Capturing Human-Centric Adaptation in Human–Robot Collaboration for Prefabricated Construction: Empirical Modeling of Mental and Physical Effort Dynamics

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Abstract –

Human–robot collaboration (HRC) is increasingly adopted in prefabricated construction to improve productivity while maintaining flexibility. However, most existing HRC planning approaches remain efficiency-oriented or rely on simplified fatigue assumptions that lack strong empirical grounding in prefabrication work, which is characterized by frequent switching between physical execution and cognitive monitoring. This study empirically models time-varying mental and physical effort dynamics through a controlled wooden wall panel manufacturing experiment. Eight participants completed a 60-min working phase followed by a 30-min seated rest phase, during which subjective measures of mental and physical effort were repeatedly collected. Phase-specific exponential functions were fitted to individual effort trajectories to characterize effort accumulation during work and recovery during rest. Results indicate smoother, near-monotonic accumulation of physical effort, whereas mental effort exhibits greater early-stage variability, suggesting transient cognitive adjustment. During rest, both effort measures demonstrate more stable and faster recovery dynamics. Parameter identifiability issues were observed for low-variance physical effort trajectories, highlighting the importance of curve-based group aggregation. Overall, the proposed framework provides interpretable empirical representations of effort dynamics that support human-centric HRC design and scheduling in prefabricated construction.

Keywords –

Human-Centric Human–Robot Collaboration; Modular Construction; Construction Robotics; Mental and Physical Effort Dynamics; Human Factors.

1 Background and motivation

Prefabricated construction is a construction approach in which building components are manufactured off-site in controlled factory environments and later assembled on-site [1]. By shifting production from traditional construction sites to factory settings, prefabrication improves productivity, quality consistency, and material efficiency, and has therefore experienced rapid global adoption [2]. Robotics has been widely regarded as key enabling technology for this transition, as it enhances precision, efficiency, and operational safety in prefabrication workflows [3, 4]. However, full robotic automation remains challenging to implement at scale due to high initial costs and the need to accommodate customized and variable component designs.

Consequently, collaborative robots and human–robot collaboration (HRC) have emerged as more flexible and cost-effective solutions for prefabricated construction. Early HRC implementations in this domain have primarily been driven by efficiency-oriented objectives, such as minimizing cycle time or maximizing throughput, with limited attention to human cognitive and physical capabilities [5]. While such efficiency-first approaches are straightforward to implement, they raise growing concerns regarding worker well-being, safety, and long-term system sustainability. Ignoring human factors in HRC can increase ergonomic risks, degrade collaborative performance and undermine the reliability of human–robot teams [6]. Consistent with the principles of Industry 5.0, the next generation of HRC systems in prefabricated construction must therefore move toward human-centric designs that balance productivity with human adaptability, health, and sustainability.

In response to these concerns, prior studies have attempted to incorporated fatigue or workload considerations into human–robot task planning and scheduling. For example, many approaches introduce generic fatigue costs [7] or simplified fatigue–recovery assumptions to constrain human workload while maintaining productivity [8, 9]. Exponential models are commonly adopted because they capture rapid initial change followed by saturation, as well as the diminishing returns during rest [9]. While such assumptions are appropriate for sustained and homogeneous task exposure, they are often detached from the actual cognitive–physical characteristics of prefabricated construction work. In practice, prefabrication tasks frequently involve customized components, material uncertainty, and repeated switching between physical execution and cognitive monitoring and decision-making. Whether generic fatigue models, including exponential functions, can adequately represent such hybrid and adaptive dynamics in HRC remains unclear, and empirical studies explicitly modeling these dynamics in prefabricated construction are still scarce.

From a resource-based human factors perspective, fatigue is considered as an outcome of resource depletion rather than its cause. The underlying mechanism lies in the regulation and consumption of cognitive and physiological resources required to meet task demands [10]. Multiple resource theory suggests that mental and physical tasks draw on partially independent resource pools, and that simultaneous or alternating demands can overload different capacities [11]. Compensatory control models conceptualize effort as an adaptive response: as task demands increase, operators allocate additional effort to maintain performance and only reduce performance once compensatory limits are reached [12]. Within this framework, mental and physical effort reflect the moment-to-moment allocation of internal resources, providing a direct behavioral manifestation of human adaptation under load.

Compared with latent and abstract representations of internal capacity resources, effort is observable, interpretable, and measurable in real time. Subjective effort scales such as the Rating Scale of Mental Effort (RSME) [13] and Borg's Rating of Perceived Exertion (Borg) [14] capture perceived cognitive effort and physical strain, respectively. Importantly, effort ratings reflect how workers experience and regulate task demands, rather than assuming a fixed fatigue capacity. This makes mental and physical effort particularly suitable for modeling adaptive, resource-based fatigue dynamics in HRC, where task demands fluctuate over time and across modes of interaction.

Building on this human-centric HRC perspective, the objectives of this study are twofold. First, a controlled wooden wall panel manufacturing experiment was designed to alternate between physical execution and cognitive monitoring tasks, reflecting key characteristics of real-world prefabrication workflows. Second, an empirical investigation was conducted to capture adaptive fatigue dynamics by modeling the accumulation and recovery of mental and physical effort during HRC. Time-series effort data were repeatedly collected and modeled using exponential functions to characterize dynamic adaptation during working and rest phases. By grounding human resource and fatigue modeling in observable mental and physical effort dynamics, this study provides quantitative insights into human resource regulation in HRC and supports the design of safer, more sustainable, and human-centric collaborative systems for prefabricated construction.

2 Methods

This section describes the experimental design, participant characteristics, and data processing procedures employed in this study.

2.1 Experimental Design

A controlled laboratory experiment was designed to capture time-varying mental and physical effort during HRC in a prefabricated construction context. As shown in Figure 1, the experiment included a 60-min working phase followed by a 30-min rest phase.

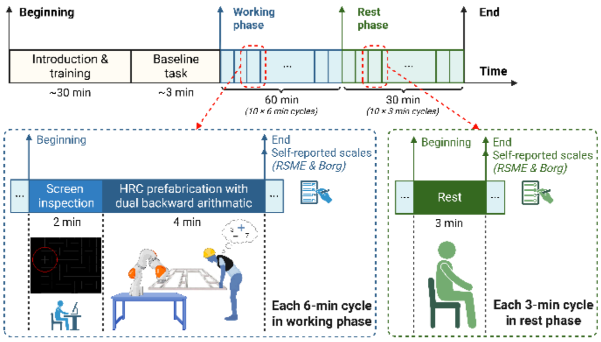


Figure 1. Overview of the experimental procedure

During the working phase, participants completed ten repeated 6-min cycles. Each cycle consisted of a 4-min primary HRC prefabrication task and a 2-min screen inspection task. This structure approximated frequent switching between physical execution and cognitive monitoring activities in real-world settings. Effort ratings were collected at the end of each 6-min cycle to track accumulation over time. During the rest phase, participants remained seated, and effort ratings were collected every 3 min to characterize recovery.

Before the formal trial, participants received an introduction and short training. They then completed a baseline task by driving ten screws into a wooden board to ensure basic tool familiarity. Effort ratings recorded after the baseline task were used as reference values for the start of the working phase.

2.1.1 Main HRC Prefabrication Task

The primary task simulated a typical prefabrication workflow for manufacturing wooden wall panels, as developed in our previous work [15]. The process was decomposed into nine sequential subtasks (T1–T9), including framing, screwing, panel handling, insulation insertion, and panel relocation. Participants were instructed to perform the manufacturing task continuously and as efficiently as possible within each 4-min working segment, and to resume the task in subsequent segments across the full 60-min working phase. The overall workflow is illustrated in Figure 2.

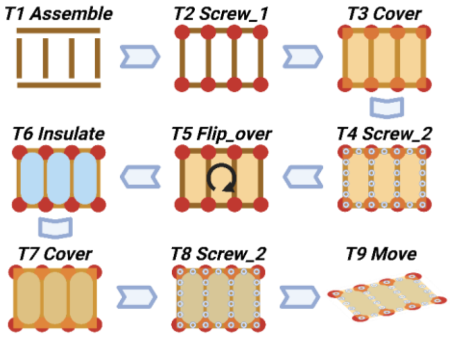


Figure 2. Workflow of the designed wooden wall panel manufacturing task [15]

To impose a continuous cognitive demand during physical execution, a backward arithmetic dual task was embedded in each 4-min working segment. At the start of each segment, participants were given a random three-digit number and instructed to repeatedly subtract seven. A browser-based script delivered an audio prompt every 12 s, and participants verbally reported the updated value after each prompt. This dual task approximated cognitive demands commonly encountered in manufacturing, such as recalling component dimensions or design parameters. It emphasized sustained attention and working memory rather than arithmetic difficulty.

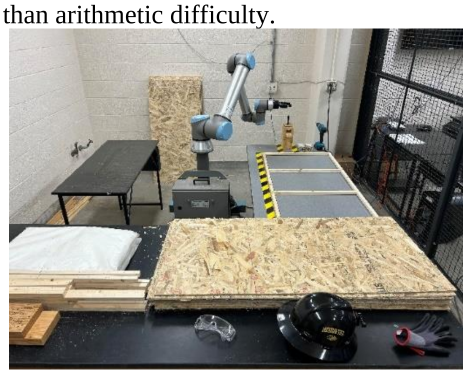


Figure 3. Laboratory workspace setup

All trials were performed in a dedicated workspace configured to resemble a prefabrication workstation (Figure 3). The setup included a standardized worktable, pre-cut timber members, OSB panels, insulation materials, and electric hand tools with screws. Basic personal protective equipment was provided throughout the experiment.

2.1.2 Robotic Programming

A UR10e robot equipped with a Robotiq 2F-85 gripper was integrated into the workspace. The robot assisted with selected positioning-intensive operations (T1) and repetitive screwing tasks (T2, T4, and T8). Robot motions were predefined and executed using RoboDK. Figure 4 illustrates the programmed robot actions and their placement within the workflow.

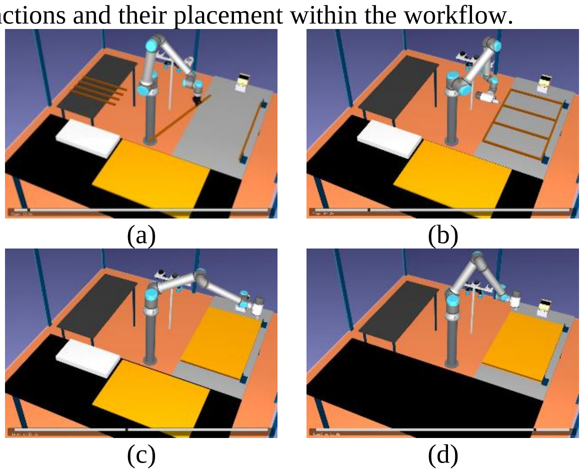


Figure 4. Robot execution and simulated actions within the task workflow: (a) T1, (b) T2, (c) T4, and (d) T8

2.1.3 Intermittent Screen Inspection Task

A 2-min screen inspection task was included in each 6-min working cycle to represent monitoring and quality checking commonly required in prefabrication. It was intended to approximate human inspection of work completed by either human workers or robotic systems (e.g., screwing quality). At predefined intervals, participants viewed a visual stimulus and made a binary decision.

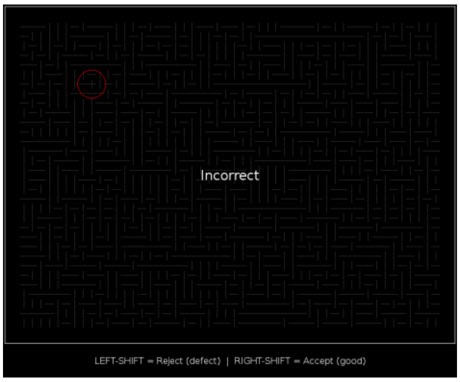
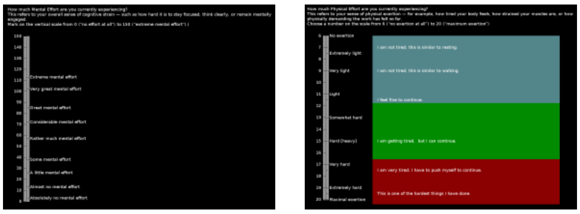


Figure 5. A demonstration example of screen inspection task

As shown in Figure 5, the display consisted of a full screen of short horizontal or vertical line segments. In some trials, a "+" intersection was present. Participants pressed the left Shift key if an intersection was detected and the right Shift key otherwise. The task was implemented using Psychology Experiment Building Language (PEBL, version 2.1) [16], with the presence of the "+" stimulus randomized across trials and displayed at randomized screen positions.

2.1.4 Measurements

Two self-report scales were used to measure effort repeatedly at the end of each 6-min or 3-min cycle during the working and rest phases. Mental effort was assessed using the RSME [13], and physical effort was assessed using the Borg's scale [14]. As shown in Figure 6, RSME was presented on a vertical scale from 0 to 150, while Borg was presented on a vertical scale from 6 to 20. Both scales were administered digitally using PEBL (version 2.1) to minimize disruption and ensure consistent presentation.



(a) (b)

Figure 6. Digital presentation of effort scales used in the experiment: (a) Rating Scale for Mental Effort (RSME) and (b) Borg Rating of Perceived Exertion (Borg)

2.2 Participants

Eight participants (six males and two females) were recruited for this study. All participants were over 18 years old and reported no musculoskeletal injuries or medical conditions that could affect physical task execution or cognitive assessment. Participants were recruited through campus-wide announcements and direct email invitations. The study protocol was approved by the Institutional Review Board (IRB) at Michigan Technological University (IRB-2024-90).

2.3 Data Processing

A two-step analysis framework was adopted. First, exponential models were fitted at the individual level to characterize effort dynamics. Second, fitted parameters and trajectories were summarized to examine group-level patterns. Effort data were segmented into working and rest phases based on task timing. For each phase, time was re-referenced to phase onset. Mental effort (RSME) and physical effort (Borg) were processed separately but followed the same analytical procedure.

2.3.1 Individual-Level Exponential Fitting

Individual mental (RSME) and physical (Borg) effort trajectories were modeled using exponential functions. Models were fitted separately for each participant, effort scale, and phase using nonlinear least squares implemented with the nls package in R (version 4.4.2) [17]. For the working phase, effort accumulation was modeled as Equation (1), whereas for the rest phase, effort recovery was modeled as Equation (2) [9].

$$y(t) = y_0 + b(1 - e^{-kt}) \quad (1)$$
$$y(t) = y_0 - b(1 - e^{-kt}) \quad (2)$$

The initial effort value y_0 was fixed for each participant and scale, corresponding to the baseline value at the beginning of the working phase and the transition point into the rest phase. The model estimated two free parameters: the amplitude b and the rate constant k. Fits with insufficient data points or non-identifiable parameters were excluded from subsequent analyses.

2.3.2 Fitting Parameter Analysis

The fitted parameters were used to summarize effort dynamics at the parameter level. The amplitude parameter b represents the overall magnitude of effort accumulation or recovery, while the rate constant k characterizes the speed of change. To capture early-stage dynamics, an initial rate parameter r_0 was derived as Equation (3).

$$r_0 = b \times k \quad (3)$$

Descriptive statistics of b, k, and r_0 were computed across participants for each effort type and phase. These parameters were summarized to compare accumulation and recovery patterns between working and rest phases, as well as between mental and physical effort.

2.3.3 Group-Level Mean Trajectories

Group-level effort trajectories were constructed based on individual fitted curves. For each effort type and phase, fitted trajectories from all valid participants were evaluated on a common time grid. The group-level mean trajectory was then obtained as the pointwise average of these individual curves. The resulting mean trajectories provide a stable and interpretable representation of typical effort dynamics across participants.

3 Results

3.1 Participant Descriptives

Trial-level effort data and demographic characteristics for all participants (N = 8) are summarized in Table 1. Mental effort (RSME) and physical effort (Borg) ratings are reported separately for working and rest phases as mean ± standard deviation, with the observed range shown in parentheses. The final "Mean" row in Table 1 represents the mean and standard deviation of participant-level summary values rather than statistics computed from all raw data points. These descriptive statistics summarize inter-individual variability prior to model-based analyses.

3.2 Individual-Level Exponential Fitting

At the individual level, the exponential model provided interpretable fits across most participant–scale–phase combinations, as shown in Figure 7.

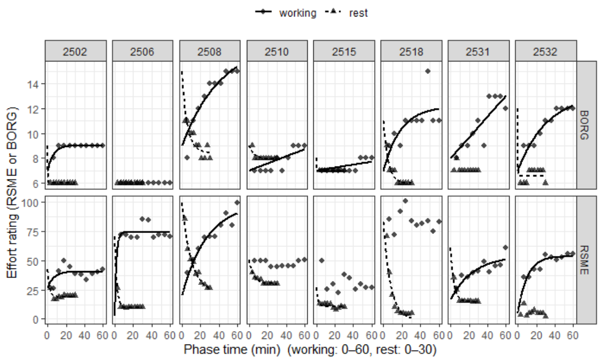


Figure 7. Individual exponential model fits for mental (RSME) and physical (Borg) effort during working and rest phases

During the working phase, effort ratings generally exhibited a monotonic increasing trend over time. This monotonicity was more consistently observed in physical effort (Borg), which showed smoother trajectories with fewer fluctuations. In contrast, mental effort (RSME) showed greater variability in the early working phase, with several subjects exhibiting a slight initial decrease. This pattern suggests a less stable adaptation process in mental effort dynamics during task initiation, potentially reflecting learning effects and individual differences in capacity (e.g., woodworking experience and mathematical ability), especially in a task setting that combines physical and cognitive demands.

By comparison, effort trajectories during the rest phase demonstrated more stable monotonic behavior for both physical and mental effort. The exponential decay during rest was generally characterized by faster rates of change than the accumulation observed during the working phase, indicating a more rapid recovery process once task demands were removed.

While the exponential model successfully captured effort dynamics for the majority of participants, a small number of individual cases showed unstable fits or non-identifiable parameters, as reflected by the absence of fitted curves in Figure 7. These cases were excluded from subsequent parameter summarization and group-level analyses to ensure robustness and transparency.

3.3 Fitting Parameter Analysis

To facilitate comparison of effort dynamics across phases and effort types, individual exponential trajectories were summarized using model parameters. Descriptive statistics of these parameters are reported in Table 2, and the distributions of individual estimates are shown in Figure 8.

Table 1. Participant demographics and descriptive statistics; mean ± standard deviation (range)

Participant	Sex	Woodworking Experience	Age (years)	Sleep (hours)	RSME_working	RSME_rest	BORG_working	BORG_rest
2510	M	Extensive	21	6.5	47.7 ± 2.6 (44.8–50.3)	32.5 ± 3.4 (30.0–40.1)	7.8 ± 0.9 (7.0–9.0)	8.1 ± 0.3 (8.0–9.0)
2531	F	A little	20	8.5	42.1 ± 9.2 (26.1–60.8)	18.2 ± 6.8 (14.6–35.5)	10.7 ± 1.9 (8.0–13.0)	7.1 ± 0.3 (7.0–8.0)
2506	M	Moderate	25	6	74.0 ± 5.9 (70.1–85.1)	11.6 ± 5.1 (9.7–26.1)	6.0 ± 0.0 (6.0–6.0)	6.0 ± 0.0 (6.0–6.0)
2508	M	A little	29	7	71.1 ± 17.9 (39.9–99.7)	43.6 ± 18.7 (26.1–85.9)	13.1 ± 2.2 (8.0–15.0)	9.3 ± 1.2 (8.0–11.0)
2502	M	Moderate	20	8.5	39.4 ± 6.2 (26.5–49.9)	19.8 ± 2.8 (16.6–26.7)	8.9 ± 0.3 (8.0–9.0)	6.0 ± 0.0 (6.0–6.0)
2532	F	Moderate	21	5	48.0 ± 8.1 (35.5–56.1)	5.4 ± 3.3 (1.8–13.4)	10.7 ± 1.3 (9.0–12.0)	6.6 ± 0.5 (6.0–7.0)
2515	M	Extensive	19	7	31.1 ± 8.2 (22.8–50.1)	11.3 ± 1.8 (8.2–13.2)	7.3 ± 0.5 (7.0–8.0)	7.0 ± 0.0 (7.0–7.0)
2518	M	Extensive	27	5	83.9 ± 8.1 (71.7–100.7)	17.2 ± 21.9 (4.1–70.7)	10.9 ± 1.7 (9.0–15.0)	6.6 ± 1.0 (6.0–9.0)
Mean			22.8 ± 3.7	6.7 ± 1.4	54.7 ± 19.0	19.9 ± 12.4	9.4 ± 2.3	7.1 ± 1.1

Table 2. Descriptive statistics of individual exponential fitting parameters; mean ± standard deviation

Scale	Phase	Number of subjects	b	k	r_0
Borg	Working	7	288.7 ± 420.1	0.04 ± 0.06	0.2 ± 0.1
Borg	Rest	6	3.6 ± 2.4	3.7 ± 3.8	11.8 ± 15.9
RSME	Working	5	46.8 ± 26.3	0.2 ± 0.2	10.5 ± 17.3
RSME	Rest	7	46.9 ± 28.1	0.3 ± 0.2	12.1 ± 7.9

