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Instilling the perception of weight in augmented reality using minimal haptic feedback

Alexandra Watkins¹✉, Ritam Ghosh², Akshith Ullal² & Nilanjan Sarkar^{1,2,3}✉

Humans perceive gravitational forces on their surroundings through a mix of visual and sensorimotor cues. The accurate presentation of such cues is a difficult task in Mixed/Augmented Reality (MR/AR), technological paradigms that blend physical and virtual elements to enhance the way we interact with our environment. Realistically perceiving the weight of virtual elements within a MR/AR scenario aids in the embodiment of those elements within the user's reality, further blurring the lines between what is real and virtual. Unfortunately, current force feedback devices are not designed for or are entirely compatible with MR/AR experiences. To address this need, we explore minimal haptic feedback for weight perception in MR/AR, aiming to simplify the rendering of gravitational cues that are crucial to an immersive experience. Our benchtop device, focused on wrist feedback, showed improved user experience even within an implicit weight feedback task, i.e., a task where weight perception was not required for task completion. However, challenges arose in mixed real-virtual environments, a cornerstone of MR/AR interaction, where weight discrimination was observed to be less accurate. To address this, we developed a compensation scheme for virtual weights, leading to performance on par with a purely virtual environment. Our work demonstrates the viability of minimal haptic feedback in MR/AR applications and highlights the importance of integrating weight perception for increased realism. Our work also fills a research gap in MR/AR development, providing insights for designing future MR/AR systems that integrate with human sensory mechanisms to create virtual interactions that more closely mirror the physical world.

Keywords Haptic feedback, Weight perception, Augmented reality

Gravity and its effects on our bodies and surroundings shape how we interact with the world, with essential human senses such as proprioception being near impossible without it^{1,2}. Our central nervous system has developed over time to incorporate an internal model of gravity³ and furthermore informs our initial assessments of grip and lateral forces when interacting with objects⁴. The absence of such a fundamental force would then have a dramatic impact on our perception of our environment. Such an absence is a concept no longer relegated to the realm of fantasy as humans become increasingly more integrated with virtual environments in the form of Virtual Reality (VR) and Mixed/Augmented Reality (MR/AR). New methods of presenting gravitational forces in an environment are then needed to maintain accurate perception in these novel environments.

Mixed and augmented reality

The term Mixed Reality (MR) was introduced to describe emerging visual displays that blended virtual and real components to create a new medium for interaction and visualization⁵. This means that, in contrast to Virtual Reality (VR) technologies, the mixed reality user is still able to see and interact with the real world around them to a varying degree depending on the level of virtuality introduced by the system. Augmented Reality (AR) was initially used to further specify MR displays that overlaid virtual components in a largely real environment (Figure 1) in an attempt to enhance or supplement reality instead of replacing it⁶.

Recent years have seen significant advances in MR/AR technology and research⁷ that has motivated its adoption in a variety of fields including education, healthcare, and industrial processes^{8–11}. In its modern usage, the concept of AR has been expanded beyond visual displays to incorporate many forms of sensory feedback and interactivity, such as spatial sound, hand/eye tracking, and speech input¹². This often takes the form of a

¹Mechanical Engineering, Vanderbilt University, 2400 Highland Ave, Nashville 37212, TN, USA. ²Electrical and Computer Engineering, Vanderbilt University, 400 24th Ave S, Nashville 37212, TN, USA. ³Computer Science, Vanderbilt University, 400 24th Ave S, Nashville 37212, TN, USA. ✉email: alexandra.watkins@vanderbilt.edu; nilanjan.sarkar@vanderbilt.edu

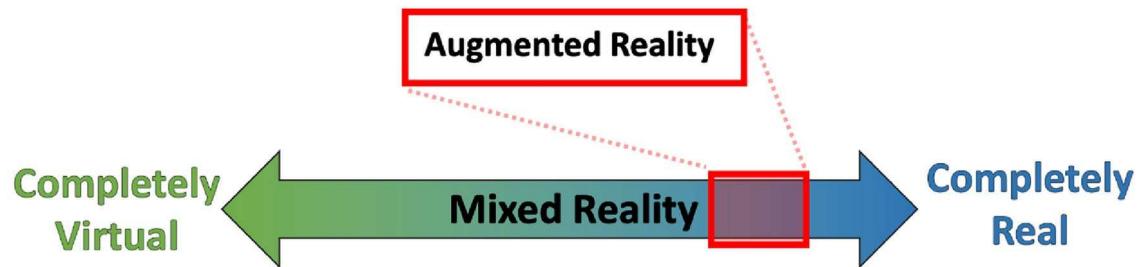


Fig. 1. The virtuality spectrum. Augmented Reality (AR) is a subset of Mixed Reality (MR) that seamlessly integrates virtual objects within a real environment.

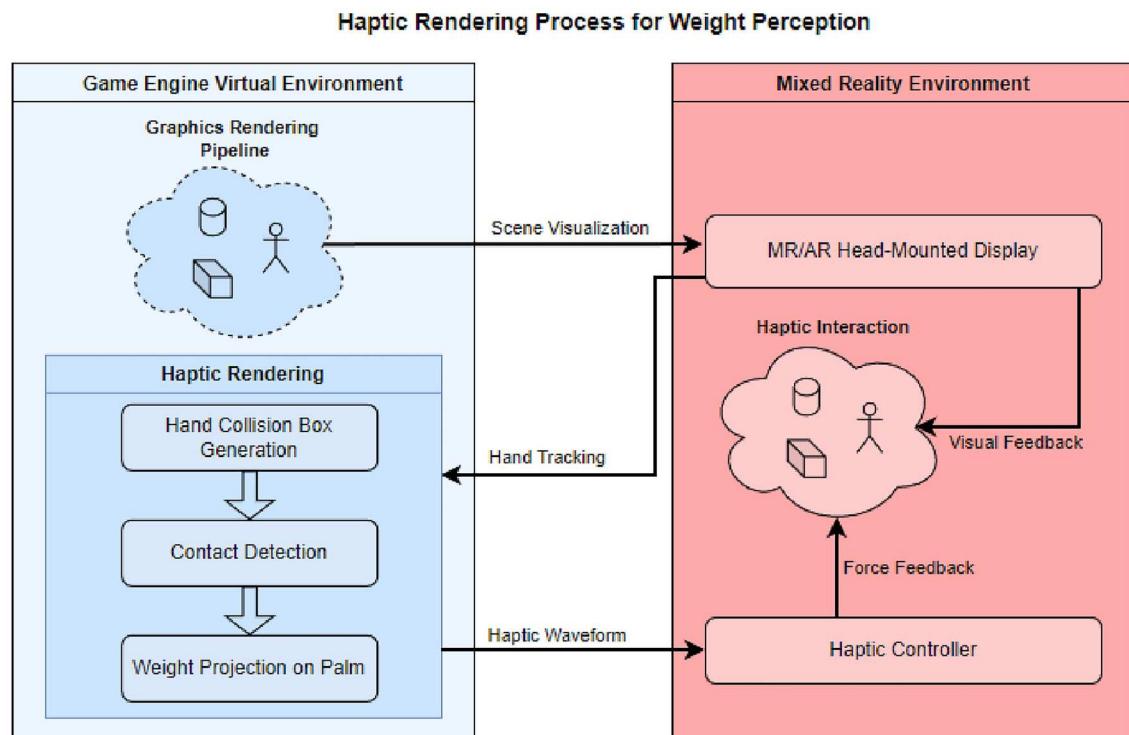


Fig. 2. Augmented Reality headsets maintain a complete virtual representation of the user's environment within the game engine with which the AR scenario was developed. Virtual elements are then overlaid with the local physical workspace to create the mixed reality environment presented to the user. An immersive haptic interactions is created when this visual feedback is combined with physical feedback rendered by a haptic device, which is calculated through a multi-step process that combines hand tracking, collision detection, and low-level interfaces to produce appropriate haptic waveforms.

head-mounted display (HMD), such as the Microsoft HoloLens 2¹³ and the Apple Vision Pro¹⁴. These devices have enabled widespread consumer adoption of MR/AR by providing a system that incorporates AR, spatial mapping/tracking, and an application development framework within which developers and researchers may create custom augmented reality experiences.

But is visual feedback alone sufficient for immersive MR/AR experiences? Recent studies suggest otherwise, calling out the need for new methods of incorporating visuo-haptic feedback to create more immersive MR/AR applications^{15–17}. Even rudimentary tactile feedback increases the perceived presence of remote users and objects, leading to more effective human-human and human-machine interaction¹⁸. Haptic feedback can even increase task focus and performance, with better immersion giving users a better outlook on MR/AR applications^{15,19}. Accurate haptic feedback can then be a way to convey the gravitational properties of virtual objects to users.

Haptic feedback in VR and MR/AR

A common form of feedback that is extremely relevant to weight perception is kinesthetic feedback. Kinesthesia refers to the sensing of force feedback that involves the sensation of movement, joint tension, and force-displacement relationships²⁰. A common function of a kinesthetic device is to apply a force about a joint to

reduce or completely counter movement, and is often the primary form of feedback for contact forces, inertial forces, and object weight. Literature has shown that the combination of kinesthetic feedback with visual feedback is sufficient to maintain a perception of object weight and its presence within a virtual environment^{21–24}.

Multiple haptic devices, designed primarily for VR, have been brought to market for use in research, industrial, and consumer applications^{25–27}. The amount of proposed solutions found in literature for rendering gravity is even more abundant and varied^{28–32}. Despite the abundance of work in gravitational haptic feedback, very little attention is given to meeting the needs of MR/AR applications. Instead, the general application is for purely virtual reality use, which is typically not directly translatable for use within an MR/AR workspace. A prominent example of this is the large amount of devices that target the fingers for kinesthetic feedback^{33–38}, are passive devices unsuited for weight perception^{39,40} or introduce extremely complex mechanisms^{32,41,42}.

Solutions for VR generally are made in consideration of the fact that the user's vision is totally occluded and their environment completely replaced with a virtual one. Users are not expected to interact with real objects in their surroundings, and instead only manipulate virtual objects and icons. Haptic devices for VR then have no need for considering how to grasp and hold real objects and therefore do not provide the necessary dexterity to do so, oftentimes completely occluding the hand via a haptic proxy, which is a prop or other graspable object that acts as a stand-in for virtual objects during manipulation. This often takes the form of an augmented controller^{42–46}, but can also be an inherent property of the device, as seen with wearable gloves^{26,27}. This technique is effective for VR because of the complete replacement of the user's real environment with a virtual one but fails to maintain its usefulness in MR/AR as it precludes grasping and interacting with real objects. Current solutions rarely allow the user to move and manipulate objects in their environment, or to maintain the dexterity needed to grasp and interact with real objects in their workspace. Nascent technologies such as nanowire interfaces⁴⁷ hold promise for future AR-compatible devices but are currently not at a development phase feasible for force feedback haptic prototyping.

Minimal haptic feedback

Providing high-fidelity and realistic force feedback for virtual objects while allowing the user to maintain the dexterity needed to grasp and interact with real objects can greatly increase the complexity of an MR/AR haptic feedback system. To reduce design complexity, carefully selected modes of feedback can be chosen for emulation in lieu of the holistic reproduction of haptic forces. Tailoring feedback for a specific type of interaction can maintain the perception of realism⁴⁸. By identifying vital modes of feedback for weight perception, the minimum stimulation necessary to maintain immersion and realism can be applied. Device complexity is then kept at a minimum while maintaining effective and immersive interactions involving weight perception.

