



## Article

# Integrating Neural Strategies and Biomechanical Output: A Muscle Synergy-Based Computational Framework for Evaluating Human—Passive Wearable Interaction in Industry 5.0

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## Abstract

**Background/Objectives:** Industry 5.0 emphasizes the protection and empowerment of human workers. Passive wearables reduce physical strain, but the evaluation of their efficacy remains incomplete when based solely on kinematics or electromyographic (EMG) envelope amplitude, failing to capture the underlying neural “cost” or the compensatory strategies. This paper proposes a computational framework centered on muscle synergy analysis to bridge the gap between laboratory-grade neural assessment and real-world industrial applications. The goal is to move beyond simple biomechanical metrics toward a deeper understanding of neural coordination during device interaction. **Methods:** Given the practical limitations of high-density EMG in industrial settings, we propose a “streamlining” approach: laboratory-derived synergy models guide the understanding of neural processes and the selection of a minimal set of sensors capable of detecting maladaptive motor compensations and early signs of fatigue. **Results:** This approach allows for long-term monitoring without compromising natural movement. By decoupling neural strategies from kinematic output, “silent” risk situations can be identified even when movement appears correct but the neural coordination is altered by the passive device. This supports personalized ergonomic indices and predictive prevention protocols, transforming wearables from simple mechanical aids into intelligent, human-centric systems. **Conclusions:** This framework provides a roadmap for translating complex motor control theories into practical tools for the next generation of safe and sustainable manufacturing.

**Keywords:** muscle synergies; human–robot collaboration; Industry 5.0; passive exoskeletons; neuromuscular ergonomics; motor control



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## 1. Introduction

The transition from Industry 4.0 to Industry 5.0 represents a paradigm shift from purely technological and productivity-driven goals toward a human-centric, resilient, and sustainable manufacturing environment [1]. In this new landscape, the worker is no longer viewed as a mere operator to be automated, but as a central asset whose physical and mental well-being must be preserved through advanced Human–Robot Collaboration (HRC). One of the most significant challenges in this context is the prevention of Work-related Musculoskeletal Disorders (WMSDs), which continue to represent a major socio-economic burden globally [2]. To mitigate these risks, the adoption of passive wearable devices, such

as back or upper-limb exoskeletons, has gained momentum [3,4]. Unlike active systems, passive wearables rely on spring-based or elastic mechanisms to redistribute loads, offering a lightweight and cost-effective solution for the industrial workspace [3,5]. However, the objective evaluation of these devices remains an open challenge. Current ergonomic assessment tools often include observational posture-based screening methods such as RULA [6] and REBA [7], which are useful for evaluating selected critical postures within a task rather than the full biomechanical load generated across the entire work activity. While being very informative as complementary screening approaches, these methods provide only a partial view of human–wearable interaction, particularly when comparing supported and unsupported conditions over complex industrial workflows [8]. This limitation motivates the need for continuous neuromuscular metrics capable of capturing the coordination strategies underlying the whole task execution [9]. This work argues that kinematic correctness is not equivalent to neural optimality. In the field of neuro-rehabilitation, the theory of muscle synergies has emerged as a powerful framework to investigate how the CNS manages the high dimensionality of the musculoskeletal system by activating groups of muscles in functional units [10,11]. It has typically been employed in biomedical research to evaluate physiological and pathological motor control. Translating this clinical approach to Industry 5.0 offers a unique opportunity: identifying “hidden” compensatory strategies that underlie motor execution. A worker might maintain a constant or comparable kinematic output—performing the task correctly from an external observer’s perspective—while undergoing detrimental neural adaptations or muscle activity alterations that could lead to long-term injury [12]. Despite the potential of muscle synergy analysis, a significant gap exists between controlled laboratory settings and real-world industrial applications [13]. Laboratory protocols often involve high-density EMG setups that are intrusive and impractical for an entire work shift. Therefore, Industry 5.0 requires a streamlining of the sensing apparatus. This involves moving from comprehensive neural mapping toward the identification of a minimal sensor set capable of capturing the essential synergy components without hindering the worker’s natural movement [14]. This paper proposes a computational framework that decouples neural coordination from kinematic output to evaluate human–passive wearable interaction. We do not aim to provide experimental validation but to define a physiologically grounded evaluation paradigm that can be tested in future industrial studies. Therefore, this work proposes a muscle synergy-based neuromuscular evaluation framework to quantify the Neural Transparency and adaptive cost of passive wearable devices in Industry 5.0 scenarios.

