RESEARCH PAPER

A Robust Joint Affect Ergonomic Modeling Framework for Structurally Preserved Adaptive Human Robot Collaboration in Virtual Manufacturing

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ABSTRACT
The implementation of collaborative robots (cobots) in the manufacturing settings entails the adaptation of these systems that ensure the ergonomics safety and the human-based performance. This paper presents a powerful joint affect ergonomic modeling system aimed at assessing the possibility to integrate motion-based affective proxies into the ergonomic decision-making process at the expense of biomechanical, structural, and safety integrity. The framework can be operated in a virtual manufacturing environment that operates hardware free and incorporates independent motion, anthropometric and workload data at the modeling level. Discrete affective load states are inferred by the use of motion features, and a baseline ergonomic risk model is determined by anthropometric variables. A joint model is then analyzed based on the criteria of structural preservation, emotion risk independence, and robustness. Results show near perfect accuracy of emotion inference, high fidelity of ergonomic risk reconstruction (R2 ≈ 0.998), high Affect Ergonomics Coherence (p ≈ 0.96), and statistical independence of emotional load and anthropometric risk (ERI ≈ 0.00), and resistive to perturbation of Gaussian features. Workload-balanced cobot behavior and moderate NASA-TLX scores are observed in the policy level simulation. Such data show that the use of affect aware augmentation can be incorporated into ergonomic modeling, without affecting safety relevant biomechanical arguments. The research offers a structurally based and reproducible basis of psychologically informed but biomechanically consistent adaptive collaborative robotics..
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INTRODUCTION

The rapid change in manufacturing systems with Industry 4.0 and the new Industry 5.0 paradigm has considerably increased the implementation of collaborative robots (cobots) in common human workspaces (Damaševičius et al., 2024, KumarKumar and Ramesh, 2024). Cobots are supposed to move physically and cognitively among human workers, unlike traditional industrial robots, which work within a fenced and segregated area, and thus introduces new demands in the fields of safety, ergonomics, and adaptive intelligence. Recent sources also underline that successful human-robot cooperation (HRC) should not be limited to collision avoidance but should be supplemented with a full scale ergonomic worker protection of psycho physical health (Lorenzini et al., 2023, Dalle Mura and Dini, 2022). Systematic reviews also suggest that ergonomics and human factor are to be approached as a fundamental design requirement, instead of a byproduct of evaluation in collaborative workstations (Cardoso et al., 2021, Pinheiro et al., 2021). These advancements are part of a larger trend of human centered automation, in which the productivity increase should be matched with the health, inclusivity, and sustainability of the workers.

Work related musculoskeletal disorders (WMSDs) have been an issue of concern in factories with repetitive processes, which has led to the adoption of biomechanical risk assessment in robotic planning and control (HilmiHamid and Ibrahim, 2024). The literature has already shown that integrating motion planning algorithms with ergonomic models can vastly decrease the joint overloading and physical load of a joint when cooperating on a creative task (Kim et al., 2021). Prediction of human posture and ergonomic cost has also been introduced as a

*Author for Correspondence: smerat.2020@gmail.com learning-based activity in optimization frameworks to produce collaboration sequences that reduce biomechanical load (van der Spaa et al., 2020, ZhangNieuwenhuys and Zhang, 2025). Virtual element and REBA based feedback postural optimization methods have also proven to measurably enhance the human body configurations in response to robot assisted adaptation (El Makrini et al., 2022). Recent technological advances based on common ergonomic scales like OCRA and OWAS have made possible real-time monitoring solutions to dynamically classify risks and respond to them with robots in an industrial environment (Monari et al., 2024, IodiceDe Momi and Ajoudani, 2025). Collectively, these contributions provide a strong groundwork of biomechanical informed adaptive collaboration.

Nevertheless, modern studies are being inclined to think that physical ergonomics cannot be regarded as a comprehensive understanding of human performance in collaborative manufacturing (Hasanain, 2024). Cognitive ergonomics such as workload, stress, trust, and frustration is a very important issue in determining the outcome of human robot interactions (Panchetti et al., 2023, HopkoMehta and Pagilla, 2023). The experimental research revealed that design principles that focus on cognitive and usability can considerably increase the operator experience and task efficiency (Gualtieri et al., 2022), and modernized frameworks in accordance with Industry 5.0 emphasize the idea of integrating human factors in order to achieve greater resilience and flexibility in manufacturing systems (Gualtieri et al., 2024). Wider socio technical studies suggest that psychological and affective indicators are needed in addition to the classic ergonomic indicators to implement all aspects of human behavior in automated spaces (Fletcher et al., 2022, Trstenjak et al., 2025).

