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# Passer Kinematic Cues for Object Weight Prediction in a Simulated Robot-Human Handover

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*Abstract*— **Object handovers, a seemingly straightforward action, involve a complex interplay of predictive and reactive control mechanisms in both partners. Understanding the cues that are used by humans to predict object properties is needed for planning natural robot handovers. In human-human interactions, the receiver can extract information from the passer's movement. Here, we show in a VR simulated agent-human object handover, that the human receiver can use passer kinematic cues to predict the transported object's properties, such as weight, and preemptively adapt the grasping strategy towards them. We show that when the agent's movement is correlated to the object weight, humans can interpret this cue and produce proportional anticipatory grip forces before object release. This adaptation is learned even when objects are presented in a random order and is strengthened with the repeated presentation of the pairing. The outcome of this study contributes to a better understanding of non-verbal cues in handover tasks and enables more transparent and efficient real-world physical robot-human interactions.**

## I. INTRODUCTION

Future assistive robots will perform complex tasks alongside diverse user groups, necessitating advanced collaborative skills such as handover – a foundational yet challenging aspect of physical human-robot interaction (pHRI). Despite extensive research [1], achieving the fluency and efficiency of human-human (H2H) handovers in robot-human (R2H) exchanges remains an open challenge. Object handover appears to be a straightforward action, but requires skilled control involving both predictive assessment of the object properties to compute the appropriate anticipatory forces, and reactive adjustments upon haptic contact. Such predictive forces are essential for a safe and natural handover, which often requires a response faster than the human feedback loop dynamics [2].

A handover action can roughly be divided into three main phases [3], [4]: the passer transport phase, the physical handover, and the receiver transport phase. The passer and receiver pose two separate control systems, each of which has to plan and execute individual movements while considering the partner's behaviour and the properties of the manipulated object. One of the main challenges in a handover is synchronizing the two involved control systems within the physical handover phase, i.e., the passer decreases and the receiver increases grip force simultaneously, effectively reducing physical handover time to a minimum [3], [4]. Due to intrinsic system delays in most robotic hands and grippers and neural delays in humans [2], such synchronization can only be achieved by accurately predicting the partner's movements and the object's physical properties. Leveraging these human predictive capabilities and representing them is, therefore, crucial to enable a fluent R2H handover action.

Human predictions can be informed by cues. In the specific case of a handover, these cues include both visual appearance (e.g., size, shape, and material) of the object, and movement kinematics of the passer. Indeed, a variety of cues have been shown to drive predictive forces during manipulation [5], [6], [7], [8], [9]. While humans have the ability to learn to associate arbitrary cues (e.g. color) with an object's physical properties, such as weight, cues on familiar features are much stronger [10].

In simple object manipulation, humans exhibit unique movement characteristics coupled to an object's weight. For example, when an object is lighter, the delay between finger contact and lift tends to be lower [11], [12] and it is lifted up and transported with higher velocities [12]. When receiving an object of identical appearance that is lifted and transported with different movement kinematics, there is evidence that humans could use this as a cue about the object's weight leading to the receiving partners adjusting their motor commands accordingly [13]. Similar to how we can learn dynamics from observation of other people's kinematics [14], previous work has demonstrated that perception of an object's weight can be modulated by observing another agent's different movement trajectories [15]. Overall, humans continually use a range of cues, including object properties and kinematics of partners, to estimate the object mass and tune our predictive control for skilful manipulation.

While it has been shown that predictability is essential to allow for smooth collaboration [4], [13], [16], [17], [18], there has been little to no research that explores or validates such features in R2H handover – despite the obvious motivation, and considering that current robotic hands and grippers are not capable of performing real-time reactive motions. In H2H handover, visual feedback during the passer