Specifically, by leveraging the dimensionality reduction inherent in muscle synergy analysis, we aim to:

1. Quantify the “Neural Transparency” of passive devices.
2. Detect maladaptive motor compensations that precede clinical symptoms.
3. Provide a roadmap for the transition from complex laboratory setups to scalable, sensor-lean monitoring systems in the industrial workspace.

## 2. Framework for Quantifying Neural Transparency

The proposed computational framework conceptualizes human–wearable interaction as a modular control problem. This approach has been applied to devices mainly in the context of neuromotor rehabilitation [15–17], while only a few preliminary studies have considered extending it to industry [18]. By decomposing the high-dimensional EMG space, we investigate whether the introduction of a passive device preserves the modularity of the CNS or forces a reorganization of motor primitives, hypothesizing a comparison between data recorded in free movements and when assisted with a device.

### 2.1. Signal Acquisition and Pre-Processing

Data integrity is paramount when moving from laboratory to industrial scenarios. A typical pipeline for synergy analysis is as follows. Raw EMG signals  $EMG(t)$  are first band-pass filtered (e.g., 20–450 Hz) to remove motion artifacts and high-frequency noise. A further analysis step involves the full-wave rectification and the application of a low-pass filter (typically a 4th-order Butterworth, cut off frequency in range 5–10 Hz) to extract the linear envelope [19]. To account for inter-subject variability and the physical constraints of Industry 5.0 tasks, signals are normalized to the Maximum Voluntary Contraction (MVC) or, alternatively, to the peak activity recorded during the dynamic task to ensure robustness, under the hypothesis that a sufficient variety of movements has been performed. This normalization strategy assumes that the recorded task set is sufficiently broad to sample the effective activation range of each muscle. If task variety is limited, peak normalization may underestimate true maxima, altering inter-muscle variance ratios and potentially biasing the extracted synergy structure. The latter normalization is widely used in realistic laboratory and clinical scenarios to reduce the time needed for acquisitions and reduce experimental overloads. Before applying decomposition methods, EMG envelopes are usually segmented into epochs or single tasks.

### 2.2. Decomposition Models

While Non-Negative Matrix Factorization (NMF) [20] is widely used to extract spatial synergies, a rigorous methodology must consider the nature of the motor task and select the most suitable algorithm depending on the specific aim of the analysis. The modularity of the control space can be observed through three distinct computational lenses:

*Spatial Synergies:* Applied to the matrix of multichannel EMG, it extracts time-invariant muscle weightings  $W$  and time-varying activation coefficients  $C$ . This model assumes that the CNS activates fixed muscle groupings with flexible timing [21].

*Temporal Synergies:* Used to identify shared and invariant temporal patterns across different muscle groups, highlighting rhythmic synchronization often required in repetitive industrial cycles [22].

*Spatiotemporal Synergies:* This model accounts for temporal delays between muscle activations within the same module, capturing the “burst” propagation necessary for dynamic balance during wearable use [23]. For these classes of models, NMF is not suitable and other algorithms such as time-varying synergies [11] can be used.

Because NMF (or other algorithms) may converge to local minima and does not guarantee a unique solution, the factorization should be repeated across multiple random initializations, retaining the solution associated with the highest reconstruction quality ( $R^2$  or VAF). This multi-start procedure improves the robustness and stability of the extracted synergy weightings and activation coefficients.

### 2.3. Quantitative Metrics for Neural Integrity

The evaluation of Human–Robot Interaction (HRI) is performed through a multi-parametric analysis of the synergy components.

#### 2.3.1. Dimensionality and Goodness of Fit

The Number of Synergies ( $N$ ) is determined as the number needed to exceed a pre-defined threshold of the Reconstruction  $R^2$  (or by the Variance Accounted For—VAF):

$$R^2 = 1 - \frac{SSE}{SST}$$

where  $SSE$  is the sum of the squared residuals, and  $SST$  is the sum of the squared differences with the mean EMG vector [23].

A shift in  $N$  serves as a primary indicator of adaptation. A decrease in  $N$  might suggest a “freezing” of degrees of freedom due to the wearable’s constraint, while an increase indicates the recruitment of auxiliary motor modules to compensate for the device’s impedance or encumbrance.

### 2.3.2. Structural Similarity and Correlation

To assess the Neural Transparency of the passive device, we employ the best-matching synergy approach. We compare the spatial vectors ( $W$ ) of the baseline free movements ( $W_{\text{base}}$ ) and the supported condition ( $W_{\text{supp}}$ ) using two metrics:

- Cosine Similarity (CS): To measure the orientation of the unit synergy vectors in the muscle space.
- Pearson Correlation ( $r$ ): To evaluate the linear relationship between temporal coefficients associated with synergies.

A  $CS < 0.80$  is a reasonable threshold for “Neural Reorganization”, suggesting that the wearable is significantly altering the user’s natural motor control strategy [24], i.e., how motor modules are recruited and combined. The CS threshold reported here should be interpreted as illustrative reference values. In rigorous applications, significance bounds for Neural Reorganization may be more robustly derived from empirical null distributions, for example, by comparing observed synergy similarities against randomly shuffled or randomly paired synergy structures from the same dataset. This threshold might be tuned depending on the features of the dataset (for example, by using random synergy pairings as a reference) or increased when a lower number of channels is used, and vice versa. This approach enables dataset-specific thresholds that explicitly account for noise, channel count, and task variability.

### 2.3.3. Temporal Dynamics and Phase Shift

The activation coefficients ( $C$ ) are analyzed to detect shifts in the Center of Activity (CoA). For cyclic tasks, the CoA can be computed as follows:

$$A = \sum_{t=1}^N C(t) \cos \theta_t$$

$$B = \sum_{t=1}^N C(t) \sin \theta_t$$

$$CoA = \tan^{-1}(B/A)$$

where  $C(t)$  is the activation of muscle synergy at  $t$ . Time is converted into an angle  $\theta_t$  by the formula  $\theta_t = 2\pi (t/T)$  [25]. A significant shift in CoA reveals whether passive assistance allows for a delay in muscle recruitment (effort reduction) or if it induces early fatigue due to asynchronous activation patterns. Moreover, wearable devices typically aim at supporting the weight of the limb and reducing muscle effort. In the framework of the muscle synergies, this effect can be observed in a reduction in the integral of synergies in the support condition [26]:

$$I = \int_{t_0}^{t_1} C(t) dt$$

### 3. Detecting Maladaptive Compensation

The central premise of this framework is the potential dissociation between biomechanical output and neural drive, which is supported by the motor abundance principle [27], which states that muscle redundancy is a resource for handling task variables and, as a consequence, the same kinematics might be associated with a manifold of muscle activations rather than with a 1:1 mapping. In Industry 5.0 scenarios, a worker wearing a passive device may preserve externally acceptable task kinematics according to standard ergonomic criteria; yet this surface-level compliance may mask high neural costs and adaptations. Our analysis targets four distinct evaluation domains: neural ergonomics, assistance efficiency, joint stability, and motor learning. Table 1 summarizes the interpretation of neural metrics.

**Table 1.** Interpreting neural metrics for industrial outcomes.

| Evaluation Domain     | Neural Metric                         | Physiological Interpretation                        | Industry 5.0 Implication                                                                                         |
|-----------------------|---------------------------------------|-----------------------------------------------------|------------------------------------------------------------------------------------------------------------------|
| Neural Ergonomics     | Vector Similarity ( $W_i \cdot W_j$ ) | Preservation of native motor primitives.            | <i>Acceptance:</i> If similarity is low, the worker perceives the device as “intrusive,” leading to abandonment. |
| Assistance Efficiency | Activation Area ( $\int C(t)dt$ )     | Net reduction in neural drive for specific modules. | <i>Durability:</i> Quantifies the actual energy saving per cycle, predicting extension of work shifts.           |
| Joint Stability       | Co-contraction Synergies              | Simultaneous recruitment of opposing muscle groups. | <i>Safety:</i> High co-contraction indicates that the device is destabilizing the user, increasing injury risk.  |
| Motor Learning        | Inter-cycle Variability ( $R^2$ )     | Consistency of synergy patterns across repetitions. | <i>Training:</i> Low variability indicates that the worker has internalized the device dynamics (Motor Mastery). |

#### 3.1. Neural Ergonomics

“Transparency” in physical HRI is typically defined mechanically (low impedance, absence of undesired interaction forces). As previously suggested in [9], we extend this concept to the neural domain.

By computing the CS between the synergy weight vectors ( $W$ ) of the unsupported ( $W_{\text{unsupp}}$ ) and supported ( $W_{\text{supp}}$ ) conditions, we quantify the preservation of the user’s motor strategy. Indeed, high CS ( $>0.80$ ) implies that the passive device acts as a transparent extension of the body, amplifying force without altering the coordination strategy. When  $0.80 < \text{CS} < 0.50$ , a partial alteration takes place. Conversely, low CS ( $<0.50$ ) with preserved kinematics (i.e., the critical “Hidden Risk” zone) indicates that while the task looks reasonably correct in the kinematics, the CNS has been forced to recruit alternative muscle groups to overcome the device’s internal stiffness or misalignment. This reorganization of the synergy space is a precursor to fatigue or maladaptation and, eventually, rejection of the technology.

Thresholds are reported here as illustrative values derived from prior synergy literature and should be tuned according to channel count and task variability.

#### 3.2. Assistance Efficacy and Joint Stability

A reduction in raw EMG amplitude is often cited as proof of device efficacy [28–31]. However, synergy analysis allows us to distinguish between functional unloading and

stabilizing stiffness. Through the analysis of activation coefficients  $C$ , it can be observed whether the reduction in agonist muscle activity is accompanied by an anomalous increase in antagonist activity (Co-contraction Index). Ideally, the device assumes the gravitational load, and the amplitude of the “Main Agonist Synergy” decreases proportionally, while the temporal structure remains stable. Instead, if the device introduces instability, the CNS responds by simultaneously activating agonist and antagonist muscles, creating a “Stiffening Synergy” to freeze degrees of freedom. This increases the metabolic cost despite the mechanical assistance, a phenomenon undetectable by kinematics alone.

### 3.3. Motor Learning

The number of extracted synergies required to reconstruct the signal (a typical threshold is  $R^2 > 90\%$ ) serves as a proxy for control complexity. This concept is borrowed from the motor control of people with motor impairments [32,33]. Once again, the reconstruction threshold reported here should be considered an illustrative reference rather than a fixed universal rule. Depending on task variability, channel count, and noise levels typical of industrial environments, the optimal number of synergies may also be identified through complementary criteria such as the knee point of the reconstruction curve, cross-validation procedures, or robustness analyses across repeated trials.

- Synergy Merging ( $N_{\text{supp}} < N_{\text{unsupp}}$ ): The device constrains the movement, merging previously independent modules. This “simplification” often correlates with reduced dexterity and a “robot-led” movement.
- Synergy Fractionation ( $N_{\text{supp}} > N_{\text{unsupp}}$ ): The worker struggles to integrate the device dynamics, forcing the CNS to break down standard modules into smaller, less efficient units to maintain control. This fragmentation is a hallmark of high cognitive load and/or poor ergonomic fit.

### 3.4. The “Neural Cost of Adaptation”

Finally, we propose the Neural Cost of Adaptation (NCA) as a composite index. While kinematic adaptation to a passive device (e.g., reaching target speed) occurs rapidly (minutes), neural adaptation (related to synergy reorganization) is a slower process [34]. Synergy analysis may reveal this latency. While a device may be kinematically validated in a short test, synergy analysis over a longer session may reveal a progressive “drift” or degradation in coordination patterns, highlighting the difference between short-term performance and long-term sustainability with relevant assessments for determining the neural expenditure of wearing a device.

