



Distinct but related abilities for visual and haptic object recognition

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Accepted: 29 January 2024
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Abstract

People vary in their ability to recognize objects visually. Individual differences for matching and recognizing objects visually is supported by a domain-general ability capturing common variance across different tasks (e.g., Richler et al., *Psychological Review*, 126, 226–251, 2019). Behavioral (e.g., Cooke et al., *Neuropsychologia*, 45, 484–495, 2007) and neural evidence (e.g., Amedi, *Cerebral Cortex*, 12, 1202–1212, 2002) suggest overlapping mechanisms in the processing of visual and haptic information in the service of object recognition, but it is unclear whether such group-average results generalize to individual differences. Psychometrically validated measures are required, which have been lacking in the haptic modality. We investigate whether object recognition ability is specific to vision or extends to haptics using psychometric measures we have developed. We use multiple visual and haptic tests with different objects and different formats to measure domain-general visual and haptic abilities and to test for relations across them. We measured object recognition abilities using two visual tests and four haptic tests (two each for two kinds of haptic exploration) in 97 participants. Partial correlation and confirmatory factor analyses converge to support the existence of a domain-general haptic object recognition ability that is moderately correlated with domain-general visual object recognition ability. Visual and haptic abilities share about 25% of their variance, supporting the existence of a multisensory domain-general ability while leaving a substantial amount of residual variance for modality-specific abilities. These results extend our understanding of the structure of object recognition abilities; while there are mechanisms that may generalize across categories, tasks, and modalities, there are still other mechanisms that are distinct between modalities.

Keywords Individual differences · Haptic perception · Visual perception · Object recognition · Latent variable modeling

The study of individual differences can uncover the functional organization of the systems that underlie behavior, facilitating the mapping of abilities onto the biological mechanisms that support them and the environmental influences that shape them. There has been a call to leverage individual differences in the study of visual perception and related functions (Goodhew & Edwards, 2019; Grzeczowski et al., 2017; Wilmer, 2008). Scientists study perception because it is important to human health, productivity, and quality of life. Recent progress has been spurred by the creation of tests designed to reliably measure high-level visual abilities in the normal population (Duchaine & Nakayama, 2006; McGugin et al., 2012; Richler et al., 2017). When many reliable tasks are available for a given construct, they can be used together

as indicators of this construct in latent variable modelling (Meyer et al., 2021; Russell et al., 1998; Tomarken & Waller, 2005). This approach reveals that individual differences for matching and recognizing objects visually is supported by a domain-general ability, called o (more specifically o_v when emphasizing that it is measured in the visual domain) capturing common variance across different tasks (e.g., Richler et al., 2019). A recent study highlighted a positive correlation between performance on a haptic object recognition test and o_v , suggesting a perceptual ability that spans across vision and touch (Chow et al., 2022a). Here, we move beyond a correlation between tasks to investigate the structure of the relationships between the latent constructs o_v and its haptic analog, o_h . To achieve this goal, we created a small battery of haptic object recognition tests.

Behavioral and neural studies largely suggest overlapping representations for visual and haptic recognition (e.g., Amedi, 2002; Gaissert et al., 2010; Sathian et al., 2011; Snow, Strother et al., 2014b). While both haptic and visual

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object recognition of novel objects are view dependent (Newell et al., 2001; Tarr et al., 1998), learning can lead to view independence and transfers across modality (Lacey et al., 2007, 2009). The similarity spaces derived from haptic and visual judgments are also highly similar and recruit the lateral occipital complex (Lee Masson et al., 2016). Such results have led to describing brain regions originally thought of as visual as supporting the neural representation of task-relevant properties like shape, texture, or orientation (Amedi et al., 2001; James et al., 2007; Reed et al., 2004; Sathian & Lacey, 2022). While the literature on haptic/visual cross-modal effects consistently points to robust overlap, the paucity of research on haptic abilities leaves us in the dark as to the degree of overlap between a putative haptic recognition ability, o_h , and the visual recognition ability, o_v .

The neural correlates of o_v are extensive across the ventral cortex, parietal, and premotor areas (McGugin et al., 2022). One study used categorization training in the visual modality followed by a categorization test in the haptic modality and related individual differences to microstructural characteristics of white matter pathways (Lee Masson et al., 2017). The microstructure of the left inferior longitudinal fasciculus (ILF), connecting occipital and temporal areas, predicted haptic categorization following visual training (another pathway connecting temporal to frontal regions also related to performance). Interestingly, the integrity of the ILF also correlates with performance in visual object recognition (Gomez et al., 2015). One possibility is that these extensive neural substrates spanning almost the entire brain support abilities that are almost entirely cross-modal in nature (although this may not be true in children; see Gori et al., 2008). It is also possible to conceive of modality-specific pathways that converge on multisensory representations (Lee Masson et al., 2016).

Latent variable, psychometric modeling of behavioral abilities can help uncover the functional structure of abilities—to ask whether they are entirely cross-modal, entirely unimodal, or hierarchically organized with both modality-specific and modality-independent sources of variance accounting for performance on object recognition tasks. Using this approach, we first seek proximal associations (correlations between tests that theoretically tap in the same ability), then construct latent variables for constructs like o_v and o_h . We then investigate the relationship between these constructs, seeking both remote associations (correlations between dissimilar tests suggesting common abilities) and proximal dissociations (lack of correlation between similar tests), which together help uncover the structure of abilities (Wilmer, 2008).

One recent example is the finding that o_v measured with unfamiliar objects is almost perfectly correlated with o_v measured with familiar objects (Sunday et al., 2022). This suggests that results obtained with novel objects will

generalize to familiar categories. Because haptic studies are more difficult and costly to conduct than visual studies, establishing that o_v and o_h are one and the same would support generalizing visual results to the haptic modality. In contrast, if o_v and o_h are substantially different abilities, this would motivate further work using both modalities. There are reasons to expect a strong relationship between o_v and o_h . On one hand, prior work at the group-average level reveals similar perceptual spaces for the two modalities (Gaissert et al., 2010), cross-modal transfer of learning and overlap in neural substrates (see Sathian & Lacey, 2022, for review). On the other hand, constructs that appear related in group-average studies can dissociate in analyses of individual differences for reasons that include heterogeneity in the population and the prominence of measurement errors and reliability issues in many cognitive measures (Hedge et al., 2017). Therefore, claims regarding abilities should be tested directly in approaches appropriate for individual differences.

To this end, we tested participants with a set of visual tasks to estimate o_v (as in Chang & Gauthier, 2021; Chow et al., 2022b; Sunday et al., 2018). Critically, we extended prior research on the measurement of haptic object recognition ability by creating two new haptic object recognition tests to be used in conjunction with those tests used in our prior work (Chow et al., 2022a), resulting in better construct coverage. We test for the existence of a domain-general haptic ability, o_h , and its relationship with o_v . To preview our results, we uncover a domain-general haptic object recognition ability that is moderately correlated with domain-general visual object recognition ability, leaving a substantial amount of residual variance for modality-specific factors.

Method

Participants

We used a Bayesian optional stopping rule to determine our final sample size: we initially collected data from 50 participants and continued to collect data until critical Bayes factors (details in the Bayesian correlation analysis section below) reached the threshold for substantial evidence, either 3 (evidence for the alternate model; Jeffreys, 1961) or 1/3 (evidence for the null model; Dienes, 2014). A total of 106 Vanderbilt University undergraduate students completed the study for course credit. Datasets for seven participants were removed due to experiment code error. Finally, to ensure that correlations were not inflated due to low motivation or failing to understand the procedures, we removed participants who had both below-chance performance and reaction times higher or lower than two standard deviations from the mean. This criterion excluded two participants. Our final sample size was 97 participants (mean age = 19.09 years, $SD = 1.84$

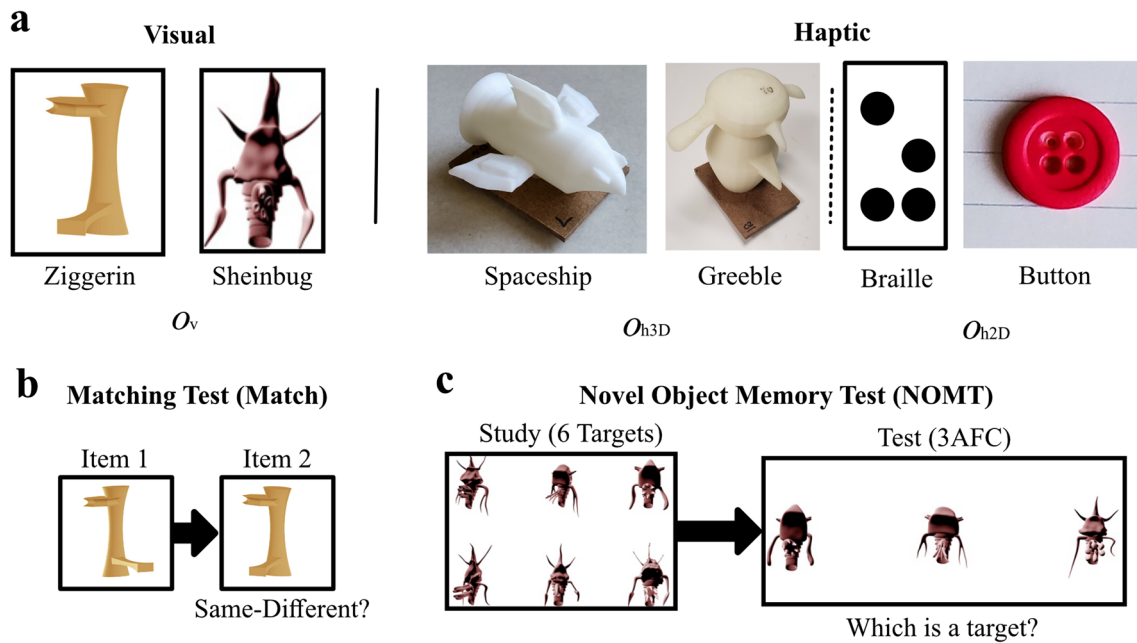


Fig. 1 Test formats and stimuli. **a** Examples of objects used in each test, broadly split between visual (O_v), haptic 3D (O_{h3D}), and haptic 2D (O_{h2D}). The Greeble stimuli and the Braille stimuli were used in new tests developed for this experiment. **b** Matching Test format where participants are tasked with determining whether two serially pre-

sented objects are the same. In this example, the correct example is “same” as it is the same object but rotated. **c** Novel Object Memory Test format where participants are tasked with remembering targets to select against foils later. In this example, the correct answer is the middle option, as it is the top middle studied target but rotated

years; 60 females, 36 males, one other). Eighty-eight participants were right-handed and the remaining nine participants were left-handed. No participants reported proficiency with Braille. All participants were naïve to the procedures and the novel objects used in the object recognition tests.

Procedures

Participants completed the study across two sessions. In the first session, participants completed a demographics survey, the visual Matching Test—Ziggerins (details below), and then the visual Novel Object Memory Test—Sheinbugs; this session was completed online on the participant’s personal computer and lasted approximately 30 minutes. In the second session, participants completed the Edinburgh Handedness Inventory (Oldfield, 1971), the haptic Matching Test—Braille, the haptic Novel Object Memory Test—Buttons, the haptic Matching Test—Spaceships, and then the haptic Novel Object Memory Test—Greebles; this session was completed in-lab and lasted approximately 2 hours. The order of the tests and trials was consistent across all participants to eliminate the contribution of order effects in our measurements, given that we were not interested in mean differences between tests (Goodhew & Edwards, 2019).

Object Recognition Ability Tests

Our individual differences tests were chosen to vary task demands and object categories across modalities (Fig. 1a). Most tests had been validated and reported in previous studies, but we also developed two new haptic tests, to increase construct coverage of haptic ability and allow us to define the latent factor o_h for the first time. One of the new tests used flat texture-like stimuli (referred to as haptic 2D) in a matching format and the other used three-dimensional stimuli (referred to as haptic 3D) in a memory format (details below). In contrast, the haptic object recognition tests in our previous work (Chow et al., 2022a) used either haptic 2D stimuli in a memory format or haptic 3D stimuli in a matching format. With these four tasks, we can better measure a haptic object recognition ability that could generalize across diagnostic features and task formats. The tests start with extremely easy trials and increase gradually in difficulty, to maintain motivation.

Haptic tests were performed exclusively using the participants’ dominant hand as determined by the Edinburgh Handedness Inventory (ambidextrous participants, scores of exactly 0, used their right hand). The haptic tests required an experimenter to place objects behind a curtain for participants to explore but all instructions and data collection was controlled using PsychToolbox (Kleiner et al., 2006) with

MATLAB 2018a (The MathWorks, Natick, MA). Compared with visual tests, the exposure duration and response time records in haptic procedures were imprecise due to the nature of reaching towards an unseen object and responding with the same hand. This was only a minor concern because our tests were designed to be accuracy-based and response times were not of interest. To best control exposure duration, participants initiated every stimuli presentation by holding the space bar and exposure durations began when they released the space bar. When the stimulus presentation ended, participants were prompted by the screen and a tone to immediately return to the space bar. If participants were slower than 1,000 ms to return to the space bar, they were prompted to perform the procedure faster. These procedures controlled exposure time to be relatively similar across participants.

Visual Matching Test—Ziggerins (vMatch-Ziggerins; Richler et al., 2019)

In the visual Matching Test, participants were tasked with deciding whether a pair of objects presented sequentially were the same or different, regardless of size or viewpoint (Fig. 1b). This test used Ziggerins stimuli (Wong et al., 2009), which are 3D-rendered objects consisting of a single vertical rod and two geometric protrusions at the top or bottom; the item identity was determined by the shape of the central rod and the protrusions. On each trial, a fixation cross was presented for 500 ms, followed by the presentation of the first Ziggerin (for 300 ms in the first half of the trials and for 150 ms in the latter half of the trials), followed by a visual mask of scrambled Ziggerin parts for 500 ms, and finally the second Ziggerin was presented alongside two on-screen buttons allowing participants to respond either same or different. The second Ziggerin and the response buttons remained on-screen for up to 3,000 ms or until a response had been made. Both Ziggerins and the mask were presented at approximately 2×2 degrees of visual angle. On trials with different object sizes, the second Ziggerin was presented at approximately 1.3×1.3 degrees of visual angle; on trials with different viewpoints, one of the two objects was rotated approximately 45 degrees along the vertical axis. These manipulations were interleaved throughout the test. Participants were given six practice trials, followed by 360 test trials, with breaks offered every 90 trials. No feedback was given during the test. The test was scored based on sensitivity (d') with chance level at 0.

Visual Novel Object Memory Test—Sheinbugs (vNOMT-Sheinbugs; Richler et al., 2017)

In the visual Novel Object Memory Test, participants were tasked with remembering six target objects to later select them against arrays of foils regardless of viewpoint or visual

noise (Fig. 1c). This test used Sheinbugs stimuli (Richler et al., 2017), which are 3D-rendered stimuli with a head, a front protrusion, and two arms; the item identity was defined by the unique combination of each component. This test began with a study phase where six Sheinbugs were presented simultaneously to study for as long as desired. This was followed by 24 test trials. On each test trial, an array of three Sheinbugs were presented where one Sheinbug was one of the six targets previously studied with two foils. All Sheinbugs were presented at approximately 2×2 degrees of visual angle. As with all our object recognition tests, these trials started extremely easy to ease participants into the task and provided discriminability for those with extremely low object recognition ability. Participants were instructed to click on the Sheinbug that they studied earlier. After these test trials, participants were told that they would now need to recognize the Sheinbugs even if they were rotated, then they were given an opportunity to study the Sheinbugs again, followed by another 24 test trials where all Sheinbugs were rotated approximately 45 degrees along the vertical axis. The latter half of each block of trials (Trials 13–24 and 37–48) had visual noise (standard Gaussian noise) overlaid at 50% opacity. No feedback was given during the test. The test was scored by percent correct with chance level at 33% accuracy.

