

SenseMatch: Smartphone-Based Cross-Modal Matching for Accessible Perceptual Assessments

A. Michael West Jr.

Dept. of Mechanical Engineering
Johns Hopkins University
Baltimore, MD, USA
awest36@jhu.edu

Anway S. Pimpalkar

Dept. of Biomedical Engineering
Johns Hopkins University
Baltimore, MD, USA
apimpall1@jhu.edu

Jing Xu

Dept. of Kinesiology
University of Georgia
Athens, GA, USA
jing.xu@uga.edu

Jeremy D. Brown

Dept. of Mechanical Engineering
Johns Hopkins University
Baltimore, MD, USA
jdelainebrown@jhu.edu

Abstract—To study the rehabilitation of sensorimotor deficits, researchers often rely on experiments with multimodal feedback. However, results from these studies can be biased if the sensory modalities involved are not perceptually balanced. Our previous work introduced an optimal cross-modal matching protocol to promote perceptual equity—the calibration of sensory cues so that no modality is inherently over- or underweighted. In this study, we present SenseMatch, a smartphone-based cross-modal matching app, and compare its ability to capture perceptual mappings to that of a clinical neurorehabilitation device in twelve healthy adults. We found that mappings obtained from SenseMatch did not generalize to the clinical device, underscoring the need for device-specific calibration. Nonetheless, comparing performance across devices offers valuable insights for future studies aimed at assessing sensory deficits. Moreover, SenseMatch provides a scalable and accessible platform for at-home perceptual assessments—enabling broader participation and laying the groundwork for objective biomarkers of sensory impairment.

Index Terms—Cross-Modal Matching, Perception, Haptic Feedback, Smartphone, Rehabilitation

I. INTRODUCTION

Stroke and other neurological injuries often impair hand dexterity, significantly reducing independence and quality of life for millions worldwide [1]. While rehabilitation research has traditionally focused on restoring motor function, it has often overlooked sensory deficits—particularly tactile and proprioceptive impairments—that are critical for skilled motor control [2]. To address this gap, multimodal rehabilitation devices have been developed to assess and improve sensorimotor function [3], [4]. These devices integrate multiple forms of sensory feedback (such as visual, haptic, and auditory cues) to support motor relearning and promote neural plasticity [2], [5], [6]. However, the effectiveness of such systems depends on achieving *perceptual equity*—ensuring that sensory cues across modalities are calibrated so that no modality is inherently over- or underweighted. Without perceptual equity, feedback comparisons may be biased, potentially obscuring which strategies truly aid recovery.

In our prior work [7], we demonstrated that cross-modal matching [8] is essential for achieving perceptual equity in multimodal neurorehabilitation. In the cross-modal matching

task, participants used the Hand Articulation and Neurotraining Device (HAND) [7], [9]—a multimodal rehabilitation tool designed to help patients improve sensorimotor deficits—and were asked to learn a prescribed linear relationship between two sensory modalities. However, due to individual differences in sensory perception, participants often internalize unique mappings, which are captured in a subsequent stimulus matching phase. Capturing and incorporating these individualized mappings into experimental protocols enables participant-specific perceptual equity. To reduce the time burden of this process, we introduced an optimized calibration protocol that shortened calibration by over 80%, making it more feasible for broader use. A key limitation, however, was the study’s reliance on a custom, non-commercial device (i.e., HAND [9]) that is not yet widely available to researchers and clinicians.

This raises an important question: does a perceptual map learned on a ubiquitous device such as a smartphone generalize to a different device that uses the same sensory stimuli? In other words, are perceptual mappings device-agnostic, or must they be recalibrated for each new platform? If they do transfer, then less expensive mobile devices (e.g., smartphones) could serve as a low-barrier tool for identifying sensory perception deficits outside the clinic. If not, each multimodal rehabilitation study will require device-specific calibration to preserve perceptual equity.

A second key question is whether participants form more accurate perceptual mappings on the consumer-grade smartphone or the clinical device. If performance is equivalent, cross-modal matching could be conducted at home using a smartphone app and applied in clinical settings. Superior performance on a smartphone would suggest that smartphone-based studies offer a viable, accessible platform for perceptual calibration. Conversely, if the clinical device yields better outcomes, clinic-based mapping may remain essential—though the process could still benefit from smartphone-guided training. Ultimately, comparing the devices can inform the design of future sensorimotor learning tools and protocols.

This paper introduces *SenseMatch*—a smartphone app for cross-modal matching to address two core research questions: (1) Are perceptual mappings device-agnostic? and (2) Is mapping performance better on a smartphone or clinical device? We begin by describing our methods for collecting and analyzing

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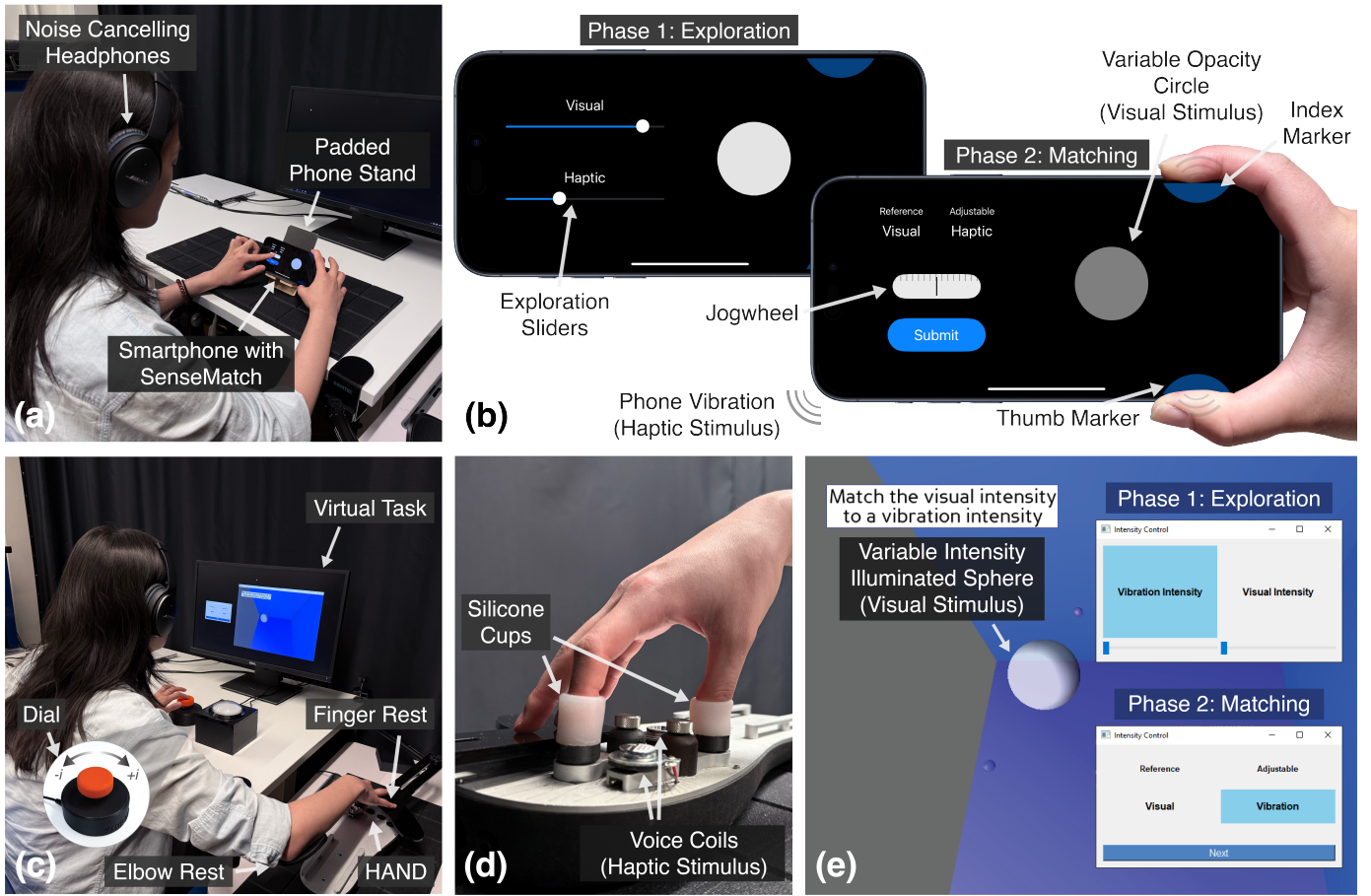


Fig. 1. Experimental setup and interfaces for cross-modal matching tasks using the SenseMatch smartphone app and the clinical HAND. (a) Participant using SenseMatch on a smartphone placed on a padded phone stand. (b) SenseMatch app interfaces, including Phase 1 (Exploration) sliders and Phase 2 (Matching) jogwheel; haptic feedback is delivered through finger placements at designated thumb and index markers. Note, font sizes and placement marker opacities have been increased in the figure for clarity. (c) Participant using the HAND during the virtual matching task. (d) Close-up of the HAND's silicone contact cups and embedded voice coil actuators used to deliver haptic feedback. (e) Virtual interface used with the HAND, showing the Phase 1 (Exploration) and Phase 2 (Matching) visual-haptic GUIs.

ing cross-modal matching data on SenseMatch and the clinical HAND. We then present results comparing task performance, mapping generalization, and subjective workload. Finally, we discuss implications for multimodal neurorehabilitation and the potential for smartphone-based perceptual diagnostics.

II. METHODS

A. Participants

Twelve neurologically intact individuals (6 male, 6 female; mean age 24.2 ± 3.2 years) participated in the study. All had no history of stroke or upper-limb impairments. Based on the Edinburgh Handedness Inventory [10], 11 were right-handed, and 1 left-handed. Participants interacted with two different devices and application platforms to perform intensity matching tasks across two sensory stimulus conditions. Each session lasted approximately 60 minutes. Participants were compensated \$10 per hour, and all procedures were approved by the Johns Hopkins School of Medicine Institutional Review Board (Protocol #IRB00209185).

B. Cross Modal Matching Protocol

As was done in our prior study [7], we implemented a two-phase cross-modal matching procedure. In the initial exploration phase, participants were given free control to explore the full range of both haptic and visual stimuli. They were instructed to attend to the perceptual relationship between the two modalities, with the goal of establishing an internal reference for subsequent matching. In the subsequent matching phase, participants were presented with a reference stimulus in one modality and asked to adjust the intensity of the other modality to “perceptually match” it, (i.e., adjust the second stimulus until it feels just as strong as the reference). Two conditions were tested: (1) *visual-to-haptic*, where participants matched a haptic stimulus to a visual reference stimulus, and (2) *haptic-to-visual*, where a visual stimulus was adjusted to match a haptic reference stimulus. Each condition consisted of two blocks of 32 trials, with 8 reference intensities randomly repeated within each block. Trial duration was capped at 90 seconds, though most responses were completed in substantially less time. The order of matching conditions was

counterbalanced across participants.

Moreover, the cross-modal matching procedure was conducted using two distinct hardware platforms to deliver visual and haptic stimuli: a smartphone running a custom-built app, *SenseMatch*, and the modified, clinically used *Hand Articulation and Neurotraining Device (HAND)* from our prior study [7], [9].

To assess subjective workload, the NASA Task Load Index (NASA-TLX), ranging from -5 to 5, was administered following each block (*visual-to-haptic* and *(haptic-to-visual)* for both (*SenseMatch* and *HAND*) [11]. Additionally, after completing both blocks on a given device, participants were asked to report any strategies they used during the tasks.

C. *SenseMatch*—A Smartphone Application

To administer the cross-modal matching task on a smartphone, we developed a custom iOS application—*SenseMatch*—using Swift (v5.10) and Xcode (v16.3) for an iPhone 15 Pro Max (Apple Inc., USA). Using their right thumb and index finger, the participants grasped the phone at a designated location to receive haptic stimuli, while their left hand operated the app’s graphical user interface (GUI) to complete the task as shown in Fig. 1a. The smartphone is placed on a padded stand atop a height-adjustable table. The table height is adjusted individually to ensure that each participant can interact with the smartphone in an ergonomically comfortable posture. Participants wore noise-cancelling headphones playing 60 Hz white noise to minimize auditory distractions and prevent potential confounds from ambient or device-related sounds.

In the smartphone app, visual feedback was rendered as a white circular overlay on a neutral black background, with stimulus intensity encoded by the circle’s opacity, ranging from 0 (fully transparent) to 1 (fully opaque), as shown in Fig. 1b, similar to previous studies with smartphone applications [12], [13]. Haptic feedback was delivered using the CoreHaptics framework (Apple Inc., USA), configured to produce a continuous vibration of fixed sharpness and variable intensity (0 to 1). During the initial exploration phase, participants used two sliders to explore the full range of visual and haptic intensities. In the subsequent matching phase, intensity was modulated via a custom jog wheel interface, allowing fine-grained control in steps of 1/255. The mapping from jog wheel displacement to stimulus intensity followed a linear scale across both modalities.

D. *Hand Articulation and Neurotraining Device*—HAND

The same modified Hand Articulation and Neurotraining Device (HAND) described in [7] was used in this study. Modified from the original HAND developed by [9], [14], the system features two silicone contact cups aligned with the thumb and index finger each embedded with a voice coil actuator (DAEX13CT-8, Dayton Audio, USA) to deliver vibrotactile feedback (Fig. 1c and 1d). These actuators are controlled via a custom MCU-based amplifier system. A synchronized virtual environment provides visual feedback via

a central sphere whose brightness varies with the set stimulus intensity. Intensity control was provided to the participants via a custom-built, limitless dial incorporating a 2-phase quadrature encoder (Taiss Electronics, China), as depicted in the inset of Fig. 1c. Unlike in the cross-modal matching experiment described in [7], this dial produced no tactile detents or clicks, preventing participants from using discrete mechanical cues for counting—mirroring the smooth, continuous jog wheel used in *SenseMatch*.

The participant’s arm was supported by an adjustable, extendable armrest to maintain a comfortable and stable posture throughout the experiment, as illustrated in Fig. 1c. A finger rest was provided for the three non-task fingers, mechanically isolated from the HAND to minimize the transmission of unintended vibrational cues. As in the *SenseMatch* protocol, participants wore noise-canceling headphones playing 60 Hz white noise to minimize potential auditory confounds.

E. Data Analysis

For each participant, we collected four datasets corresponding to the combinations of two devices: HAND and *SenseMatch*, and two reference modalities: haptic (i.e., haptic reference to visual matching) and visual (i.e., visual reference to haptic matching). Prior to analysis, matched intensities were normalized to a 0–1 scale to enforce a one-to-one relationship between modalities. Our analyses focused on two primary goals: (1) evaluating participant performance across devices and reference conditions, and (2) assessing whether perceptual mappings remained consistent across the two devices.

1) *Task Performance*: To assess task performance, we computed error as the absolute difference between the normalized matched intensity and the normalized reference intensity: $error = |matched - reference|$. Since the relationship between modalities was designed to be linear, normalization established a one-to-one mapping. Thus, if participants fully internalized this mapping during the exploration phase, their matched intensity would exactly equal the reference intensity.

For each participant, we calculated the average error across each combination of device and reference modality. This data was analyzed with a 2×2 ANOVA (Device $\times$ Reference Modality), with participant included as a random factor.

2) *Comparison of the Perceptual Mappings*: Although average error quantifies how well participants learned the prescribed intensity mapping, it does not tell us whether each participant’s underlying perceptual “scale” itself transfers from one device to another (e.g., from *SenseMatch* to HAND). In other words, if a participant’s mapping between visual and haptic intensity is learned on the smartphone, does that same mapping hold when they switch to the clinical device? To answer this, we next compare the perceptual mappings derived from each platform using an F-test.

Specifically, for each participant and each reference modality, we first fit a linear regression model to the *SenseMatch* data (x_{SM}, y_{SM}) using MATLAB’s `fitlm` function, where x and y denote the reference and matched intensities, respectively. This yielded model parameters: intercept β_0 and slope β_1 .

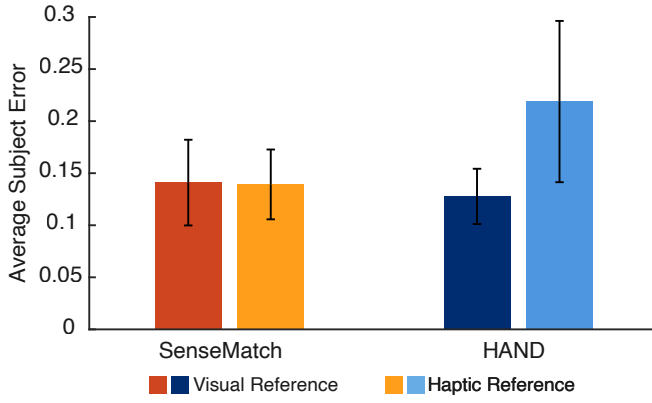


Fig. 2. Average subject error across reference modality (visual vs. haptic) and device (SenseMatch vs. HAND). Bars represent mean error; error bars indicate standard deviation across participants.

We then evaluated the fit of this SenseMatch-derived model on the HAND data ($x_{\text{HAND}}, y_{\text{HAND}}$) by computing the restricted sum of squared errors:

$$\text{SSE}_R = \sum_{i=1}^{n_{\text{HAND}}} \left(y_{\text{HAND},i} - (\beta_0 + \beta_1 x_{\text{HAND},i}) \right)^2.$$

Next, we fit an unrestricted linear model directly to the HAND data using `fitlm` to compute the corresponding unrestricted sum of squared errors SSE_U . We then evaluated the null hypothesis that the SenseMatch model adequately fits the HAND data using an F-test:

$$F = \frac{(\text{SSE}_R - \text{SSE}_U)/2}{\text{SSE}_U/(n_{\text{HAND}} - 2)},$$

where $n_{\text{HAND}} = 32$ trials. The resulting statistic was compared to an $F_{2,30}$ distribution, and the associated p -value was computed. A non-significant result ($p > 0.05$) was interpreted as failing to reject the null hypothesis—that is, the perceptual mapping obtained from the SenseMatch app sufficiently describes the data from the HAND.

3) *NASA TLX*: In addition to objective performance and mapping comparisons, we analyzed participants' subjective workload using the NASA-TLX. Perceived mental demand, physical demand, temporal demand, effort, frustration, and performance were each analyzed with a 2×2 ANOVA (Device $\times$ Reference Modality), with participant included as a random factor.

III. RESULTS

A. Task Performance

Fig. 2 displays the average error across participants as a function of device (SenseMatch vs. HAND) and reference modality (visual vs. haptic). Participants exhibited significantly greater error during the Haptic Reference condition on the HAND compared to SenseMatch. In contrast, during the Visual Reference condition, participants showed slightly lower error on the HAND compared to SenseMatch.

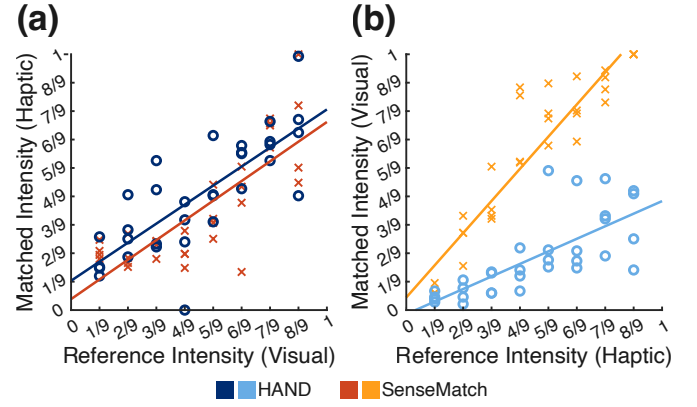


Fig. 3. Perceptual mappings for Participant #6 across devices and reference modalities. Solid lines show linear fits for the SenseMatch (red and orange, cross markers) and HAND (dark and light blue, circle markers) data. In the Visual Reference condition (a), the HAND fit is given by $y = 0.67x + 0.11$, $R^2 = 0.61$, $p = 1.2 \times 10^{-7}$; the SenseMatch fit is $y = 0.69x + 0.043$, $R^2 = 0.64$, $p = 4 \times 10^{-8}$. In the Haptic Reference condition (b), the HAND fit is $y = 0.44x + 0.016$, $R^2 = 0.55$, $p = 1.3 \times 10^{-6}$; the SenseMatch fit is $y = 1.1x + 0.049$, $R^2 = 0.87$, $p = 8 \times 10^{-15}$. Only in the Visual Reference condition did the SenseMatch-derived model statistically generalize to the HAND data.

A two-way ANOVA (Device $\times$ Reference Modality) revealed significant main effects of Device ($F_{1,44} = 5.55$, $p = 0.023$) and Reference Modality ($F_{1,44} = 10.06$, $p = 0.0028$), as well as a significant interaction between the two factors ($F_{1,44} = 10.86$, $p = 0.0019$). These results suggest that task performance was not only affected by the reference modality and device individually, but also by their combination.

B. Comparison of the Perceptual Mappings

Fig. 3 illustrates the perceptual mappings for a selected participant (Participant #6). As determined by the F-test, the regression model derived from the SenseMatch data statistically generalized to the HAND data in the Visual Reference condition, but not in the Haptic Reference condition. Note, we show Participant #6's mappings to illustrate a case where the SenseMatch data both did and did not generalize to the HAND data, providing a concrete example of each scenario.

Table I summarizes the F-test results across all participants. As shown, the SenseMatch-derived perceptual mapping significantly fit the HAND data for only a subset of cases—specifically, Participants #6 and #10 in the Visual Reference condition, and Participants #2 and #10 in the Haptic Reference condition. These findings suggest that perceptual mappings are not consistently transferable across devices, even within the same individual and for similar task structures.

C. NASA TLX

Fig. 4 displays the mean NASA-TLX ratings for participant perceived mental, physical, and temporal demand, effort, frustration, and performance across devices and reference modalities. A separate 2×2 ANOVA (Device $\times$ Reference Modality) was performed for each of these six workload dimensions. None of the analyses revealed a significant main effect of device or reference modality, nor a significant interaction.

TABLE I
F-TEST RESULTS COMPARING SENSEMATCH-DERIVED FITS TO HAND DATA. EACH COLUMN PAIR SHOWS THE $F_{2,30}$ STATISTIC AND CORRESPONDING p -VALUE (IN SCIENTIFIC NOTATION) FOR THE VISUAL AND HAPTIC REFERENCE CONDITIONS, RESPECTIVELY. VALUES BELOW 10^{-5} ARE DISPLAYED AS “ $< 10^{-5}$ ”. ENTRIES IN BOLD INDICATE $p > 0.05$ (I.E., THE SENSEMATCH MAP DESCRIBES THE HAND DATA).

Participant	Visual Reference		Haptic Reference	
	$F_{2,30}$	p	$F_{2,30}$	p
1	6.00	$< 10^{-5}$	32.30	$< 10^{-5}$
2	11.34	2.1e-04	0.52	6.0e-01
3	11.78	1.7e-04	11.40	$< 10^{-5}$
4	4.81	1.5e-02	47.35	$< 10^{-5}$
5	15.44	2.4e-05	150.2	$< 10^{-5}$
6	3.01	6.4e-02	284.2	$< 10^{-5}$
7	15.91	1.9e-05	195.6	$< 10^{-5}$
8	12.43	1.2e-04	63.86	$< 10^{-5}$
9	4.64	1.8e-02	285.9	$< 10^{-5}$
10	2.82	7.5e-02	1.65	2.1e-01
11	64.53	$< 10^{-5}$	9.94	4.9e-04
12	6.48	4.6e-03	36.30	$< 10^{-5}$