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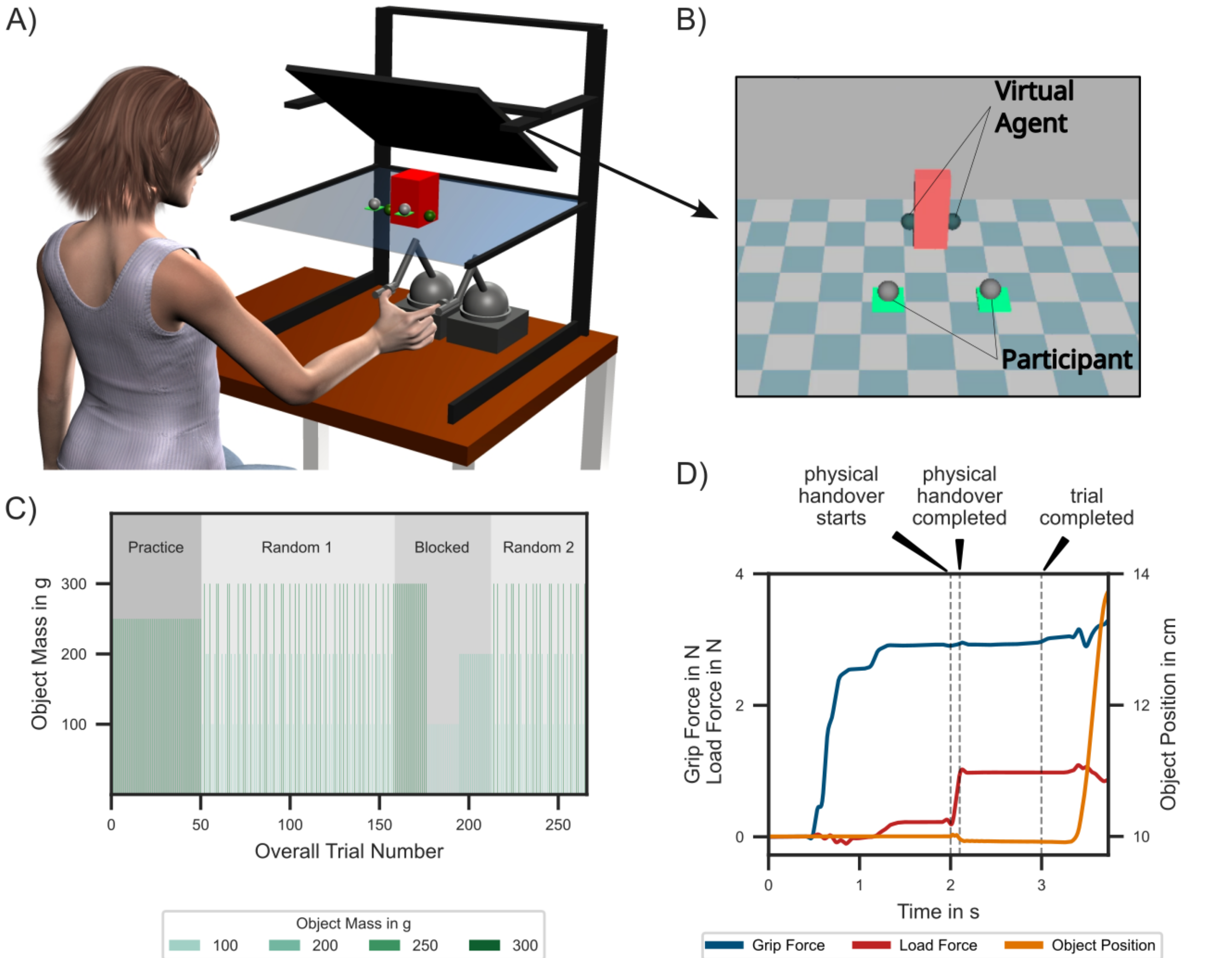


Fig. 1. Experimental setup and design. A) Virtual grasping setup with two haptic robots, connected to the participant's index and thumb. A monitor-mirror system provides visual feedback of the simulation. B) Visual on-screen feedback as viewed by participants, grey cursors represent thumb and index fingertips, teal cursors represent the virtual agent grasping and transporting the object. C) Experimental Design. Task practice was followed by an initial random part, a blocked part, and a second random part. The height of the bars indicates object weight in individual trials. D) Exemplary grip (blue) and load force (red) and vertical object position (orange) traces across the trial. Dashed lines indicate different states of the trial.

transport phase is crucial to enable predictive mechanisms in the handover phase [16]. Furthermore, recent work showed that when humans hand over objects of identical visual appearance, but different weight to another human, the passer exhibits slightly different movement patterns which allow the receiver to scale grip force rates to object weight [13]. However, we do not know whether this is also true for R2H handovers. First, such cues may not fully transfer to robot-human scenarios, as humans exhibit different behaviour when collaborating with robots compared to humans [19], [20], [21]. Second, it is unclear if movement patterns at the hand level are the only non-verbal cue humans use to make a prediction about the object's weight and, most importantly, if that information alone is sufficient in a R2H interaction.

Much work in the field of robotics has focused on the use of speech [22], gaze [23], [24], [25] and kinematics [26], [27] for communication of intent to initiate and adjust handover actions to pass or receive an object. While robotic facilitation and adaptation is an important feat, Ivanova et al. [18], showed that humans prefer a more predictable artificial partner and show better performance in joint actions with it. Humans are adept learners [28] and, in collaborative tasks, aim to facilitate their partners [29]. In a similar fashion, we aim to explore robotic motion legibility, making it as predictable as possible with cues natural to H2H interaction. It is worth mentioning that while a range of different objects has been used to investigate R2H handovers, to the best of our knowledge, no work has studied the effect of kinematic cues or the gripping response to different object weights – despite the obvious importance to adaptation and safety during pHRI.

