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Sensory substitution can improve decision-making

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ABSTRACT

New technologies are often considered direct competitors to humans in the realm of decision-making. This paper explores a novel approach to augmenting human decision-making through technology. Specifically, drawing on the brain's unique ability to learn from sensory experiences, we introduce *sensory substitution*, the encoding of information in an alternative sensory modality, as a method to improve decision-making. In a within-subject design (N = 48), we show that translating numerical information into sensory experiences (i.e., tactile stimulation administered to a person's body) results in higher decision accuracy in a multiple-cue learning task. Response time analyses, participants' self-reports, and cognitive modeling all suggest that the benefits afforded by sensory substitution are the result of a shift from explicit rule abstraction to configural learning. That is, rather than deliberately inferring decision rules, participants develop intuitive, perceptual strategies to accurately predict outcomes. Together, our findings suggest that sensory substitution could enhance decision-making by training "gut instincts" rather than deliberate decision-making skills.

1. Introduction

People frequently make consequential decisions based on abstract, numerical information. For example, they might use several quantitative performance metrics when investing in stocks or making lending decisions. Past research has shown that human decision-making is oftentimes flawed when it comes to drawing inferences from numerical data (Dimara et al., 2021), in particular when the data contain nonlinear relationships and interactions (Ashby & Valentin, 2017; Juslin et al., 2008; Olsson et al., 2006). The present research investigates the use of *sensory substitution* as a method to improve decision-making based on quantitative data.

Sensory substitution refers to the encoding of information through a sensory modality that is typically not involved in the processing of such information (Bach-y-Rita, 2004; Bach-y-Rita et al., 1969). For instance, information captured by a camera can be transformed into a vibro-tactile sensation on a person's skin, allowing blind individuals to interact with visual stimuli in their environment (Bach-y-Rita et al., 1969; Maidenbaum et al., 2014). Similarly, auditory information can be transformed into a tactile stimulation through wearable vibro-tactile interfaces to support patients with hearing impairments (Novich & Eagleman, 2015). We propose that sensory substitution, in particular the transformation of numerical data into tactile information, can improve decision-making by shifting learning processes from explicit rule abstraction to configural learning (Juslin et al., 2008). Our work integrates the literatures on sensory substitution, decision-making, and human-computer interaction (HCI), testing novel theoretical predictions while laying the groundwork for practical applications in user interfaces and decision aides.

1.1. *Theoretical background: Sensory substitution and intuitive decision-making*

The term *sensory substitution* was first coined in the context of cross-modal encoding of sensory information. Specifically, the term refers to the transformation of a stimulus that is typically processed by one sensory modality into a set of signals that can be displayed as a stimulus to a different sensory modality (Bach-y-Rita et al., 1969; Visell, 2009). The most widely used approach is tactile sensory substitution, where information (typically visual or auditory) is transformed into tactile sensations that are displayed on a user's skin (e.g., Bach-y-Rita et al., 1969; Cancar et al., 2013; Guémann et al., 2022; Nagel et al., 2005). Tactile stimulation is well suited for sensory substitution for several reasons. First, many of the psychophysical mechanisms involved in the processing of tactile information are well understood (e.g., Kandel et al., 2021). Second, the hardware required to implement tactile stimulation is relatively cheap and can be adjusted to the receptive fields of even the most sensitive parts of the human body (Visell, 2009). Finally, the

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processing of tactile information can happen in parallel to the processing of information through other channels. While visual and auditory channels are prone to interference, the skin provides a lot of idle surface area that can be used to display information while visual or auditory attention is directed elsewhere (Novich & Eagleman, 2015; Tikuisis et al., 2001).

Past research has explored a wide range of applications for tactile sensory substitution including the treatment of sensory deficits (e.g., Bach-y-Rita et al., 1969; Bach-y-Rita & Kercel, 2003; Maidenbaum et al., 2014), navigation (Kerdegari et al., 2016; Neugebauer et al., 2020), the rehabilitation of motor function (e.g., Bach-y-Rita, 2004; Guémann et al., 2022; Lynch et al., 2022), and interface design for virtual environments (e.g., Visell, 2009). For example, it has been shown that visual information recorded by a camera can be transformed into a vibro-tactile representation that is projected on a person's skin, such that a visually impaired individual can learn to interact with their environment based on tactile cues (Bach-y-Rita et al., 1969; Maidenbaum et al., 2014). Similar results have been presented with regard to the vestibular system, where tactile information was used to inform head-body postural coordination in patients with bilateral vestibular damage (Bach-y-Rita, 2004). Other research has explored the potential of sensory substitution from auditory to tactile stimulation and pioneered the construction of wearable vibro-tactile interfaces (Novich & Eagleman, 2015; Perrotta et al., 2021).

The present research proposes a novel application of sensory substitution for decision-making. We suggest that the transformation of abstract numerical data into tactile stimuli can improve the quality of decision-making by shifting learning processes from explicit rule abstraction to configural learning (Juslin et al., 2008; Olsson et al., 2006). Explicit rule abstraction is commonly employed when individuals are presented with tabular numerical data and asked to make predictions about the data. The abstraction is based on analytical, rule-based thinking and deliberation, and has been shown to work well for additive, linear cue environments, but not when the cues involve nonlinear relationships (Juslin et al., 2008; Olsson et al., 2006). Configural learning, on the other hand, is an implicit, intuitive process that is better suited to learn holistic representations rather than individual cues (Enkvist et al., 2006; Olsson et al., 2006).

The distinction between explicit rule abstraction and configural learning is aligned with a vast field of research on dual processing systems that juxtaposes rational, deliberate, rule-based thought against implicit, automatic, experiential, intuitive processing (e.g., Dane & Pratt, 2007; Epstein, 2012; Hogarth, 2001; