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Reliance on haptic assistance reflected in haptic cue weighting

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Abstract—When using an automated system, user trust in the automation is an important factor influencing performance. Prior studies have analyzed trust during supervisory control of automation, and how trust influences reliance: the behavioral correlate of trust. Here, we investigated how reliance on haptic assistance affects performance during shared control with an automated system. Subjects made reaches towards a hidden target using a visual cue and haptic cue (assistance from the automation). We sought to influence reliance by changing the variability of trial-by-trial random errors in the haptic assistance. Reliance was quantified in terms of the subject's position at the end of the reach relative to the two cues. Our results show that subjects aimed more towards the visual cue when the variability of the haptic cue errors increased, resembling cue weighting behavior. Similar behavior was observed both when subjects had explicit knowledge about the haptic cue error variability, as well as when they had only implicit knowledge (from experience). However, the group with explicit knowledge was able to more quickly adapt their reliance on the haptic assistance. The method we introduce here provides a quantitative way to study user reliance on the information provided by automated systems with shared control.

Index Terms—Trust, reliance, Haptic assistance, Haptic shared control, Cue weighting, Trial-by-trial variability

1 Introduction

Our willingness to rely on the information or actions provided by an automated system depends on how much we trust the automation [1]. Trust is a psychological construct of how one feels about the automation, which can influence one's reliance on the automation. In other words, reliance is a behavioral correlate of trust. Inappropriate reliance can cause misuse and disuse of the automation [2], [3].

Designing for properly calibrated trust and reliance [4] can be achieved by giving information about how the automation works and what its limitations are [2], [5], [6], [7]. More specifically, providing the user with information about automation reliability helps to foster appropriate user reliance and thereby improve human-automation interaction [8], [9], [10], [11].

Reliance on automation has been mainly studied in terms of supervisory control. When the user assumes a supervisory role, reliance on the automated system is often defined in terms of how often users decide to disable the automation and switch back to manual control. In contrast to supervisory control, where either the user or automated system is in control at a given time, shared control involves both the user and automated system concurrently sharing control [12]. One option for shared control is implemented in the form of haptic assistance, i.e., haptic shared control [13], [14], [15], [16], where assistive forces guide the operator towards what the automation considers the optimal control input. These forces are usually designed to be relatively low, such that the user can overrule the suggested control input from the automation. Thus, the user can vary the extent to which he follows the assistance on a continuous scale, in contrast to supervisory control, where the user can only choose between switching the automation on or off. Little is known about how reliance affects behavior during shared control. In the current study, we focus on user reliance on the information provided by an automated system, here via haptic assistance, and introduce a method to quantify reliance during shared control.

Under real world conditions, the haptic assistance generated by an automated system may be erroneous due to hardware failures, sensor inaccuracies, or model uncertainties. There have been a few studies that considered errors in the haptic assistance. These have, however, been limited to gross failures, such as faulty obstacle detection [17] or complete deactivation of the haptic feedback [18]. Another study introduced systematic inaccuracies in a peg-in-hole task and found that the benefits of haptic assistance were robust against small inaccuracies [19]. Accuracy of the haptic assistance, however, can also vary over time. We will refer to this as trial-by-trial random errors. The effect of such random errors on reliance on the assistance, and consequently task performance, is largely unknown.

Trial-by-trial random errors may cause the haptic assistance to be inaccurate on any given trial. However, in the case of zero-mean random errors, the haptic assistance will be accurate when averaged over many trials. The likelihood of the haptic assistance's accuracy on any given trial can be inferred from the variability of the previous trial-by-trial random errors. Recent studies suggest that humans can estimate the trial-by-trial variability of sensory cues [20], [21]. In [20], we investigated how people rely on haptic assistance (reliance on a haptic cue versus a visual cue) when the haptic assistance contained trial-by-trial random errors. Here, the trial-by-trial variability of the haptic assistance (i.e., haptic

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cue) was kept constant. Our results provided evidence that people estimated the variability of the trial-by-trial random errors and used this information to decide how much to rely on the haptic cue versus the visual cue.

Here, we investigate how reliance on haptic assistance is affected by *changes* in the haptic cue's trial-by-trial variability. In addition, we examine the time course of this adaptation in reliance and the effect of explicit knowledge of the variability change on the time course of reliance adaptation. In this study, subjects performed an arm movement towards a hidden target while visual and haptic cues (i.e., guidance forces) were provided. Both cues contained trial-by-trial variability, but only the variability of the haptic cue was systematically varied. Upon movement completion, the actual location of the target was shown. This indicated how accurate the haptic and visual cues were on each trial, thereby allowing subjects to make an estimate of the trial-by-trial variability over trials. We evaluated the effects of trial-by-trial variability on the amount of reliance on the haptic assistance in terms of how much the subjects chose to follow the haptic cue versus the visual cue. In other words, the less they rely on the haptic assistance, the closer the end-point of their movement would be to the location suggested by the visual cue. To investigate whether explicit knowledge of the trial-by-trial variability facilitated in adapting reliance on the haptic cue, we included two experimental groups: one group received explicit information about the current state of the variability of the trial-by-trial random errors, whereas the other group did not. We hypothesized that subjects with explicit knowledge would adjust their reliance on the haptic assistance earlier than the implicit group.

2 Materials and Methods

2.1 Subjects

Sixteen subjects (13 male, 12 right-handed, age 24 - 30) participated in the experiment and were randomly divided into two groups (Implicit, Explicit). The experiment was approved by the Delft University of Technology Human Research Ethics Committee and complied with the principles of the Declaration of Helsinki. All subjects gave informed consent prior to participating.