From a signal-processing perspective, the proposed Neural Cost of Adaptation can be formalized as a composite non-stationary metric. It quantifies the progressive drift in coordination by combining spatial reorganization, temporal shifts, and activation variability over a sliding window ( $sw$ ) relative to an initial healthy baseline ( $base$ ). We define NCA mathematically as a weighted sum of these three functional domains:

$$NCA(sw) = \alpha \cdot D_{\text{spatial}}(sw) + \beta \cdot D_{\text{temporal}}(sw) + \gamma \cdot D_{\text{var}}(sw)$$

where

$$D_{\text{spatial}}(sw) = 1 - \frac{1}{N} \sum_{n=1}^N CS(W_{\text{base}}, W_{\text{sw}})$$

$D_{\text{spatial}}(sw)$  quantifies the loss of Neural Transparency (drop in Cosine Similarity),

$$D_{\text{temporal}}(sw) = \frac{1}{N} \sum_{n=1}^N |(CoA_{\text{sw}} - CoA_{\text{base}})|$$

$D_{temporal}(sw)$  captures phase shifts or delayed recruitment mechanisms indicative of early central fatigue, and:

$$D_{var}(sw) = 1 - \frac{R_{sw}^2}{R_{base}^2} \quad (1)$$

$D_{var}(sw)$  represents the decay in inter-cycle consistency and Motor Mastery. The weighting factors  $\alpha$ ,  $\beta$ , and  $\gamma$  sum to 1 and can be tuned according to the specific industrial task requirements (e.g., prioritizing spatial preservation in precision tasks versus temporal stability in repetitive lifting). Tracking the NCA allows for the identification of a progressive drift in coordination, enabling predictive prevention before fatigue leads to task rejection or clinical injury.

#### 4. Sensor Streamlining and Physiological Digital Twin

A bottleneck in the translation of neuro-ergonomics to Industry 5.0 is the intrusiveness versus information trade-off. While laboratory protocols demand high-density EMG (HD-EMG) or at least multi-channel EMG to fully capture motor unit behavior, the industrial workspace requires minimal, robust, and wearable sensing solutions. We argue that the inherent mathematical property of muscle synergies (i.e., dimensionality reduction) may provide the theoretical foundation to solve this trade-off, allowing for the transition from “Musculoskeletal Monitoring” to “State-Space Estimation”.

##### 4.1. The Mathematical Basis for Sensor Streamlining

The fundamental hypothesis of synergy framework is that the descending control input to the actuators (muscles) resides in a low-dimensional space. If a task involving  $M$  muscles (e.g.,  $M = 16$ ) is governed by  $N$  synergies (typically  $N = 3/5$  [22,35]), the system is theoretically over-determined.

We propose a Reconstruction-Based Selection Algorithm to identify the minimal sensor set ( $M_{\text{optim}}$ ):

1. Matrix Factorization ( $W_{\text{full}}$ ): Extract the full weight matrix from laboratory benchmark data.
2. Lead-Muscle Identification: For each synergy  $S_i$ , identify the muscle  $m$  with the highest weighting coefficient ( $w_{m,i} > \text{threshold}$ ).
3. Subset Validation: Mathematically reconstruct the original activation patterns using only the reduced subset  $V_{\text{subset}}$ . The quality of this reconstruction is quantified by Reconstruction  $R^2$ .

If  $R^2_{\text{rec}}$  remains  $>$  a predefined threshold (e.g., 75%) despite removing 50+% of the sensors, the reduced set is validated as a sufficient proxy for the worker’s neural state. These thresholds should be considered as illustrative values derived from the prior synergy literature and should be tuned according to channel count and task variability. In practical implementations, the fidelity of the reduced sensor set should be quantified through complementary metrics such as RMSE or normalized RMSE, together with statistical confidence bounds estimated across repeated trials, to explicitly characterize the information loss introduced in the Neural Digital Twin.

The mathematical property of dimensionality reduction inherent in muscle synergies provides a rigorous foundation for sensor streamlining in the industrial workspace. By identifying the “lead muscles” within each synergy through laboratory-grade benchmarks, it becomes possible to reconstruct the global neural state of the worker using only a minimal subset of wearable sensors. This approach ensures that the transition from the laboratory to the industrial floor does not sacrifice information depth for the sake of worker comfort, maintaining a high Reconstruction  $R^2$  while significantly reducing the physical footprint of the monitoring system. However, to improve robustness in industrial environments,

lead-muscle selection should not rely solely on the highest weighting coefficient. Channels associated with unstable electrodes, motion artifacts, or excessive variance may become unreliable despite their high contribution to a given synergy. Therefore, weighting-based ranking should be complemented by additional criteria such as signal quality, inter-trial repeatability, and reconstruction stability, while preserving limited sensor redundancy to prevent single-point failures.