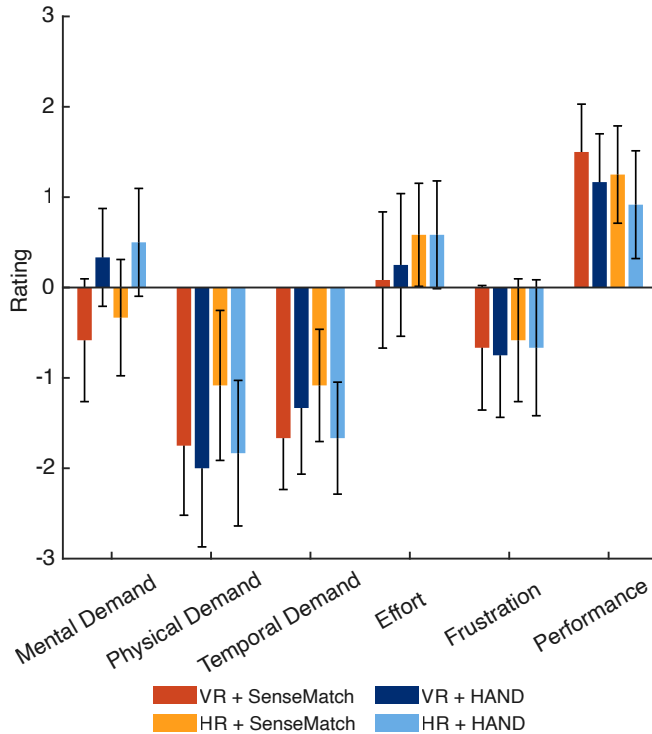


Fig. 4. Mean NASA-TLX ratings ($\pm 2SE$) for six workload dimensions under four conditions. Abbreviations VR and HR denote Visual Reference and Haptic Reference respectively.

IV. DISCUSSION

In prior work [7], we demonstrated that cross-modal matching can promote perceptual equity—the calibration of sensory cues across modalities such that no single modality is inherently over- or underweighted—in multimodal neurorehabilitation. In that paradigm, participants internalized a

prescribed linear relationship between two sensory modalities, first introduced during an exploration phase. However, because individuals differ in how they perceive sensory stimuli, they tend to learn distinct mappings, even when the underlying relationship is fixed. During the subsequent matching phase, we assess each participant’s internalized mapping by asking them to match stimulus intensities across modalities. Capturing these individualized mappings enables participant-specific calibrations to achieve perceptual equity in multimodal studies.

Here, we extended that work by implementing cross-modal matching on a more accessible platform: a custom-built iPhone application called SenseMatch. Using both SenseMatch and the previously developed HAND, we examined two core questions: (1) Do perceptual mappings learned on a smartphone generalize to a different device using the same sensory stimuli (i.e., does a smartphone-derived mapping transfer to a clinical device)? and (2) Are such mappings learned more effectively on the smartphone or the clinical device? Results suggest that perceptual mappings do not fully transfer across devices; device type significantly affected task performance, particularly under haptic reference conditions.

As shown in Table I, perceptual mappings derived from SenseMatch generally did not describe the data collected on the HAND. Although care was taken to ensure task consistency across platforms—participants maintained a pinch grip with the thumb and index finger and judged the brightness of a visual stimulus—the resulting mappings were consistently device-dependent. This likely reflects subtle but meaningful differences in how each platform delivers sensory stimuli. For example, the smartphone’s vibrotactile “buzz” may feel sharper or more salient than the HAND’s voice-coil feedback, which some participants reported as difficult to perceive at higher amplitudes. Similarly, the brightness of the on-screen circle on the phone may not match the luminance of the virtual sphere in the HAND environment. Together, these discrepancies likely alter the perceived intensity range, effectively imposing a different psychophysical “gain” on each platform. As a result, participants appear to internalize and reproduce distinct perceptual mappings depending on the device. To address these discrepancies, future work should first quantify and align the physical output scales of each device (e.g., brightness, vibration amplitude) prior to normalizing stimuli to a 0-to-1 range. This will help disentangle variation due to device mechanics from individual perceptual differences and inform the design of multimodal rehabilitation platforms that provide perceptually equivalent feedback. Nonetheless, these findings reinforce the importance of cross-modal matching in achieving perceptual equity. If researchers aim to compare results across different devices in multimodal studies, a shared baseline is essential. Pre-calibrating equipment using subject-specific perceptual maps can help establish this baseline and mitigate device-induced biases.

