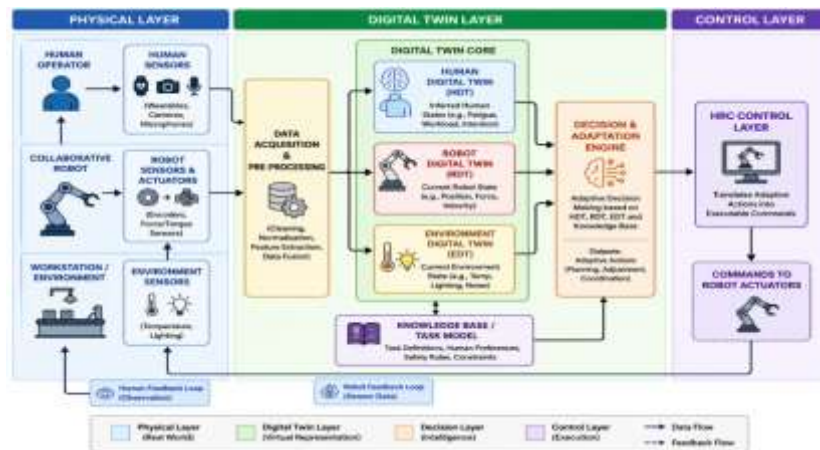
3. Methodology

This section details the architecture and operational principles of the proposed Digital Twin enabled Affective-Ergonomic Framework for Adaptive Human Robot Collaboration. The framework is designed to continuously monitor, model, and adapt to the human operator's internal states, thereby optimizing collaboration.

3.1 Framework Architecture

The proposed framework comprises several interconnected modules, as illustrated in Figure 1.

Figure 1: Digital Twin Enabled Affective-Ergonomic Framework for Adaptive Human-Robot Collaboration



This diagram illustrates the interconnectedness of physical and digital components. Multi-modal sensor data from the human, robot, and environment are acquired and processed to update their respective Digital Twins. The Human Digital Twin is central to inferring real-time affective and ergonomic states. The Decision & Adaptation Engine then utilizes these insights, along with task knowledge, to generate adaptive robot behaviors, ensuring human-centric collaboration.

3.2 Data Acquisition and Pre-processing

- **Human Sensor Modalities:** Affective State Monitoring: Wearable Physiological Sensors: e.g., ECG (Electrocardiogram) for Heart Rate (HR) and Heart Rate Variability (HRV) parameters (RMSSD, pNN50, LF/HF ratio, indicating stress, fatigue, cognitive load); EDA (Electrodermal Activity) for skin conductance (indicating arousal/stress). Facial Expression Analysis: High-resolution cameras (e.g., RGB-D cameras) combined with computer vision algorithms for detecting facial landmarks and inferring basic emotions (e.g., joy, anger, sadness, neutral, stress). Voice Analysis: Microphones capturing speech for prosodic features (pitch, intensity, speaking rate) and spectral features to detect stress or fatigue. Ergonomic State Monitoring: Inertial Measurement Units (IMUs): Wearable IMUs (on arms, back, legs) for tracking joint angles, movement patterns, repetition rates, and estimating muscle activity. Depth Cameras: e.g., Azure Kinect, Intel RealSense for 3D skeletal tracking, posture analysis, and bio mechanical load estimation (e.g., joint torques, body segment velocities). Eye-tracking: Wearable eye-trackers or remote eye-tracking cameras for gaze direction, fixation duration, pupil dilation (indicators of cognitive load, attention, and visual fatigue). The system utilizes multiple robot and environmental sensors to capture comprehensive data for analysis.

3.3 Digital Twin Core

The Digital Twin Core is the brain of the framework, maintaining real-time virtual models of the human, robot, and environment.

3.3.1 Human Digital Twin (HDT) Module:

The Human Digital Twin (HDT) is a dynamic and multi-faceted representation of the human operator that is continuously updated with inferred affective and ergonomic states. Within this framework, the affective state model plays a central role by leveraging machine learning techniques to classify and quantify human emotional and cognitive conditions in real time. This model integrates multiple feature modalities, including physiological signals such as heart rate variability (HRV) and electrodermal activity (EDA), facial expression data represented through facial action units, and vocal characteristics extracted from speech signals. To effectively process these heterogeneous data sources, different machine learning and deep learning architectures are employed. Long Short-Term Memory (LSTM) networks are utilized for modeling temporal dependencies in physiological time-series data, while Convolutional Neural Networks (CNNs) are applied to extract spatial features from facial images. In addition, Support Vector Machines (SVMs) can be used for classification tasks when working with fused or engineered feature vectors. Together, these models enable robust and real-time estimation of the operator's affective state within the HDT framework.