2.2 Experimental setup

To perform the target-hitting task, subjects made two degree-of-freedom reaching movements while holding an admittance-controlled haptic device (HapticMaster, Moog Inc.). Movement was confined to a horizontal plane via virtual hard constraints. The virtual inertia and damping of the device were set to 2.5 kg and 5 Ns/m, respectively. The device was controlled with a VxWorks RT operating system running at 2048 Hz. A second controller (real-time Bachmann GmbH) recorded the handle position (0.001 mm resolution) and force measured at the handle (0.01 N resolution) at 1000 Hz. The subject's hand position, along with other visual cues for the target-hitting task, were displayed on a monitor (refresh rate 60 Hz, resolution 1920 x 1080 pixels, size 88.5 x 50.0 cm) approximately 140 cm in front of the subject (Fig. 1a). Hand movement in the rightward direction caused the cursor to move right on the screen,

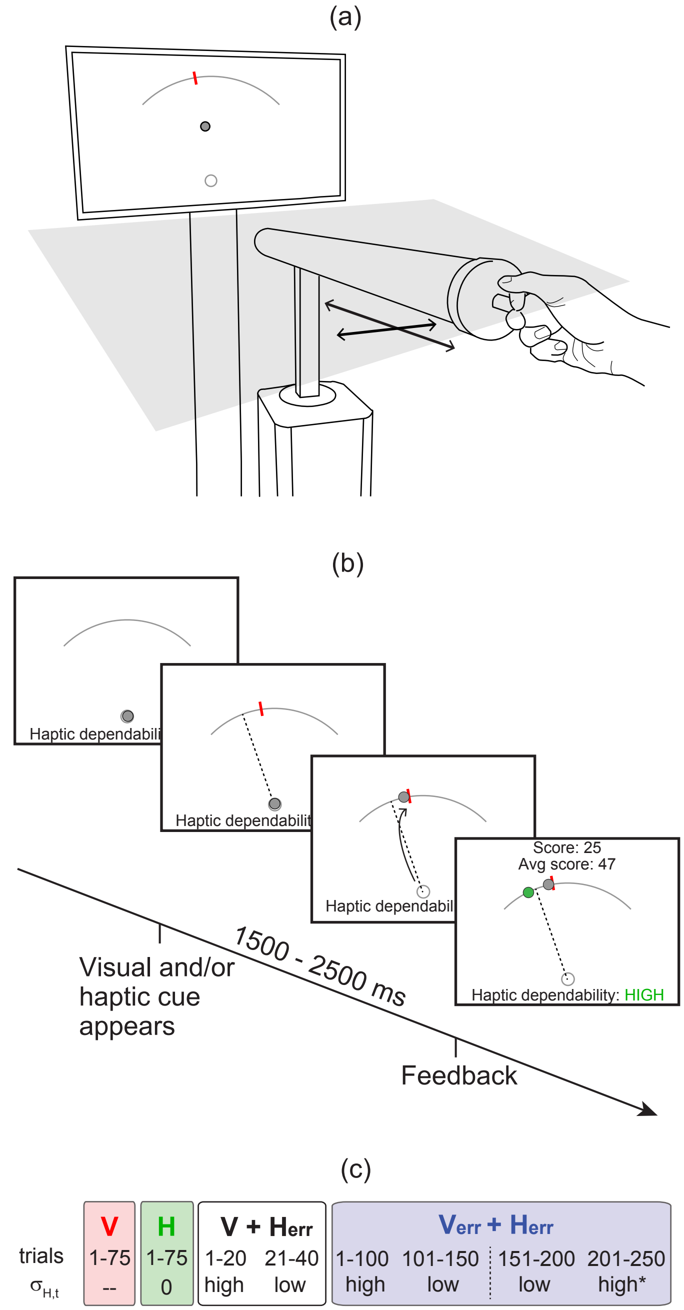

Fig. 1. Experimental setup and protocol. (a) Subjects made 2-DOF reaching movements with a haptic device and tried to hit targets, using visual (red dash) and haptic cues about the target location. The haptic device was not visible to the subject. (b) Order of events in a single trial. The visual cue was one red dash at the wall. The haptic cue was a force channel (direction indicated by dotted line) that guided movement along a straight path from the start position to the wall. Location of the hidden target (green circle) was revealed upon trial completion when the cursor reached the wall. The on-screen text about haptic dependability was only available for the Explicit group. (c) Subjects' target-hitting performance with a single cue was calculated from the V (visual) and H (haptic) blocks. In the $V + H_{err}$ blocks, subjects learned of the two possible distributions (high, low) of the haptic cue trial-by-trial variability. Subjects' performance in the combined cue conditions was measured from the $V_{err} + H_{err}$ blocks (two blocks indicated by dotted line), where both visual and haptic cues with random errors were available. The asterisk indicates that the haptic dependability was intentionally displayed incorrectly for the Explicit group.

and hand movement in the forward direction caused the cursor to move up (one-to-one mapping). The haptic device was hidden from view beneath a black cloth to encourage subjects to focus on the screen.

2.3 Visual and haptic cues

Target locations were chosen randomly and uniformly along the visible curved wall (100° span, 25 cm radius). Cues were presented via the visual and/or haptic sensory modalities to provide information about the target location. Here, we make the distinction between within-trial noise (perceptual uncertainty within a trial) and trial-by-trial variability (random errors over trials). Classical cue integration studies have mainly dealt with within-trial noise [22], [23], arising from naturally occurring noise (e.g., sensory noise), in addition to artificially modulated cue noise (e.g., visual blur). In our study, we focused on trial-by-trial variability, or random error over trials with zero-mean.

The visual cue was one red dash along the curved wall (Fig. 1a). The location of the visual cue was chosen randomly and independently from a normal distribution centred on the target location (arc length SD $\sigma_{V,t}$ = 1.6 cm), thus determining its error on a given trial. The spread of the distribution controlled the variability of the visual cue trial-by-trial random error. If a subject reached perfectly for the visual cue, the theoretical target error would likewise have a standard deviation of 1.6 cm over trials.