This then leads to a new design paradigm for haptic devices: minimal feedback. Minimal feedback is the presentation of feedback to achieve a specific goal using the minimum number of actuators needed, i.e., minimizing the degrees of freedom (DOF) of the device, as well as presenting feedback in a way that does not inhibit the regular functionality of the limb or body part it is attached to.

Presented work

We hypothesize that (H1) a haptic feedback modality that can provide an immersive experience in MR/AR is the application of a force on the hand in the extension/flexion direction of the wrist (Figure 3a). To test this hypothesis, we constructed a mobile benchtop test stand wherein the user places their hand under a powered vertical plunger (Figure 3b). The device was created to be movable along a flat surface by the user while allowing

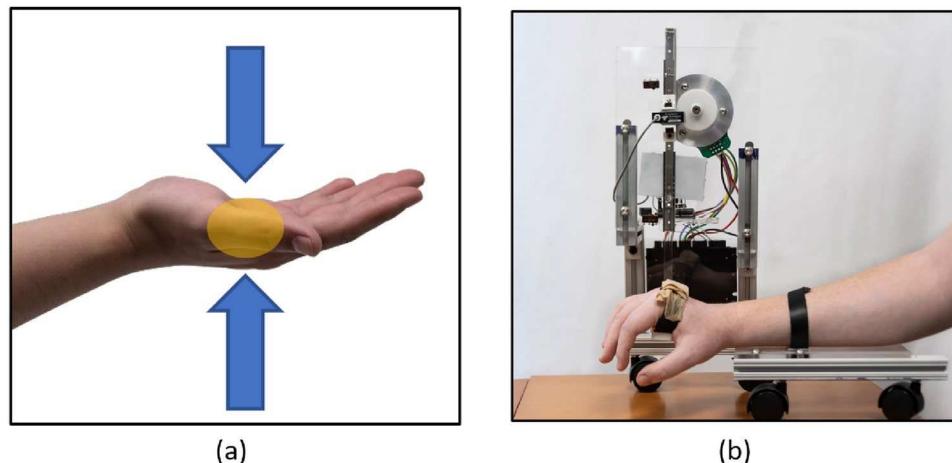


Fig. 3. (a) Hand points of contact. By targeting the base of the hand, we aim to avoid occluding the fingers from grasping and interacting with both real and virtual objects. (b) The developed test stand consists of an acrylic plunger that ends with a 3D printed hand interface. Contact forces are transmitted to the base of the palm or the back of the hand, depending on the direction of the applied force. An acrylic platform and strap serves as a stabilizer for the user's forearm, ensuring that only movements of the wrist are elicited by the force of the plunger.

the wrist to flex and extend, creating a simple 3D volume as the workspace. The device was then controlled using an interface developed in Unity in order to integrate with MR/AR that applications run on the Microsoft HoloLens 2⁴⁹ (see Fig. 2). The performance of the device was characterized, including the calculation of its Just Noticeable Difference (JND). This platform serves as a single DOF device that is non-intrusive as it targets the base of the hand. By targeting the hand instead of fingers we can create an interface that does not inhibit hand dexterity or occlude the fingers from tactile interaction with objects in the environment, a claim investigated by conducting an object manipulation task with two conditions: without force feedback and with implicit (task-irrelevant) force feedback. Post-task qualitative data supported the claim that wrist-localized feedback increases immersion in MR/AR.

Additionally, we hypothesize that **(H2) the minimal haptic feedback device developed in H1 is sufficient for the user to accurately perceive the weight of both real and virtual objects**. We conducted a weight sorting experiment with three conditions: sorting a set of real weighted blocks, sorting a set of virtual blocks, and sorting a set that contained both real and virtual blocks. We validate the experimental results by comparing to simulated results based on the device's previously observed JND. From this experiment, we find that while sorting purely real or virtual objects while using the benchtop device is sufficiently accurate, the sorting accuracy of the mixed set was significantly lower. This means that the realistic and accurate perception of weight of a mixed real-virtual set of objects cannot be achieved simply by applying a one-to-one facsimile of weight for a virtual object. We believe that this is due to the presence of additional forms of feedback in the fingers when interacting with a physical object.

To validate this belief, a follow-up experiment analyzing virtual-real weight equivalence was then conducted with three modalities of force feedback: neither kinesthetic nor tactile feedback available to the fingers while gripping a virtual object, but present for a real object, only tactile feedback available to the fingers while gripping a virtual object, while both are present for a real object, and neither kinesthetic nor tactile feedback available to the fingers while gripping both real and virtual objects. The results of this experiment showed that when no feedback is available to the fingers for both real and virtual objects, there is parity in the perceived weight of real and virtual object. The presence of feedback to the fingers only when interacting with a real object led to a necessary increase in applied force to achieve real-virtual weight parity. Furthermore, the presence of only tactile feedback when interacting with a virtual object while both kinesthetic and tactile feedback was available for a real object was shown to require an even higher increase in force to achieve parity, possibly due to contradicting information from the tactile and kinesthetic stimuli.

The outcome of the weight equivalence experiment leads to our last hypothesis, that **(H3) perceived parity in real-virtual object weight can be achieved by compensating for missing kinesthetic and tactile sensorimotor cues from the virtual object through the inclusion of a mass-proportional “force offset” when rendering the weight of virtual objects**. This new compensation scheme was then implemented and tested by revisiting the mixed real-virtual condition of the previous weight sorting experiment, with the proportional force offset calculated using the results of the weight equivalence experiment. With virtual weight compensation in place, we found that there was no significant difference in sorting accuracy between a mixed and purely virtual set of objects.

The validation of our hypotheses shows the compatibility of minimal haptic feedback devices with MR/AR applications. Furthermore, we highlight the importance of simulating gravitational interactions with objects in creating a more immersive environment for the user. We believe the insights provided by our work will aid the future selection and integration of select forms of sensorimotor cues for viable MR/AR haptic feedback, paving the way for unobtrusive haptic devices that significantly enhance user experience and expand the possibilities of mixed reality interaction.

Results

Just noticeable difference testing

Before performing any experiments to validate our current claims and hypothesis, it is important to ensure that the haptic test stand does not impact the user's ability to sense forces. To verify this, we measured the Just Noticeable Difference (JND) associated with the test stand. The JND is the minimum difference in intensity between a reference stimulus and a test stimulus that can be detected by a human with a given reliability. For our experiment, we calculated the JND at the 75% threshold, i.e., the difference in stimuli that results in a user recognizing that they are different 75% of the time.

Our experimental procedure consisted of conducting three sets of 32 trials each on all participants (N=15), wherein a reference force was applied using the test stand, followed by a second force that was either the same or higher in intensity. For each trial, participants were asked to choose whether the pair of forces was the same or different. Each condition (same intensity or higher intensity) occurred with an equal a priori probability. A reference stimulus value of 4N was chosen as it was within the range of forces producible by the test stand and representative of typical weights associated with objects graspable by the hand. Each set of 32 trials had a percentage increase in intensity between the reference and test stimuli of 5%, 10%, and 15%, respectively. A 2x2 response matrix for each individual was recorded and analyzed to derive a JND(%), also known as a Weber Fraction⁵⁰. See Figure 4 for an overview of this process and refer to the Methods section for a more in depth explanation of the statistical method used to calculate the JND(%).

Once JND(%) was calculated for each individual (see Figure 5). We found the mean JND(%) across all participants to be 7.96% (95% Confidence Interval (CI): 6.27%-9.66%). This means that a 7.96% increase in stimulus intensity is detectable 75% of the time by users of the test stand. This falls within the range found in literature of 5%-10% for typically-abled humans⁵¹⁻⁵³. The bias criterion beta deviated little from an unbiased value of 1 across all individuals, with a mean beta of 1.09, indicating there was little bias towards one answer (same or different) in subject responses. As the JND(%) falls within an expected range, we can proceed with

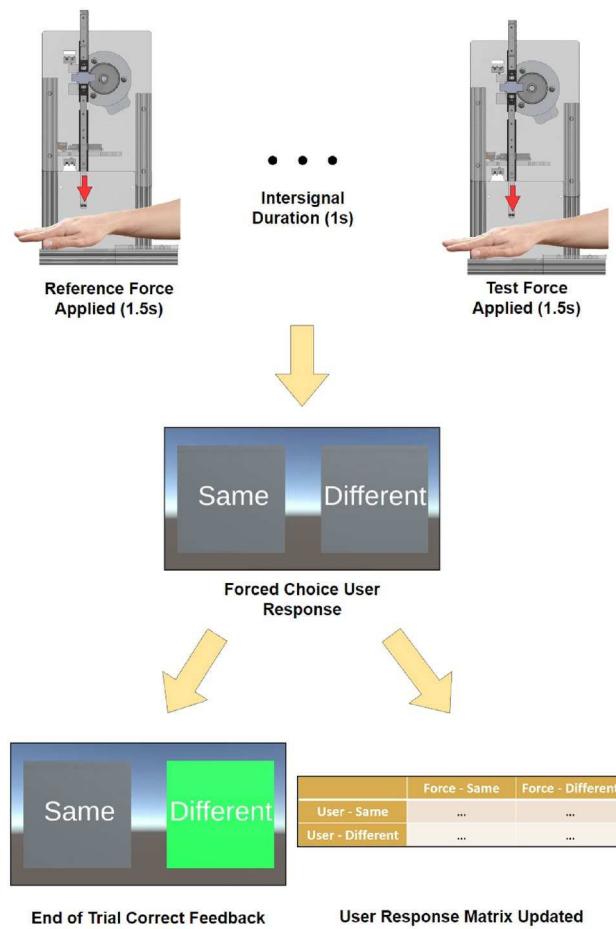


Fig. 4. Each trial of the JND testing consists of the application of a standard reference force, followed by a pre-defined delay, and then the trial's test force. Users are prompted to select whether the forces were the same or different, and their selection recorded in the experiment's 2x2 response matrix.

further experiments with the reasonable assumption that there is no hindrance to the user's ability to detect forces applied to the hand while using the test stand.

Implicit haptic feedback qualitative data

We expect our form of minimal haptic feedback to be able to represent gravitational effects on objects by rendering object weight, but how does the presence of force feedback impact other factors of user experience? To quantify both the effectiveness of our device at instilling a perception of weight and its impact on user experience, we asked participants ($N=15$) to perform a simple task with and without implicit haptic feedback and then conducted a post-task survey. The survey questions measured participant responses regarding task difficulty, mental effort, enjoyment, focus, and feelings of immersion for both conditions of the task (i.e., absence or presence of haptic feedback), as well as gauged feelings of realism regarding object weight and the participant's preferred condition.

Participants wore a HoloLens 2 headset and were presented with a MR/AR application where they were asked to manipulate a set of numbered virtual blocks (see Figure 6). Each block was configured to utilize the HoloLens' built-in hand tracking such that participants were able to grasp and move them using their right hand while engaged with the haptic test stand as well as assigned a random unique mass from the following values: 300g, 400g, 500g, 600g, or 700g. This mass value was used to calculate the force rendered to the user when haptic feedback was enabled. Participants were asked to physically arrange or group the numbered blocks by various metrics, such as in ascending order, descending order, by evens and odds, and by prime and non-prime. This arrangement task was conducted with and without haptic feedback, with both conditions having an equal chance of being experienced first by each subject.