Haptic Matching Test—Braille (hMatch-Braille)

In the new haptic Matching Test, participants were tasked with determining if a pair of serially presented objects were the same or different. This test used fingertip-sized Braille letter sticker stimuli (representing *a–z*; the dots were approximately 0.2 cm in diameter, each dot was at least 0.05 cm apart, one letter was maximally 0.6 cm \times 0.4 cm); the flat Braille stickers were attached to the center of index cards (12.7 cm \times 7.6 cm) presented to participants in a consistent manner. On each trial, the first Braille letter was presented to be explored for 4,000 ms, followed by the presentation of a second Braille letter. Participants had 8,000 ms to respond same or different by pressing keyboard buttons labeled *same* or *different*. The next trial began when a response was made or the response window ended. Participants started this test with a single practice trial with feedback until they completed it quickly and accurately; this was followed by 91 test trials. Not every letter was used equally.¹ No feedback

¹ As these tests are focused on reliably measuring individual differences, the stimulus manipulations across trials are not necessarily equated—some objects appear more than others. Instead, we use stimuli manipulations like viewpoint, size, and the stimuli themselves to increase construct coverage and vary difficulty. These tests were refined with pilot testing by replacing or removing less useful or problem trials to keep the tests as short as possible with good psychometric properties. In the final dataset, every participant took the same set of tests and trials, in the same order.

was given during the test trials. Participants did not explicitly study any of the stimuli outside of exposure during the same–different task. The test was scored based on sensitivity (d') with chance level at 0.

Haptic Novel Object Memory Test—Buttons (hNOMT-buttons; Chow et al., 2022a)

The haptic Novel Object Memory Test is based on the visual Novel Object Memory Test where participants were tasked with remembering six target objects to be recognized against two foils. This test used a collection of fingertip-sized clothing buttons (sized between 0.7 cm to 3.7 cm in diameter) mounted on index cards (12.7 cm × 8.6 cm).

This test began with a study phase where participants were introduced to the six target buttons. Participant began by studying a single target button for 8,000 ms. This was followed by three test trials where the target button and two distractor buttons were presented with at least 2.0-cm distance between the sides of each button. Participants had unlimited time to respond on the keyboard which object was the studied target; no feedback was given. These procedures repeated for each target button. After the six target buttons had been studied, participants reviewed each target button one at a time for 4,000 ms each in preparation for the upcoming test phase where any target may be presented on each trial. On each trial in the test phase, one of six target buttons could be the target. A total of 59 test trials were performed across the study phase and test phase. Before any buttons were studied, participants studied one practice object and performed three practice test trials for that practice object with feedback to familiarize them with the procedures. This test was scored with percentage correct with chance level at 33%.

Haptic Matching Test—Spaceships (hMatch-Spaceships; Chow et al., 2022a)

The haptic Matching Test with Spaceships is similar in format to the hMatch-Braille. The Spaceships stimuli are a set of 3D-printed spaceships (8.0 cm × 8.0 cm × 5.0 cm) with a consistent cylindrical body and three morphable diagnostic features: nosecone, wings, and rocket. Each Spaceship was mounted on the center of a wooden base (7.15 cm × 5.1 cm). The procedure for this test was the same as the

hMatch-Braille except that in 23 trials, a spaceship was presented rotated² 180 degrees from the usual nosecone pointing forward. This test had a total of 62 trials, scored based on sensitivity (d') with chance level at 0.

Haptic Novel Object Memory Test—Greebles (hNOMT-Greebles)

The new haptic Novel Object Memory Test with Greebles is similar in format to the hNOMT-buttons. The Greebles stimuli are a set of 3D-printed Greebles (James et al., 2005; 9.8 cm × 8.0 cm × 5.0 cm) with different body shapes and protrusions on the head and torso. Each Greeble was mounted on the center of a wooden base (7.15 cm × 5.1 cm). The procedure for this test is the same as the hNOMT-buttons except that the review time was 8,000 ms and in six trials, all Greebles were rotated 180 degrees from the usual forward-facing position. As this is a newly developed test, we refined the test by removing four trials that negatively correlated with participants' score on the entire test; all participants still performed the original set of trials, though our analyses only used the finalized trials. This resulted in 29 test trials in the final test, scored based on percent correct with chance level at 33%.

Statistical analysis

Statistical analysis was performed in R with a collection of packages, specifically *BayesFactor* and *BFpack* for Bayesian analyses, *psych* for reliability calculations, and *lavaan* for confirmatory factor analysis.

Measures and reliability

Reliability for our tests was calculated using Guttman's lambda 2 (Callender & Osburn, 1979). We formed aggregate measures for o_v , o_{h2D} , o_{h3D} , and o_h by z-scoring test scores and averaged the relevant test scores for each participant. Each test in an aggregate measure is weighted equally and as such, reliability is also calculated with equal weighting (Wang & Stanley, 1970).

Bayesian correlational analysis

Bayesian correlational analyses were performed using a default Jeffreys prior (Jeffreys, 1961). As we hypothesized that our correlations would be positive with effect sizes between $r = .2$ and $r = .4$, we used directional hypotheses with a scale factor of $r = 1/3$ for the prior. To index the relative likelihood between a positive correlation hypothesis (H_+) against a point null correlation (H_0), we report Bayes Factors (BF_{+0}). We used highest posterior densities as our 95% credible intervals to index uncertainty for our point estimates of correlation coefficients.

² Note that while many of our tests involve recognizing objects across viewpoint changes, this task is not the same as a mental rotation task, which requires judging whether similar objects have the same handedness or not. Our rotated trials target viewpoint invariance, which is a defining feature of object recognition (Peissig & Tarr, 2007; Gauthier & Tarr, 2016). Indeed, mental rotation and object recognition across viewpoint changes have been dissociated behaviorally (Cheung et al., 2009; Hayward et al., 2006) and they also rely on different neural substrates (Gauthier et al., 2002).