#### 4.2. Toward a “Physiological Digital Twin”

Once the optimal sensor set is deployed (e.g., four sensors positioned on the skin or integrated into the textile of workwear), the monitoring paradigm shifts from observing raw signals to tracking the physiological digital twin of the worker. Instead of analyzing noisy EMG amplitudes, the system compares an estimation of the projected synergy activation ( $C_{\text{real-time}}$ ) against a healthy reference template calibrated at the start of the shift or derived from a population norm, according to a traffic light protocol:

- Green Zone (Transparency):  $C_{\text{real-time}}$  aligns with the template. The passive device is working as intended.
- Yellow Zone (Drift/Fatigue): A progressive widening of the activation bursts ( $\Delta t$ ) or a decrease in similarity. This signals the onset of central fatigue before physical failure occurs.
- Red Zone (Compensation): The sudden appearance of activity in a sensor typically silent for that synergy (e.g., upper trapezius activation during a low-load task). This triggers a “Stop/Recalibrate” warning, indicating maladaptive compensation.

This concept aligns with recent trends in digital ergonomics and physiological digital twins, where reduced bio-signal sets are used to track internal states rather than raw outputs. A critical prerequisite for the traffic-light protocol is a preliminary signal-integrity layer capable of distinguishing physiological deviations from technical artifacts such as electrode displacement, sweat-induced impedance fluctuations, or transient motion noise. Only deviations that persist after this fault-detection stage should be interpreted as genuine maladaptive compensations within the Neural Digital Twin.

#### 4.3. Prescriptive Ergonomics for Passive Devices

Passive wearables lack actuators to adjust themselves dynamically. However, synergy-based monitoring transforms them into “Smart-Passive” systems. The data collected via the streamlined sensor set serves a prescriptive function:

1. Daily Calibration: The synergy analysis can dictate the optimal mechanical settings (e.g., spring pre-tension, support angle) before the worker engages in the task, tailored to their daily physiological condition.
2. Long-term Durability: By tracking the decay of synergy stability over weeks, safety managers can identify when a specific worker requires a rotation to a different task, not based on generic timetables but on their specific neural resilience.

#### 4.4. Comparison with Standard Metrics

Current ergonomic assessment methods for wearable devices primarily rely on kinematic indicators, observational scales, or reductions in EMG amplitude as proxies for biomechanical load and fatigue. These approaches implicitly assume that improvements in external posture or local muscle activation correspond to a proportional reduction in physiological cost. The proposed framework challenges this assumption by separating kinematics and force production from the coordination structure. While classical metrics quantify “how much” a muscle is activated, synergy-based analysis characterizes “how” muscles are organized and combined to generate movement. As a result, two conditions

with comparable joint kinematics and mean EMG levels may exhibit different neural control strategies, reflecting distinct levels of motor efficiency, stability, and long-term sustainability. In this sense, the present approach does not aim to replace established ergonomic indices but to complement them by providing an additional layer of interpretation focused on neural organization rather than solely on mechanical output. The core advantage of the muscle synergy framework over traditional ergonomic metrics lies in its ability to decouple the mechanical outcome from the neural effort required to achieve it. While standard tools like RULA or raw EMG amplitude focus on “what” the worker does and “how much” local effort is produced, they remain blind to the underlying motor control strategy—the “how”. In the context of Industry 5.0, this distinction is critical for three reasons:

- (i) **Detection of Silent Maladaptation:** a worker interacting with a passive wearable may maintain ideal kinematic posture (e.g., correct trunk inclination) while the CNS implements detrimental muscle substitutions to overcome device misalignment or internal resistance. Synergy analysis identifies these shifts in muscle weightings ( $W$ ) as “hidden risks” that precede clinical symptoms.
- (ii) **Functional Unloading vs. Stabilizing Stiffness:** unlike raw EMG, which might show a generic reduction in amplitude, synergy activation coefficients ( $C$ ) allow researchers to distinguish between true functional assistance and maladaptive co-contraction. If the device introduces instability, CNS may increase the recruitment of a “stiffening synergy” to freeze degrees of freedom, an adaptation that increases metabolic cost despite appearing supported on the surface.
- (iii) **Long-term Sustainability and Neural Drift:** traditional metrics provide a snapshot of performance, whereas the stability and variability of synergy patterns over time serve as a proxy for “Motor Mastery” and neural resilience. Tracking the NCA allows for the identification of a progressive drift in coordination, enabling predictive prevention before fatigue leads to task rejection or injury. By analyzing the modularity of control, we move from observing a worker as a mechanical system to understanding them as a neuro-centric asset, transforming wearables from simple tools into transparent extensions of the human body.

To further clarify the advantages of the proposed methodology, Table 2 summarizes the key differences between traditional ergonomic assessment tools and the muscle synergy framework in the context of human–wearable interaction.

**Table 2.** Comparison between standard ergonomic assessment and the proposed muscle synergy framework.

| Feature                  | Standard Ergonomic Metrics<br>(RULA/REBA, Kinematics, EMG Envelope)             | Proposed Muscle Synergy Framework                                       |
|--------------------------|---------------------------------------------------------------------------------|-------------------------------------------------------------------------|
| Primary Focus            | Observational posture and local muscle activation levels.                       | Neural control strategies and coordination patterns.                    |
| Data Interpretation      | Quantifies “how much” a muscle is activated.                                    | Characterizes “how” muscles are organized and combined.                 |
| Hidden Risk Detection    | Limited; fails to capture compensatory strategies if kinematics appear correct. | High; identifies “silent” neural strain and maladaptive substitutions.  |
| Assessment of Assistance | Based on the reduction of local EMG amplitude.                                  | Based on “Neural Transparency” and synergy space preservation.          |
| Complexity Analysis      | Not applicable (focuses on individual degrees of freedom).                      | Quantifies control complexity through synergy merging or fractionation. |
| Long-term Sustainability | Snapshot of current physical strain.                                            | Predictive; tracks “Neural Drift” and adaptation costs over time.       |

#### 4.5. Illustrative Industrial Case: Overhead Drilling with Passive Support

To demonstrate the practical utility of the proposed framework, we consider a high-intensity industrial task: overhead drilling using a passive shoulder-support exoskeleton. While traditional ergonomics (e.g., RULA) would focus on the static shoulder angle, our synergy-based approach enables a multi-layered assessment of the interaction.

*Step 1: Baseline Synergy Identification.* Initially, the framework establishes the worker's "neural signature" in an unassisted condition. In overhead drilling, at least three functional synergies are involved: (1) a Postural Synergy (stabilizing the trunk and lower back), (2) a Reaching/Elevation Synergy (deltoid and trapezius activation to hold the drill), and (3) a Manual Dexterity Synergy (fine motor control of the forearm for trigger management and precision).

*Step 2: Quantifying Neural Transparency.* Once the exoskeleton is donned, the framework monitors the Neural Transparency via Cosine Similarity (CS). In an optimal interaction, the device reduces EMG amplitude while maintaining a high similarity (e.g.,  $CS > 0.80$ ) with the baseline synergy structure. This indicates that the mechanical assistance is "transparent" to the nervous system, augmenting the worker's strength without forcing a reorganization of their natural motor coordination.

*Step 3: Detecting Hidden Maladaptation.* The primary value of the framework emerges when kinematics appear stable but neural cost increases. For instance, if the exoskeleton provides excessive torque, the worker might unconsciously "fight" the device to maintain precision. In this case, while a RULA score might remain low (indicating an acceptable posture), our framework would detect a rising Neural Cost of Adaptation (NCA). This drift is captured by a shift in the Center of Activity ( $D_{\text{temporal}}$ ) and a drop in inter-cycle consistency ( $D_{\text{var}}$ ), signaling early-onset central fatigue or device-induced resistance.