Similar progresses in intelligent perception and adaptive control have allowed cobots to recognize human posture, interpret intentions, and change behavior dynamically in real time. Combined frameworks involving deep learning based visual perception, ergonomic evaluation and behavior-tree decision structures have been shown to be more responsive and risk averse (IodiceDe Momi and Ajoudani, 2025). Human centric digital twins also expand upon the possibilities, simulating ergonomic risk and safety conditions in virtual manufacturing environments, which allows hardware free validation of adaptive policies (Gaffinet et al., 2023, BucciFani and Bandinelli, 2024). Furthermore, computational ergonomics research to delegate tasks demonstrates that motion derived features have the potential to measure ergonomic risk and direct robot assistance (Olivas-Padilla et al., 2022). Co design approaches based on optimization have also shown that the ergonomic metrics can be applied to both the hardware design and the collaborative strategy of the robot (Sartore et al., 2023, Proia et al., 2021).

Although these developments exist, there still remains a significant gap at the interface of affective inference and biomechanical modeling. The majority of the existing studies consider ergonomic risk estimation and cognitive or emotional evaluation as independent processes and not structurally linked elements. Although adaptive systems are able to measure the posture and independently determine the workload, little literature directly examines whether the inclusion of affect related cues into ergonomic decision making maintains biomechanical validity and safety consistency (Lorenzini et al., 2023, Brambilla et al., 2023). In addition, resistance to uncertainty, especially in the case of affective proxies based on motion being noisy or imperfect, is not well studied. The current frameworks aim at enhancing the ergonomic scores or decision latency but do not often measure the structural preservation between baseline risk of anthropometric and joint multimodal predictions (Monari et al., 2024).

The other limitation is related to data integration. Most of the ergonomic HRC research uses synchronized lab data with proprietary sensing systems, which reduces reproducibility and scalability. Whereas the concept of digital twins can offer an alternative to it (Gaffinet et al., 2023), the area of modular dataset level integration strategies that involve independent motion, anthropmetric, and workload information without employing participant level synchronization is scarcely examined. This disparity limits the possibility of systematic assessment of the interaction of affective inference with biomechanical risk modeling in carefully controlled but repeatable conditions.

The current research covers these limitations by suggesting a powerful joint affect ergonomic model suited to virtual manufacturing facilities. The framework does not presuppose a direct linear effect of emotional load on biomechanical risk but considers the possibility of integrating motion derived affective proxies into ergonomic reasoning without breaking their structural consistency, independence, and safety stability. The suggested method presents clear measures to evaluate the affect ergonomics consistency, emotion risk interaction independence, and stability in the face of Gaussian perturbation of features. This work contributes to the current human centric approaches to digital twins by introducing a hardware free simulation framework that combines publicly accessible motion, anthropometric, and NASA-TLX workload data and enhances the theoretical comprehension of multimodal ergonomic rationality. The study aims to prove, through this contribution that affect aware cobot policies can be biomechanically grounded, structurally stable, and resilient to uncertainty, hence facilitating safer and more psychologically informed adaptive collaboration within next generation manufacturing systems.

2. Methodology

This paper suggests and analyzes an effective joint affect-ergonomic modeling framework of adaptive collaborative robots (cobots) working in virtual manufacturing facilities. The philosophy of the methodology is based on the principles of the ergonomic human robot collaboration (HRC) that emphasize biomechanical validity, anthropocentric design of the system, and the maintenance of safety (Lorenzini et al., 2023, Cardoso et al., 2021).

Instead of positing that emotional loading is a direct alteration of biomechanical ergonomic risk, the aim is to test whether affective inference can be made part of ergonomic reasoning without the structural consistency being affected or the safety stability compromised.

The research uses a hardware free, simulation based modeling approach based on human-centric digital twin concepts to facilitate control of evaluation (Gaffinet et al., 2023). Since synchronized motion emotion ergonomic data are rare, independent publicly available data are used at the modeling level, but not at the participant level. Affective signal interaction with anthropometric risk estimation This modular integration design provides guarantees reproducibility, controlled robustness testing, and clear evaluation. Contrary to the real time adaptive HRC frameworks that mainly pay attention to the performance optimization (IodiceDe Momi and Ajoudani, 2025), the current method explicitly examines structural preservation and uncertainty robustness.