Task difficulty was assessed using the Single Ease Question (SEQ), and mental effort with the Subjective Mental Effort Question (SMEQ)⁵⁵. Mental effort was then calculated as a ratio of effort with feedback to without feedback. Enjoyment, focus, immersion, and realism of object weight were assessed by asking participants to rate on a Likert scale how intensely they felt each trait. Participants were then asked to choose between "Without Haptic Feedback", "With Haptic Feedback", or "No Preference" as their preferred condition of the experiment. All questions were tested for significance between conditions using the Wilcoxon Signed Rank test.

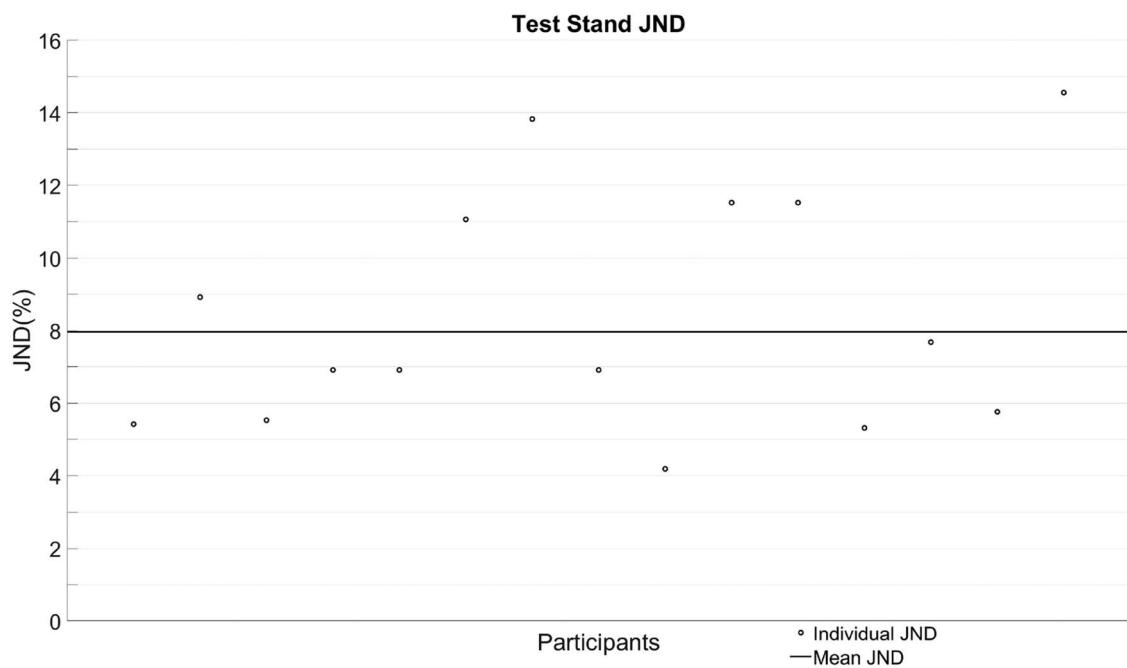


Fig. 5. JND Results. Individual JNDs ranged from just over 4% to nearly 15%, with an overall JND of 7.96%. Such variations in individual JND are consistent with previous studies^{52,54}.

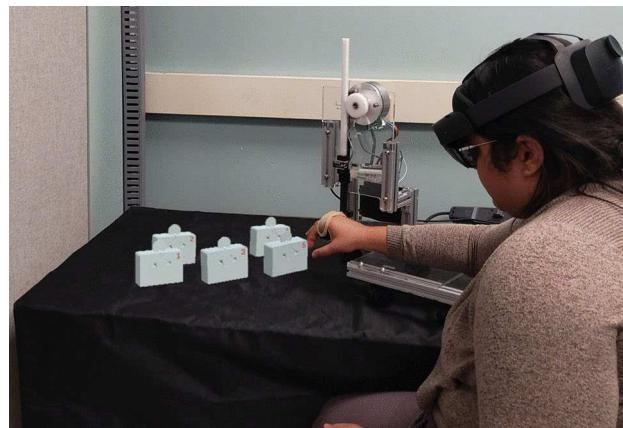


Fig. 6. Virtual blocks were presented within the participants' workspaces using an MR/AR HMD. The blocks were numbered to distinguish individual blocks and to enable the sorting of blocks as part of the implicit haptic feedback task. Participants manipulated the virtual blocks while tethered to the haptic feedback test stand.

Figures 7, 8, 9, and 10 show the results of the questionnaire. There was no significant difference in task difficulty ($p = 0.5488$), the subject's mental load ($p = 0.9375$), or in participant's focus ($p = 1$). This implies that the mere presence of haptic feedback alone was not enough to perturb the user in a significant way. The inclusion of haptic feedback, even though it was not utilized for the task, was sufficient to increase feelings of enjoyment and immersion, with a significant difference in both metrics compared to no feedback ($p_{\text{enjoyment}} = 0.0215$, $p_{\text{immersion}} = 0.0073$). Participants responded well to the notion that the feedback enabled the perception of weight for the virtual blocks, with an average Likert scale response of 6.47 (95% CI: 6.06-6.89). Haptic feedback was the preferred condition, and was chosen by 2/3 of the participants ($p = 0.0417$).

Explicit feedback sorting tasks

Beyond feelings of realism and immersion, it is important to look at how accurately users can perform tasks with explicit feedback for gravitation cues, i.e., tasks that require the use of gravity for completion. This is more than just establishing a monotonic relationship between object mass and force feedback. While such a relationship is fine for interacting with entirely virtual environments, absolute accuracy becomes important when interacting

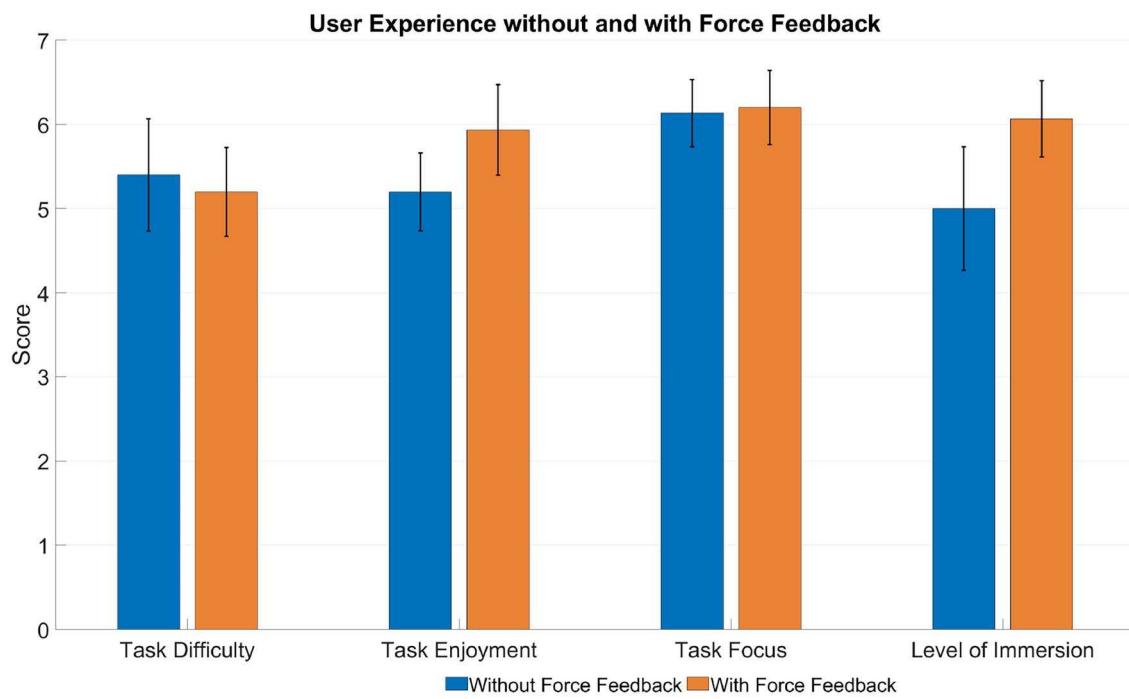


Fig. 7. User Experience without and with force feedback. Participants were asked to rate on a Likert scale their feelings of task difficulty, enjoyment, focus, and immersion. The lack of significant differences in difficulty and focus implies that the addition of force feedback does not negatively impact user experience. In fact, the significant improvements in enjoyment and immersion show that the presence of force feedback positively effects user experience, even when not actively utilized by users.

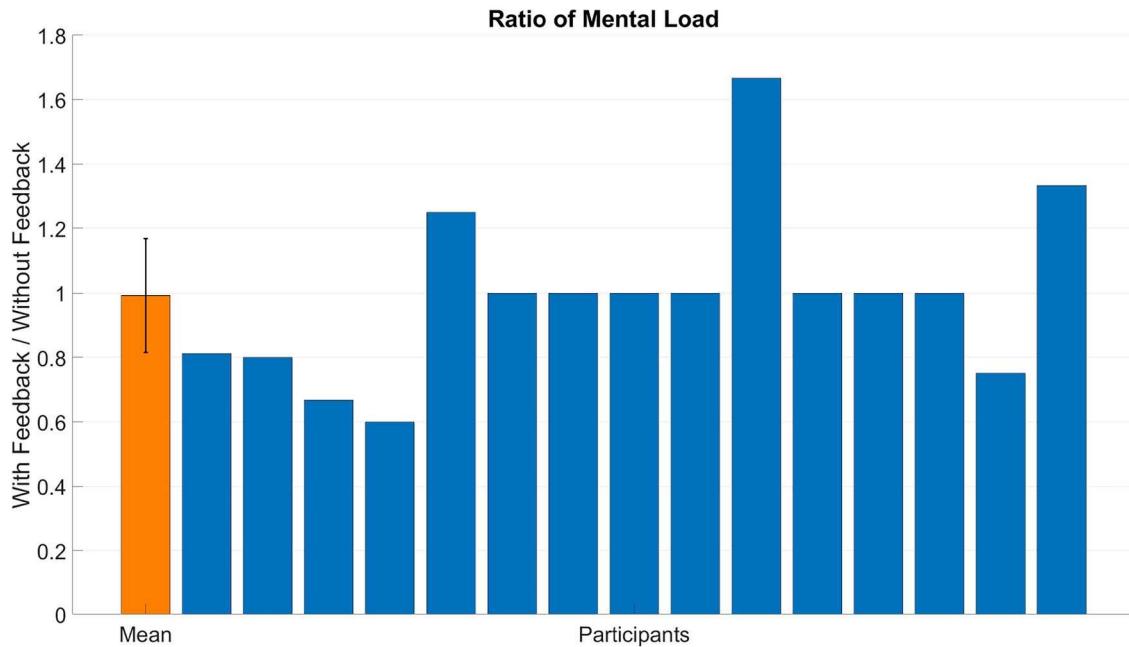


Fig. 8. Mental Load. Participants were asked to write a number between 0 and 150 to describe the mental effort of accomplishing the block sorting task. The ratios of each pair of ratings with/without feedback were then computed to evaluate the effect of force feedback on mental load. An average ratio near 1 implies no impact on mental load.

