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Productive Inconvenience: Facilitating Posture Variability by Stimulating Robot-to-Human Handovers

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***Abstract*— Collaborative robots that physically interact with humans in an ergonomic and safe manner are essential to the future of industry. A common task across many industrial applications is *robot-to-human handover*, in which the location of object exchange is vital in cultivating a seamless interaction. Most prior work on computing these exchange locations aims to adjust human posture towards a better ergonomic state during a *single* handover. This procedure typically involves the robot estimating the human's biomechanical properties, *e.g.* center of mass and base of support, before determining an *optimal* handover location according to some ergonomics assessment scale. In a similar vein, we compare two methodologies for object handover, whereby the handover location is computed to either "assist" or "stimulate" the human receiver. Unlike existing approaches, we posit that improvements in human posture can be derived by stimulating the receiver's movement dynamics to facilitate posture variability, rather than constrain or stabilize it. To compare methodologies, we conduct a within-subjects study where participants perform 78 object handovers with a collaborative robot architecture. Our findings indicate an improvement in ergonomics scores for the "stimulating" approach, hinting at the importance of *productive inconvenience* in long-term robot-to-human handover.**

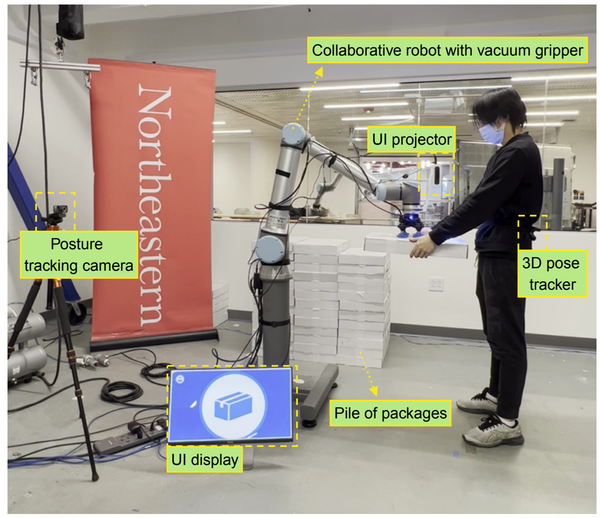

Fig. 1. Overview of our robot-to-human handover setup and the robotic architecture components. For each experimental trial, the robot would pick up a package from the pile and move to its computed handover location, allowing the participant to complete the exchange.

I. Introduction

Work-related musculoskeletal disorders (MSDs) are the largest factor responsible for absence from work in both Europe [1] and the US [2]. As such, reducing the risk of work-related injuries by improving workplace ergonomics is a critical goal in any industrial setting, especially those involving human-machine interaction. Nevertheless, injury and fatality rates remain high, with 13% of occupational fatalities being caused by equipment and machines [3].

In many industries, robots have replaced conventional machines and human-robot collaboration (HRC) is becoming more prevalent in the workplace. Existing approaches to improving ergonomics during HRC involve estimating human posture, evaluating an ergonomic score [4], [5], and then having the robot act in a way that induces the human to adjust into a more ergonomic posture. One common example of this procedure in HRC is *robot-to-human handover*, in which the robot must decide an object transfer point (OTP) that will maximally improve ergonomic metrics [6]. Most prior studies focus on human biomechanics to determine OTPs, stipulating that an OTP should guarantee the least deviation in a receiver's Center of Mass (CoM), while maintaining it within their Base of Support (BoS) [7]–[9].

Despite the plausibility of using this policy in some settings, *e.g.* standing idle, stabilizing a receiver's CoM constrains how humans naturally perform whole-body reaching tasks [10]. In contrast, humans allow their CoM to be freely displaced during natural whole-body movement that is not machine-mediated, enabling transitions between comfortable postures. Although workplace setups and machines tend to optimize towards reducing posture change, some studies underline the importance of human posture variability in work processes [11], [12]. Based on this perspective, a robot-to-human handover strategy that elicits more dynamic and varied receiver movement can be overall less restraining and potentially more ergonomic.

In this work, we hypothesize that a more variable strategy for robot-to-human handover, one that is not centered around CoM regulation, may lead to healthier receiver postures, as reflected by standard ergonomic metrics [5]. To test this hypothesis, we develop an "assistive" and "stimulating" mode of handover. In the *assistive* behavior, the robotic system monitors human biomechanics to hand objects over at an OTP deemed more convenient and CoM-stabilizing for the receiver. On the other hand, the *stimulating* mode introduces

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variability into its handover behavior, nudging the receiver to go beyond repetitive body postures, seeking to maintain their attention, engagement, and healthy posture flow.