The haptic cue was a force channel that guided movement along a straight path, producing forces perpendicular to the channel direction. The force increased from 0 to 2 N within 0 to 0.5 cm, then more gradually from 2 to 5 N within 0.5 to 7 cm, and was a constant 5 N outside 7 cm. The force channel could otherwise be described by a piecewise linear stiffness function:

$$f = \begin{cases} k_1 x & |x| < \delta_1 \\ (k_1 - k_2)\delta_1 + k_2 x & \delta_1 \leq |x| < \delta_2 \\ (k_1 - k_2)\delta_1 + k_2 \delta_2 & |x| \geq \delta_2 \end{cases} \tag{1}$$

where k_1 and k_2 are 400 N/m and 46 N/m, and δ_1 and δ_2 are 0.5 cm and 7 cm, respectively. The forces were strong enough to be discernible, yet weak enough to be overridden if desired. As with the visual cue, the direction of the channel in a given trial was chosen randomly and independently from a normal distribution centred on the target location. There were two possible distributions for the haptic cue, resulting in either high (arc length SD $\sigma_{H,t}$ = 3.2 cm) or low (arc length SD $\sigma_{H,t}$ = 0.8 cm) variability of the trial-by-trial random error. If a subject perfectly followed the force channel, the theoretical target error would have a standard deviation of 3.2 cm and 0.8 cm in the high and low haptic variability conditions, respectively

The selection of $\sigma_{V,t}$ and $\sigma_{H,t}$ was informed by pilot studies and related published studies [20], [24], [25]. The standard deviations were chosen to be large enough such that the trial-by-trial variability was discernible and not masked by perceptual noise. At the same time, the standard deviations were chosen to be small enough such that it was feasible to override the haptic guidance (if desired) and still appeared as a reasonably useful cue for target location. With too large a standard deviation, people will fail to see the correlation between a cue and the target location, and cue weighting behavior breaks down.

2.4 Task

Subjects performed quick reaching movements to hit hidden targets, using the available visual and/or haptic cues to determine the target's location x_t. To begin a trial, subjects brought the cursor (5 mm diameter) to the start position (Fig. 1b). Once the cursor was in the start position for 0.8 s, the visual and/or haptic cue appeared. Subjects then made a reaching movement (25 cm) to try and hit the hidden target, located somewhere along the wall. The haptic device simulated a wall (stiffness = 400 N/m, damping = 20 Ns/m), so subjects did not need to actively bring their hand to rest. At the end of each trial, the true position of the target (9 mm diameter), the current trial score, and the average score over the current block of trials was displayed. The score was based on the arc length error between the cursor and target, with a maximum score of 100 (0 cm error) that linearly decreased to 0 (2 cm error or greater). When the arc length error was less than 0.6 cm, subjects heard a series of ascending beeps. For all trials, subjects had to complete the task within 1500-2500 ms, starting from when the visual cue appeared; thus, the time limit included both the reaction and movement time. If the trial was not completed within the time limit, or the hand speed dropped below a threshold of 0.015 m/s during movement, a warning message was displayed and a series of descending beeps would sound. For all other trials, the default sound indicating task completion was one monotone beep.

2.5 Experimental protocol

The experiment began with a visual block (V) that consisted of 75 trials (Fig. 1c). Only the visual cue was displayed and its location corresponded exactly with that of the hidden target (no error). During this block, subjects became familiar with the task and the visual cue. These trials also provided an estimate of the subjects' ability to hit the visual cue. As previously mentioned, the theoretical standard deviation of hitting the target using the visual cue is given by $\sigma_{V,t}$. However, this is corrupted by within-trial noise resulting from human motor noise $\sigma_{h,V}$, which was measured from these trials.

Next, subjects were told that they would also receive guidance forces (haptic cue) to help steer them in the direction of the target. During this haptic block (H) of 75 trials, only the haptic cue was present (no visual cue). Instead, the word 'go' appeared on the screen to signal when to begin movement. Subjects were instructed to follow the force channel as best as possible. This block was used to familiarize the subjects with the guidance forces, while also providing an estimate of the subjects' ability to follow the haptic cue. The theoretical standard deviation of hitting the target using the haptic cue is given by $\sigma_{H,t}$, assuming that the force channel is perfectly followed. This, too, is affected by additional within-trial noise from the human $\sigma_{h,H}$, comprising noise in force perception and motor noise.

Subjects then performed combined cue trials with both the visual and haptic cues available. Subjects first performed practice trials, where they were informed that the visual cue

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would be veridical, but the haptic cue may not always be correct ($V+H_{err}$). They were told that the error of the haptic cue could differ from trial-to-trial, and the spread of these errors was determined by one of two possible distributions (high or low variability). Subjects first performed 20 practice trials with high variability of the haptic cue error, then 20 practice trials with low variability. Here, subjects became familiar with using the forces to help them perform the task, in addition to overriding the forces when they noticed a difference between the direction of the haptic cue and the visual cue. During these blocks, both groups of subjects were told about the current state of the haptic cue variability. For the Explicit group, text at the bottom of the screen indicated the dependability of the haptic cue (e.g., 'Haptic dependability: HIGH'), where high dependability corresponded to low variability, and vice versa.

Lastly, subjects performed two blocks of trials with both the visual and haptic cues, where both cues contained random errors ($V_{err}+H_{err}$). Subjects were told about the additional errors of the visual cue: the visual cue error could vary from trial-to-trial, with the spread of errors determined by a single distribution. As with the $V+H_{err}$ trials, the variability of the haptic cue error could be either high or low. Subjects were told that the haptic cue variability would stay the same for a series of trials (e.g., tens or hundreds of consecutive trials), and may change once in a while. For the Explicit group, the on-screen text regarding haptic cue dependability would change accordingly, accompanied by a series of beeps to alert subjects of the change. Subjects were not told how the variability of the visual and haptic cue errors related to one another. The first $V_{err}+H_{err}$ block started with 100 trials of high haptic cue error variability (trials 1-100), followed by 50 trials of low haptic cue error variability (trials 101-150). The second $V_{err}+H_{err}$ block continued with 50 trials of low haptic cue error variability (trials 151-200), and ended with 50 trials of high haptic cue error variability (trials 201-250). For the Explicit group, the final change in haptic cue error variability was intentionally indicated incorrectly by the on-screen text; instead, it continued to display 'Haptic dependability: HIGH'. This represents a worst-case scenario in which the user is informed that the haptic cue is reliable, when in fact it is not.

2.6 Data analysis

All measurements were computed in terms of arc length along the wall. Trials that were not completed within the time limit, or wherein the hand speed dropped below the set threshold, were omitted from analysis. Of the 4000 total trials used for analysis, 222 trials (5.6%) were omitted from analysis because they were either not completed within the time limit or the hand speed dropped below the set threshold.