Realism of Weight Perception using Haptic Feedback

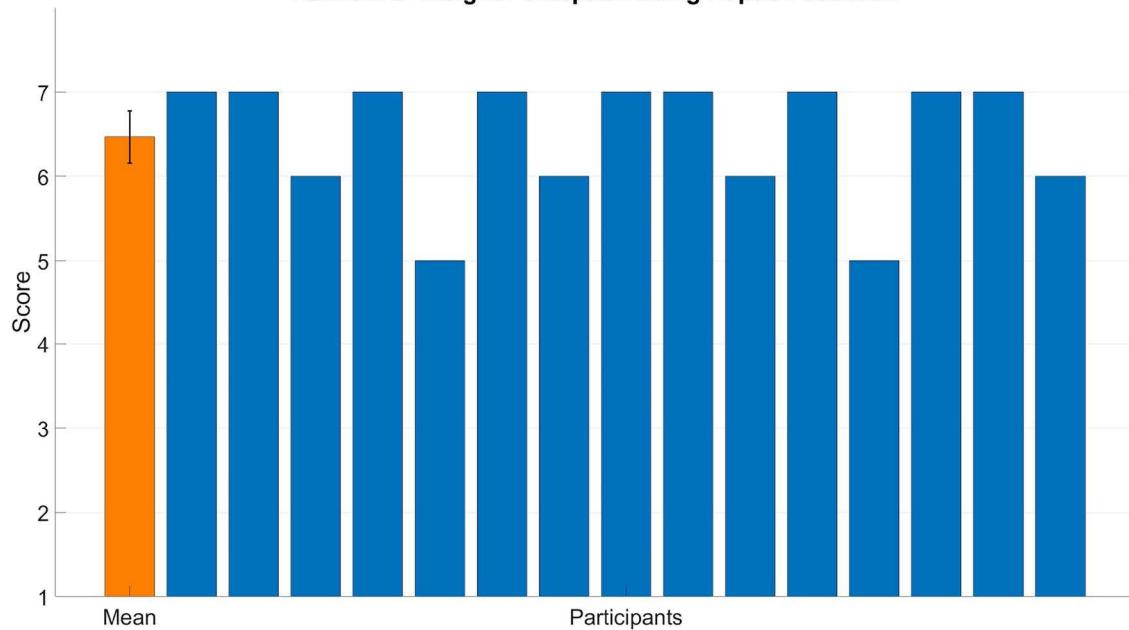


Fig. 9. Participants were asked to rate the realism of object interactions with the provided force feedback on a Likert scale, with 4 indicating a neutral opinion towards realism, 1 a negative opinion, and 7 a positive opinion. All participants indicated at least a small positive opinion.

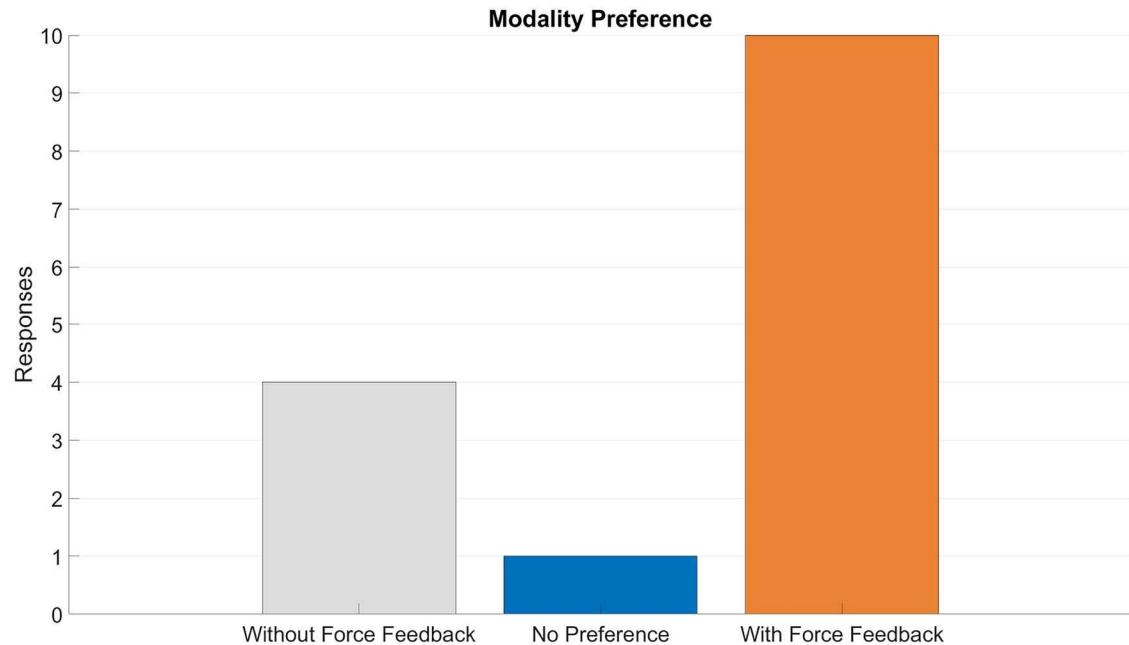


Fig. 10. Modality Preference. Two thirds of participants preferred the presence of force feedback even when it was not necessary for the completion of the task at hand.

with a mixed real-virtual environment. Weight feedback in MR/AR must be able to maintain the proportions of weight between all objects in the environment.

The initial thought is that we can establish such a relationship between objects with different mass properties by directly emulating object weight under standard gravity conditions ($g = 9.81 \text{ m/s}^2$). To characterize our test stand's performance with such conditions, we asked participants ($N=15$) to perform a weight sorting task wherein they arranged blocks in order by weight. Participants sorted four separate sets, each consisting of five real blocks with inter-set mass differences (referred to as "mass deltas" for the rest of this paper) of 100g, 50g,

25g, and 15g, respectively, while equipped in the haptic test stand and without feedback. Additionally, as shown in Figure 11, participants were asked to perform the sorting task, this time with force feedback from the test stand, with four virtual sets and four mixed real-virtual sets (three real blocks, two virtual), all with mass deltas matching the all physical control condition.

Each block set had an average mass of 500g, with the middle block of the set having a mass of exactly 500g, two blocks with masses less than 500g, and two blocks with masses more than 500g (one and two deltas above/below 500g). For example, the 100g-delta set consisted of blocks with masses of 300g, 400g, 500g, 600g, and 700g. The mass deltas of 100g, 50g, 25g, and 15g were chosen to provide of groups of masses that exist above and below the measured JND of the system ($7.96\% * 500g = 39.82g$). With this design choice, we expect to observe noticeable changes in sorting performance between sets, with performance monotonically decreasing along with mass deltas.

To verify that the observed results of the weight sorting task align with the expected results for our test stand's calculated JND of 7.96%, we made a simulation of the weight sorting task in Matlab. The simulation implemented a modification of the Quick Sort algorithm⁵⁶ that sampled from a probability distribution based on the JND when making comparisons between block weights. See the methods section for a detailed description of the modified algorithm. We ran the simulation with both the lower and upper confidence intervals of the test stand's JND, (6.27% and 9.66%, respectively). Each simulated run was conducted for mass deltas in a range from 120g to 1g and consisted of 1000 trials for each mass delta to create an upper and lower bound for the expected sorting results.

Prior to conducting the experiment and simulation we established two performance metrics, Spearman's Rho and Kendall's W, to compare performance between the real, virtual, and mixed real-virtual conditions. Spearman's Rho is a monotonic rank correlation metric we used between each participant's sorted blocks and the true order to evaluate accuracy in sorting. A correlation metric of 1 indicates parity between a sorted group and its true order, while a value of 0 or -1 indicates no correlation or an inverse correlation, respectively. Kendall's W, also known as Kendall's coefficient of concordance, was used to ascertain inter-rater (participant) consistency in weight rankings, i.e., did participants tend to sort groups of blocks with a certain order, even if that order was not the correct ranking. A W metric of 1 indicates complete agreement between raters, while a value of 0 indicates complete randomness among the rankings of each rater. In order to measure significance between correlation metrics we used Fisher's z-transformation⁵⁷ along with Bonferroni correction for multiple comparisons.

Figure 12 shows the results of the weight sorting human subjects experiment. Comparing the purely real and purely virtual conditions, we see that the real condition trends towards both higher accuracy and consistency. We observed a significant difference in Spearman's Rho between the 100g, 50g, and 15g mass delta sets ($p_{100g} < 0.001, p_{50g} < 0.001, p_{15g} = 0.0086$). The 25g mass delta set did not show a significant difference between the real and virtual conditions ($p = 0.0187$). Significant differences in Kendall's W were found for the 100g and 50g conditions ($p_{100g} < 0.001, p_{50g} < 0.001, p_{25g} = 0.018, p_{15g} = 0.017$).

The mixed real-virtual condition had a lower performance than the pure virtual condition, with significant differences in Spearman's Rho and Kendall's W between the 100g, 50g, and 25g mass delta sets (Rho: $p_{100g} < 0.001, p_{50g} < 0.001, p_{25g} = 0.0073$, W: $p_{100g} < 0.001, p_{50g} = 0.004, p_{25g} = 0.005$). There was no significant difference between the virtual and mixed 15g sets (Rho: $p_{15g} = 0.1712$, W: $p_{15g} = 0.071$).

There is good alignment between the results of the pure virtual condition to the lower and upper bounds generated with the simulated sorting task (Figure 13). For both performance metrics, only Kendall's W for the virtual 25g mass delta set was observed to deviate out of the bounding area of the simulation ($W_{virtual} = 0.626, W_{simUpperBound} = 0.606$). The results of the real and mixed sets were above the upper simulation bounds and below the lower simulation bounds, respectively, except for the results of the mixed set with a 15g mass delta. While far from conclusive, this observation does motivate further consideration into the role unequal sensory feedback plays in weight discrimination.

The difference in performance between the real and virtual conditions highlights the advantages the human nervous system gains when combining multiple sensory stimuli. Not only did subjects grasping the real blocks



Fig. 11. The mixed set of blocks for this task consisted of two virtual blocks and three real blocks. Users were asked to grasp each block (real and virtual) using the circular tab on the top of the block.