Key to this proposition is the notion of *productive inconvenience*, which we anticipate holds great promise for the future of work. The core idea is to develop machines that are convenient for humans – "convenient" meaning literally "to come together" from its Latin origin. As workplace machines become robotic, however, they are capable of more than coming towards the human, *e.g.* for ergonomic posture improvement. On the contrary, a robotic agent behaving in an *inconvenient* manner, under some constraints, may result in their human counterpart being more attentive and hence more cognizant of their posture when performing physical HRC tasks, such as object handover. Productive inconvenience is, therefore, a way to look at variability in HRC as a more comprehensive understanding of ergonomics, *i.e.* a human worker's productivity and well-being.

To investigate this claim, we conducted a robot-to-human handover experiment comparing the proposed assistive and stimulating methods in a simulated workplace, where participants performed *multiple* object exchanges (see Fig. 1 for overview). In summary, this paper's experimental findings are the following:

- Stimulating receiver motion, as opposed to optimizing for stability, yielded safer ergonomic scores of posture;
- More dynamic receiver movement generated heightened levels of alertness at no expense to frustration, perceived workload, or preference;
- Over multiple handovers, human receivers entered into closer proximity with the robot, hinting at improvements in "trust" or "comfort".

II. Related Work

Robot-to-human handovers, where robots are givers and humans are receivers, have been extensively investigated in collaborative robotics [6], [13]. Previous research has focused on developing robot handover policies that ensure ergonomic human posture and healthy physical behavior throughout the exchange by selecting an "optimal" OTP. To that end, numerous approaches have been developed, each with different criteria defining the robot's handover policy.

Most studies propose that robots should choose OTPs to maintain the human receiver's CoM within the BoS [7], [8]. While constraining CoM in this framework presents an elegant formulation for optimization, it may not produce entirely natural human movement. In fact, certain studies have shown that in bimanual whole-body lifting tasks, humans perform anticipatory postural adjustments that do *not* minimize CoM displacements [14].

Another line of research exists that advocates for robot handover strategies to optimize biomechanically-derived metrics [15], in addition to CoM. For example, Kim et al. developed a method of estimating overloaded human joint torques, and then framed the interaction as an optimization problem with the cost function being a weighted sum of joint torques and CoM deviations from the BoS [8], [9]. A similar technique was developed in [7], with CoM displacements replaced by deviations in center of pressure.

Algorithm 1: Assistive/Stimulating Handover Policy

Input: CoM projection on the BoS plane $\vec{C}_t$; BoS center $\vec{B}_t$; scale parameter ϵ; previous OTP $\vec{O}_t$
Output: next OTP $\vec{O}_{t+1}$;
if *Stimulating* **then**
  Pick random corner point $\vec{E}_t$ of BoS polygon
  $\overrightarrow{CE}_t = \vec{E}_t - \vec{C}_t$
  $\vec{O}_{t+1} = \vec{O}_t + \epsilon \cdot \overrightarrow{CE}_t$ `// Nudge OTP towards random BoS corner`
else
  $\overrightarrow{CB}_t = \vec{B}_t - \vec{C}_t$
  $\vec{O}_{t+1} = \vec{O}_t + \epsilon \cdot \overrightarrow{CB}_t$ `// Deviate OTP towards BoS polygon centroid`
end if

Finally, some studies have instead *directly* applied human posture and ergonomics as the target criteria for the interaction. In these works, the robot policy chooses OTPs that optimize standard ergonomic assessments of human posture, such as the Rapid Upper Limb Assessment [16] and Rapid Entire Body Assessment (REBA) [17], [18]. In this work we introduce a collaborative robotic (cobot) architecture designed to *indirectly* augment REBA scores by relying solely on a human receiver's adaptive capabilities.

III. Cobot Architecture

In this section, we present a cobot architecture for robot-to-human handover in industrial scenarios, based on our more comprehensive *Gymnast_CoBot* project[1]. This architecture is composed of three core processes: handover control policies, 3D human pose estimation, and user interfacing.

A. Robot Platform

The main platform was a Universal Robot 10 e-Series (UR10e) robotic arm, chosen due to its long reaching motions, high working payload, and inherent joint force limitation to foster safe physical HRC. Given that we were primarily concerned with handovers in industrial settings, the UR10e's end-effector was extended with a Robotiq AirPick Vacuum gripper, which can suction a maximum payload of 16 kg (sufficient for most corrugated industrial packages). To capture the environment and human receiver during handovers, a wide-angle webcam NexiGo N980P with 120° field-of-view was positioned near the robot. Additionally, human subjects were equipped at their waist with an HTC Vive (3.0) motion tracker purely for the post-evaluation of their position in a "world" frame of reference. As a user interface, a projector and display in the vicinity provided real-time feedback on the task and robot state. Fig. 1 outlines the hardware components of this cobot architecture.