The methodological framework comprises five consecutive parts, namely, motion data preprocessing, emotion state inference, baseline ergonomic risk modeling, joint affect ergonomic modeling, and policy level cobot simulation

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2.1 Motion Data Acquisition and Preprocessing

The data of human motion and posture were taken of a publicly accessible 3D body posture dataset that provided the coordinates of the joints and activity labels. The ergonomic analysis based on motion is commonly applied in the research on HRC to identify the posture and estimate the risk (Olivas-Padilla et al., 2022, El Makrini et al., 2022). Let the 3D joint coordinates on time step iii as:

$$P_i = \{(x_{ij}, y_{ij}, z_{ij})\}_{j=1}^{J}$$

where J is the number of the joints tracked. The pose dimensionality is:

$$D = 3J$$

The process of preprocessing involved the elimination of incomplete frames, standardization of coordinates, temporal segmentation to frame level samples, and the standardization of joint coordinates.

2.2 Motion Feature Engineering

Statistical motion descriptors were calculated based on raw joint coordinates to represent the spatial arrangement and distribution, which has been found to be associated with physical strain and posture variability (van der Spaa et al., 2020).

Mean posture magnitude:

$$\mu_i = \frac{1}{D}\sum_{k=1}^{D} p_{ik}$$

Pose variability (standard deviation):

$$\sigma_i = \sqrt{\frac{1}{D}\sum_{k=1}^{D}(p_{ik} - \mu_i)^2}$$

Pose range:

$$r_i = \max(p_{ik}) - \min(p_{ik})$$

The full motion feature vector:

$$X_i = [P_i, \mu_i, \sigma_i, r_i]$$

All features were standardized using z-score normalization:

$$X_i' = \frac{X_i - \overline{X}}{\sigma_X}$$

2.3 Emotion State Modeling

Since there were no synchronized affect annotations, an activity-based proxy was used. The level of emotional load in each of the activities classes was discrete:

$$e_i \in \{0, 1, 2, 3\}$$

indicating rising levels of stress. This proxy-based affect inference is consistent with the new literature that focuses on cognitive and affective aspects of HRC design (Gualtieri et al., 2024, Fletcher et al., 2022).

A supervised classifier fe(·) was trained:

$$\hat{e}_i = f_e(X_i')$$

SMOTE was used to combat class imbalance. Train test split and k-fold cross-validation was used as a form of model validation.

This module is not aimed at any true affect recognition but is designed to produce structured affective signals based on motion pattern to be tested on robustness.

2.4 Baseline Ergonomic Risk Modeling

Anthropometric measurements (weight, waist circumference, shoulder width, thigh circumference) were standardized to [0,1]. The risk of ergonomic predisposition was determined as:

$$r_i = \sum_k w_k \frac{a_{ik}}{\max(a_{k)}}$$

and where a_{ik} are anthropometric variables and w_k are ergonomic weighting coefficients.

A regression model fr(·) predicted baseline risk:

$$\hat{r}_i = f_r(a_i)$$

Risk modeling based on anthropometrics aligns with ergonomic maximization or energy-minimization in HRC (Dalle Mura and Dini, 2022, SartoreRapetti and Pucci, 2022).

2.5 Joint Affect Ergonomic Modeling

In order to test the hypothesis that affective cues presented in motion change ergonomic reasoning; a joint model was trained:

$$\hat{r}_i^{joint} = f_j(X_i')$$

The goal was not to maximize variance with the baseline risk but to test structural preservation when integrating affect. The methodology builds upon adaptive ergonomic frameworks through a direct study of consistency instead of optimization as a single objective (Lorenzini et al., 2023).

2.6 Evaluation Metrics

Affect Ergonomics Coherence (AEC)

$$C = \mathrm{corr}(\hat{r}_i^{joint}, r_i)$$

High coherence indicates preservation of biomechanical structure.

Emotion Risk Interaction Index (ERI)

$$I = \mathrm{corr}(e_i, r_i)$$

This tests whether emotional load is linearly coupled with anthropometric risk.