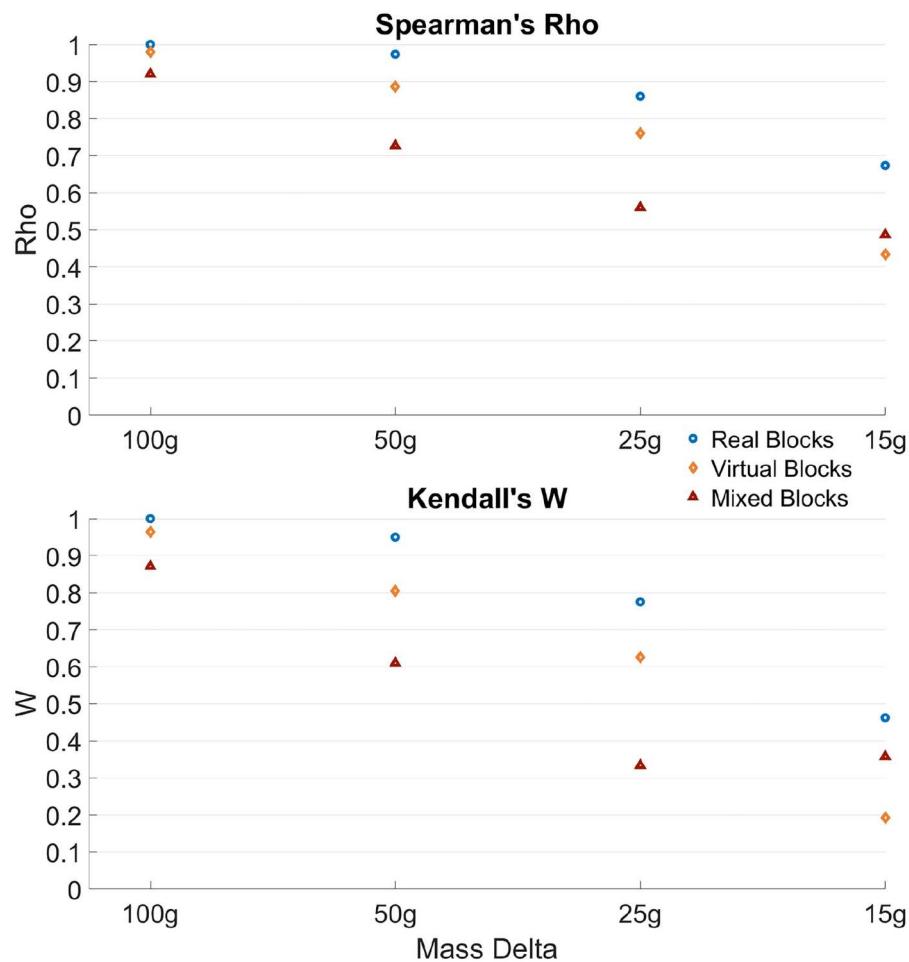


Fig. 12. Spearman's Rho and Kendall's W for the Real, Virtual, and Mixed block sets. As the difference in mass between blocks (mass delta) decreased, the ability to accurately and consistently discriminate between blocks also decreased. Participants were found to be less accurate for the virtual block set than the real block set, and a further decline in performance was noted for the mixed block set.

experience kinesthetic feedback from their wrist, but also tactile and kinesthetic feedback from their fingers. Participants were able to use this extra data to discriminate smaller differences between block masses. While the absence of this extra sensory information is a drawback of minimizing the forms of feedback given to users, it does not in itself imply that minimal feedback is insufficient for perceiving virtual weight. Instead, it simply means that users of such a modality of feedback will have an increased threshold of discrimination between objects. The further decrease in performance between the virtual and mixed conditions initially is cause for concern. This discrepancy indicates that another factor is at play besides the differing thresholds of discrimination between virtual and real objects. This factor is addressed in the following section, detailing virtual-real weight equivalence.

Virtual-real weight equivalence

Based on the results of our block sorting experiment, it is clear that the direct emulation of gravitational forces about the wrist is not sufficient for accurate perception of the mass properties of a virtual object. A noticeable decrease in sorting accuracy and consistency was observed for block sets containing both real and virtual objects. One potential explanation for this can be found by investigating the relation between sensory input and weight perception. Literature shows that a lack of grip strength and finger slip can lead to the perception of objects having a lighter weight^{21,48}.

Indeed, a post hoc analysis (Figure 14) of the average rankings for each block in the mixed real-virtual sets showed that the virtual blocks were ranked on average -0.3 steps below their true ranking, while the real blocks were ranked an average 0.2 steps above their true ranking. This is a drastic change from the average rankings for a particular block from the pure virtual set of ± 0.05 or the average ranking for the pure real set of ± 0.067 . With this analysis, we can confidently say that the lack of tactile and kinesthetic feedback of the fingers alters the perception of a virtual block with a given mass to have a lighter weight than a real block with the same mass.

But which of these stimuli is the main contributor? We hypothesize that the missing kinesthetic feedback from the fingers is the main culprit for the perception of reduced weight. To test this, we conducted a virtual-

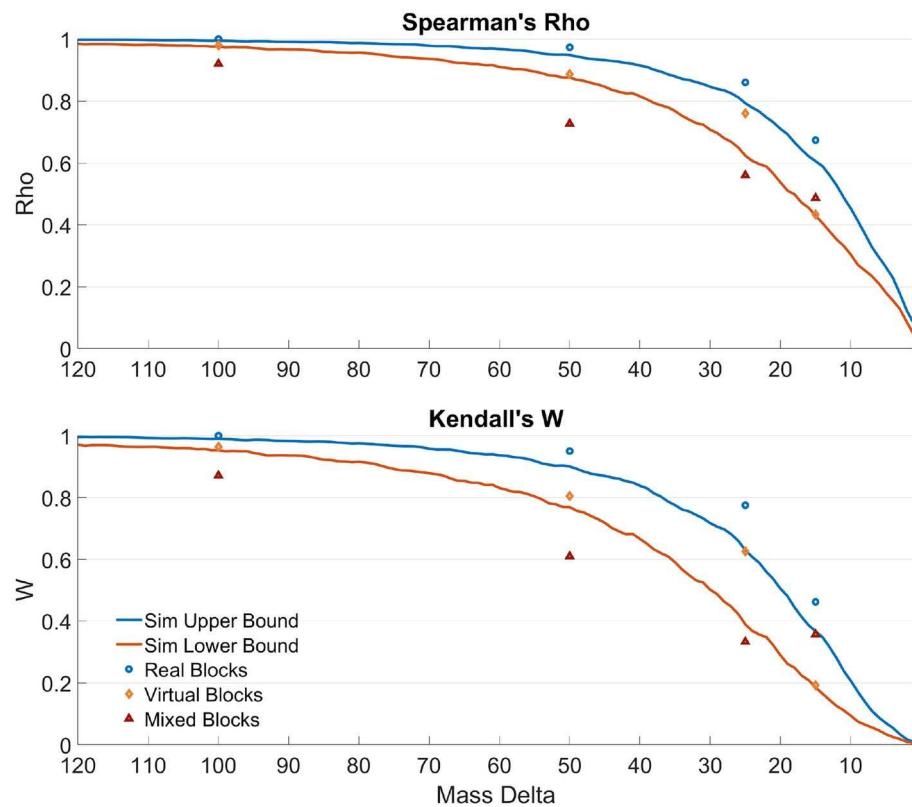


Fig. 13. A probabilistic simulation of weight sorting was performed to establish the expected behavior of sorting virtual blocks. An upper bound for both Spearman's Rho and Kendall's W was established by running the simulation using the lower confidence interval of the JND (6.27%) established in Section 2.1. Similarly, a lower bound was computed using the upper confidence interval of the JND (9.66%).

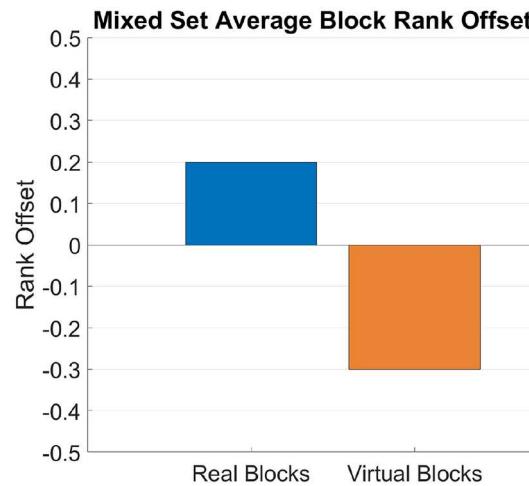


Fig. 14. Average rank offsets for virtual and real blocks in the mixed set. Note that virtual blocks were consistently perceived as lighter than their real counterparts.

real weight equivalence experiment. Participants ($N=15$) were again asked to wear a HoloLens 2 headset and presented with a MR/AR scenario that compared a real block to a virtual one. Three conditions were tested: pinching both the real and virtual objects to lift (no tactile or kinesthetic feedback to the fingers for the virtual object), pinching the real object and a tactile proxy for the virtual object (no kinesthetic feedback to the fingers for the virtual object, see Figure 15), and setting both the real and virtual object on the palm (an ablation condition, where no kinesthetic or tactile feedback is applied to the fingers for either real or virtual objects, meaning that both objects provide the same type of feedback, in the same location, to the participant). For each of a set of

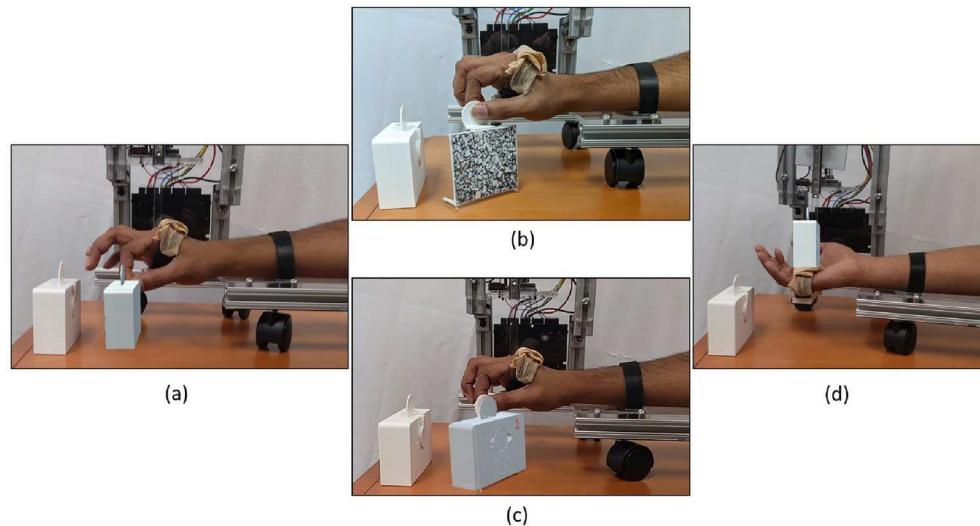


Fig. 15. Three conditions were tested for real-virtual weight equivalence: **(a)** pinching the real and virtual objects, **(b, c)** pinching the real object and a tactile proxy within the virtual object, and **(d)** placing the real and virtual objects on the palm. The tactile proxy was implemented by overlaying a virtual block **(c)** onto a lightweight (15g) 3D printed proxy **(b)**. Tracking the position of the proxy and updating the corresponding position of the overlayed virtual block was implemented using Vuforia's image tracking SDK for the HoloLens.

400g, 500g, and 600g weights we asked participants to compare a real and virtual version by lifting the blocks using the above conditions. We implemented a one-up/one-down adaptive staircase method⁵⁸ to determine the virtual weight that was perceived as equivalent to the real weight. The one-up/one-down weighting scheme was chosen to derive the threshold at which there is a 50% chance of successful discrimination between the presented real and virtual object weights. This equal success/fail rate was chosen to mimic the presumed outcome of a theoretical forced choice task wherein the participant is asked to identify the heavier of two identical real objects with equal masses. Participants gave feedback as to whether the virtual object was lighter or heavier, at which point the mass of the virtual object was increased or decreased, respectively, by a stepsize of 10%. The trial stopped when 10 reversals were observed, or if a total of 40 runs was executed. The last 8 observed reversals were then averaged to calculate the percentage mass offset for the virtual weight.