We found that participants generally performed better—i.e., with lower task error—when using SenseMatch compared to the HAND (Fig. 2). Error was also lower in the visual reference condition than in the haptic reference condition.

Notably, the largest discrepancies arose in the HAND's haptic reference condition, where task error increased substantially. Interestingly, in the visual reference condition, participants performed slightly better on HAND than on SenseMatch, suggesting that the observed device effect is driven primarily by degraded performance in the HAND's haptic reference condition. This may reflect differences in haptic salience; several participants noted that HAND's haptic feedback was difficult to perceive—especially at higher reference intensities. This was evident in performance data, where many subjects showed increased error at high amplitudes (e.g., Fig. 3b, light blue curve). In contrast, participants reported that SenseMatch's smartphone vibration felt more noticeable and distinguishable.

These trends were echoed, though not statistically significant, in the NASA TLX ratings (Fig. 4). Participants reported better perceived performance, lower mental demand, and less frustration with SenseMatch. Conversely, HAND was associated with lower physical demand, likely due to its ergonomic design. These observations have important implications for designing future multimodal rehabilitation devices. Specifically, they suggest that designers can leverage the perceptual salience of smartphone-based haptic rendering while also incorporating ergonomic features of the HAND to support comfortable, effective use across both home and clinical settings.

A. Impact and Future Work

Beyond the aforementioned applications, this work offers broader impacts and highlights promising future directions.

First, our findings highlight the value of careful device-specific calibration. Because perceptual mappings learned on a smartphone only sometimes transferred to the HAND, cross-modal matching remains a key step in multimodal rehabilitation protocols for maintaining perceptual equity. Fortunately, our prior work [7] introduced an optimized calibration procedure that can be seamlessly integrated into device-specific workflows to minimize patient burden.

Second, although SenseMatch-derived mappings did not generalize directly to the clinical HAND, SenseMatch remains a valuable clinical alternative. Building on recent work examining perception via mobile devices [12], [13], this important new research direction offers fertile ground for discovery. Moving perceptual calibration onto smartphones, can reduce—or even eliminate—the need for specialized lab visits, lowering costs and increasing accessibility for patients in remote or underserved areas. Because installing a smartphone app is far simpler than designing, shipping, and maintaining rehabilitation hardware, SenseMatch also enables multi-site studies of cross-modal matching. Labs and clinics worldwide could adopt the same calibration app, enabling large-scale trials of sensory-motor training without each site needing expensive equipment.

Perhaps the most impactful outcome of this work is the potential to quantify perceptual deficits using cross-modal matching error as an objective biomarker. This fine-grained metric may correlate more closely with sensory deficits than traditional clinical scales often designed to measure motor deficits (e.g., Fugl-Meyer Assessment).

To realize this, two key next steps are required. First, we must evaluate the test-retest reliability of individuals' perceptual mappings, determining whether they remain stable over time—or shift with experience, device changes, or other factors. A longitudinal study with neurologically intact individuals will help address this. Second, we must collect cross-modal matching data from stroke survivors, individuals with traumatic brain injury, or those with peripheral neuropathies. Comparing their error profiles to healthy controls will reveal how impairments distort perceptual mappings, helping establish a quantitative index of sensory deficits.

SenseMatch offers a practical foundation for pursuing these next steps. By democratizing perceptual calibration and transforming cross-modal matching into a robust, quantitative assessment tool, we move closer to a vision of personalized, data-driven neurorehabilitation accessible to all patients.

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