## II. Problem Definition

This work aims to address the above gaps and investigate whether or not humans are able to interpret the kinematic cues of an agent similarly to the kinematic cues of another human in a handover task. Our focus lies specifically on using the passer transport phase to non-verbally communicate information about the passed object weight to the receiver. Using a virtual environment with a simulated agent transporting an object, we reduce the information available to participants to isolate it to movement kinematics directly related to object grasping, lifting and transport. We hypothesize that humans are able to inherently use this cue and integrate it into their motor plan for object manipulation. This work is a building block for the robotics community to design more transparent and effective R2H handover actions, understanding and leveraging human response behaviour to pHRI.

To test this hypothesis, we used a simulated handover task, where human participants received an object from an artificial agent. In the virtual environment, participants received haptic feedback via two haptic robots connected to their index and thumb, respectively (see Fig. 1A), and visual feedback via a mirror-monitor system (see Fig. 1B). In the experiment, the task was to receive an object with one out of four weights from the agent without dropping it. The object was identical in visual appearance, but the agent's movement was modified according to the weight. Therefore, the agent's movement could be used to predict the transferred object's weight. To quantify the participants' prediction of the object weight, we recorded grip and load forces as well as maximum vertical object displacement after the handover action (for exemplary traces, see Fig. 1D).

## III. Materials and Methods

### A. Participants

A total of 10 right-handed [30] volunteers (4 women, 6 men) aged 24 years (SD=1.6) participated in the experiment. All individuals reported to have normal or corrected to normal vision, no neurological disorders, and to be free of acute upper limb injuries. Before the experiment, participants provided written informed consent. This study was approved by the institutional ethics committee of the Technical University of Munich.

### B. Experimental Setup

We used a custom-built setup, with two haptic robots (Phantom Premium 1.5 HF, 3D Systems, Rock Hill, USA) providing position and force feedback, and a monitor-mirror system providing visual feedback (for a more detailed description refer to [31] and [32]). The participant's index and thumb were connected to a robot each using a custom, 3D-printed connector and rigid medical tape. The mirror blocked the view of their hand (see Fig. 1A). Participants were seated in a chair in a fixed position in front of the system.

In the experiment, participants viewed a virtual environment, programmed using CHAI3D [33] and Open Dynamics Engine libraries [34]. Within this environment, the participants' finger tips were represented by two dark gray spheres (see Fig. 1B). Positions and forces in the environment were sampled at 500Hz, the monitor-mirror system provided visual feedback at 60Hz.

### C. Experimental Paradigm

Participants had to grasp and hold a box-shaped object that was handed to them by a virtual agent. The object's size was 2x4x10cm and the coefficient of friction was 1. The object was represented as a rigid object (stiffness=700N/m) with uniform mass distribution and a mass of 100, 200 or 300g in the experiment or 250g in the practice phase. The agent reached toward the object, lifted it up and then transported it toward the participant's hand. The agent's movement was therefore split into five intervals: reach, grasp (cursors move in towards object), hold, lift and transport interval. We used a standard duration for each interval (from [15]) and modulated this duration with the object weight (see Tab. I). That is, a shorter duration and, therefore, faster movement was applied for a lighter object. For each interval, the movement trajectory was modelled according to the minimum jerk model [35].

At the beginning of each trial, participants placed their fingers on the starting position. The agent, visualised by two dark blue cursors, then transported the object toward a fixed position between the fingers. During the agent's movement, participants had to remain in the starting positions, otherwise the trial was restarted. Once the agent reached the final position, the object was fixed in space for 2s. Within this time participants had to generate grip and load forces to take over the object, after which the object was "released" (fixation removed) and the gravitational acceleration applied to the object was linearly increased over a duration of 100ms from 0 to $9.81 m/s^2$. The task was to hold the object without dropping it. After 900ms of holding the object, participants lifted it up by 3 cm to a reference plane to complete the trial.