Reliance was assessed using data from the $V_{err}+H_{err}$ combined cue blocks, assuming that a greater reliance on a particular cue indicates more trust in that cue. The random generation of the cues results in a discrepancy between the visual and haptic cue location. To determine how strongly a subject relied on the visual cue, the distance between the subject's final position at the wall and the haptic cue was plotted versus the distance between the visual and haptic cues (Fig. 2a, similar to [24], [25]). For each subject, a multiple regression model was fit to the data:

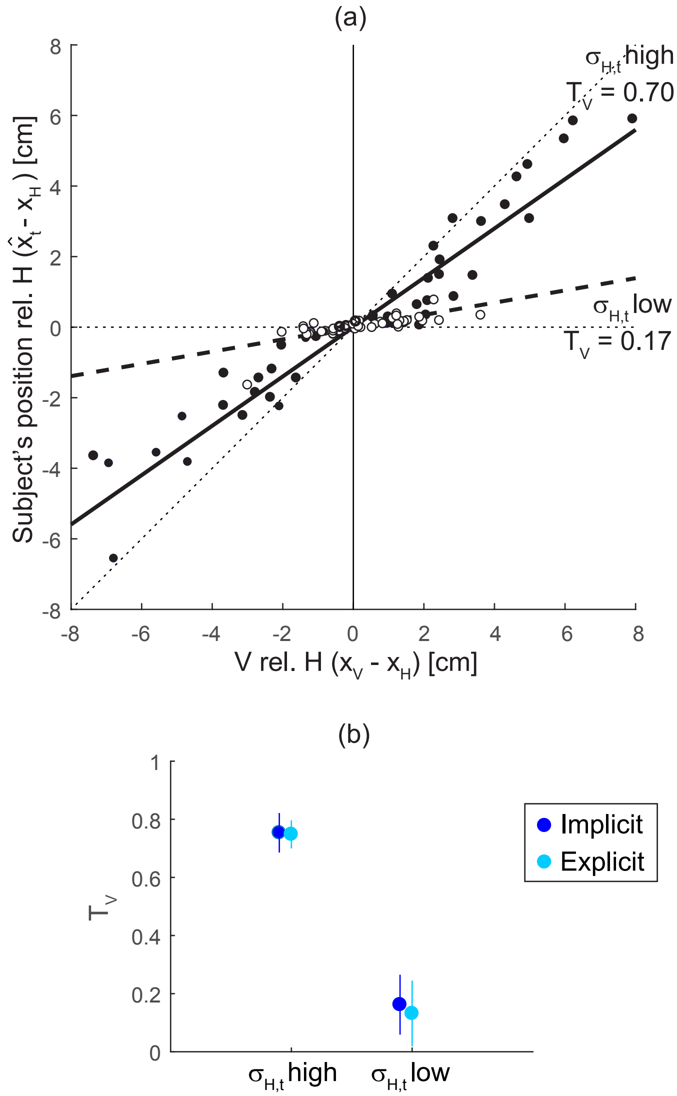

Fig. 2. Measure of reliance on the visual cue. (a) Representative subject data. Reliance on the visual cue T_V (regressed slope) calculated from trials 51-100 (closed circles, solid line) and 151-200 (open circles, dashed line) for the combined cue conditions with high and low haptic cue error variability, respectively. Steeper slope indicates higher reliance on the visual cue. The dotted diagonal line indicates reliance on only the visual cue, whereas the dotted horizontal line indicates reliance on only the haptic cue. Behavior suggests cue weighting rather than a probabilistic cue switching strategy. In the latter case, one would expect a percentage of the data points to lie on the dotted diagonal line, with the remaining data points on the horizontal line. Instead, the data points are clustered around a line that lies between the two dotted lines. (b) Group data. Reliance on the visual cue (mean ± standard deviation) for the two combined cue conditions for Implicit (dark blue) and Explicit (light blue) groups.

$$Y = a_0 + a_1 X + a_2 XD \tag{2}$$

$$Y = \hat{x}_t - x_H$$

$$X = x_V - x_H$$

$$D = \begin{cases} 0 & \text{high haptic cue error variability} \\ 1 & \text{low haptic cue error variability} \end{cases}$$

where $\hat{x}_t$ is the subject's final position, x_H is the haptic cue location, x_V is the visual cue location, and D is a categorical variable depending on the haptic cue error variability. A measure of reliance on the visual cue T_V is calculated from the regressed slopes, given by a_1 and $a_1 + a_2$ for the high and low haptic cue variability conditions, respectively. A slope close to 1 indicates that the subject relied heavily on the visual cue, whereas a slope near 0 signifies a greater reliance on the haptic cue. A significant interaction term a_2 indicates that the slope is significantly different between the two levels of haptic cue error variability. Note that this analysis assumes that the position reached at the end of movement reflects the subject's belief about where the target is located.

To see how reliance on the visual cue changed over time, T_V was calculated using a moving window of 25 consecutive trials. Differences between the two groups over time were detected by performing a two-sample t-test using Statistical Parametric Mapping (SPM) [26], [27], a procedure for correcting thresholds based on random field theory [28]. One might imagine running a separate t-test at each time point (n = 202) and correcting for multiple comparisons (e.g., Bonferroni correction), but this would lead to an overly conservative threshold. SPM offers a more realistic significance threshold by taking into consideration the regional correlation of smooth continuum changes in the data. The temporal smoothness of the data is first estimated using a scalar parameter, the FWHM (full-width-at-half-maximum of a Gaussian kernel). The smoothness value and time series length are used to compute a significance threshold corrected for multiple comparisons across time points, t*, keeping the family-wise error rate at 0.05. As such, 5% of random time series with equivalent smoothness under the null hypothesis (no difference between groups) would exceed this corrected threshold. This analysis was performed using Matlab functions from the open-source software package 'spm1d' [27] (www.spm1d.org).

Recalibration of reliance on haptic cues due to the change in their error variability is not expected to occur immediately: the trial-by-trial variability can only be assessed after experiencing many trials (unlike within-trial noise, which can be estimated within a single trial). Assuming that 50 trials after a change in haptic cue error variability is sufficient for recalibration, the steady-state T_V was calculated over trials 51-100 and trials 151-200 for the high and low haptic cue error variability, respectively. A two-way ANOVA was used for statistical analysis, with a between-subject factor of group (Implicit vs. Explicit) and a within-subject factor of condition (combined cue conditions with low vs. high haptic cue variability).

Task performance was evaluated using target error, defined as the subject's final position relative to the target position. From the $V_{err} + H_{err}$ combined cue blocks, the target error standard deviation σ_{V+H} was calculated over trials 51-100 and trials 151-200 for the high and low haptic cue error variability, respectively. For the single cue analysis, the target error standard deviation was calculated from the human uncertainty measured during the last 50 trials of the V and H single cue blocks ($\sigma_{h,V}, \sigma_{h,H}$) and the defined distributions used to generate the cues ($\sigma_{V,t}, \sigma_{H,t}$). Assuming that these factors are independent, the trial-by-trial variability in locating the target with the single visual or the single haptic cue is calculated by:

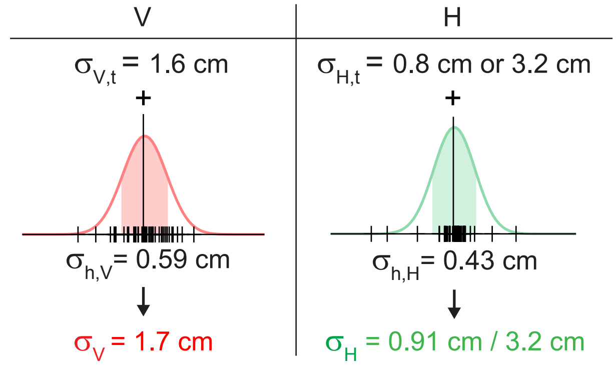

Fig. 3. Task performance with single cue determined by trial-by-trial target error variability. The standard deviation of the target error over trials using only the visual cue σ_V or haptic cue σ_H was calculated from Equations 3 and 4, respectively, which sums the variability resulting from human uncertainty measured from the respective V or H trials ($\sigma_{h,V}$ or $\sigma_{h,H}$) and the defined distribution used to generate the respective cue random error ($\sigma_{V,t}$ or $\sigma_{H,t}$, with low or high variability shown for the haptic cue). Data from a representative subject (black vertical lines) show the human uncertainty in following the visual or haptic cue (set at zero), with corresponding probability density function ($\pm$ 1 standard deviation in shaded region).

$$\sigma_V = \sqrt{\sigma_{h,V}^2 + \sigma_{V,t}^2} \tag{3}$$

$$\sigma_H = \sqrt{\sigma_{h,H}^2 + \sigma_{H,t}^2} \tag{4}$$

respectively (Fig. 3). In the visual V block, $\sigma_{h,V}$ was determined by calculating the standard deviation of the error of the subject's final position from the visual cue location. Likewise, in the haptic H block, $\sigma_{h,H}$ was determined by calculating the standard deviation of the error of the subject's final position from the center of the force channel. Two-way ANOVAs were used for statistical analysis, with a between-subject factor of group (Implicit vs. Explicit) and a within-subject factor of condition (combined cue vs. single cue).

2.7 Cue integration models

Classical cue integration studies define two models that can be used to describe how people rely on different cues: Maximum Likelihood (ML) estimation and Probabilistic Cue Switching (PCS). In the ML estimation framework, the two cues are weighted [22], [23], [29]. In other words, on a given trial, a person relies partially on the visual cue and partially on the haptic cue, ending up somewhere between the two cues. The amount of reliance on the haptic assistance can be quantified in terms of the relative weighting between the visual and haptic cues. In the PCS framework, a person completely relies on the visual cue during certain trials, then completely relies on the haptic cue during other trials [30], [31], [32]. The ratio of trials during which the user uses the haptic cue can then be interpreted as a measure for how much the user relies on the haptic assistance. Here, we investigate whether the subjects' observed behavior can be described by either the ML estimation or PCS model.

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2.7.1 Maximum Likelihood estimation model

An ML estimation model predicts optimal performance using a cue weighting strategy for the $V_{err}+H_{err}$ combined cue blocks. In cue integration studies, ML predictions are typically based on the within-trial noise of an estimate (variance of its likelihood function) [33]. Here, we use the variability in the target location estimate across trials, thus considering both within-trial noise and trial-by-trial variability. Thus, the ML model maximizes the percentage of correct target location estimates, or in other words, minimizes the target error variability over trials.

On a given trial, the ML estimate of target location $\hat{x}_t^*$ is the weighted sum of the estimates from the individual cues:

$$\hat{x}_t^* = w_V x_V + w_H x_H \tag{5}$$

with the weight inversely proportional to the target error variance with the respective individual cue estimate:

$$w_V^* = \frac{1/\sigma_V^2}{1/\sigma_V^2 + 1/\sigma_H^2} \tag{6}$$

$$w_H^* = \frac{1/\sigma_H^2}{1/\sigma_V^2 + 1/\sigma_H^2} \tag{7}$$

If a subject uses optimal cue weighting, the calculated T_V would be equal to w_V^*. The ML estimate also minimizes the target error variability over trials:

$$\sigma_{V+H}^* = \sqrt{\frac{1}{1/\sigma_V^2 + 1/\sigma_H^2}} \tag{8}$$

Thus, performance in the $V_{err}+H_{err}$ combined cue blocks with a cue weighting strategy can be predicted by the performance achievable with the single cues.

2.7.2 Probabilistic Cue Switching model

In the alternate PCS model, or cue veto model, the estimate is based on only one cue at a time rather than a combination of cues. The probability of selecting a cue estimate is proportional to its relative reliability, i.e., its weight from the ML model determines its probability of being chosen in the PCS model [32]. Upon averaging over trials, this strategy resembles a cue weighting strategy. In other words, the calculated T_V may also give a value close to w_V, although the cues are not weighted. The PCS strategy, however, will not result in improved performance relative to single cue performance, but rather an increase in the target error variability.