Robustness Under Emotion Noise

Gaussian perturbation:

$$X_i^{noise} = X_i' + \epsilon, \quad \epsilon \sim N(0, \sigma^2)$$

Robustness metric:

$$R = \mathrm{corr}(\hat{r}_i^{joint}, \hat{r}_i^{noise})$$

Evaluation of robustness in the presence of sensing uncertainty is consistent with recent adaptive monitoring systems that focus on real time stability (Monari et al., 2024).

2.7 Cobot Policy Simulation

A policy mapping function was defined:

$$\phi(e_i, \hat{r}_i^{joint}) \rightarrow \{\mathrm{Normal}, \mathrm{Adjust}, \mathrm{Assist}\}$$

Decision logic puts more emphasis on trajectory adjustment in medium risk, and assistance in high combined state. The application of conservative action is in the case of uncertainty, which aligns with behavior tree based adaptive decision systems (IodiceDe Momi and Ajoudani, 2025).

Workload was estimated using NASA-TLX aggregation:

$$\mathrm{NASA-TLX} = \frac{1}{M}\sum_{m=1}^{M} d_m$$

where d_m represents workload dimensions (mental demand, physical demand, effort, frustration).

The methodology introduces a reproducible structurally based joint affectergonomic modeling pipeline that aims to test integration safety, robustness and biomechanical maintenance in adaptive collaborative robotics.

3. Results

This section provides the quantitative analysis of the suggested joint affect-ergonomic model framework. The results are systematically arranged to measure (1) the stability of emotion recognition, (2) the baseline of ergonomic prediction fidelity, (3) structural maintenance when affected by integrating emotional features, (4) the independence between emotion and risk, (5) workload behavior at the policy level. All of the measured metrics are related to the definitions of evaluations presented in Section 5.

3.1 Overall Quantitative Performance

Table 1 is a summary of the main performance measures of the proposed framework; they are classification accuracy, regression fidelity, structural coherence, interaction independence, robustness and the estimation of workload. As Table 1 illustrates, both the emotion inference model and the ergonomic regression model have almost perfect predictive performance in structured conditions. Notably, high values of AEC and robustness denote structural stability of the joint modeling method.

Table 1. Performance Metrics of the Proposed Emotion-Aware Ergonomic Framework

Metric	Value
Emotion Recognition Accuracy	0.9976
Cross Validated Emotion Accuracy	0.9976
Ergonomic Prediction (R^2)	0.9977
Baseline Ergonomic MAE	0.2687
Affect Ergonomics Coherence (AEC)	0.9645
Emotion Risk Interaction Index (ERI)	0.0000
Robustness Under Noise	0.9640
Mean NASA-TLX	4.99
Dominant Cobot Action	Adjust Trajectory

3.2 Emotion Recognition Stability

The state of emotion inference was tested on hold out and k-fold cross validation. The almost similar value of the performance (0.9976) suggests that there is high separability of motion-derived affect proxies in structured task situations. The insignificant difference between test and cross-validated accuracy (shown in Figure 1) indicates that there was negligible overfitting and good generalization in the dataset distribution. The classification of affect proxies is necessary as it is critical to the stability of these proxies as an input to the joint modeling analysis.