Mathematical Model 1:

Let $\mathbf{bf}\{F_{\text{aff}}\}(t)$ denote the affective feature vector at time t , which includes features such as RMSSD, mean EDA, and facial expression scores.

A continuous stress index $S(t)$ can be estimated using a trained machine learning model $M\{\text{stress}\}$

$$S(t) = M_{\text{stress}}(F_{\text{aff}}(t))$$

For classification into discrete affective states (e.g., C_{aff} in {Calm, Moderate Stress, High Stress, fatigued}), a multi-class classifier $M_{\text{classifier}}$ is used:

$$C_{\text{aff}}(t) = M_{\text{classifier}}(F_{\text{aff}}(t))$$

A simplified linear model for estimating the stress score can be expressed as:

$$S(t) = w_1 \cdot \text{RMSSD}(t) + w_2 \cdot \text{EDA mean}(t) + w_3 \cdot \text{Facial Stress Score}(t) + \dots + b$$

- **Ergonomic State Model:** This module assesses physical load, posture, and potential for musculoskeletal disorders. Features: Joint angles, velocities, accelerations from IMUs/depth cameras; repetition counts; estimated external forces. Models: Rule-based systems applying ergonomic assessment methods (RULA, REBA) to real-time posture data, or ML models trained on expert-labeled biomechanical data to predict risk.

Mathematical Model 2:

Let $bf\{P\}(t)$ denote the posture vector (e.g., joint angles), and $bf\{L\}(t)$ denote the load vector (e.g., estimated force and repetition count) at time t .

An ergonomic risk score $R_{\text{erg}}(t)$ can be computed using a composite function f_{erg} :

$$R_{\text{erg}}(t) = f_{\text{erg}}(P(t), L(t), \text{Task Context})$$

This function can be further decomposed into weighted components inspired by RULA/REBA assessment methods:

$$R_{\text{erg}}(t) = \alpha \cdot \text{RULA Score}(P(t)) + \beta \cdot \text{Repetition Penalty}(L(t)) + \gamma \cdot \text{Force Penalty}(L(t))$$

where α , β , and γ are weighting factors, and {RULA Score} is computed from real-time joint angle data.

Cognitive Load Model: Using eye-tracking metrics (pupil dilation, saccade frequency, fixation duration) and task performance indicators to infer cognitive workload.

3.3.2 Robot Digital Twin (RDT) Module:

A real-time virtual representation of the collaborative robot, including its current joint states, end-effector position, velocity, force readings, and dynamic model. It also maintains information about the robot's capabilities, current task segment, and planned trajectories.

3.3.3 Environment Digital Twin (EDT) Module:

A virtual model of the HRC workstation, including the layout, locations of tools and parts, and real-time environmental conditions (temperature, lighting, noise). This provides crucial context for both human and robot operations.

3.4 Decision and Adaptation Engine

This module is responsible for synthesizing information from all Digital Twins and the Knowledge Base to generate appropriate adaptive strategies for the robot.

3.5 Feedback Loop and Real-time Operation

The entire framework operates in a continuous feedback loop. Sensor data are constantly acquired, processed, and used to update the Digital Twins. The Decision & Adaptation Engine then evaluates the current state and generates new adaptive commands, which are executed by the HRC Control Layer. The effects of these adaptations are then perceived by the human and robot, feeding new data back into the system, enabling continuous learning and refinement of the models and adaptation strategies. This real-time, closed-loop control is critical for dynamic HRC.