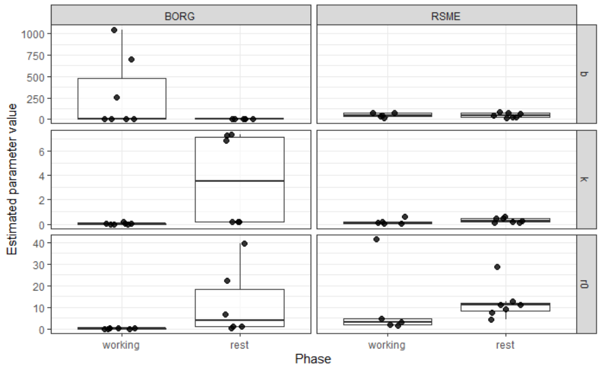


Figure 8. Distributions of individual exponential fitting parameters

For physical effort (Borg), the working phase exhibited large variability in the estimated amplitude parameter b. However, this variability does not solely reflect inter-individual differences in physical effort accumulation. Instead, it is partly attributable to the bounded nature of the Borg scale (6–20) and the limited variation observed for several participants during the working phase, where ratings remained near the lower end of the scale. Under these conditions, the exponential model can yield large amplitude estimates combined with small rate constants to reproduce near-flat trajectories within the observed time window, leading to inflated b values that exceed the practical range of the scale. In contrast, Borg parameters during the rest phase showed smaller amplitudes but larger rate constants, resulting in higher values of the derived initial rate r_0.

For mental effort (RSME), both working and rest phases exhibited moderate amplitudes and rate constants, with rest phase estimates generally associated with higher k and r_0 values compared to the working phase. Across both effort measures, the derived parameter r_0 provided a compact summary of early-stage dynamics that complemented interpretations based on b and k alone. Compared with the inter-individual variability for Borg parameters, whereas RSME parameters showed more concentrated distributions.

3.4 Group-Level Mean Trajectories

Constructed from individual fitted trajectories, Figure 9 presents the group-level mean exponential trajectories of mental (RSME) and physical (Borg) effort. The clear separation between working and rest trajectories across both effort types reflects distinct accumulation and recovery behaviors captured by the exponential model, with rest-phase changes generally occurring at faster rates than effort accumulation during working.

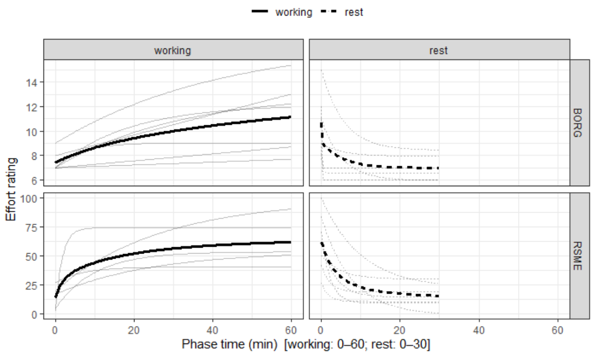


Figure 9. Group-level mean exponential trajectories; light lines show individual and the bold line shows the pointwise mean trajectory

For physical effort (Borg), the working phase is characterized by relatively smooth and gradual increases, with the mean trajectory approaching a plateau over time. This pattern suggests that the physical demands of the task were light to moderate for most participants, and that the one-hour working period did not drive them into a pronounced physical fatigue state. Consequently, during the rest phase, physical effort decreases rapidly for nearly all participants, yielding recovery trajectories marked by steep initial declines followed by stabilization near baseline levels.

For mental effort (RSME), the mean trajectory during the working phase reaches a plateau earlier than the corresponding physical trajectory, indicating a relatively rapid adjustment of mental effort followed by sustained engagement with the task. During the rest phase, mental effort recovers more gradually than physical effort, with trajectories showing a slower return toward baseline levels. Compared with physical trajectories, this pattern suggests that cognitive effort may require a longer adjustment period during recovery, even after physical task demands are removed.