*Step 4: Toward a Neural Digital Twin.* Finally, by applying the Reconstruction-Based Selection Algorithm, the monitoring system can be streamlined. Instead of a full-body EMG suit, the framework identifies that monitoring just a subset of "lead muscles" (e.g., the Anterior Deltoid and the Erector Spinae) is sufficient to reconstruct the task-specific synergies with  $W_{\text{subset}} > 75\%$ . This reduced sensor set feeds the Neural Digital Twin, providing real-time "traffic-light" feedback to the worker: a green light for transparent assistance, yellow for early neural drift, and red for high-risk maladaptive compensation, enabling proactive intervention before physical discomfort occurs.

#### 4.6. Limitations and Future Directions

While promising, this framework faces challenges in electrode placement consistency and sweat-induced impedance changes, which are critical in industrial environments. Future work must focus on developing "shift-invariant" synergy extraction algorithms capable of normalizing these artifacts without constant recalibration. Furthermore, the integration of non-invasive kinematic proxies (e.g., IMUs embedded in the wearable) with sparse EMG could further improve the robustness of the estimate of the user's intention. A promising future extension of the present framework lies in the development of multi-objective learning architectures capable of jointly optimizing external kinematic performance and internal neural cost. In this perspective, preserved task kinematics combined with reduced synergy similarity may serve as a supervisory signal for detecting hidden maladaptation and guiding personalized wearable calibration strategies. A major challenge in translating laboratory-based neuromuscular assessments to industrial environments is not limited to sensor intrusiveness but also concerns ecological validity. Real occupational tasks are substantially more variable, multi-phase, and context-dependent than the highly stereotyped movements typically reproduced in laboratory protocols. Furthermore, many validation studies rely on inexperienced participants, such as university students, whose

neuromuscular strategies may differ significantly from those of skilled workers with consolidated task-specific motor habits. These differences may affect both synergy structure and adaptive responses to passive wearable support, highlighting the need for future validation in ecologically realistic work scenarios and trained worker populations. Thus, our approach should consider a task segmentation layer tuned on specific applications and consider monitoring specific tasks rather than full workspace activities.

## 5. Conclusions

This study establishes a novel neuromuscular framework for evaluating human–passive wearable interaction, moving beyond surface-level kinematics to unveil the underlying neural cost of industrial tasks. By leveraging the dimensionality reduction of muscle synergies, we demonstrated that it is possible to quantify “Neural Transparency” and detect maladaptive compensatory strategies that precede musculoskeletal injuries. Furthermore, the proposed sensor streamlining approach provides a mathematically grounded roadmap for transitioning from high-density laboratory setups to scalable, sensor-lean monitoring in the industrial workspace. This methodology aligns with the Industry 5.0 paradigm by placing the worker’s physiological integrity at the center of the technological ecosystem, transforming passive supports into intelligent, human-centric systems capable of ensuring long-term motor health and sustainable manufacturing performance. Overall, this approach establishes the foundation for a new generation of synergy-informed assessment instruments that can transform passive wearables into intelligent, adaptive, and truly human-centric tools.

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## Abbreviations

The following abbreviations are used in this manuscript:

|        |                           |
|--------|---------------------------|
| C      | Activation coefficient    |
| CoA    | Center of Activity        |
| CNS    | Central Nervous System    |
| CS     | Cosine Similarity         |
| EMG    | Electromyography          |
| HD-EMG | High-Density EMG          |
| HRC    | Human–Robot Collaboration |

|                |                                       |
|----------------|---------------------------------------|
| HRI            | Human–Robot Interaction               |
| IMU            | Inertial Measurement Unit             |
| NCA            | Neural Cost of Adaptation             |
| NMF            | Non-Negative Matrix Factorization     |
| PCA            | Principal Component Analysis          |
| r              | Pearson’s Correlation Coefficient     |
| R <sup>2</sup> | Reconstruction                        |
| REBA           | Rapid Entire Body Assessment          |
| RULA           | Rapid Upper Limb Assessment           |
| SSE            | Sum of the Squares Error              |
| SST            | Sum of the Squares Total              |
| VAF            | Variance Accounted For                |
| W              | Spatial Synergy Vector                |
| WMSD           | Work-related Musculoskeletal Disorder |

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