[1] xdlab.camd.northeastern.edu/gymnast_cobot/

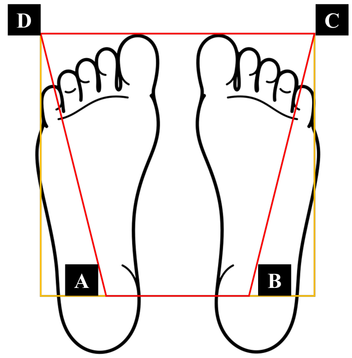


Fig. 2. Base of support polygon estimated as a convex hull between the left and right heels (A & B, respectively), and the intersections of the first toe tips with the outermost toe edges (C & D).

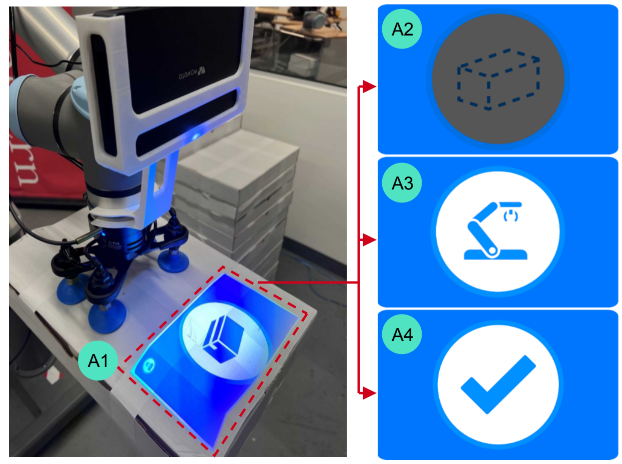


Fig. 3. User interface projected onto each handover package. Four intuitive icons inform the human receiver about the current robot state. **A1**: Package is ready to be taken. **A2**: No package picked by the robot yet. **A3**: Robot is delivering the package. **A4**: Package successfully handed over.

B. *Handover Control Policies*

Two handover control policies governed the robot's behavior: assistive and stimulating. These control "modes" are formulated in Algorithm 1 and described below.

Assistive: In this control mode, the robot attempted to keep the human receiver's CoM within the BoS. More specifically, OTPs were selected to push the CoM towards the BoS center based on prior handover estimates of these biomechanical properties. Numerous studies have shown that the distance between the CoM and BoS center is a good predictor of human stability, especially when lifting packages [19], [20]. This mode of interaction thus aimed to maintain stability in the hopes of healthier and more ergonomic posture.

Stimulating: By contrast, for this mode the robot sought to "stimulate" the human user into making more dynamic movements. As such, the robot opted for OTPs that nudged human receivers into configurations where their CoM was momentarily outside of their BoS. The motivation here was to keep human movement active and their posture dynamic during whole-body reaching, even if it resulted in temporary destabilization [10], [21], rather than imposing a stabilizing policy on motion. As per our hypothesis on *productive inconvenience*, this mode helped us examine whether a randomly varying and unstructured policy causes receivers to be more attentive and engaged, resulting in posture variability that is overall favorable and ergonomic.

Across both control modes, the tempo of robot motion was dictated by the receiver's pace, such that the robot and human arrive near the OTP almost simultaneously. This synchronous design improved smoothness of the HRC by reducing idle time for the human receiver.

C. *Real-Time Estimation of Human 3D Pose*

Rapid yet accurate analysis of 3D skeletal information serves as the basis for ergonomic posture assessment [22]. While using full-body motion-capture suits for pose tracking is common [18], [23], our work relied on a vision-based approach, BlazePose [24], due to its markerless, non-invasive setup, which is ideal for in-work environments. BlazePose is a lightweight framework that performs real-time 3D body pose estimation from RGB images by combining a neural network pose detector with a fast skeleton keypoint tracker.

Given these tracked 3D keypoints, we can determine two imperative parameters of a human subject in real-time: the CoM and BoS. The CoM was estimated using an approach similar to [25], where the human body was approximated as a system of particles, with each particle representing a body segment, such as the head, shoulder, trunk, etc. Each body segment was assigned a percentage of body mass. To account for the mass of the package being lifted, hands were assigned different masses before and after handover. Provided with 3D positions of each body segment, the CoM was calculated as:

$$\vec{C} = \frac{\sum_i m_i \mathbf{x}_i}{\sum_i m_i}, \tag{1}$$

where $\mathbf{x}_i \in \mathbb{R}^3$ denotes the instantaneous 3D location of the i^{th} body segment, and $m_i \in \mathbb{R}$ denotes its mass.

The BoS was then defined as the area beneath the person that includes every point of contact made with the ground. In this work, we approximated the BoS as the convex hull between the left and right heels, and the intersection of the first toe tips with the outermost toe edges of each foot. This is illustrated by the polygon ABCD in Fig. 2.

D. *User Interface*

To create fluent and smooth HRC, mutual trust must be established between the robot and human [26]. In terms of robotic behavior, our system monitored the human receiver's physical activity and generated trajectories using the methods described above. Nonetheless, there was also a need for the humans to understand the robot's intent and plan their actions accordingly. In line with this need for transparency, we designed a user interface consisting of an on-board projector (see Fig. 3) and an external monitor display (see Fig. 1). The projection system is flexible enough to project interface icons onto any industrial package with a flat surface, becoming an ad-hoc shared workspace between human and robot.

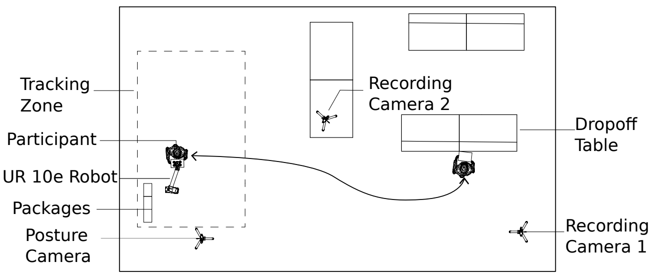
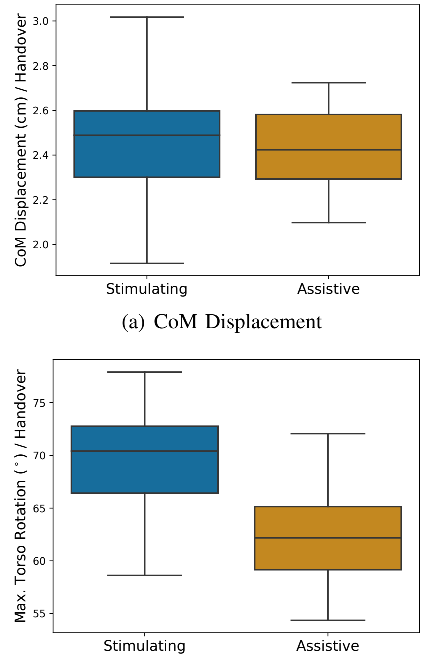


Fig. 4. Top-down diagram of the experiment setup.



(a) CoM Displacement

(b) Maximum Torso Rotation

Fig. 5. Physical motion characteristics of participants for each control mode: **(a)** Average CoM displacement recorded on a handover basis; **(b)** Maximum torso rotation angle registered per handover.

The external monitor also served to guide receivers who might either approach or leave the handover zone. To avoid unnecessary distractions, four simple but intuitive icons demonstrated the robotic system's current state, as shown in Fig. 3.

IV. Experiment

In order to explore the effects of different control strategies for robot-to-human handover, we conducted a within-subjects study replicating typical pick-and-place tasks found in industry. An overview of the experiment layout and environment is provided in Fig. 4.

A crucial aspect of the experiment was that there were *multiple*, repeated package handovers.

The hypotheses for this experiment were threefold:

- **H1**: Human receivers will exhibit heightened movement depending on the handover policy, as measured by CoM displacements and torso rotations.
- **H2**: Stimulating receiver movement will garner improvements in ergonomic scores.
- **H3**: Subject comfort with a robot engaging in dynamic handover will grow over the experiment duration, as reflected by diminished proximity to the end-effector.

User perceptions of workload, frustration, alertness and preference are also reported.

A. Experimental Protocol

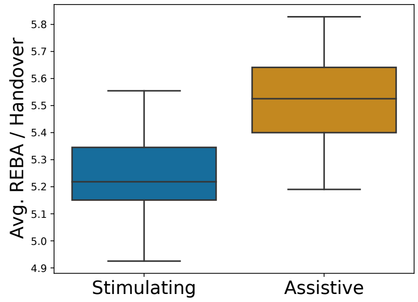
A total of 16 subjects (6 female; aged 20-34) participated in the study. All participants provided written consent prior to data collection and were naive to the purpose of the experiment. The experimental protocol was approved by Northeastern University's Institutional Review Board. Participants were recruited using online advertisements around the university campus and the robotics facility where the experiments took place. In turn, the subject demographic is a young (median age 23) and robotics-oriented adult population (75% with prior experience). Nevertheless, ergonomics and the emergence of MSDs is not only a concern for older workforces [1], [2], nor is it an unfair assumption that workers are trained prior to handling the robot.

The experiment was comprised of three blocks: *Training*, followed by *Assistive* and *Stimulating*. Subjects always began with *Training* and the order of subsequent blocks was counterbalanced. Importantly, subjects were unaware that the robot control policy differed between *Assistive* and *Stimulating*. For the *Training* block, subjects were requested to move 7 packages (each weighing 6.8 kg), one at a time, by receiving the package from the robot at a fixed OTP. Participants then had to carry the package over to a drop-off location approximately 4 m away from the shared handover workspace, where they were required to place the package. In *Assistive* and *Stimulating*, participants repeated this task for a total of 39 packages per block at varying OTPs.