4 Discussion

4.1 Individual-Level Variability and Model Identifiability

Although the exponential model provided interpretable fits for most participant–scale–phase combinations, several individual trajectories could not be reliably fitted or yielded non-identifiable parameters. These cases are informative rather than anomalous and reflect meaningful interactions between task demands, individual capability, and measurement characteristics.

For physical effort (Borg), several participants exhibited consistently low ratings throughout the working phase. For example, participants 2506, 2510, and 2515 in Figure 7 showed near the lower bound of the Borg scale with minimal temporal variation. When such near-constant trajectories are fitted using an exponential function, mathematically large amplitude (b) estimates paired with very small rate (k) constants can arise, despite negligible practical change in perceived effort. These inflated parameters therefore reflect limited identifiability under bounded, low-variance conditions rather than unusually high effort accumulation. This pattern is plausible given the light-to-moderate physical demands of the task and the prior woodworking experience of some participants, indicating a mismatch between task demand and individual physical capacity.

Future experimental designs could address this issue in two complementary ways. One approach is to introduce multiple task difficulty levels to better activate physical effort dynamics across participants. Another is to stratify participants based on relevant experience or capability and model effort dynamics separately within these groups. Such designs would help balance cross-subject consistency in controlled experiments while preserving meaningful individual differences.

For mental effort (RSME), non-monotonic behavior was more frequently observed during the early portion of the working phase. For several participants such as 2502, 2515, and 2518, mental effort initially fluctuated or even decreased before increasing (Figure 7), indicating a transient adjustment period rather than smooth accumulation. This pattern may reflect early learning, strategy formation, or task familiarization, which appear less pronounced in physical effort measures. Such reduced monotonicity also contributed to less stable model fits for some participants, suggesting that early mental effort dynamics may not fully follow a simple exponential form. Future work could test alternative nonlinear or system-dynamics models and incorporate multiple working–rest cycles with nonlinear mixed-effects modeling to better separate learning-related changes from effort accumulation.

4.2 Group-Level Representation and Aggregation Strategy

At the group level, effort dynamics can be summarized either by averaging model parameters or by averaging fitted trajectories. In this study, group-level mean trajectories were built using curve-based averaging to reduce the influence of extreme or weakly identifiable parameter estimates. As shown in Figure 10, alternative group-level curves can also be derived from mean parameter values; however, such representations are more sensitive to outliers, particularly for bounded effort scales. This robustness check shows that both approaches yield similar dynamic patterns, which supports the overall findings. Nevertheless, the curve-based approach (Figure 9) provides a more stable and interpretable summary of typical effort dynamics across participants. In future studies, a larger sample size should be included to improve the statistical power of the model.

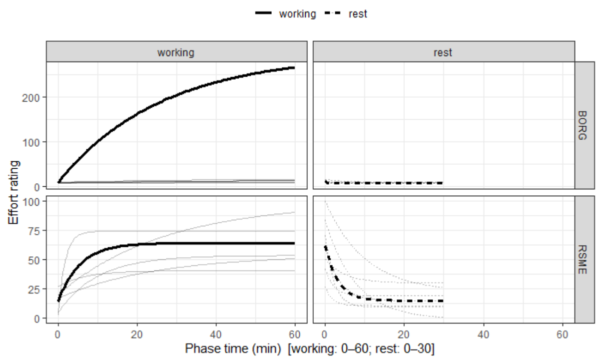


Figure 10. Group-level mean exponential trajectories; light lines show individual and the bold line shows the mean trajectory obtained via parameter averaging

4.3 Implications for Human-Centric HRC Modeling and Scheduling

This work provides an exploratory framework for modeling adaptative, time-varying mental and physical effort in HRC. Rather than treating effort as a static quantity, the proposed approach captures accumulation and recovery dynamics at the individual level and summarizes them at the group level in a transparent manner. These dynamic representations can serve as building blocks for human-centric HRC task allocation models, where robot assistance or task sequencing may be adapted based on predicted effort trajectories.

At a broader level, the group-level effort curves offer a compact description of typical subjective workload evolution during collaborative tasks. With additional validation and extended experimental designs, such trajectories could inform adaptive work–rest scheduling strategies or real-time adjustment of collaboration modes.

Integrating continuous physiological sensing could help capture short-term workload fluctuations more effectively and reduce reliance on subjective self-reports in future studies. By linking effort dynamics to task structure and individual capability, this line of work supports the development of more responsive and human aware HRC systems in prefabricated construction.