Table 1 Test descriptive statistics

Test	Mean	SD	Reliability
vMatch-Ziggerins (d')	1.08	0.51	.95
vNOMT-Sheinbugs (%)	48.30	12.48	.74
hMatch-Braille (d')	1.16	0.62	.80
hNOMT-buttons (%)	78.12	10.26	.80
hMatch-Spaceships (d')	1.44	0.64	.74
hNOMT-Greebles (%)	58.63	13.49	.62
o_v	0	0.84	.89
o_{h2D}	0	0.82	.85
o_{h3D}	0	0.76	.74
o_h	0	0.67	.86

Note. Individual measure reliability is indexed by λ_2 . Reliabilities of aggregate o constructs were calculated with equally weighted reliability. The mean of aggregate constructs is definitionally 0

Confirmatory factor analysis

We tested successively complex models based on the number of higher-order latent variables. To assist in convergence and stability of estimates, we parceled each test based on even and odd trials, resulting in a total of 12 indicators for factor analysis. The simplest model had every indicator loading onto a single latent factor, representing a single general object recognition ability across modalities. We first compared this with a nested model with the addition of correlated method variance between tests of the same type within modality. We adopted the rule where if this nested model resulted in better fits for the simplest model, we would continue to use correlated method variance in all models. We compared the single factor model with a two-factor model where the indicators loaded separately on two different correlated factors dependent on modality, representing distinct object recognition abilities for each modality. We finally defined the most complex model suitable for our dataset: a three-factor model where the haptic indicators were further split based on feature type and each of the three-factors were allowed to correlate.

Results

Descriptive statistics for each measure are reported in Table 1. Every test had the expected range of performance with acceptable reliability (Cook & Beckman, 2006). We assessed zero-order correlations between pairs of tests with objects of the same type (visual, haptic 3D, haptic 2D). As expected, we found (per common interpretation standards of a positive correlation; Jeffreys, 1961) a positive correlation between our visual tests, $r = .38$, 95% CI [.21, .54], $BF_{+0} = 1313.56$ (Fig. 2a). We also found a positive correlation

between the two haptic 3D tests, $r = .20$, 95% CI [.03, .37], $BF_{+0} = 3.46$ (Fig. 2b) and between the two haptic 2D tests, $r = .33$, 95% CI [.15, .50], $BF_{+0} = 199.58$ (Fig. 2c). To estimate the true effect sizes for each of these correlations, we calculated disattenuated correlations (r^*) that correct for measurement error (Nunnally, 1994): visual tests: $r^* = .45$; haptic 3D tests: $r^* = .30$; haptic 2D tests: $r^* = .42$. A complete set of zero-order correlations between tests is available in supplemental Table S1. As each pair of tests correlated well, we continued our analyses using only the aggregates of each pair of tests. Because each aggregate measure combines two tests that differ in test formats and in the specific categories they use, but share stimulus type (visual, haptic 3D, or haptic 2D), they are used to measure abilities related to stimulus type, generalizing across categories and tasks.

Our first goal was to characterize the relationship between haptic and visual higher-order object recognition abilities. We tested whether o_{h3D} and o_{h2D} are completely distinct constructs and how they relate to the visual ability, o_v . We previously reported that haptic object recognition performance across tests with different diagnostic features did not necessarily correlate with one another, and that only a haptic test with graspable objects correlated with o_v (Chow et al., 2022a). Contrary to these previous results, here we found a positive correlation between o_{h3D} and o_{h2D} , $r = .40$, 95% CI [.23, .56], $BF_{+0} = 3987.77$ (Fig. 2d). Further, we tested whether each haptic ability correlated with visual ability. We found a positive correlation between o_{h3D} and o_v , $r = .26$, 95% CI [.07, .43], $BF_{+0} = 18.52$, and between o_{h2D} and o_v , $r = .31$, 95% CI [.14, .49], $BF_{+0} = 95.36$. Again, to estimate the true effect sizes correcting for test reliability, we calculated disattenuated correlations for each pair of aggregate measures: o_{h3D} and o_{h2D} : $r^* = .52$; o_{h3D} and o_v : $r^* = .32$; o_{h2D} and o_v : $r^* = .36$. To follow up on the prediction based on earlier results that o_{h3D} may correlate with o_v better than o_{h2D} , we compared two competing hypotheses via Bayesian analysis, H_0 : the correlations were equivalent, against H_1 : the correlation between o_{h3D} and o_v was larger than o_{h2D} and o_v . We found that the correlations were equivalent, $BF_{10} = 0.09$. These results suggest that the relationship between visual and haptic abilities does not depend on the type of features used for object recognition and offer little support for separate haptic abilities dependent on the exploratory procedures or haptic features.

We asked if the correlation between our two haptic abilities was due to the shared variance with o_v . To test this possibility, we calculated the partial correlation between o_{h3D} and o_{h2D} while controlling for o_v . We still found a positive correlation despite controlling for o_v , $r = .35$, 95% CI [.17, .51], $BF_{+0} = 328.63$, $r^* = .43$. Compared to the zero-order correlation between the two haptic abilities ($r^* = .52$), the partial correlation (partial $r^* = .43$) demonstrated that o_v accounts for only for a portion of the correlation between