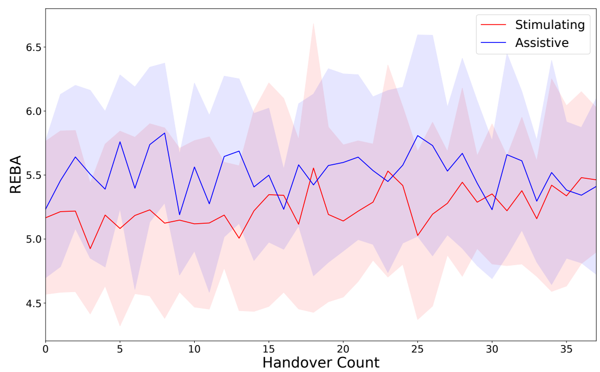
B. Evaluation Metrics

An array of quantitative and qualitative metrics was employed to assess the differences between *Assistive* and *Stimulating*. The aim of these metrics was to decipher whether a less "convenient" handover strategy in a workplace HRC task, such as package transfer, could foster a trade-off in benefits for the human receiver. In particular, we examined the ergonomic safety and physical characteristics of receivers' movement, as well as cognitive workload and other general subjective interpretations.

For quantitative evaluation of ergonomics and physical variation in receiver posture, we measured deviations in CoM, torso rotation, and divergence in REBA scores [5]. We elected to compute REBA over estimated 3D joint poses from Section III-C, as it is a widely accepted scoring mechanism for ergonomic posture in whole-body motion (one-sided view), and has been applied in similar prior work on robot-to-human handover [16]–[18]. Another metric of major importance in manufacturing settings with HRC is execution time, *e.g.* to measure efficiency. As this metric can be partly controlled by the robot's generated trajectories,

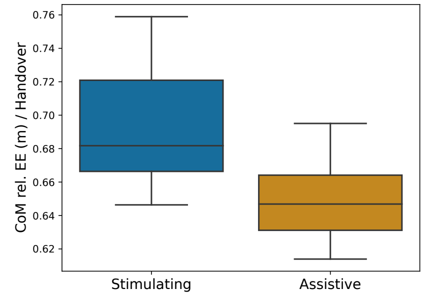


(a) REBA Handovers

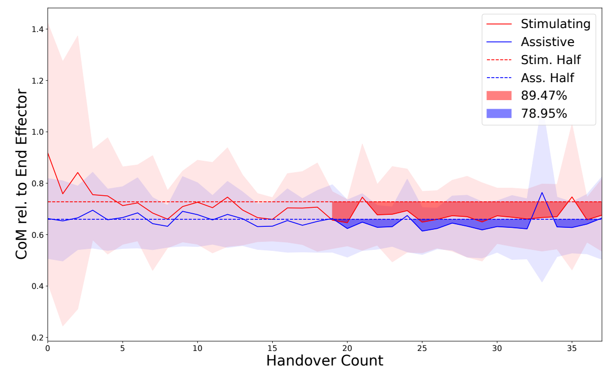


(b) REBA Handover Time-Series

Fig. 6. Average REBA scores of participants per handover: **(a)** Box plot of scores for each mode; **(b)** Mean and standard error of scores. Note that REBA scores range from 1-15.



(a) CoM to End-Effector (EE) Handovers



(b) CoM to EE Handover Time-Series

Fig. 7. CoM of participants relative to the robot's end-effector, *i.e.* using coordinates in the world frame: **(a)** Box plot of relative distances; **(b)** Mean and standard error in relative distances across the two modes, with later handovers occupying closer proximity to the end-effector, as reinforced by the horizontal lines delineating each mode's half-trial average.

and as participants were not requested to complete the task quickly, we chose not to evaluate time-to-completion.

To evaluate user perceptions of the two control modes, a selection of subjective questionnaires was provided to subjects. The well-known NASA-TLX [27] tool was used to assess perceived workload, as well as custom-designed surveys specific to our handover experiment to identify traits of *preference*, *alertness* and *frustration*. At the end of each block, subjects were asked to complete the NASA-TLX questionnaire and answer the custom-designed mode-specific survey. Participants filled out an additional survey comparing the two control modes at the end of the experiment.

V. Results

To test each of the three hypotheses for significance, one-way repeated ANOVAs were run on the aforementioned evaluation metrics, treating the *control modes* as the within-subjects factor.

A. Wider Range of Torso Movement in Stimulating Mode

Fig. 5 demonstrates the deviations in physical motion characteristics between subjects, for both control modes. The results of a repeated-measures ANOVA found no main effect of mode on the CoM displacement ($F(1,15) = 0.256$, $p = 0.621$), with average displacement per handover shown in Fig. 5(a). However, there is a significant effect revealed in maximum torso rotation ($F(1,15) = 4.89$, $p = 0.043$), where higher maximum rotation angles are observed for *Stimulating* mode (mean $= 68.7$; SD $= 11.8$) in comparison to *Assistive* (mean $= 63.5$; SD $= 13.7$). The distribution of maximum angles recorded per handover are plotted in Fig. 5(b). Maximum torso angles were considered, since they are more indicative of the full extent of unconstrained whole-body motion [10]. This result partially supports **H1** in favor of our *Stimulating* handover policy inducing greater variability in range of receiver motion.