Each dataset (9 datasets total: 3 masses * 3 conditions) was then checked for normality using the Shapiro-Wilk test. All datasets failed to reject the null hypothesis that they came from a normal distribution ($p_{palm,500} = 0.026$, $p_{palm,600} = 0.006$, all other $p < 0.001$). Following this, a one-way ANOVA was conducted to test whether the datasets came from the same distribution. The ANOVA rejected the null hypothesis ($p < 0.001$). A post hoc multiple comparisons analysis was then conducted using Tukey's test.

The results of this experiment are shown in Figure 16. The pinching condition had an overall mean percentage offset of 13.53% (95% CI: 11.88%–15.18%), meaning that the average mass of the virtual block was 13.53% higher than the real block to which it was deemed equivalent. The tactile condition had an overall mean percentage offset of 32.88% (95% CI: 30.96%–34.80%). The palm condition had an overall mean percentage of 0.163% (95% CI: −1.35%–1.67%).

There were no significant differences for intra-condition datasets (all $p > 0.96$), i.e., there was no significant difference between the 400g, 500g, and 600g percentage offsets within all three grasping conditions. There was significant difference between the pinching and both the tactile and palm conditions (all $p < 0.001$). The palm condition was also significantly lower than both the tactile conditions (all $p < 0.001$). A one sample t-test was performed on the offsets for the palm condition, failing to reject the null hypothesis that the mean is 0% for all three masses (all $p < 0.001$). Due to this, from now on we treat the palm condition as having no percentage offset, i.e., there is no difference necessary in the masses between the virtual and real blocks for them to feel the same.

The results show that a discernible disparity exists between the pinch and tactile conditions, with the tactile condition requiring nearly double the percentage weight offset to achieve real-virtual weight equivalence. We believe this is due to a mismatch in sensorimotor stimuli between the tactile feedback provided to the fingers (a light weight plastic proxy) and the kinesthetic feedback provided to the wrist by the haptic device. As a result, additional kinesthetic feedback to the wrist is required to compensate for this discrepancy. This distinction between the pinch and palm conditions leads us to postulate that the absence of adequate kinesthetic feedback contributes to the variation in the perception of real-virtual weights. These findings also provide a potential solution to address the weight perception disparity experienced while pinching both blocks, at least in the context of a single paired sample: weight parity can be achieved by merely increasing the presented mass of the virtual block by a fixed percentage.

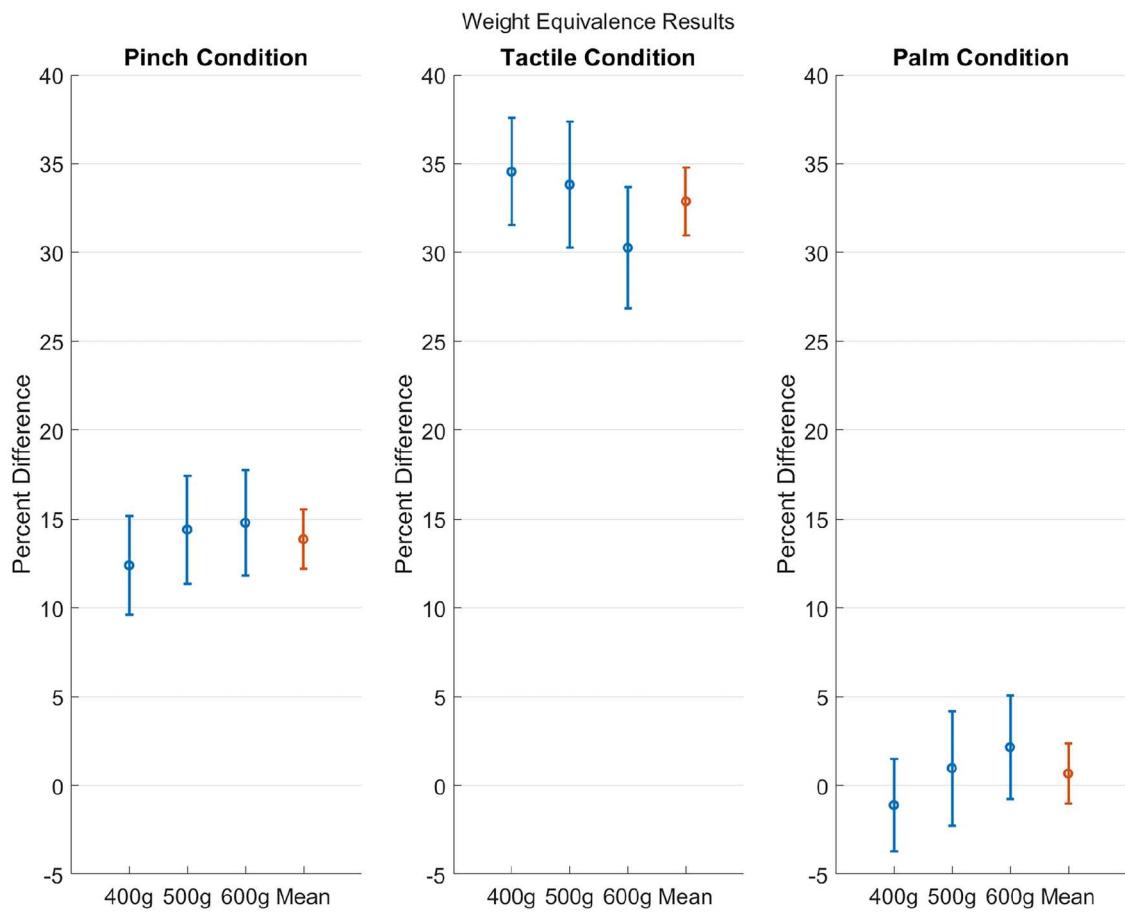


Fig. 16. Pinching a completely virtual object requires a 13.53% increase in presented weight to approximate a real object of the same weight. This percentage increase rises to 32.88% for the tactile proxy condition. Discrepancies between the perceived real and virtual weights trend to zero for the palm condition. All three conditions exhibit similar variance.

Virtual weight compensation

The previous conclusion leads to our last hypothesis: missing kinesthetic stimuli can be compensated for by proportionally increasing the force presented to the user when grasping a virtual object. To test this hypothesis, we revisited the weight sorting task previously described with a new condition: a set of mixed real-virtual objects with compensated feedback for virtual objects, i.e., the force presented to a participant for a virtual object was 11.83% higher than the weight calculated from the mass of the object. 11.83% was chosen as it was the mean percentage offset of the pinching condition in the previous experiment. Participants (N=15) were once again asked to sort four sets of mixed blocks (3 real, 2 virtual) with decreasing mass deltas of 100g, 50g, 25g, and 15g. Spearman's Rho and Kendall's W were calculated for each and the same statistical comparisons made.

The results are shown in Figure 17. Spearman's Rho was significantly higher at most mass deltas for mixed sorting with virtual weight compensation than without ($p_{100g} = 0.002$, $p_{50g} < 0.001$, $p_{25g} = 0.014$). The only mass delta at which there was no significant difference was the 15g increment ($p_{15g} = 0.218$), which was well below the JND of humans for this task. This finding also holds true for Kendall's W, with only the 15g set showing no significant difference ($p_{100g} = 0.007$, $p_{50g} < 0.001$, $p_{25g} = 0.005$, $p_{15g} = 0.223$). Additionally, there was no significant difference between the performance of the compensated mixed sorting and the pure virtual condition except for the 100g mass delta ($p_{100g} = 0.030$, $p_{50g} = 0.250$, $p_{25g} = 0.196$, $p_{15g} = 0.143$). Similarly, Kendall's W shows no significant difference except for the 100g mass delta ($p_{100g} = 0.018$, $p_{50g} = 0.133$, $p_{25g} = 0.245$, $p_{15g} = 0.057$).

These results show that virtual weight compensation when sorting a mixed set of virtual and real objects brings user accuracy and consistency up to the level of sorting a purely virtual set of objects. This is a drastic improvement over the naive approach of presenting a facsimile of object weight to the user.

Discussion

In this study, we aimed to investigate the effectiveness of minimal haptic feedback in representing gravitational effects on virtual objects in MR/AR environments. Our results from the Just Noticeable Difference testing indicate that the haptic test stand did not significantly impact the users' ability to sense forces, as the calculated

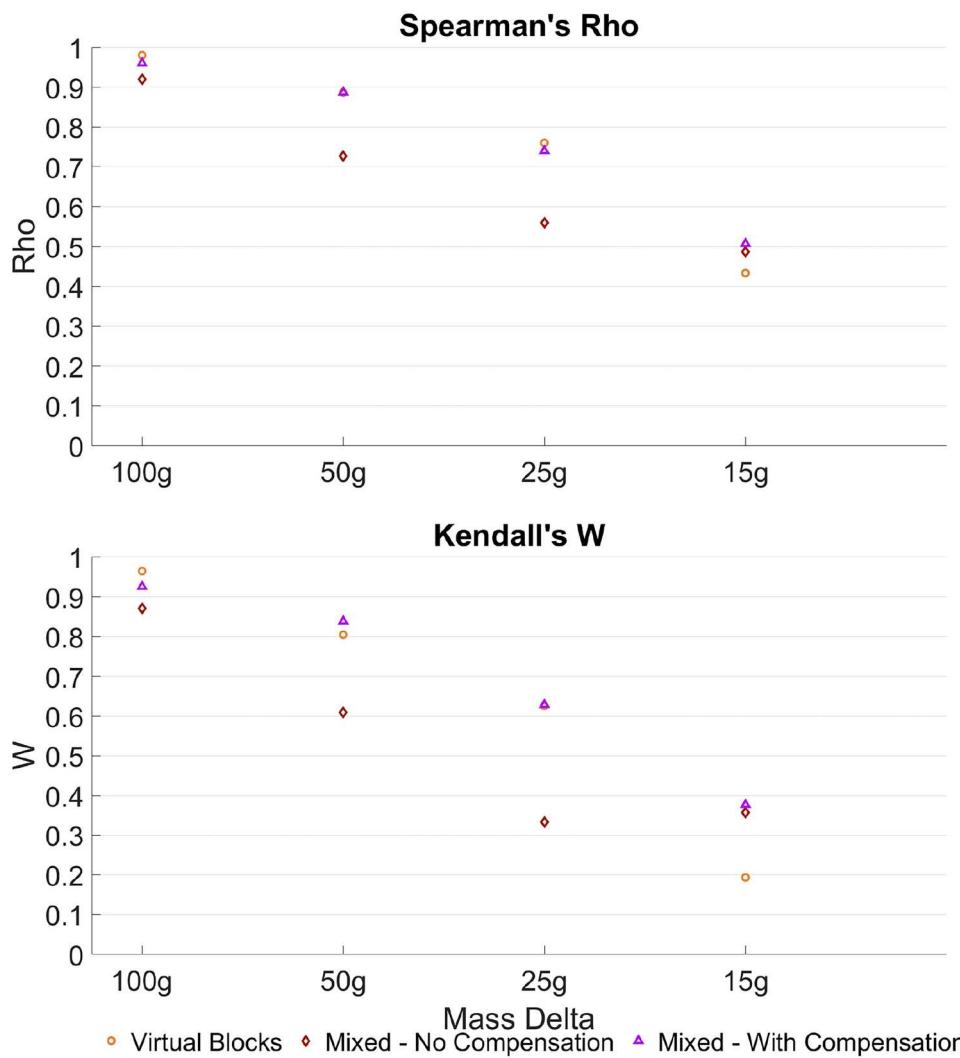


Fig. 17. Spearman's Rho and Kendall's W for the Virtual, Mixed (No Compensation), and Mixed (With Compensation) block sets. Compensating for virtual weights in the mixed set based on the value derived in Section 2.4 leads to performance on par with sorting purely virtual weights.