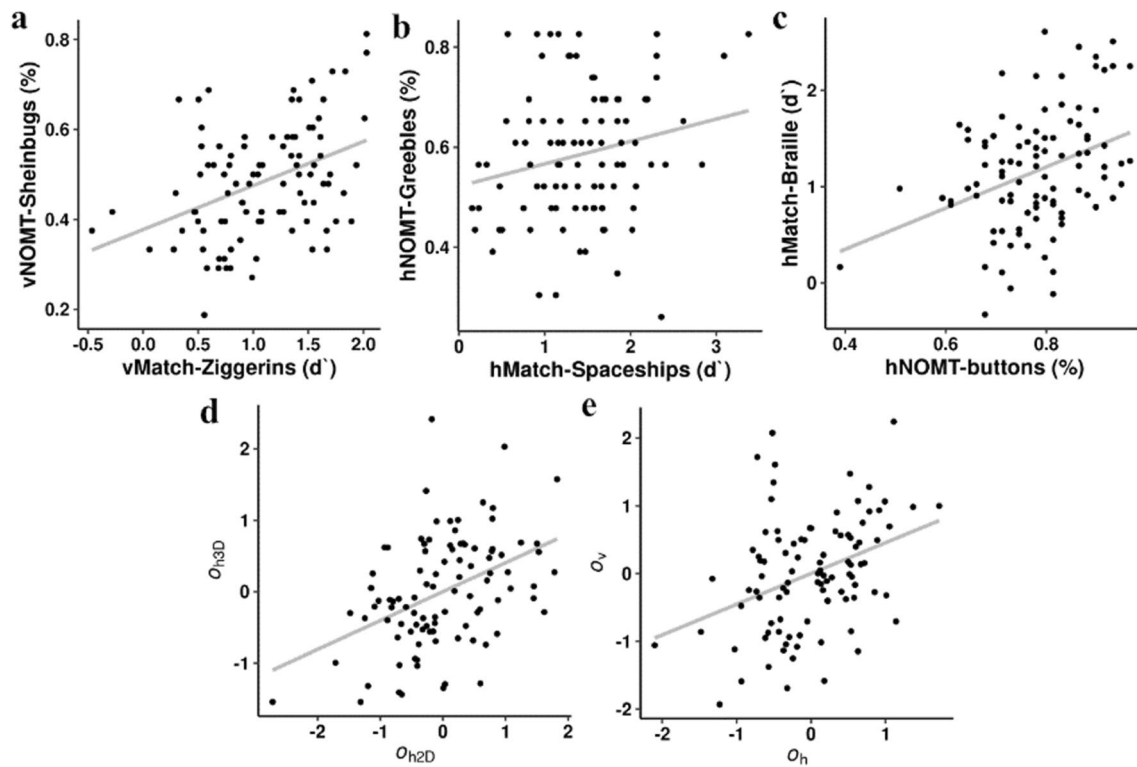


Fig. 2 Scatterplots for haptic measures with fit lines. **a** Visual tests. **b** Haptic tests using graspable objects. **c** Haptic tests using flat restricted objects. The correlation remains even with the low performing participant removed. **d** Haptic aggregate measures. The cor-

relation remains even with the low performing participant removed. **e** General haptic object recognition ability with general visual object recognition ability

the haptic abilities. This points to a distinct haptic object recognition ability, independent of a modality-general ability common to haptics and vision. Our estimation of o_h is the first available estimate of a general haptic object recognition ability using a variety of tasks and complex objects.

Given the robust correlation between the two haptic abilities and the evidence for equivalent correlations across modalities, we further aggregated all haptic tests into a single general haptic object recognition ability (o_h) and tested whether o_h correlates with o_v . We found a positive correlation, $r = .34$, 95% CI [.16, .50], $BF_{+0} = 283.35$, $r^* = .39$ (Fig. 2e). Interestingly, the correlation with o_v was similar in magnitude to that many times observed between pairs of visual tests in previous work (Chang & Gauthier, 2021; Chow et al., 2022b; McGugin et al., 2012; Sunday et al., 2018) suggesting they could tap a common, amodal source of variance.

Confirmatory factor analysis allowed us to compare possible structures for the entire dataset using higher-order latent factors corresponding to our constructs of interest while accounting for the total error structure in the data. To assess model fits, we used a chi-squared test (nonsignificant is good), root mean square error of approximation (RMSEA; lower is better), Akaike information criterion

(AIC; lower is better), and Bayesian information criterion (BIC; lower is better). A single factor model without correlated method variance fitted worse, $\chi^2(54) = 272.98$, $p < .001$; RMSEA = .20, AIC = 3122.65, BIC = 3108.66, than the same model with correlated method variance, $\chi^2(54) = 272.98$, $p < .001$, RMSEA = .20, AIC = 2929.17, BIC = 3108.66, therefore we applied correlated method variances to all models in the main analysis. When comparing the single factor model (representing a single higher-order latent variable o accounting for performance across all tests) to the two-factor model (two higher-order latent variants, o_v and o_h , for visual and haptic tests, respectively; Fig. 3) the single factor model fitted worse, $\chi^2(38) = 51.5$, $p = .11$; RMSEA = .05, AIC = 2929.17, BIC = 3027.00, than the two-factor model, $\chi^2(39) = 42.38$, $p = .33$; RMSEA = .03, AIC = 2922.04, BIC = 3022.46. Notably, in the two-factor model, the correlation between the latent o_h and o_v was $r = 0.53$, suggesting a moderate correlation between the two higher-order factors once task-specific measurement error and correlated method variance were accounted for. A three-factor model where the o_h latent factor was further split into two factors for o_{h2D} and o_{h3D} produced inadmissible solutions (negative variance) suggesting that the model could not be reasonably estimated with our data.