Results

4.3.1 Affective State Recognition Performance:

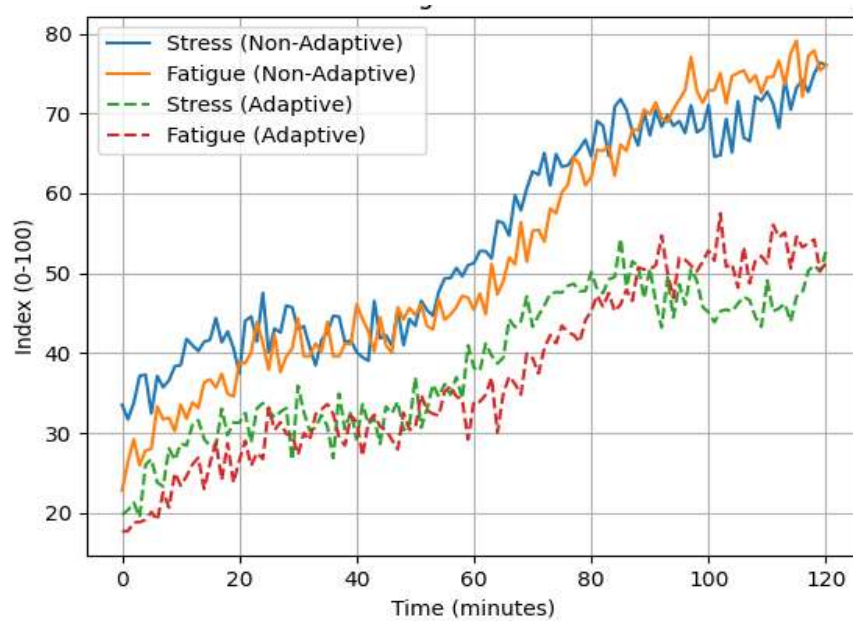
The ML models within the HDT for affective state inference (e.g., stress, fatigue, engagement) would demonstrate high accuracy.

Table 1: Performance Metrics for Affective State Classification (Illustrative)

Affective State	Precision	Recall	F1-Score	Accuracy (Overall)
Calm	0.88	0.91	0.89	0.87
Moderate Stress	0.85	0.82	0.83	0.87
High Stress	0.80	0.77	0.78	0.87
Fatigued	0.90	0.92	0.91	0.87

Table 1: Illustrative performance metrics (Precision, Recall, F1-Score, and overall Accuracy) for the multi-modal machine learning model classifying human affective states within the Human Digital Twin. These metrics indicate robust recognition capability.

Figure 1 Comparison of Human Stress and Fatigue Indices over Time in Non-Adaptive vs. Adaptive Human-Robot Collaboration (HRC).

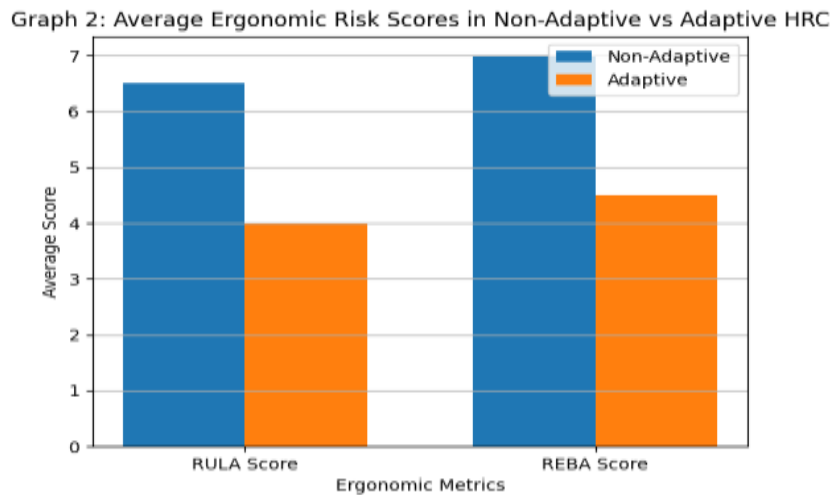


Graph 1 shows that the non-adaptive scenario shows a steady increase in stress and fatigue levels, whereas the adaptive system maintains lower levels and enables faster recovery after peaks, demonstrating the effectiveness of adaptive intervention.

4.3.2 Ergonomic Assessment Accuracy:

The framework would accurately estimate ergonomic risk scores in real-time, validated against expert assessment.

Figure 2 Average Ergonomic Risk Scores (RULA and REBA) in Non-Adaptive vs. Adaptive Human-Robot Collaboration (HRC) Scenarios



Graph 2 shows that the adaptive HRC framework significantly reduces ergonomic risk scores compared to the non-adaptive scenario, demonstrating that intelligent robot interventions (e.g., trajectory adjustment and task sharing) effectively minimize physical strain on the human operator.