B. Improved Ergonomic Scores in Stimulating Mode

Average REBA scores per handover for the two modes are depicted in Fig. 6, where lower scores qualify as more ergonomic. A significant main effect between modes was found ($F(1,15) = 9.88$, $p \leq 0.01$) with *Stimulating* scores determined to be less (mean $= 5.25$; SD $= 0.41$) than those of *Assistive* (mean $= 5.51$; SD $= 0.32$). This test result suggests that *Stimulating* garners better ergonomic postures on the basis of REBA. Furthermore, Fig. 6(b) portrays how subjects sustained improved ergonomic postures even as the experiment progressed. One might argue that variability in OTPs generated by the *Stimulating* mode helped maintain consistency by preventing subjects from losing attention and becoming sloppy, which pertains to postural awareness. Taken together with the previous result on range of motion, these results validate the second hypothesis, **H2**, and provide evidence to support the claim that a stimulating robot handover policy can lead to improved ergonomics for the human receiver.

C. Closer Proximity between Human and Robot in Prolonged Interaction

By attaching a HTC Vive tracker to participants, we were also able to explore the patterns in receivers' movement around the handover workspace shared with the robot, termed the "world" frame. For example, Fig. 7(a) illustrates a significant effect in the relative distance between receivers and the robot's end-effector $(F(1,15) = 8.51,\ p = 0.011)$. The repeated-measures ANOVA reveals higher proximity from the robot in the *Stimulating* setting (mean $= 0.70$; SD $= 0.12$) than *Assistive* (mean $= 0.66$; SD $= 0.10$). These findings are to be expected, as receivers occupied a wider span of the shared workspace due to the nature of OTPs selected by the *Stimulating* variant. This is graphically portrayed in Fig. 8, where a subject spread further about the world frame across three consecutive handovers during the *Stimulating* mode, echoing our previous claims on heightened receiver dynamics.

Another interesting observation on receiver movement across both handover modes is how proximity to the robot diminishes over a prolonged interaction. Fig. 7(b) captures this trend through half-trial average delimiters in subject distances to the end-effector, where 78.95% and 89.47% of the remaining handovers are closer for the *Assistive* and *Stimulating* modes, respectively. This relationship supports **H3**, notably so for the *Stimulating* case, and implies gradual increases in user "trust" or "confidence".

D. Survey Results

Fig. 9 demonstrates the subjective feedback results. Fig. 9(a) identifies no significant differences between the perceived workload of subjects when conducting the task in either *Stimulating* or *Assistive* mode. Though a general trend

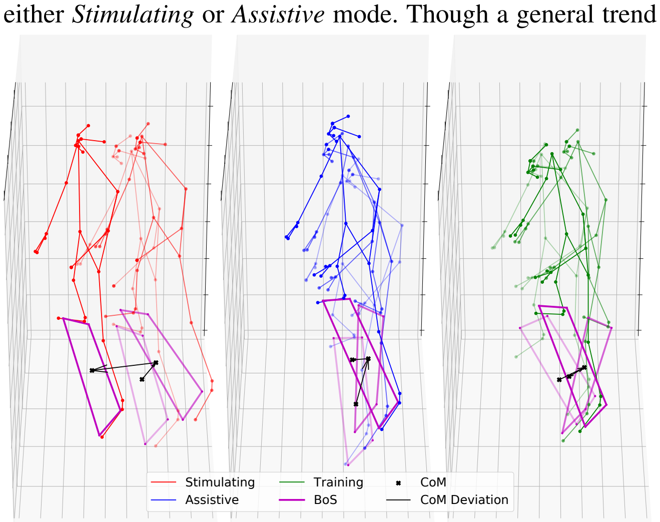
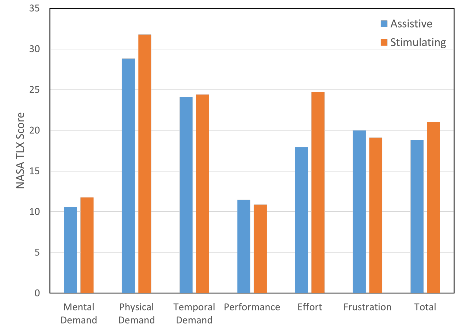
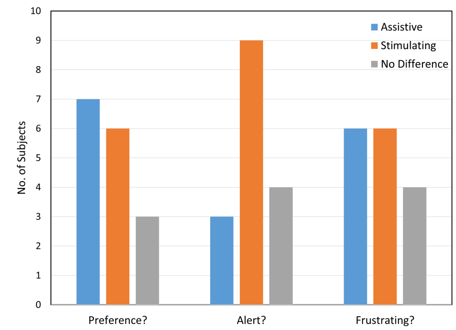


Fig. 8. Movement in whole body pose and CoM across three consecutive handovers (*Stimulating* in red, *Assistive* in blue, *Training* in green). Change in shading represents sequence order, with bolder colors for later handovers. The BoS and CoM displacements relative to the world frame appear to be of greater magnitude for *Stimulating* than that of the other modes.



(a) NASA-TLX



(b) Survey Ratings

Fig. 9. Subjective responses to: **(a)** NASA-TLX following each control mode; **(b)** A post-experiment survey comparing the control modes in terms of preference, alertness and frustration.

towards higher physical exertion, effort and frustration is perceived for the *Stimulating* variant. Post-experiment survey results in Fig. 9(b) observe similarities in "Preference" and "Effort", yet noticeably higher "Alert" ratings for our proposed *Stimulating* method.

VI. Discussion

Before proceeding with key takeaways, we acknowledge certain experimental limitations. From a system design perspective, errors in sensing and camera-based body pose estimation will directly influence the handover behavior, as well as our metrics for evaluation. As a result, a more robust perception system, *e.g.* using motion-capture, is required for future work. Even with perfect sensing capabilities, improving ergonomics via CoM is questionable, given that CoM is itself a debatable measurement of a postural system [28]. Likewise, we admit OTPs produced using our specific method of *Stimulating* receiver motion failed to significantly deviate CoM away from the BoS. However, movement across the handover zone was still observed to be of greater proportion. Another variable that likely influenced our results is the handover object's weight. Different package weights would impact the preferred OTP, thus requiring further investigation. Lastly, future studies should be conducted over a wider subject age range to better represent the entire workforce population.

A few major insights on the relevance of *productive inconvenience* in robot-to-human handover are drawn from this study. First, our proposed approach of computing OTPs obtained significantly more dynamic receiver behavior (**H1**) with improved posture ergonomics (**H2**), at no expense to frustration or trust (**H3**). Second, underpinning this notion on productivity is the objective of augmenting user engagement. Many participants validated this objective, citing that for *Stimulating* they "had to pay more attention/be more aware" or found it "more engaging, as if working with a partner". Yet this also created mixed interpretations of preference and frustration, with some subjects criticizing *Stimulating* on its "more random/harder to predict/inconsistent" behavior and others advocating for its "excitement/fluidity/smoothness". Finally, we re-emphasize the impact of investigating *multiple* handovers, especially as this temporal factor shed light on substantial findings, including "trust" being established.

VII. Conclusions

In this paper, we introduced the idea of "stimulating", rather than optimally "assisting", human receivers of robot handovers to facilitate posture variability for enhanced ergonomics. At the crux of this idea is productive inconvenience, where we proved that perceptually inconvenient forms of robot handover can have surprisingly positive effects on human receivers. Yet to uncover these effects, it is of paramount importance that a longitudinal HRC study be conducted, *e.g.* multiple exchanges. Inspired by our preliminary findings on the benefits of productive inconvenience, we plan to extend this concept beyond the scope of handover and into the broader area of physical HRC.

Acknowledgments

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References

[1] S. Bevan, T. Quadrello, R. McGee, M. Mahdon, A. Vavrovsky, and L. Barham, "Fit for Work?" *Musculoskeletal disorders in the European workforce*, 2009.

[2] K. Summers, K. Jinnett, and S. Bevan, "Musculoskeletal Disorders, Workforce Health and Productivity in the United States," *The center for workforced health and performance*, 2015.

[3] U.S. Census Bureau, "National census of fatal occupational injuries," *Retrieved from https://www.bls.gov/news.release/pdf/cfoi.pdf*, 2020.

[4] L. McAtamney and E. Nigel Corlett, "Rula: a survey method for the investigation of work-related upper limb disorders," *Applied Ergonomics*, vol. 24, no. 2, pp. 91–99, 1993.

[5] S. Hignett and L. McAtamney, "Rapid entire body assessment (reba)," *Applied Ergonomics*, vol. 31, no. 2, pp. 201–205, 2000.

[6] V. Ortenzi, A. Cosgun, T. Pardi, W. P. Chan, E. Croft, and D. Kulić, "Object handovers: A review for robotics," *IEEE Transactions on Robotics*, pp. 1–19, 2021.

[7] L. Peternel, W. Kim, J. Babič, and A. Ajoudani, "Towards ergonomic control of human-robot co-manipulation and handover," in *IEEE-RAS International Conference on Humanoid Robotics*, 2017, pp. 55–60.

[8] W. Kim, J. Lee, L. Peternel, N. Tsagarakis, and A. Ajoudani, "Anticipatory robot assistance for the prevention of human static joint overloading in human–robot collaboration," *IEEE Robotics and Automation Letters*, vol. 3, no. 1, pp. 68–75, 2018.