The PCS estimate for target error variability was computed by sampling 100,000 times from either a Gaussian distribution with σ_V (calculated from Eq. 3) with probability $p(V) = w_V$ (calculated from Eq. 6), or a Gaussian distribution with σ_H with probability $p(H) = w_H = 1 - w_V$. The standard deviation of the resulting samples σ_{V+H}^{PCS} predicts the performance in the $V_{err}+H_{err}$ combined cue blocks with a cue-switching strategy.

3 Results

Of the analyzed trials, the average reaction and movement time (mean $\pm$ standard deviation) was 297 $\pm$ 136 ms and 1592 $\pm$ 226 ms, respectively.

TABLE 1
Reliance on the visual cue T_V, correlation coefficient R, and p-value of interaction term a_2 from the multiple regression model (Eq. 2) fit to each subject's combined cue data.

		T_V			
	Subj	$\sigma_{H,t}$ low	$\sigma_{H,t}$ high	R	a_2 p-value
Implicit Group	1	0.17	0.70	0.95	5.5 * 10^{-12}
	2	0.18	0.67	0.90	7.1 * 10^{-7}
	3	0.30	0.78	0.96	1.2 * 10^{-11}
	4	0.26	0.71	0.88	1.2 * 10^{-4}
	5	0.19	0.80	0.94	6.6 * 10^{-10}
	6	0.11	0.68	0.93	1.2 * 10^{-10}
	7	0.04	0.80	0.95	8.7 * 10^{-15}
	8	0.002	0.78	0.91	5.8 * 10^{-10}
Explicit Group	9	0.12	0.73	0.92	4.8 * 10^{-10}
	10	0.23	0.68	0.92	1.5 * 10^{-6}
	11	0.15	0.59	0.88	3.1 * 10^{-5}
	12	0.08	0.71	0.92	1.8 * 10^{-9}
	13	0.34	0.69	0.91	4.4 * 10^{-4}
	14	0.07	0.67	0.91	9.1 * 10^{-9}
	15	0.02	0.64	0.88	2.4 * 10^{-7}
	16	0.02	0.69	0.91	3.3 * 10^{-10}

3.1 Cue reliance

The steady-state measure of reliance on the visual cue was determined for the combined cue conditions, when both the visual and haptic cues contained random errors ($V_{err}+H_{err}$). Figure 2a shows the measure of reliance on the visual cue for a representative subject, as determined by the regressed slopes (Eq. 2). Reliance on the visual cue was greater when the variability of the haptic cue error was high. This trend was observed across subjects (Fig. 2b), with all 16 subjects showing a significant difference in reliance between the two combined cue conditions (Table 1). A two-way ANOVA showed a within-subject effect of haptic cue error variability ($F(1,28) = 528.5, p < 0.001$). There was no significant between-subject effect of group ($F(1,28) = 0.3, p = 0.62$) and no significant interaction ($F(1,28) = 0.2, p = 0.64$). Thus, all subjects were able to recalibrate their reliance on the visual cue after sufficient exposure to the trial-by-trial cue errors (trials 51-100 and trials 151-200 for the high and low haptic cue error variability, respectively).

The maximum likelihood (ML) model was used to predict reliance on the visual cue, assuming a cue weighting strategy was used. For each subject, the optimal visual cue weight w_V was calculated based on the trial-by-trial variability in target error for the single cue conditions. In accordance with the T_V values calculated from the experimental results, the ML model predicts a decrease in weight (reliance) of the visual cue when the variability of the haptic cue error is low (0.23 $\pm$ 0.06) compared to when it is high (0.79 $\pm$ 0.01).

The time course of reliance on the visual cue over the $V_{err}+H_{err}$ trials is shown in Figure 4a, where T_V is calculated over 25 consecutive trials. The changes in reliance follow the changes in the ratio of cue error variability ($\sigma_{H,t}/\sigma_{V,t}$), i.e., as the haptic cue trial-by-trial error variability increases relative to that of the visual cue, reliance on the visual cue also increases. Note that the ratio of the cue error variability was also calculated over 25 consecutive trials, and thus deviates from the defined ratio of 2 ($\sigma_{H,t}$

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high = 2 * $\sigma_{V,t}$) and 0.5 ($\sigma_{H,t}$ low = 0.5 * $\sigma_{V,t}$).

The SPM two-sample t-test revealed a significant difference in reliance between the two groups when the haptic cue error variability changed from high to low (Fig. 4b). With the additional on-screen text about the increased haptic cue dependability, the Explicit group made an earlier transition to relying more on the haptic cue than the Implicit group. There was no significant difference in reliance recalibration when the haptic cue error variability changed from low to high. Note that for the Explicit group, this change occurred in spite of the incorrect on-screen text about haptic cue dependability.

3.2 Task performance

As a measure of steady-state performance, the trial-by-trial variability in hitting the target was compared between the combined cue and single cue conditions. The variability with only the visual or haptic cue was calculated from the defined distributions used to generate the cues ($\sigma_{V,t}$, $\sigma_{H,t}$) and the human uncertainty measured during the control experiments ($\sigma_{h,V}$, $\sigma_{h,H}$) (Fig. 3). The human uncertainty, i.e., the measured standard deviation in following the visual or haptic cue, across all subjects was 0.5 $\pm$ 0.1 cm and 0.4 $\pm$ 0.3 cm, respectively. The target error variability in the combined cue conditions was directly measured during the $V_{err} + H_{err}$ trials, then compared with the more reliable of the two individual cues.

The target error variability with both the visual cue and the haptic cue with high variability was higher than that of the visual cue alone (Fig. 5a), as shown by the significant within-subject effect in a two-way ANOVA ($F(1, 28) = 12.2, p = 0.004$). There was no significant between-subject effect of group ($F(1, 28) = 0.4, p = 0.55$) and no significant interaction ($F(1, 28) = 0.4, p = 0.54$). Alternatively, subjects were able to hit the target with reduced trial-by-trial variability when both the visual cue and the haptic cue with low variability were present, compared to the haptic cue alone (Fig. 5b). A two-way ANOVA confirmed a significant within-subject effect ($F(1, 28) = 5.7, p = 0.032$), while there was no significant between-subject effect of group ($F(1, 28) = 0.1, p = 0.83$) and no significant interaction ($F(1, 28) = 0.3, p = 0.62$).