5 Conclusion

This study proposed an empirical framework to capture human-centric adaptation in prefabricated construction HRC by modeling mental and physical effort accumulation and recovery using exponential functions. A controlled wooden wall panel manufacturing experiment was designed to reflect key characteristics of prefabrication workflows involving repeated physical execution and cognitive monitoring. Results indicate smoother accumulation of physical effort during work, whereas mental effort exhibits greater early-stage variability, suggesting transient cognitive adjustment. During rest, both effort measures exhibit more stable and faster recovery dynamics.

We further identified limitations in exponential parameter estimation for bounded, low-variance Borg ratings, where individual-level parameters may become weakly identifiable. Curve-based aggregation at the group level provides a more robust representation of typical effort dynamics under such conditions. Overall, the proposed effort-dynamics modeling approach offers interpretable building blocks for human-centric HRC analysis. With larger samples and extended experimental designs, future work can integrate nonlinear mixed-effects models and support adaptive task scheduling that balances productivity and worker well-being in prefabricated construction.

References

[1] V. W. Tam, C. M. Tam, S. X. Zeng, and W. C. Ng. Towards adoption of prefabrication in construction. *Building and Environment*, 42(10):3642–3654, 2007.

[2] D. A. Steinhardt and K. Manley. Adoption of prefabricated housing: The role of country context. *Sustainable Cities and Society*, 22:126–135, 2016.

[3] B. Xiao, C. Chen, and X. Yin. Recent advancements of robotics in construction. *Automation in Construction*, 144:104591, 2022.

[4] Y. Wang, X. Hou, T. Chen, and B. Xiao. Recent advancements of applied robotics in construction project management: A life cycle perspective. *ASCE Open: Multidisciplinary Journal of Civil Engineering*, 3(1):03125002, 2025.

[5] Y. Wang, X. Hou, B. Xiao, and S. T. Mueller. Understanding cognitive impacts of robots in worker–robot collaboration in modular construction. In *Proceedings of the 42nd International Symposium on Automation and Robotics in Construction (ISARC)*, pages 837–844, 2025.

[6] S. Hopko, J. Wang, and R. Mehta. Human factors considerations and metrics in shared space human–robot collaboration: A systematic review. *Frontiers in Robotics and AI*, 9:799522, 2022.

[7] F. Zeng, C. Fan, S. Shirafuji, Y. Wang, M. Nishio, and J. Ota. Task allocation and scheduling to enhance human–robot collaboration in production line by synergizing efficiency and fatigue. *Journal of Manufacturing Systems*, 80:309–323, 2025.

[8] Y. You, B. Cai, D. T. Pham, Y. Liu, and Z. Ji. A human digital twin approach for fatigue-aware task planning in human–robot collaborative assembly. *Computers and Industrial Engineering*, 200:110774, 2025.

[9] B. Yao, X. Li, Z. Ji, K. Xiao, and W. Xu. Task reallocation of human–robot collaborative production workshop based on a dynamic human fatigue model. *Computers and Industrial Engineering*, 189:109855, 2024.

[10] J. Flanagan and D. Nathan-Roberts. Theories of vigilance and the prospect of cognitive restoration. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, volume 63(1), pages 1639–1643, Los Angeles, USA, 2019.

[11] C. D. Wickens. Multiple resources and mental workload. *Human Factors*, 50(3):449–455, 2008.

[12] G. R. J. Hockey. Compensatory control in the regulation of human performance under stress and high workload: A cognitive-energetical framework. *Biological Psychology*, 45(1–3):73–93, 1997.

[13] F. R. H. Zijlstra. Efficiency in work behaviour: A design approach for modern tools. PhD diss., Delft University of Technology, Delft: Delft University Press, 1993.

[14] G. A. V. Borg. Psychophysical bases of perceived exertion. *Medicine and Science in Sports and Exercise*, 14(5):377–381, 1982.

[15] Y. Wang, B. Xiao, S. T. Mueller, and W. Yi. Task–Taxon–Task framework for modeling and predicting the cognitive impact of collaborative robots on worker performance in modular construction. *Journal of Construction Engineering and Management*, 154 (4):04026033, 2026.

[16] S. T. Mueller and B. J. Piper. The psychology experiment building language (PEBL) and PEBL test battery. *Journal of Neuroscience Methods*, 222:250–259, 2014.

[17] R Core Team. R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing, 2024.