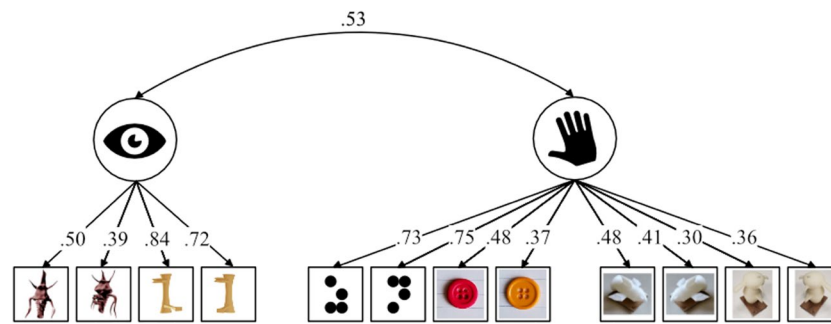


Fig. 3 Path diagram for the best fitting confirmatory factor analysis model. Standardized path coefficients are presented. Correlated method variance paths within modality as well as error terms are omitted for simplicity

Discussion

We found evidence for a domain-general ability for haptic object recognition, o_h . This is built on testing with several reliable haptic tests that differ in test format and stimulus type. These haptic tests required either hand-grasp exploration of shape (haptic 3D) or fingertip exploration of flat texture-like features (haptic 2D). The shared variance in the performance on these tests provided construct validity for our tests as indicators of a haptic ability that transcended the specifics of each haptic task. This hitherto unexplored source of variability in human perception offers new opportunity to explore the structure of abilities supporting object recognition.

Evidence for o_h makes it possible to ask whether this ability overlaps with o_v . We found approximately 25% variance shared between o_v and o_h , supporting contributions of both modality-specific and modality-general (cross-modal) mechanisms. While the CFA models we tested do not directly speak to the exact mechanisms at play, we can consider the make-up of tests underlying o_h and how they relate to the wider literature of experimental findings in visual and haptic perception.

Despite our efforts to increase construct coverage with a diverse set of tests with different task demands, there are still overlapping components that are strong candidates of mechanisms common across modalities. Most saliently, all tests contain shape information (even the Braille test can be seen as configurations). In prior work, we suggested that the buttons task may depend more on texture perception because of the way in which buttons were explored with fingertips (Chow et al., 2022a). But there is work suggesting that at least some individuals can integrate surface properties into haptic object representations (Lacey et al., 2011). Given we did not replicate a compelling distinction between o_{h2D} and o_{h3D} , it seems plausible that the processing of shape may underlie the common ability between o_h and o_v . Vision and haptics both support the acquisition of information about shape (Lederman & Klatzky, 1987; Reed et al., 1990).

Group-average work describes similar shape-based representation spaces across vision and haptics (Cooke et al., 2007; Gaissert et al., 2010). Modality-specific representations are found in some brain areas (e.g., in the occipital lobe for vision and parietal lobe for touch) but ventral occipitotemporal cortex contains a more multisensory shape representation (Lee Masson et al., 2016). Accordingly, we surmise that the shared variance we measure is explained by shape processing in multimodal brain areas.

However, our results also point towards modality-specific mechanisms and even in the realm of shape perception, there is evidence of mechanisms that could be unique to o_h . Encoding of haptic features is largely a serial process whereas (at least the initial) encoding of visual features is more parallel (e.g., Buetti et al., 2016). Studies have suggested differences between visual and haptic shape representations, including the fact that we can explore objects in 3D haptically, while vision reconstructs the 3D world from 2D inputs (e.g., Klatzky & Lederman, 2011; Norman et al., 2004). Some patients with damage in the ventral temporal cortex exhibit object recognition deficits in both vision and haptics (Feinberg et al., 1986; James et al., 2006; Ohtake et al., 2001), though cases of dissociations exist (e.g., Riddoch & Humphreys, 1987a, 1987b). Overall, our results are consistent with the proposal of a dual route of encoding of shape information through the visual or haptic mode, converging on cross-modal representations of shape (Lee Masson et al., 2016).

Aside from aspects of shape perception, familiarity is another factor that could distinguish performance in the visual and haptic tests (outside of just their modality). The modality-specific effects could point towards mechanisms that uniquely rely on familiarity in haptic but not vision. When measuring at the latent level using several categories, visual object recognition ability for familiar objects is virtually perfectly predicted by an analogous ability for novel objects (Sunday et al., 2022). When measurements are limited (in terms of tasks, categories, or sample size), this ability is best estimated with novel objects, avoiding the confounds of variability in experience (Richler et al.,

2017). But familiarity could matter in haptic object recognition in a different way. Haptic shape perception is modulated by object familiarity and visual imagery preference (e.g., Craddock & Lawson, 2008; Lacey et al., 2010). One model suggests that spatial imagery (supported in part by parietal areas) is more important to haptic perception of novel objects, while object imagery (via top-down influences from frontal areas) is more important for haptic perception of familiar objects (Lacey et al., 2014). Some of the stimuli we used could be considered familiar (buttons and Braille), while others are novel (Greebles and Spaceships). However, familiarity individuating the different buttons and Braille stimuli in our sample would be limited (familiar objects in haptic studies have so far meant one example for each one of different categories, such as a rubber duck, a spoon, a toy car). Therefore, we expect that object imagery likely played a minor role in our results. Future work could explicitly manipulate object familiarity as well as individual differences in the ability to use mental imagery for spatial relations vs. object information. It is possible that visual familiarity with objects explored haptically could further increase the overlap in latent visual and haptic abilities.