The observed trial-by-trial target error variability was compared to the predictions of the maximum likelihood (ML) and probabilistic cue switching (PCS) models. Using the ML model, the trial-by-trial target error variability of the resulting cue combination is slightly lower than that of the more reliable single cue. For the combined cue condition with low haptic cue variability, subjects from both groups behave similar to the ML prediction (Fig. 4b). The probabilistic cue switching (PCS) model, on the other hand, predicts an increase in target error variability for the combined cue condition compared to the more reliable single cue. For the combined cue condition with high haptic cue variability, subjects' target-hitting performance is between that of the ML and PCS estimates (Fig. 4a).

4 Discussion

Our results show that subjects modulate reliance in haptic assistance depending on the trial-by-trial random error of the haptic cue. Subjects chose to deviate more from the haptic cue when its trial-by-trial random error was larger than that of the visual cue. Similar behavior was observed for both the Implicit and Explicit groups. This means that subjects were able to estimate the trial-by-trial variability and adjust the amount of reliance in the haptic assistance accordingly.

Analysis of the modulation of reliance over trials showed a small advantage for the Explicit group. Subjects in this group adjusted reliance on the haptic assistance significantly earlier than those in the Implicit group. This confirms our hypothesis that reliance would be adjusted earlier with explicit knowledge of the limitations of the assistance, and is in agreement with studies suggesting that providing this type of information can improve performance with automated systems [9], [11]. Although the Explicit group gained reliance on the haptic assistance more quickly than the Implicit group, both groups lost reliance on the haptic assistance at the same rate. Interestingly, although the Explicit group was told they could rely on the haptic assistance during this time, they quickly noticed the increase in trial-by-trial random errors and began to rely less on the haptic cue. Seven of the eight subjects in the Explicit group verbally expressed that they thought the on-screen text about haptic dependability was not correct. Even though one subject in the Explicit group failed to notice any discrepancy, all subjects exhibited significant reweighting (Table 1). Differences in the speed of gaining and losing reliance may be caused by differences in the learning speed of variability. It has been shown that the learning speed of variance is faster when the distribution changes from narrow to wide as compared to the opposite direction [25].

In terms of task performance, when the haptic random error had high variability, performance with both cues present was worse than when only the visual cue was present (Fig. 5a). However, when the haptic random error was low, performance with both cues was better than with either of the cues individually (Fig. 5b). This difference in performance between the two combined cue conditions might be due to the fact that subjects had to exert effort to override the haptic assistance. In the high variability case, the haptic assistance was more perturbing than in the low variability condition. Nonetheless, our results show that having the appropriate amount of reliance can improve performance, even if both cues contain trial-by-trial random errors.

Our results suggest that this performance was achieved by weighting of the visual and haptic cues, rather than cue switching, because the performance observed in the combined cue conditions was better than that predicted by the PCS model. Rather than choosing to follow one of the two cues on a given trial, subjects aimed somewhere in between the locations suggested by the two cues. Whether weighting of the cues was optimal, in the sense that variance was minimized, is unclear. Weighting appeared suboptimal when the haptic cue random error variability was high, but when the variability was low, performance was close to that of the ML estimate. In classical cue weighting studies, the ML estimate is generally assumed to be determined by the reliability of a cue, which is estimated within a single trial [33]. In our study, on the other hand, subjects had to learn

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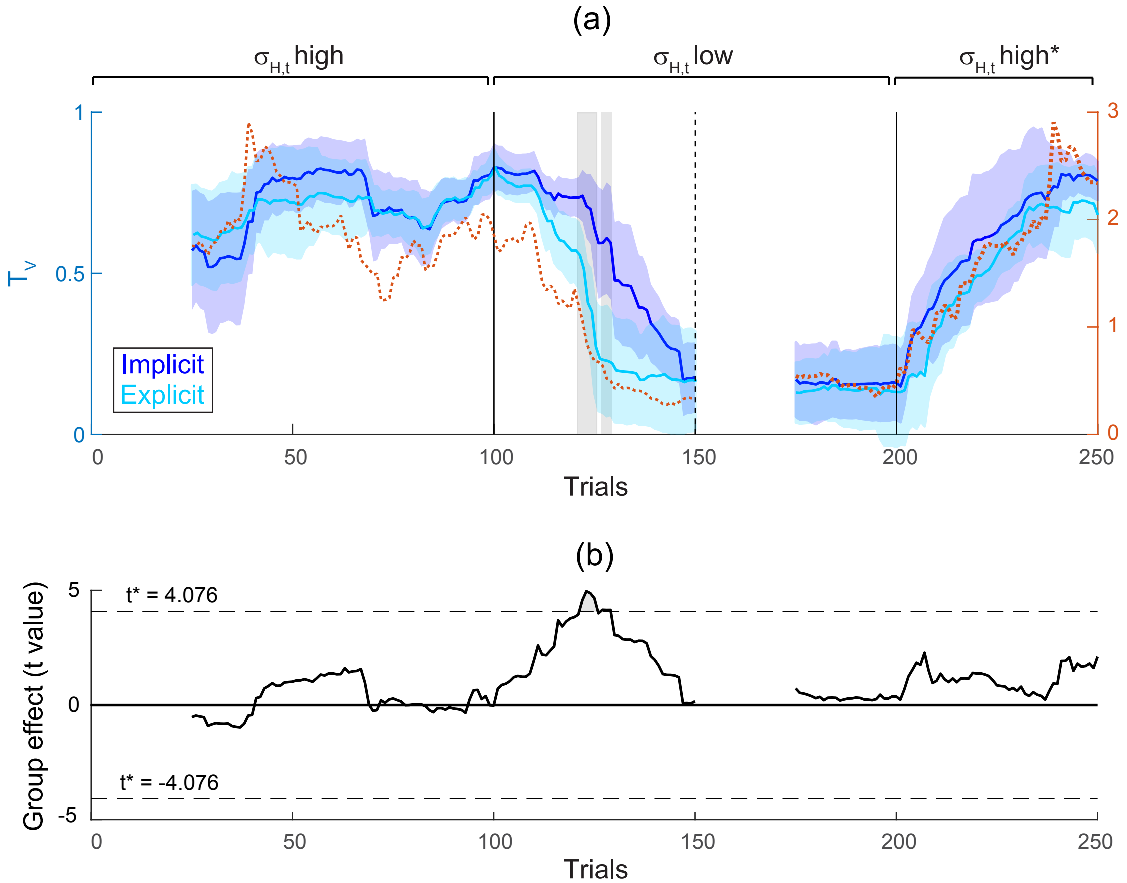