TABLE I
Durations of agent's movement phases for different experimental conditions, adapted from [15].

| Interval | Duration in s | | | |
|---|---|---|---|---|
| | Fast | Standard | Slow | Practice |
| Object Mass in kg | 0.1 | 0.2 | 0.3 | 0.25 |
| Reach | 1.1000 | 1.1000 | 1.1000 | 1.1000 |
| Grasp | 0.0020 | 0.0200 | 0.1000 | 0.0500 |
| Hold | 0.0156 | 0.1560 | 0.7800 | 0.3900 |
| Lift | 0.4380 | 0.8760 | 1.3140 | 1.0950 |
| Transport | 0.5020 | 1.0040 | 1.5060 | 1.2550 |

Within the experiment, pairs of object mass and trajectories were constant (Tab. I). Participants completed four experimental parts: a practice, a initial random, a blocked and a final random part (see Fig. 1C). In the practice, participants completed 2 blocks of 25 trials, with constant object mass and agent trajectory. In the first random part participants completed 6 blocks of 18 repetitions and in the final random part 3 blocks of 18 repetitions. Within each block of 18 trials, each of the three mass-trajectory pairs was presented six times in a pseudo-random order. The blocked part consisted of 3 blocks of 18 repetitions, where the mass-trajectory pair was constant within a block. Before the task practice, participants completed 15 repetitions of an object lifting task (see [31]) with an object weighing 250g to familiarize themselves with the setup.

### D. Data Analysis

We calculated grip and load forces generated by the participant from the forces produced by the haptic robots and the object orientation in the virtual environment. Grip force ($GF$) is the normal component of digit force with respect to the object's surface and the load force ($LF$) is the vertical digit force component normal to the ground. Both forces were filtered with a 6th-order zero-phase butterworth low pass filter with a 20Hz cutoff. Using this data we then detected the anticipatory grip ($GF_{ant.}$) and load forces ($LF_{ant.}$), that were defined as the mean of generated forces from 20ms before, to the start of the release of the object by the agent. Therefore, they were purely predictive and provide an accurate measure of the participant's prediction of the object weight. Finally, we found the maximum vertical deviation of the object after the handover, by detecting the largest magnitude of displacement in either direction.

To intuitively summarize the relationship of outcome variables between all object weights, we pooled values over six repetitions (random) or 18 repetitions (blocked) per weight and participant, and fit a linear function to the means

$$y = a + bx. \tag{1}$$

This resulted in intercept ($a$) and slope ($b$) values that provided a block-wise quantification of adaptation.
In the statistical analysis, p-values less than 0.05 were considered statistically significant and were denoted with $*$ ($p<0.05$), $**$($p<0.01$), and $***$ ($p<0.001$).

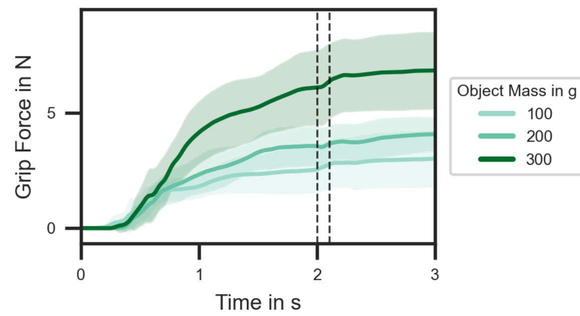


Fig. 2. Averaged grip force profiles for one participant over 18 repetitions of the same object weight (blocked part of experiment). Start and end times of physical handover are indicated by the dashed vertical lines.

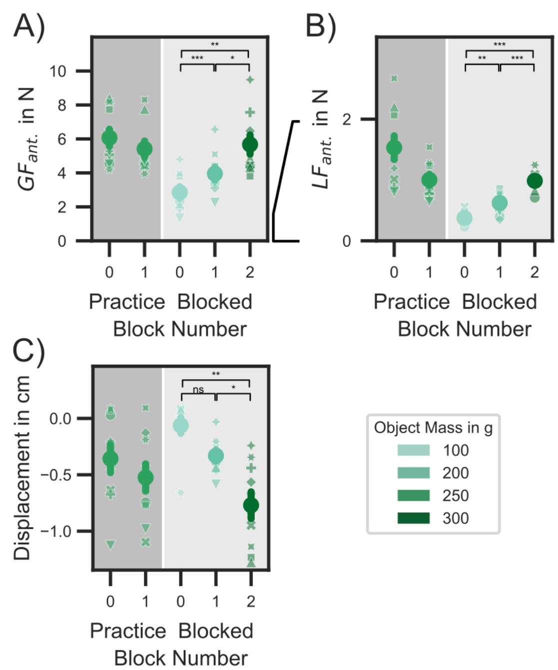


Fig. 3. Anticipatory grip and load forces and max. vertical displacement in the blocked parts of the experiment (Practice, Blocked). Large markers indicate mean values, error bars indicate standard error across participants. Small markers indicate individual participant data. Background shading shows practice (dark gray) and blocked (light gray) parts of experiment. A) Anticipatory grip force B) Anticipatory load force C) Maximum vertical object displacement.