In addition, we caution that we only compared modalities best suited for shape perception. Consider comparing to a modality that cannot as robustly represent shape like the auditory modality (although see Arnott et al., 2013; Kim & Zatorre, 2011)—the cross-modal relationship may be different. Some neuroimaging work with haptic and auditory stimulation suggests cross-modal object representations in ventral temporal cortex (Kassuba et al., 2013). Visually impaired individuals using sensory substitution devices exhibit activation in visual areas when object information is extracted using sound (e.g., Amedi et al., 2007). Single-cell recordings in monkeys have revealed category-specific responses in the auditory cortex with visual stimuli (Hoffman, 2008). General object recognition ability measured in the auditory modality correlates nearly perfectly with o_v , suggesting robust overlap despite the auditory modality not well suited for shape representations (Chow et al., 2023). Therefore, the exact nature of the cross-modal representations supporting the shared variance between o_h and o_v will need to be assessed in the context of even broader multivariate testing such as including the measurement of auditory object recognition abilities.

Our results differ from the findings in our previous work with hMatch-Spaceships and hNOMT-buttons (Chow et al., 2022b), where these two haptic tests did not correlate ($r = .09$) and only hMatch-Spaceship correlated with o_v . While hMatch-Spaceships had similar average performance across studies (present work: mean $d' = 1.44$, $SD = 0.64$; Chow et al., 2022b: mean $d' = 1.43$, $SD = 0.57$), participants in the present work performed markedly worse on the

hNOMT-buttons than in Chow et al. (2022b) (present work: mean accuracy = 78.1%, $SD = 10.3\%$; Chow et al., 2022b: mean accuracy = 82.23%, $SD = 8.78\%$; see Fig. S1). This suggests that the difference in performance was unlikely due to a sample difference or to fatigue. In the present work, participants performed the hMatch-Braille before the hNOMT-buttons, which may have influenced strategy, making the hNOMT-buttons harder, but also tapping a more similar ability to our 3D haptic tests and to our o_v tests. This context effect is an example of why many studies, including ours, use fixed orders of tasks and trials to ensure order is not confounded with individual differences (Goodhew & Edwards, 2019). This unexpected result makes it difficult to compare results between studies, but it does not change our conclusions, because all participants in the present work experienced the same order. In addition, the other haptic test with 2D stimuli (hMatch-Braille) was performed first and is correlated with the 3D haptic tests. Even when removing hNOMT-buttons from our CFA models, our results remain largely the same (see the Supplementary Materials for details). In all, despite the discrepancy in the correlations presented here and those in our previous work with the same tests, our main conclusion is robust.

One limitation of this work is that we did not control for intelligence. However, our participant sample was composed of undergraduate students at a highly selective university, and therefore a restriction of range could limit the magnitude of correlations between general intelligence and o . In prior work with a similar sample, we found Bayesian evidence supporting the absence of a correlation between general intelligence and both the hMatch-Spaceships and the hNOMT-buttons (Chow et al., 2022a). Further, prior work with our visual tasks found that general intelligence did not account for the shared variance between them (Richler et al., 2017, 2019) nor did including general intelligence in a model reduce how well o_v predicted learning in a medical diagnostic task (Sunday et al., 2018). There is, however, some evidence from aging research that cross-modal haptic-visual performance can be related to a decline in cognitive abilities (Kalisch et al., 2012). Therefore, we recommend that future efforts in this area target more diverse populations and continue to assess the potential role of general cognitive skills in object recognition abilities across modalities.

Finally, one interesting possibility is that an even stronger correlation could exist between o_v and o_h if we had tested participants in visual tasks with physically present objects. There is strong evidence that when tested visually, a single o_v applies to the recognition of familiar and novel objects (Sunday et al., 2022). But the evidence for a cross-modal component may warrant another look at the role of familiarity, in particular for objects presented physically to participants. Real objects, at least real familiar objects, especially when they are graspable, elicit different neural responses

than images of the same objects (Fairchild et al., 2021; Snow et al., 2011). The neural representation of actions is also affected by whether grasping and reaching actions are directed towards real objects (Freud et al., 2018). Objects that are physically present are more memorable (Snow, Skiba et al., 2014a). Because many visual decisions involve images, it is reasonable and important to measure abilities with images. But when it comes to partitioning variance into modality-specific versus cross-modal contributions, results could depend on the physicality of stimuli. The saliency of different object parts may be influenced by affordances (Borghi, 2004) that are more important with physically present objects. However, the difference between physically present objects and images may not apply to novel unfamiliar objects. This is supported by the fact that the evocation of grasp representations, when tested with images of objects, depends on familiarity and knowledge (Chua et al., 2018). These considerations motivate and justify the effort required to meet the technical challenges associated with testing visual recognition ability with real objects.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.3758/s13423-024-02471-x>.

Acknowledgements The authors thank Mel Kacin, Giselle Fiestan, and Cameron Stockwell for help with data collection and recruitment.

Authors' contributions J.K.C., I.G., and T.J.P. conceptualized the experiment. J.K.C. designed and conducted the experiment. J.K.C. and I.G. wrote the initial draft. J.K.C., I.G., T.J.P. reviewed and edited the final manuscript.

Funding This work was supported by the David K. Wilson Chair Research Fund (Vanderbilt University)

Availability of data, materials, and code Reported data, experimental code, analysis code, and test materials for the visual object recognition tests are available in the osf.io repository (<https://doi.org/10.17605/OSF.IO/RXG6V>). This experiment was not preregistered.

Declarations

Conflicts of interest The authors declare no competing interest.

Ethics approval The experimental procedures were approved by the Vanderbilt Institutional Review Board.

Consent to participate Participants provided informed consent.

Consent for publication Participants provided consent for their research data to be published.

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