Fig. 4. (a) Over trials, the change in reliance on the visual cue (left y-axis) with the change in the ratio of cue error variability (right y-axis, dotted orange). Mean $\pm$ standard deviation across Implicit (dark blue) and Explicit (light blue) groups. Reliance and ratio of cue error variability calculated over previous 25 trials within each of the two $V_{err} + H_{err}$ blocks (separated by dashed line). Thus, within each of the two $V_{err} + H_{err}$ blocks, the first data point occurs after 25 trials (at 25 and 175, respectively). Additionally, the first data point calculated from only $\sigma_{H,t}$ low trials occurs at 126. Grey shaded region indicates a significance difference between groups, as determined by (b) the SPM two-sample t-test. Dashed horizontal line represents the corrected threshold beyond which t values are statistically significant.

the likelihood of either cue being correct on any given trial by estimating the variability of the trial-by-trial random errors over several trials. Therefore, the ML estimation model might not hold in this situation. On the other hand, previous studies have observed experience-dependent reweighting of cues [34], [35].

In the human perception and motor control studies where ML estimation is generally applied, subjects are mostly unaware of conflicts between the cues and the resulting weighting behavior. In our study, however, the conflicts were clearly noticeable and subjects were even told that the cues had variable accuracy. Nevertheless, previous studies have shown that cue weighting can be affected by subjects' awareness of the conflict, but weighting of the individual perceptual estimates can still occur [36], [37]. Note that previous studies that applied the ML framework assume weighting of the perceptual estimates derived from the individual cues, based on their relative uncertainty. In applying the ML framework to our study, we assumed that weighting was affected not only by the uncertainty of the perceptual estimates, but largely by the likelihood of these perceptual estimates corresponding to the hidden target position. Thus, it is likely that the cue weighting behavior resulting from reliance on the cues, as observed in this study, is a different weighting mechanism than that which is responsible for sensory reweighting in human perception and motor control.

Another interesting point of discussion involves the dynamics of the presentation of the haptic versus visual cue. While the cues appeared simultaneously, subjects could immediately extract information about the target location from the visual cue, whereas the haptic cue was only felt during movement with a magnitude dependent on the perpendicular distance within the force channel. In other words, haptic percepts are typically built up over time, unlike visual percepts [38]. Additionally, it has been shown that the way in which haptic exploration occurs can affect whether haptic and visual cues are even integrated [39]. When forming a percept of surface orientation, visual and haptic cues were only combined when the exploration method (parallel vs. serial) was the same. In our study, the additional cognitive component about cue correspondence may explain why both the visual and haptic cues were used to locate the hidden target [40].

In this study, we specifically addressed reliance on the *information* (e.g., haptic assistance) provided by an automated system. It is not clear how this relates to a user's trust in the automated system as a whole. Future studies

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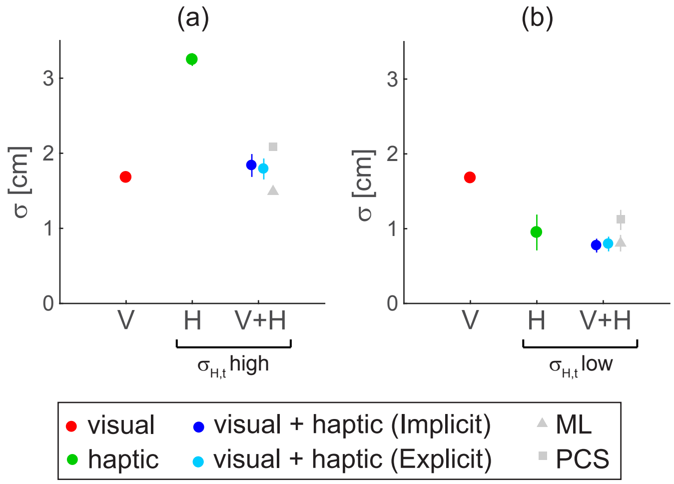

Fig. 5. Task performance. Trial-by-trial target error variability (standard deviation) for combined cue conditions (dark blue: Implicit group, light blue: Explicit group) and the two corresponding single cue conditions (red: visual, green: haptic). $V_{err} + H_{err}$ trials 51-100 and 151-200 were used for combined cue conditions with (a) high and (b) low haptic cue error variability, respectively. Predictions for target error variability in combined cue conditions made from single cue data using maximum likelihood estimation (ML, grey triangle) and probabilistic cue switching (PCS, grey square) for each subject (mean $\pm$ standard deviation). Data collapsed across all subjects for single cue conditions, ML, and PCS since there was no difference between groups.

can compare users' reliance on the information provided by an automated system (using the method proposed here) with their reported feelings of trust in the automated system (typically measured by questionnaires [41]).

5 Conclusion

We conclude that reliance on haptic assistance is adapted based on the variability of trial-by-trial random errors in the cues, resulting in cue weighting behavior rather than cue switching. This weighting behavior was observed in all subjects, regardless if they received explicit information about the current state of the variability of the trial-by-trial random errors. However, explicit knowledge about the haptic cue random error variability enabled subjects to adjust their reliance on the haptic assistance more quickly than subjects who did not receive such knowledge. The implications of this study are favorable for haptic assistance under practical conditions. Our results suggest that automated systems do not have to be perfect, as users can learn to deal with errors by dynamically modulating their reliance on the assistance.

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