## IV. RESULTS

Participants were repeatedly handed objects of different weights by an artificial agent. The agent's movements were adapted to the respective object weight, that is, the agent moved faster when handling a lighter object and slower when handling a heavier object (see Tab. I). All participants reported to have recognized the trajectory of the reaching movement as a cue to the object's weight after the experiment.

### A. Blocked

We first examine adaptation within the practice and blocked part of our experiment, to ensure that participants were generally able to adapt both grip and load forces to the task demands. In the practice and blocked part of the experiment, participants were repeatedly handed an object with identical mass and agent trajectory. Participants clearly adjusted their grip force profile to the object weight (see Fig. 2, for exemplary participant). This modulation occurred before the start of the release, therefore, when no information about the object weight was provided. Consequently, the anticipatory grip force across participants varied with the agent kinematics indicating object weight (RMANOVA: F(2,18)=20.02, $p<0.001$; ttest:100g–200g T(10)=-9.00, $p_{corr.}$ $<0.001$; ttest:100g–300g T(10)=-5.00, $p_{corr.}$=0.002; ttest:200g–300g T(10)=-3.30, $p_{corr.}$=0.028; see Fig. 3A). We also observed some reduction between the first and second block of practice, indicating adaptation to the task after the initial trials. However, evaluation of trial-by-trial values showed that this adaptation occurred mostly within the first 10 trials and levelled off afterwards (see Fig. 4). Despite no requirement to minimize vertical movement, participants also scaled anticipatory load forces to the object's weight, when exposed to the same object repetitively multiple times in a row (see Fig. 3B). A RMANOVA (F(2,18)=84.76, $p<0.001$) and post-hoc ttest revealed that these differ-

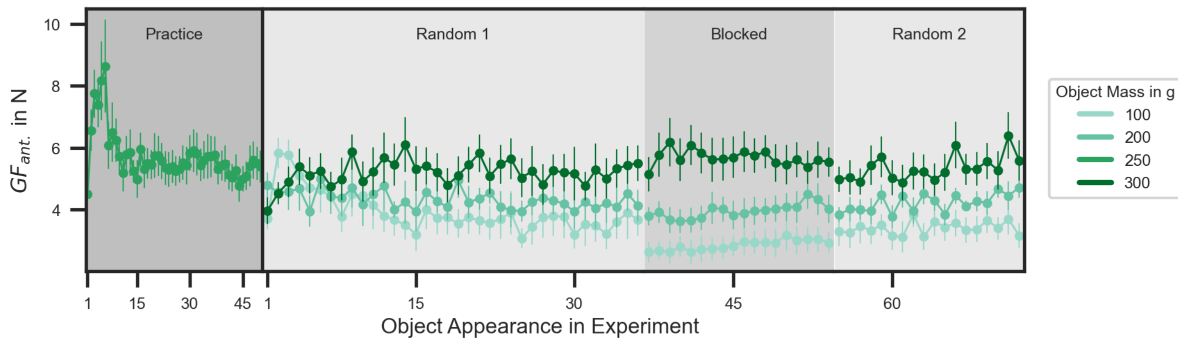


Fig. 4. Evolution of $GF_{ant.}$ across full experiment. Background shading indicates different parts of the experiment (practice, random, blocked, random). Markers show the mean, error bars the standard error of forces averaged across participants. In practice trials, participants initially overshoot anticipatory grip forces, then reduce to a stable value after ca 15 repetitions. In random parts, participants progressively learn to anticipate the different object weights over the initial 12-18 repetitions of each object weight. In the blocked part of the experiment, this adaptation is even stronger, but returns to similar values in the second random part compared to the first random part. Consequently, participants already learned to understand cues and to adapt their motor commands according to the cues in the initial random presentation.

ences were statistically significant (100g–200g T(10)=-5.17, $p_{corr.} < 0.001$; 100g–300g T(10)=-13.48, $p_{corr.} < 0.001$; 200g–300g T(10)=-7.54, $p_{corr.} < 0.001$). However, it is noticeable that the anticipatory grip forces showed a much higher scaling than anticipatory load forces in this part of the experiment. The object displacement shows that while anticipatory load forces were applied proportionally to the object's weight, this scaling was also evident in the vertical displacement after the handover. The largest displacement (object mass = 300g) was, on average, 8mm (see Fig. 3C). Again, a RMANOVA (F(2,18)=15.87, p<0.001) and post-hoc ttest (100g–200g T(10)= 2.91, $p_{corr.}$=0.052; 100g–300g T(10)=4.28, $p_{corr.}$=0.006; 200g–300g T(10)=3.95, $p_{corr.}$=0.010) revealed that most of the differences between object weights were statistically significant. Overall, this data shows that our setup and experimental task allowed participants to adapt grip and load forces in anticipation to the agent-human handover. Further, grip force profiles before handover do not significantly vary from those observed when interacting with physical objects, showing that participants' interaction forces in our simulation is generally similar to those generated when manipulating physical objects.