[9] W. Kim, M. Lorenzini, P. Balatti, Y. Wu, and A. Ajoudani, "Towards ergonomic control of collaborative effort in multi-human mobile-robot teams," in *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2019, pp. 3005–3011.

[10] P. J. Stapley, T. Pozzo, G. Cheron, and A. Grishin, "Does the coordination between posture and movement during human whole-body reaching ensure center of mass stabilization?" *Experimental Brain Research*, vol. 129, no. 1, pp. 134–146, 1999.

[11] S. E. Mathiassen, T. Möller, and M. Forsman, "Variability in mechanical exposure within and between individuals performing a highly constrained industrial work task," *Ergonomics*, vol. 46, no. 8, pp. 800–824, 2003.

[12] D. Srinivasan and S. E. Mathiassen, "Motor variability in occupational health and performance," *Clinical Biomechanics*, vol. 27, no. 10, pp. 979–993, 2012.

[13] K. Strabala, M. K. Lee, A. Dragan, J. Forlizzi, S. S. Srinivasa, M. Cakmak, and V. Micelli, "Toward seamless human-robot handovers," *Journal of Human-Robot Interaction*, vol. 2, no. 1, p. 112–132, 2013.

[14] D. A. Commissaris, H. M. Toussaint, and H. Hirschfeld, "Anticipatory postural adjustments in a bimanual, whole-body lifting task seem not only aimed at minimising anterior–posterior centre of mass displacements," *Gait & Posture*, vol. 14, no. 1, pp. 44–55, 2001.

[15] H. B. Suay and E. A. Sisbot, "A position generation algorithm utilizing a biomechanical model for robot-human object handover," in *IEEE International Conference on Robotics and Automation*, 2015, pp. 3776–3781.

[16] A. Shafti, A. Ataka, B. U. Lazpita, A. Shiva, H. Wurdemann, and K. Althoefer, "Real-time Robot-assisted Ergonomics," in *International Conference on Robotics and Automation*, 2019, pp. 1975–1981.

[17] B. Busch, M. Toussaint, and M. Lopes, "Planning ergonomic sequences of actions in human-robot interaction," in *IEEE International Conference on Robotics and Automation*, 2018, pp. 1916–1923.

[18] L. v. der Spaa, M. Gienger, T. Bates, and J. Kober, "Predicting and optimizing ergonomics in physical human-robot cooperation tasks," in *IEEE International Conference on Robotics and Automation*, 2020, pp. 1799–1805.

[19] W. C. Whiting and S. Rugg, *Dynatomy: Dynamic human anatomy*. Human Kinetics 1, 2006, vol. 10.

[20] M. Alamoudi, F. Travascio, A. Onar-Thomas, M. Eltoukhy, and S. Asfour, "The effects of different carrying methods on locomotion stability, gait spatio-temporal parameters and spinal stresses," *International Journal of Industrial Ergonomics*, vol. 67, pp. 81–88, 2018.

[21] N. Dounskaia, D. Peterson, and R. P. Bruhns, "Destabilization of the upright posture through elevation of the center of mass," *Annals of biomedical engineering*, vol. 46, no. 2, pp. 318–323, 2018.

[22] M. MassirisFernández, J. Álvaro Fernández, J. M. Bajo, and C. A. Delrieux, "Ergonomic risk assessment based on computer vision and machine learning," *Computers & Industrial Engineering*, vol. 149, p. 106816, 2020.

[23] L. Fortini, M. Lorenzini, W. Kim, E. De Momi, and A. Ajoudani, "A framework for real-time and personalisable human ergonomics monitoring," in *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2020, pp. 11 101–11 107.

[24] V. Bazarevsky, I. Grishchenko, K. Raveendran, T. Zhu, F. Zhang, and M. Grundmann, "Blazepose: On-device real-time body pose tracking," *arXiv:2006.10204*, 2020.

[25] J. Eng and D. Winter, "Estimations of the horizontal displacement of the total body centre of mass: considerations during standing activities," *Gait & Posture*, vol. 1, no. 3, pp. 141–144, 1993.

[26] T. Kim and P. Hinds, "Who should i blame? effects of autonomy and transparency on attributions in human-robot interaction," in *ROMAN IEEE International Symposium on Robot and Human Interactive Communication*, 2006, pp. 80–85.

[27] S. G. Hart and L. E. Staveland, "Development of nasa-tlx (task load index): Results of empirical and theoretical research," in *Human Mental Workload*, ser. Advances in Psychology, P. A. Hancock and N. Meshkati, Eds. North-Holland, 1988, vol. 52, pp. 139–183.

[28] J. Scholz, G. Schöner, W. Hsu, J. Jeka, F. Horak, and V. Martin, "Motor equivalent control of the center of mass in response to support surface perturbations," *Experimental brain research*, vol. 180, no. 1, pp. 163–179, 2007.