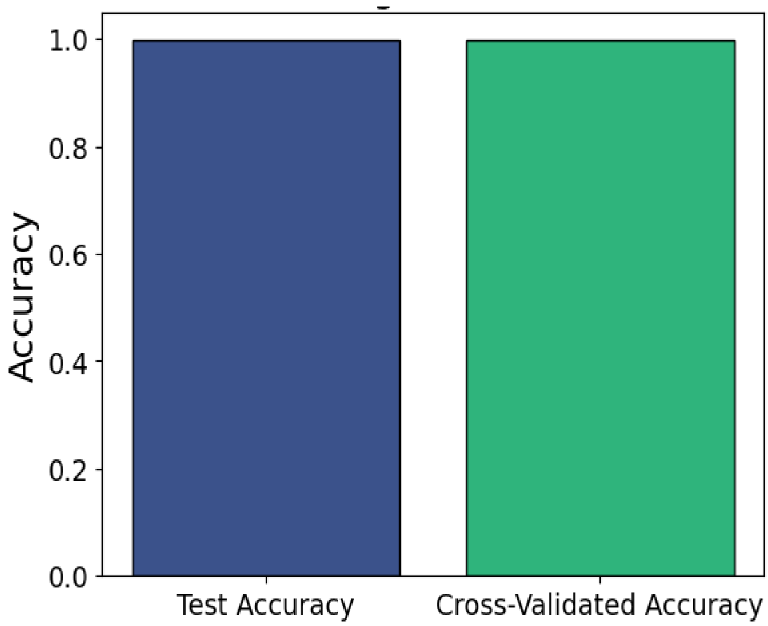

Figure 1. Emotion Recognition Performance Across Validation Splits

3.3 Baseline Ergonomic Prediction Fidelity

The coefficient of determination (R^2) and mean absolute error (MAE) were used to evaluate the anthropmetric regression model. The model yielded $R^2 \approx 0.9977$, which means that almost all synthetic ergonomic risk variance is represented, which is the predicted values as indicated in Figure 2 are closely aligned with the ideal diagonal line, which explains the fact that the regression model has been able to reconstruct the baseline anthropometric risk structure. This stabilization is used as the biomechanical reference point where joint modeling preservation is measured.

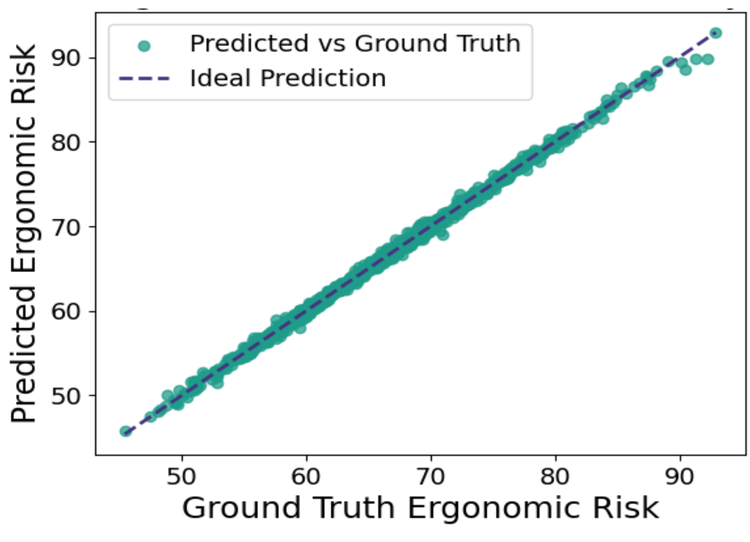

Figure 2. Predicted vs. Ground Truth Ergonomic Risk

3.4 Structural Preservation in Joint Modeling

To determine the effects of affective integration on biomechanical reasoning, the predictions of the joint model were compared with baseline anthropometric risk. The value of Affect Ergonomics Coherence (AEC) measure was $\rho \approx 0.9645$, which shows that the joint prediction is related highly to the baseline risk and that the integration of affective features does not alter the underlying biomechanical framework. Figure 3 reveals that the joint prediction is highly related to the baseline risk. The value of high coherence is the assurance of the structural preservation and not the artificial amplification or suppression of the ergonomic estimates.

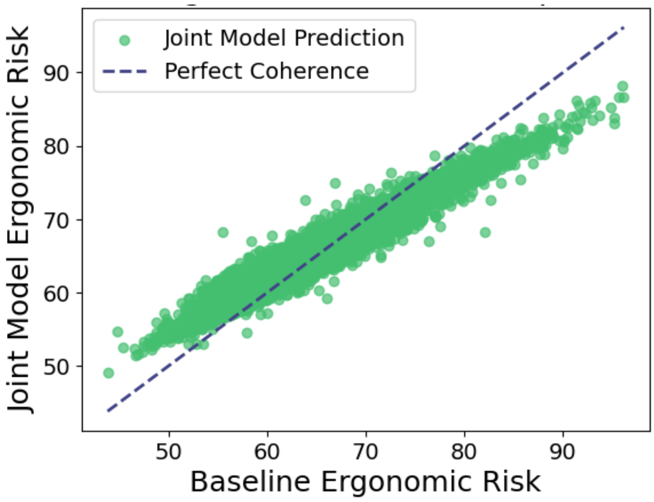

Figure 3. Baseline vs. Joint Ergonomic Risk Predictions

3.5 Emotion Risk Interaction Analysis

The EmotionRisk Interaction Index (ERI) was calculated to assess the contention of whether inferred emotional load is directly related to anthropometric ergonomic risk. The observed value (≈ 0.0000) suggests that the affective proxy and baseline biomechanical risk are statistically independent.