### B. Random

After the practice phase, participants were repeatedly handed one of three different objects that varied only in weight but not in physical appearance. The agent trajectory was always matched to the same object weight, such that it could be used as a cue. We compared outcome variables across the full experiment (see Fig. 4 for $GF_{ant.}$). We could summarize block-wise adaptation with intercept ($a$) and slope ($b$) values (see Eq. 1). The resulting slopes and intercepts for both random and blocked parts of the experiment and all outcome variables are shown in Fig. 5.

*a) Anticipatory Grip Force ($GF_{ant.}$):* After some trials where the $GF_{ant.}$ was scaled similarly for all object weights, participants learned to adapt the $GF$ in a predictive manner (see Fig. 4). While the separation between weights was stronger in the blocked compared to the random part of the experiment (Fig. 5A), it was already clearly present after 12-18 repetitions per object weight in the initial random phase. The $GF_{ant.}$ shows a clear adaptation over the initial three random blocks, after which both slope and intercept remain constant (Fig. 5A). The slope increased in the first block of trials to the third block of trials, where on average $GF_{ant}$ increased by 0.87N per 100g of object mass. In the context of $GF$, the intercept may be interpreted as baseline grip force or safety margin [36]; that is, the level of grip force applied minus the minimal level of grip force required to not let the object slip. A reduction of the intercept, therefore, can be interpreted as a reduced safety margin. Similar to the increase in slope, the intercept decreased during the first three blocks of trials. A RMANOVA indicated that while interaction between different object masses was not significant in the initial block (F(2,18)=1.23, p=0.315), it was significant in the stable blocks (2-8) (F(2,18)=9.82, p=0.001). Post-hoc paired t-tests with Bonferroni correction revealed significant differences between all pairs of weights (100g–200g: T(10)=-3.09, $p_{corr.}$=0.039; 100g–300g: T(10)=-3.19, $p_{corr.}$=0.033; 200g–300g: T(10)=-3.02, $p_{corr.}$=0.044; see also Fig. 6A). Comparing blocked and random parts of the experiment, our data show a higher slope and lower intercept in the blocked parts, indicating that participants' prediction was further improved when the same object weight was presented repetitively.

*b) Anticipatory Load Force ($LF_{ant.}$):* In contrast, the $LF_{ant.}$ did not show the same pattern as the grip forces (Fig. 5B). While a clear separation was present in the blocked part of the experiment (see Fig. 3B), in the random parts, $LF_{ant.}$ values converged to similar levels for different object weights, resulting a slope approaching 0. At the same time, the intercept reduced. Therefore, $LF_{ant.}$ was not scaled according to object weight, and reduced over the course of the experiment when the order of object weights