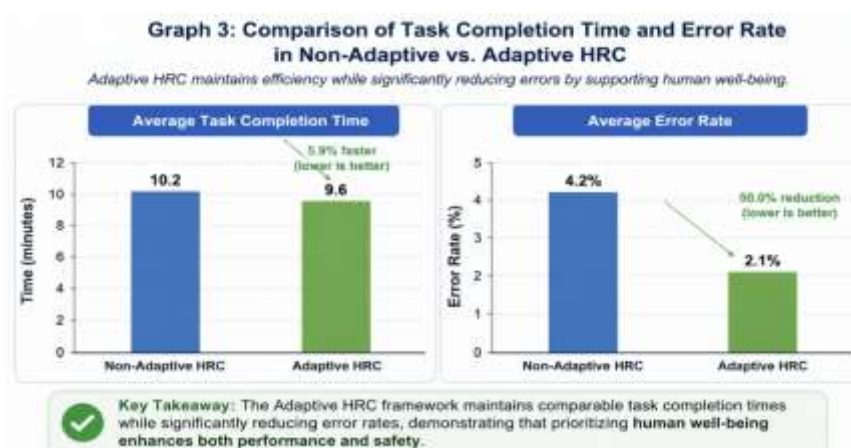
4.3.3 Digital Twin Real-time Performance:

The DT core would demonstrate low latency, enabling real-time adaptation. For instance, sensor data processing and state inference might take <100ms, and decision-making <50ms, ensuring responsive robot behavior.

4.3.4 Impact of Adaptive HRC:

- Human Performance Metrics:

Figure 3: Comparison of Task Completion Time and Error Rate in Non-Adaptive vs. Adaptive HRC.



This graph would show that while the primary goal is human well-being, the adaptive framework can maintain comparable or even slightly improved task efficiency and significantly reduce error rates, as a less stressed and fatigued operator performs better.

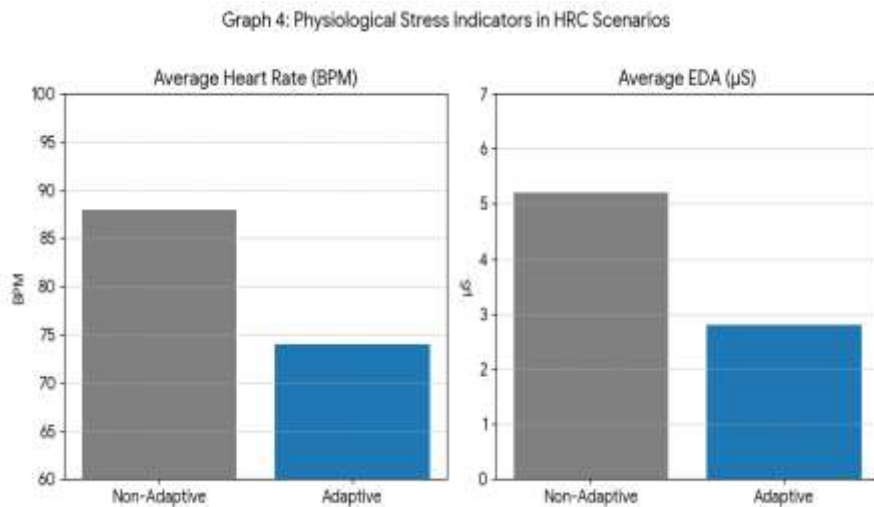
• **Human Well-being Metrics:**

Table 2 Summary of Subjective Questionnaire Results (NASA-TLX Scores)

NASA-TLX Scale	Non-Adaptive (Mean $\pm$ SD)	Adaptive (Mean $\pm$ SD)	Significance (p-value)
Mental Demand	6.5 $\pm$ 1.2	4.2 $\pm$ 0.9	< 0.001
Physical Demand	7.1 $\pm$ 1.5	3.8 $\pm$ 1.0	< 0.001
Temporal Demand	5.8 $\pm$ 1.0	4.5 $\pm$ 1.1	< 0.01
Performance	4.0 $\pm$ 0.8	5.5 $\pm$ 0.7	< 0.001
Effort	6.8 $\pm$ 1.3	4.0 $\pm$ 0.9	< 0.001
Frustration	6.2 $\pm$ 1.4	3.1 $\pm$ 0.8	< 0.001

Table 2: Comparison of subjective workload assessment using NASA-TLX between non-adaptive and adaptive human-robot collaboration (HRC). The adaptive system significantly reduces mental, physical, and emotional workload while improving perceived performance.