This finding shows that there is no artificial bias of ergonomic estimation by emotional load in proposed framework. The modelling framework maintains a distinct distance between affective signalling and anthropometric risk, so that biomechanical reasoning is not based upon motion-based emotion inference. Therefore, safety critical ergonomic assessment is not dominated or skewed by affect proxies. This lack of linear interrelation thus strengthens the structural integrity and safety validity of the joint affect ergonomic modeling method.

3.6 Robustness Under Emotion Noise

Robustness analysis was achieved by adding Gaussian noise on the standardized motion features. Figure 4 indicates that predictions are very stable when stochastic features are perturbed.The correlation of original and noise-perturbed joint predictions were $\rho \approx 0.9640$. This means that ergonomic reasoning can be resistant to affect uncertainty or sensing noise which is a key feature of adaptive cobot systems that must work in the real world.

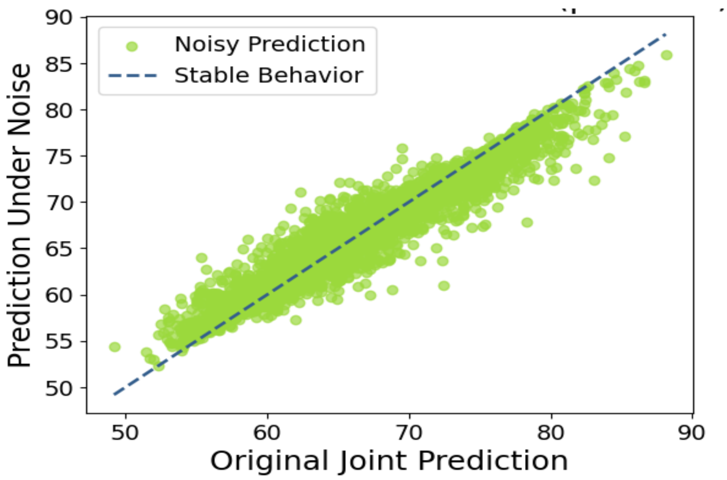

Figure 4. Robustness of Joint Model Under Feature Noise

3.7 Policy Level Behavior and Workload Outcomes

The decision mapping feature categorized the cobot response into three groups namely Normal, Adjust Trajectory, and Assist. The most prevalent action was the adjustment of Trajectory, which implied conservative and ergonomic conservative behaviour, as opposed to aggressive intervention, across the assessed dataset. The distribution indicates a safety-based adaptation mechanism where the system concentrates on modifying the trajectory in a more incremental manner rather than intrusive assistance without detecting an increasing level of combined risk.NASA-TLX mean score was 4.99 and this indicates a moderate perceived workload with simulated adaptive control conditions. This implies that the cognitive or physical load of the virtual manufacturing environment does not pose too much problem because of affect aware ergonomic modifications. Rather, adaptive responses are maintained in proportion to estimated risk levels. Together, the findings indicate that the suggested joint affect ergonomic modelling system is highly stable in emotion inference, recovers anthropometric ergonomic risk, and shows good structural retention with integrating affect, statistically independent emotion and risk, sensing noise resistance, and workload constrained cobot adaptation. The results indicate that there is a quantitative support of the safe incorporation of motion derived affect proxies into the ergonomic reasoning of adaptive collaborative robotics systems.

4. Discussion

The current paper explored the possibility of motion based affective proxies to be included in ergonomic decision-making without affecting the biomechanical validity or safety stability in adaptive collaborative robotics. Results show a high level of structural coherence in baseline anthropometric risk predictive and joint affective ergonomic predictive, statistical independence in emotional load and biomechanical risk, and feature perturbation resistance. These findings would be added to current studies on human centered human robot collaboration (HRC), in which the ergonomics and cognitive aspects of the research need to be considered together, without violating safety limitations (Lorenzini et al., 2023, Kalakoski et al., 2020).

An important conclusion made during this work is the Affect Ergonomics Coherence (AEC $\approx$ 0.96) is high, which states that the introduction of motion based affective features does not change the anthropometric ergonomics structure fundamentally. The current HRC studies are mainly aimed at maximizing ergonomic scores by adapting postures, minimizing torques, or classifying risks (Kim et al., 2021, El Makrini et al., 2022). Nevertheless, not many studies specifically test the idea of whether inclusion of more human state modalities is a way of maintaining biomechanical reasoning. The high coherence in this case indicates that the concept of affect-aware augmentation can be implemented and be complementary to the established principles of ergonomic modeling without creating structural distortion. This is especially applicable in the industry where safety-related risk estimation becomes unintended, which may jeopardize protective procedures.