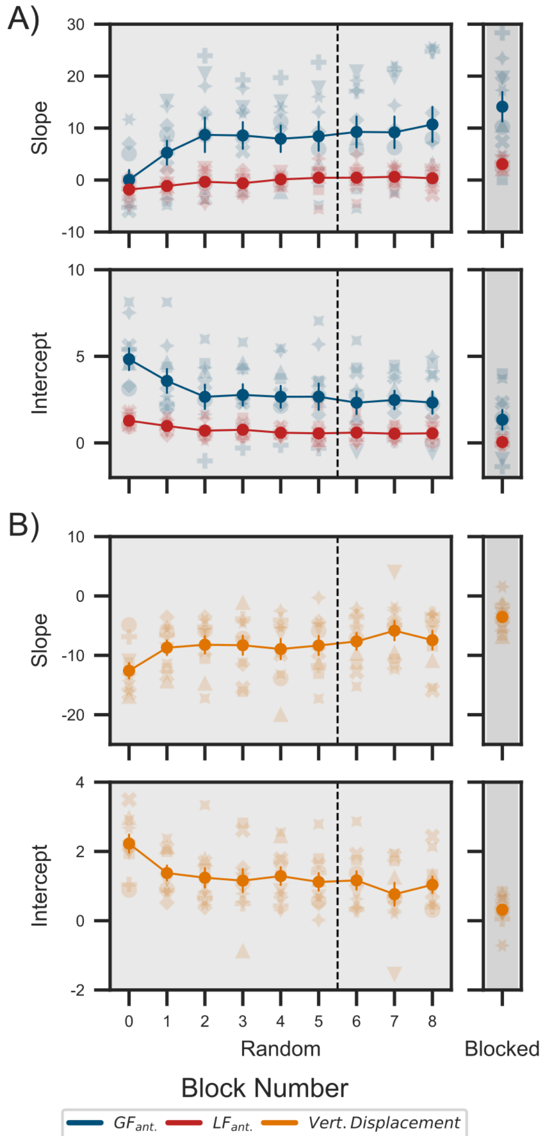


Fig. 5. Slope and intercept values across full experiment for $GF_{ant.}$ (blue) and $LF_{ant.}$ (red) in A) and maximum vertical object displacement (orange) in B). Values for the blocked part of the experiment are shown on the right side of individual plots, values for the random parts of the experiment are shown on the left side and initial and second random parts are separated by a dashed line.

was random. A RMANOVA showed that while interaction between different object masses was significant in the initial block (F(2,18)=8.98, p=0.002), it was not significant in the stable blocks (2-8) (F(2,18)=0.59, p=0.567). Post-hoc paired t-tests with Bonferroni correction revealed significant differences in the initial phase between 100g and 200g objects (T(10)=5.12, $p_{corr.}$=0.002) and 100g and 300g objects (T(10)=3.26, $p_{corr.}$=0.030), but not 200g and 300g objects (T(10)=0.20, $p_{corr.}$=1.000). These differences disappeared in the later stable parts of the experiment (see also Fig. 6B). As excessive $LF_{ant.}$ would lead to an upward movement at the beginning of the handover phase, it is likely that participants increased $LF$ only when the release action was started to compensate for gravitational forces.

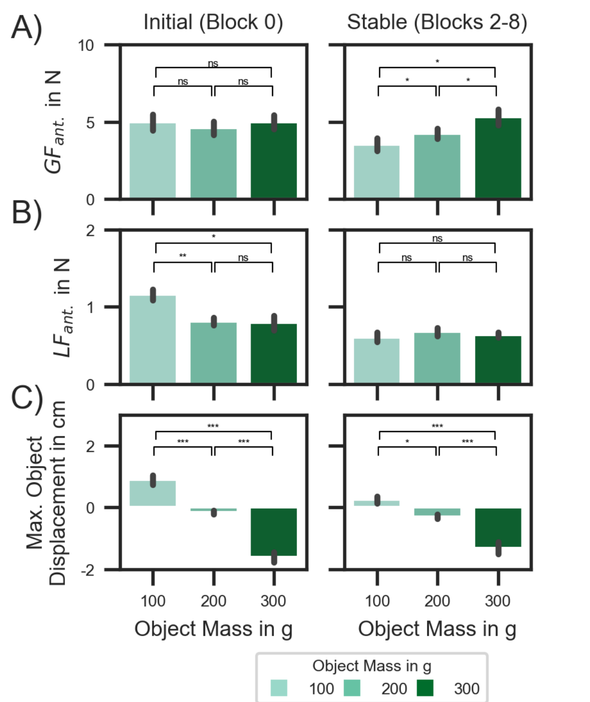


Fig. 6. Pooled values for outcome variables in initial (first column) and stable (second column) parts of the experiment. Bars show mean values, errorbars the standard error across participants. A) Anticipatory grip force B) Anticipatory load force C) Maximum vertical object displacement.

*c) Maximum Vertical Object Displacement:* Finally, the magnitude of the slope of maximum vertical object displacement decreased from the initial to the second random block, but showed little modulation in the rest of the experiment (Fig. 5C). The sign of the slope for this value was negative, indicating that lighter objects were lifted upwards (positive displacement) and heavier objects were moved downwards (negative displacement). Similarly, the intercept reduced from the first to the second block. Therefore, the increase in slope and reduction of intercept indicate that upward movement for the lightest object was reduced to a bigger extent than downward movement of the heaviest object. When comparing between the initial and stable part of the experiment, our data show that during the full experiment, the maximum vertical object displacement differs between different weights (initial: F(2,18)=84.90, p<0.001; stable: F(2,18)=32.04, p<0.001). Anticipatory load force does not seem to predict vertical object displacement. On the contrary, the reduction of general displacement in the second block of the first random object presentation indicates that load force was adjusted in synchrony with the agent's object release rather than in a predictive and proportional manner.