JND fell within the expected range reported in the literature for typically-abled humans. This finding supports the use of the haptic test stand as a proof of concept for providing haptic feedback in MR/AR applications.

Furthermore, our qualitative data analysis revealed that the presence of haptic feedback, even when not directly utilized for the task, had a positive impact on user experience, validating **H1**. Participants reported increased enjoyment and immersion when haptic feedback was present, indicating that the feedback contributed to a more engaging and realistic experience. This aligns with our hypothesis that the minimal haptic feedback provided by the test stand can create the illusion of weight for virtual objects in MR/AR environments, as the inclusion of physical properties of objects in the user's workspace is known to increase immersion and presence in virtual environments.

In terms of explicit feedback sorting tasks, we observed that participants performed more accurately and consistently in the real condition compared to the virtual condition. This suggests that the combination of kinesthetic and tactile feedback from the real blocks provided additional sensory information that facilitated better discrimination between different block masses. A further experiment then indicated that kinesthetic feedback was the primary factor that allowed for a lower discrimination threshold for real blocks.

This finding highlights the need to consider virtual-real weight equivalence for accurate representation of object weights in MR/AR environments. The concept of virtual-real weight equivalence is crucial for maintaining accurate weight proportions between real and virtual objects in mixed environments. We want to emphasize the results of the virtual-real weight equivalence experiment's palm condition, in which feedback to the fingers is absent for both real and virtual interactions, as it indicated that in a scenario where no additional feedback is present for real objects, no disparity in weight perception exists. This complete absence of a need for the force compensation required in the other test conditions underscores the importance of accounting for unequal feedback in the perception of weight equivalence of real-virtual object pairs. Our study found that a simple flat

percentage increase in displayed virtual weight vs actual virtual weight was sufficient to achieve parity with real objects, validating **H2** and **H3**. Anecdotally, after applying virtual weight compensation and asking participants to sort the mixed set of blocks, many participants reported that part way through testing they would often reach for virtual blocks expecting them to be real. This occurrence was not reported by the participants in earlier tests without weight compensation.

This study is limited in the range of motion allowed to participants while using the test stand. Currently, only forces in the wrist's extension/flexion direction is able to be rendered by the test stand. Future work should aim to build off of the current prototype and extend feedback into the abduction/adduction direction of the wrist as well. This would allow users to grasp and orient objects in space while still feeling gravitational effects. Additionally, when investigating the discrepancy in weight equivalence between virtual and real objects, we did not test for grip strength and finger slippage. Literature shows that finger slip and cutaneous feedback provide tactile cues for grip forces^{459–61}, which in turn affect perceived weight²¹. Future work to establish a link (if any) between grip strength and the necessary force offset to compensate for virtual weights could lead to more accurate feedback customized to a particular individual.

Future work in a related field is also worth mentioning. The use of haptic feedback for proprioceptive sensing is already well studied^{62,63}, even with current work looking into the role of wrist feedback for proprioception⁶⁴. By leveraging haptic feedback on the wrist, users can receive real-time tactile cues that augment their proprioceptive perception, enabling a heightened sense of body awareness and control. In the realm of rehabilitation and motor skill training, wrist haptic feedback can play a crucial role in aiding patients in their recovery process. Proprioceptive deficits are common in individuals recovering from neurological injuries or undergoing rehabilitation. By utilizing feedback on the wrist^{65–67}, therapists can provide patients with targeted sensory cues that facilitate the reestablishment of proprioceptive awareness and motor control. This has the potential to improve the effectiveness of rehabilitation programs and enhance overall recovery outcomes.

In conclusion, our study demonstrates the potential of minimal haptic feedback for representing weight in MR/AR environments. The haptic test stand proved to be effective in providing haptic feedback without hindering users' ability to sense forces. An effective method of achieving parity between real and virtual objects was demonstrated, allowing users to operate with the same discrimination thresholds as observed with purely virtual objects.

Methods

IRB approval

This research study underwent ethical review and was approved by the appropriate Institutional Review Board (IRB) prior to its initiation. The purpose of the IRB review is to ensure the protection of human participants involved in the research and to ensure compliance with applicable ethical guidelines and regulations.

Participants

A total of 15 subjects were recruited from Vanderbilt University to participate in the study. The recruitment process involved reaching out to potential participants from the university's undergraduate and graduate student populations. The participants were selected based on their willingness to take part in the study and their availability during the designated experimental sessions. The recruited participants were provided with detailed instructions about the experiment and gave their written informed consent prior to their involvement.

Upon recruitment, the participants were thoroughly instructed about all aspects of the experiment, including the purpose, procedures, potential risks and benefits, and their rights as research participants. They were given the opportunity to ask questions and seek clarification before providing their written informed consent.

The study consisted of three one-hour visits for each participant. During these visits, the participants engaged in the research tasks and activities described in this paper. The duration of one hour per visit was deemed sufficient to gather relevant data while minimizing participant fatigue or discomfort.

The demographic characteristics of the participants revealed that the median age of the participants was 27.4 years, with a standard deviation of 4.5 years. All participants reported either infrequent or no previous use of HMD VR/AR displays, ensuring a relatively uniform level of experience with the technology within the sample. Furthermore, two participants identified as left-handed, but were still deemed appropriate for inclusion in use of the test stand designed for right-handed users as their data did not differ in any noticeable way from the right handed participants.

Test stand design

The test stand (Figure 3) is equipped with wheels for easy mobility across flat surfaces. It incorporates a current-controlled Brushless Direct Current (BLDC) motor mounted on a rack-and-pinion mechanism to control a plunger. A 3D printed mount and strap are securely attached to the end of the plunger, providing an interface for the user's right hand. Additionally, an acrylic platform with a Velcro strap is utilized to fasten the user's forearm in place, restricting movement solely to the wrist. This configuration ensures precise control over hand movements and facilitates focused examination of wrist-related forces, making it an ideal setup for studies involving hand force interactions. See Figure 18 for a functional diagram of the test stand.

The inherent force of gravity, always acting downwards, served as the primary justification for the up/down plunger mechanism in the system. This mechanism allows for controlled upward and downward movements, enabling simulations that replicate real-world scenarios that utilize extension/flexion of the wrist.

An in-line load cell on the plunger was utilized to provide real-time feedback on the applied forces on the hand. The feedback obtained from the load cell facilitated the implementation of closed-loop control. A feed-forward current control law (Figure 19) was employed to generate force responses that mimic the behavior of an object suddenly appearing and settling onto the hand and is as follows:

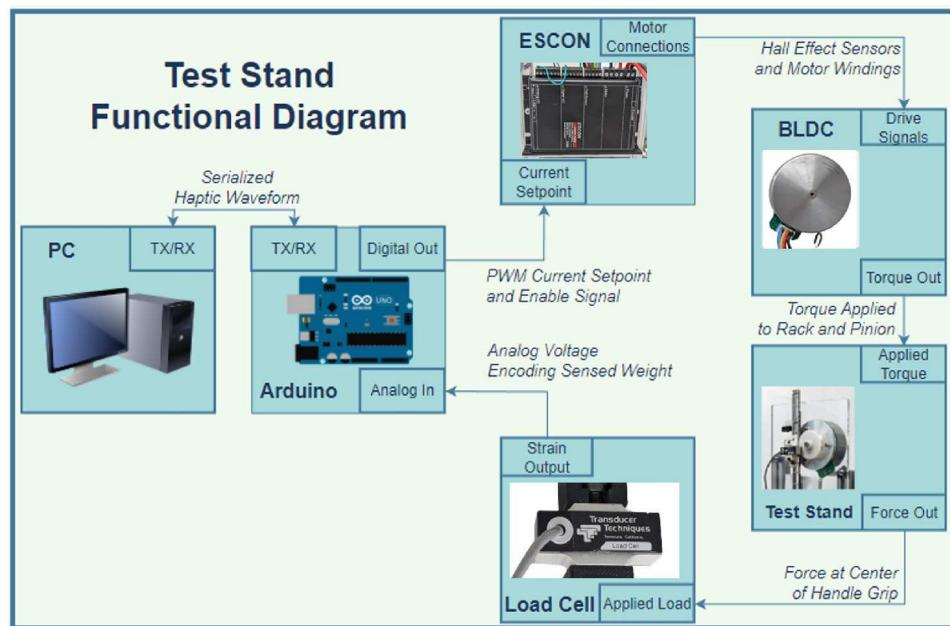


Fig. 18. The test stand's functional diagram, detailing the flow of information and actions within the haptic device. The haptic waveform calculated within the AR scenario is transmitted via a local pc to a microcontroller attached to the test stand which acts as the device's force controller. Command current is sent from the microcontroller to an off-the-shelf brushless motor driver. The motor torque is transformed into a linear force via the test stand's rack and pinion mechanism. An in-line load cell provides force measurements back to the microcontroller, allowing the implementation of closed-loop control schemes.

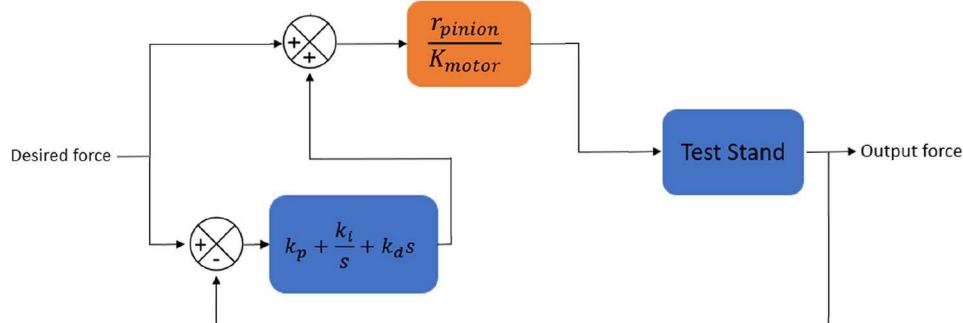


Fig. 19. The closed loop transfer function of the test stand's force control. A PID feed forward component is used along with the modeled dynamics of the rack-and-pinion system.

$$i = \frac{r_{pinion} (F_d + K_p F_e + K_i \int F_e(t) dt + K_d \frac{dF_e}{dt})}{K_{motor}} \quad (1)$$

where r_{pinion} is the radius of the gear used in the rack-and-pinion design, F_d is desired force, F_e is error between desired and current force, K_p , K_i , K_d are PID gain constants, and K_{motor} is the BLDC's motor constant.

The control parameters were tuned accordingly to achieve the desired simulation of inertial interactions. Consequently, an initial overshoot in force was observed in response to a step input (Figure 20), replicating the inertial interactions experienced during object settling on the hand.

Just noticeable difference testing

The JND for the test stand was derived using the process introduced by Berliner and Durlach⁶⁸ and later adapted for use with force perception^{52,53}. As with the study designed by Pang, Tan, and Durlach, participants were tested using a one interval, two alternative, forced choice paradigm. A base force of 4N was chosen, with test forces scaled by either 5%, 10%, or 15% of the base force. 32 trials were run for each scale increment, with 16 trials

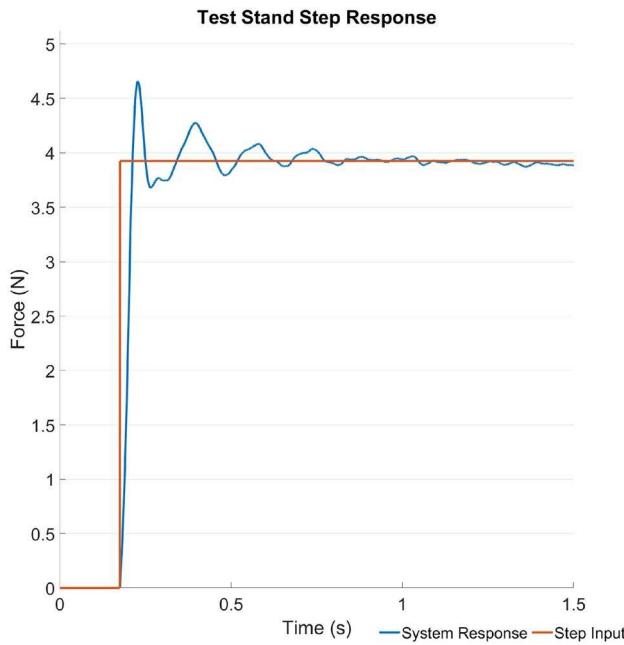


Fig. 20. The force applied by the test stand emulates an object being gently dropped into the user's hand.

consisting of base-base force pairs and 16 trials consisting of base-test force pairs, presented in random order. A 2x2 matrix of performance data was collected for each set of 32 trials, as detailed in Figure 4.

A sensitivity index, d' , was calculated for each set of force-increment trials based on the performance pattern of the subjects. The formula used for computation is as follows:

$$d' = (a - b)/\sigma \quad (2)$$

where a represents the hit rate, b represents the false alarm rate, and σ represents the common standard deviation in response rates among all test subjects. The assumption underlying this d' is that a subject's perceptual response to a specific stimulus condition can be represented by a standard normal curve. Discriminating between two different stimulus conditions involves differentiating between overlapping perceptual response curves with the same common variance. A decision criterion is set at a certain perceptual level, where values above and below the criterion are assigned to different responses. To specify the criterion, we calculate a value, β , as the ratio of the height of two normal curves at the perceptual threshold:

$$\beta = e^{\frac{1}{2}(a^2 - b^2)} \quad (3)$$

The β value represents the subject's bias towards one response over another, with $\beta = 1$ indicating no bias as it occurs where the two normal curves intersect.

We then define a proportionality constant δ as:

$$\delta = \frac{d'}{\frac{\Delta F}{F}} \quad (4)$$

where F is the base force used and ΔF is the difference between the base and test force. An average value $\bar{\delta}$ was calculated for each individual based on their δ values for each tested force increment.

The percentage Just Noticeable Differences, $JND(\%)$ s, were calculated as the percentage increment in force that resulted in a d' of 1, corresponding to 75% correct discrimination (assuming $\beta = 1$). In other words:

$$JND(\%) = \frac{1}{\bar{\delta}} \times 100 \quad (5)$$

Real and virtual blocks

For use in our experiments, hollow blocks were 3D printed from PLA with the dimensions of 100mmx32mmx70mm (LxWxH). A small round grip (diameter of 30mm) was attached to the top of each block to enable grasping in a manner similar to the way one grasps virtual objects while wearing the HoloLens 2. The hollow blocks were filled with metal weights and sealed with hot glue. The mass of each block was held to an error of $\pm 0.5g$. Weights were applied in a way as to not affect the center of mass of each object. For their virtual twins, the 3D models

Question/Statement	Response Scale			
Overall, the task was:*	Very Difficult	1 - 7	Very Easy	
Based on the following scale, mental effort associated with the task was:*	No Effort	0 - 150	Max Effort	
I enjoyed the experience.*	Strongly Disagree	1 - 7	Strongly Agree	
I was able to focus on the task activities.*	Strongly Disagree	1 - 7	Strongly Agree	
I found the experience to be immersive.	Strongly Disagree	1 - 7	Strongly Agree	
Overall, how realistic was the perception of weight with haptic feedback?	Completely Unrealistic	1 - 7	Completely Realistic	
Which condition do you prefer?	Without Force Feedback	With Force Feedback	No Preference	

Table 1. Post-Task Survey Questions.

Mass Delta	Weight Set				
	300	400	500	600	700
100g	300	400	500	600	700
50g	400	450	500	550	600
25g	450	475	500	525	550
15g	470	485	500	515	530

Table 2. Weight sets for each mass delta.

of the real blocks were imported into Unity and displayed using the HoloLens 2. These virtual blocks were then configured to send haptic waveforms of their assigned weights to the haptic test stand when the HoloLens' hand tracking identified a successful grasp event.

Implicit feedback qualitative data

The MR/AR block manipulation task was designed in Unity (v2021.3) using the Microsoft Mixed Reality Toolkit (MRTK, v2.7) and run using the holographic remoting option in sync with the Holographic Remoting app on the Microsoft HoloLens 2. With this method, the virtual blocks were able to be manually placed in front of test subjects without having to calibrate or sync to world frames or anchors. The virtual blocks were designed to make use of the MRTK's Object Manipulator script to enable grasping with the participants' actual hands. Table 1 contains questions asked in the post-task questionnaire.

Weight sorting task

Participants performed the weight sorting task with a random order of conditions (Real, Virtual, Mixed). Sets of blocks of varying mass deltas (Table 2) within each condition were always sorted from largest mass delta to smallest mass delta (100g, then 50g, then 25g, then 15g). The order of blocks within each set was randomized by hand before each sorting trial.

Weight sorting simulation

The weight sorting sim was made in Matlab r2021a. This simulation was made in an attempt to emulate human sorting behavior assuming the probabilistic sampling model used in the calculation of the JND(%). To do this, we implemented a probabilistic version of the Quicksort algorithm. Quicksort is a widely utilized sorting algorithm that utilizes a divide-and-conquer strategy. It begins by selecting a pivot element from a given array and dividing the remaining elements into two subarrays: one for elements smaller than the pivot and the other for elements larger than the pivot. This partitioning process is repeated recursively for the subarrays until the entire array is sorted. The main steps of quicksort involve choosing a pivot, reorganizing the elements based on the pivot, and applying the process recursively to the subarrays. Quicksort is known for its efficiency and is commonly favored for sorting large datasets due to its average time complexity of $O(n \log n)$. Quicksort was chosen due to its efficiency (small number of total comparisons made), as we anecdotally observed that most participants naturally sorted each set of objects with a minimum number of comparisons between objects.

The modification to turn Quicksort into a probabilistic algorithm was simple: when comparing two elements of an array to establish ordinal ranking, the correct ranking was returned with a given probability, p , derived from sampling from a normal curve based on a provided JND(%). The incorrect ranking was then returned with frequency $1 - p$. The full algorithm is defined in Algorithm 1. The weight sorting sim was run for JND(%) values of 6.27% (lower CI) and 9.66% (upper CI), and for sets with mass deltas ranging from 120g to 1g to generate the bounding lines presented in Figure 13.

```

Require:  $\forall x, y \in S, (x \neq y) \rightarrow (x \cap y = \emptyset)$ 
1: function PROBABILISTICQUICKSORT( $x, jnd$ )
2:   if length( $x$ )  $\leq 1$  then
3:     return  $x$ 
4:   else
5:      $pivot \leftarrow x_1$ 
6:      $x_{lower}, x_{higher} \leftarrow \text{Compare}(x, pivot, jnd)$ 
7:      $x_{lower} \leftarrow \text{ProbabilisticQuickSort}(x_{lower}, jnd)$ 
8:      $x_{higher} \leftarrow \text{ProbabilisticQuickSort}(x_{higher}, jnd)$ 
9:      $y \leftarrow [x_{lower}, pivot, x_{higher}]$ 
10:    return  $y$ 
11:   end if
12: end function
13:
14: function COMPARE( $x, pivot, jnd$ )
15:    $x \leftarrow x \setminus pivot$ 
16:    $\mu \leftarrow 0$ 
17:    $\sigma \leftarrow \frac{jnd - \mu}{\text{InveCDF}(0.75)}$ 
18:    $x_{lower} \leftarrow \emptyset$ 
19:    $x_{higher} \leftarrow \emptyset$ 
20:   for  $el$  in  $x$  do
21:      $pct \leftarrow \frac{|el - pivot|}{\min(el, pivot)}$ 
22:      $r \leftarrow \text{random}(0, 1)$ 
23:     if  $r < \text{cdf}(pct, \mu, \sigma)$  then
24:       if  $el > pivot$  then
25:          $x_{higher} \leftarrow x_{higher} \cup el$ 
26:       else
27:          $x_{lower} \leftarrow x_{lower} \cup el$ 
28:       end if
29:     else
30:       if  $el > pivot$  then
31:          $x_{lower} \leftarrow x_{lower} \cup el$ 
32:       else
33:          $x_{higher} \leftarrow x_{higher} \cup el$ 
34:       end if
35:     end if
36:   end for
37:   return  $x_{lower}, x_{higher}$ 
38: end function

```

Algorithm 1. Probabilistic Quicksort Algorithm.

Weight equivalence

Weight equivalence between real and virtual blocks was conducted for real-virtual block pairs with masses of 400g, 500g, and 600g. These masses were chosen as they are representative of the spread of block masses encountered in the weight sorting task. Virtual blocks were displayed using the holographic remoting option within unity paired with the Holographic Remoting app on the Hololens 2. By using this option, the masses associated with the virtual objects could be increased or decreased in real time within the Unity editor.

Weight compensation

The same experimental design and statistical methods were used for Weight Compensation as the Weight Sorting task. The only difference was that a single condition was tested for in this experiment: sorting a mixed real-virtual set with mass compensation for the virtual blocks. The performance metrics for the new mixed condition were then compared to the pure virtual and mixed (no compensation) conditions using Bonferroni correction for multiple comparisons.

Data availability

All data collected that support the findings of this study are available in the following public GitHub repository: <https://github.com/VU-RASL/MinimalHapticFeedbackData>

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Author contributions

A.W, A.U, and N.S conceptualized and designed the research. A.W. and R.G designed and built the experimental hardware and conducted the experiment. A.W. and N.S analyzed the data. A.W. wrote the manuscript and prepared figures. All authors reviewed the manuscript.

Declarations

Competing interests

The authors declare no competing interests.

Additional information

Correspondence and requests for materials should be addressed to A.W. or N.S.

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