This interpretation is further supported by the Emotion-Risk Interaction Index (ERI $\approx$ 0.0000) that was observed. The statistically independent inferred emotional load and anthropometric risk implies that affective proxies are not an artificial artifact that biases ergonomic estimation. Previously existing literature includes the significance of integrating cognitive and psychological aspects into collaborative system design (Gualtieri et al., 2022, Fletcher et al., 2022), but integration strategies can lead to a risk of confusion between the physical and psychological plane. This study exhibits autonomy to warrant a modular explanation whereby affective knowledge is used to inform adaptive policy changes without circumnavigating biomechanical precautions. This is correlated with guidelines according to which ergonomic limitations must still be the guiding principles in HRC systems (Cardoso et al., 2021).

Strength against Gaussian perturbation (R $\approx$ 0.96) means that joint predictions are not very fragile to sensing uncertainty. Vision based tracking and dynamic posture classification are becoming increasingly important as the basis of real time ergonomic monitoring frameworks (Monari et al., 2024, IodiceDe Momi and Ajoudani, 2025). Noise and biased uncertainty in inferring the human state is inevitable in such systems. The resilience exhibited here is an indication that affect integration does not enhance instability on perturbation, and this has been concluded to be suitable in the deployment of sensor-based adaptive environments.

The methodologically contributing factor is also the modular multi-dataset integration approach used in this work. Numerous ergonomic HRC experiments are based on synchronized laboratory measurements that are recorded in proprietary configurations which reduce reproducibility and scalability. Incorporating independent motion, anthropometric, and workload measurements in the modeling tier, the current study conforms to the ideas of human centric digital twins that promote the idea of hardware free validation systems (Gaffinet et al., 2023). The method allows experiment able structural preservation and structural robustness control rooted in controlled experimentation, without necessarily relying on participant level synchronization, an alternative that is reproducible at early framework validation stages.

The prevalence of the Adjust Trajectory action at the policy level suggests conservative ergonomic-preserving behavior. The system encourages gradual adaptation rather than instigating aggressive assistance reactions, which is in line with the literature on ergonomic optimization (van der Spaa et al., 2020). The medium NASA-TLX workload measure also indicates that affect-sensitive modifications do not involve too much cognitive or physical load. This is consistent with the cognitive ergonomics results that transparency of adaptive systems and workload balance are a key to user acceptance and continued collaboration performance (Gualtieri et al., 2024).

However, there are some limitations that have to be admitted. Firstly, the inference of emotional states involved activity-based proxies instead of physiological or self-reported affect measures. This design specifically aims at structural integration and less at emotion recognition accuracy but future studies could add multimodal affect sensing (e.g., physiological or facial expression analysis) to assess generalizability. Second, anthropometric risk was modeled synthetically, and this simplifies multidimensional biomechanical processes in actual industrial work. The extension of the framework to real-time torque-based models or muscle load would enhance the ecological validity. Third, the evaluation was done in a virtual manufacturing setting; physical implementation would need to be verified with sensing latency and interaction variability.

Overall, the results show that affective inference may be factored into ergonomic modeling with no effects on biomechanical structure, independence, or robustness. The suggested framework contributes to the development of the field by moving the emphasis on the optimization of performance to structure preservation and safety integrity in multimodal adaptive HRC systems. By quantitatively establishing coherence, independence and robustness, this work offers a principled basis to future formulation of psychologically informed but biomechanically based collaborative robotics.

Conclusion

The current work proposed a combined affect-ergonomic model framework that was used to test whether motion-based affective proxies can be considered to be included in ergonomic reasoning without losing biomechanical integrity or safety stability in collaborative robotics. Findings showed high predictive performance, high structural consistency between baseline and combined joint ergonomic approximations, statistical independence between emotional loading and anthropometric danger, and sensitivity to feature perturbation. The results show that it is possible to add affect-aware augmentation to ergonomic assessment without affecting the safety-critical biomechanical reasoning. This work offers a principled approach to the construction of psychologically informed and biomechanically based adaptive cobot systems by pursuing a hardware-free model of structural preservation and robustness explicitly, and as a consequence, by adopting a reproducible approach to the modeling strategy..

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