## V. Discussion

We examined the effect of different trajectories of a passing agent on the prediction of the object weight by the receiver in a simulated robot-human handover task. Even when object weights are presented in a random order, participants gradually learned to produce grip forces in an anticipatory manner. That is, they interpreted the kinematic cue to predict the transported object weight and form a corresponding motor command. In contrast, predictive load forces were not scaled to the object weight when presented in a random order, even though scaling occurred in the blocked presentation. Finally, the vertical object displacement reduced during random object presentation, but did not reach the same performance as during blocked presentation.

### A. Predictive mechanisms in H2H handover

A number of studies have previously investigated H2H handovers and showed that predictability is a key factor in efficiently handing over objects. For example, visual feedback during the passer transport phase is crucial to enable predictive control mechanisms in the physical handover [16]. Further studies showed passer lift delay and maximum lift velocity provided sufficient cues about object weight for receivers to scale their grip force in an anticipatory manner [13]. However, other parameters such as posture of the passer were not recorded in this work. As the used weights ranged from 400g to 1000g, such postural differences could provide an additional cue to the receiver. We extend this prior work [13] by isolating the effect of passer kinematics through use of a simulated agent and showing it provides sufficient information to predict object weight.

### B. Predictive mechanisms in R2H handover

While [16] expanded their work on H2H handovers to a R2H handover, they did not include any grasp or reach movements of the robotic partner. Therefore, cues to enable more advanced predictive human motor control were given. Other work investigated preference of and reaction times of human receivers to different movement trajectory shapes [37], [38] in R2H handovers, but to the best of our knowledge, we are the first to show that humans are able to integrate grasp-lift-transport trajectories to anticipate different object weights.

### C. Cues in predictive human motor control

Based on our knowledge of human pick-lift-replace and pick-lift actions (e.g. [11], [12], [13]), we used a cue that participants should intuitively be able to integrate to form a prediction about the transported object's weight. It has been shown that familiar cues result in stronger association compared to arbitrary cues [10]. While we clearly show that participants recognized the cue, and after some repetitions adapted their motor behaviour to reflect accurate predictions of object weight, an intuitive cue should lead to immediate adaptation of motor behaviour. For example, Kopnarski and colleagues [13] demonstrated in an H2H handover where weights were randomly interchanged, the receiving partner immediately adapted their grip force rates to the expected weight. In pick-lift-replace tasks, humans commonly adapt their motor behaviour after one trial [6], [39], even if presented with more than one object weight [9]. This extended adaptation phase could be related to performance of the task in a virtual environment [31], [32]. Additionally, participants were informed that they were handed the object by an artificial agent, not a human partner. Both of these factors could have led to prolonged adaptation of motor behaviour in our participants. Consequently, follow-up studies will have to show if the reason for longer adaptation times is based on the intuitiveness of kinematic cues or on other factors.

### D. Predictive adaptation of grip and load forces

We observed a clear difference between adaptation of grip and load forces and the vertical object displacement in the random parts of the experiment (Fig. 5). After some repetitions (≈12-18 per weight) participants grip force indicates successful adaptation (Fig. 5A). In the same time frame, predictive load force production decreased to a stable value across different object weights (Fig. 5B). As indicated by the development of vertical object displacement (Fig. 5C), participants nonetheless manage to produce sufficient compensatory forces to hold the object somewhat stationary. Therefore, we assume that the decreased scaling of anticipatory load force actually indicates a better synchronization of participants with the ”release” of the agent, enabled by a better prediction of the time of release. While grip and load forces in object manipulation are usually coupled [40], it has been shown that this is not always the case [41], [42]. The fixed time from stop to release in our task may have lead to the observed decoupling of the two forces.

Finally, we assume that the reduction of object displacement occurs earlier (after ≈6 repetitions per weight) compared to that of anticipatory grip force (after ≈12-18 repetitions per weight), as participants receive a clear error signal in the case of object displacement, which is not present for grip force. If the object were deformable or could break when applying excessive grip forces, we would expect this adaptation to occur in similar time-frame as the vertical object displacement.

## VI. Conclusion

We demonstrate that humans are able to predictively scale their grip forces according to the expected weights in a simulated agent-human handover task simply by exploring the agent's motion profile, addressing an important gap in the literature related to legibility and predictability during pHRI. Furthermore, based on thorough experimental results, this work aims to formally inform future developments and applications in robot-human physical handovers and general physical robot-human collaboration. Using human-like movement kinematics, we demonstrate a more predictable and, therefore, intuitive handover action. Finally, while this work aimed to evaluate the sufficient conditions for predictability and adaption based solely on the object's motion profile, in future work we aim to explore the performance of such adaptability when interacting with embodied robots.

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