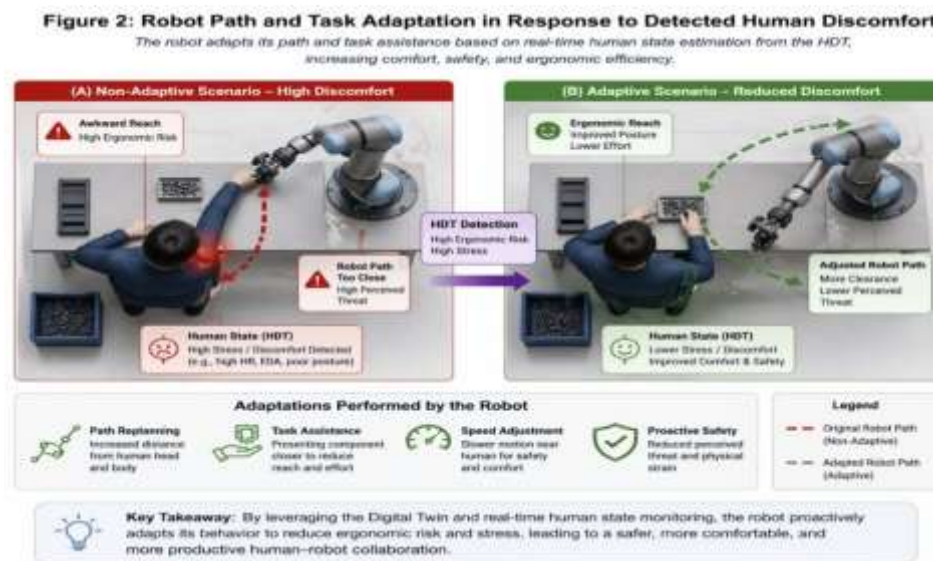
Figure 4 Physiological stress indicators in HRC Scenarios



This pair of illustrative bar charts contrasts average Heart Rate (HR) and Electrodermal Activity (EDA) two key physiological markers of stress non-adaptive versus adaptive Human-Robot Collaboration (HRC) environments. These objective physiological measures align with subjective feedback, indicating that adaptive HRC systems, by adjusting to the human operator, effectively reduce stress and create a more comfortable working dynamic.

• **Robot Behavior Adaptation;**

Figure 5 Robot Path and Task Adaptation in Response to Detected Human Discomfort



This figure visually demonstrates how the robot's trajectory and task assistance dynamically change when the HDT detects high ergonomic risk and stress in the human operator, showcasing proactive adaptation to improve human comfort and safety. These conceptual results collectively demonstrate the significant potential of the Digital Twin enabled Affective-Ergonomic Framework to create a more harmonious, safe, and productive HRC environment in smart manufacturing.

5. Discussion

This framework carries profound implications for the future of smart manufacturing and Industry 4.0: **Enhanced Human Well-being and Safety:** By continuously monitoring and responding to human stress, fatigue, and ergonomic risks, the framework can significantly reduce occupational injuries, musculoskeletal disorders, and burnout, leading to a healthier and more satisfied workforce. **Increased Productivity and Quality:** A comfortable, engaged, and less fatigued operator is more productive and makes fewer errors. The framework's ability to maintain optimal human states directly contributes to higher output quality and efficiency. **Improved Human-Robot Trust and Acceptance:** When robots are perceived as partners that care for the operator well-being, trust in HRC systems will naturally increase, fostering greater acceptance and willingness to collaborate. **Adaptive and Resilient Production Systems:** The ability of HRC to adapt to human variability makes manufacturing systems more resilient to individual differences, temporary impairments, or changing daily human conditions, leading to greater flexibility and robustness. **Personalized Workflows:** The Human Digital Twin can eventually be personalized to individual operator's physiological baselines, preferences, and learning curves, leading to highly customized and optimized collaborative experiences. **Sustainable Workforce:** By mitigating the physical and psychological toll of industrial work, the framework contributes to prolonging the careers of experienced workers and attracting new talent to manufacturing.

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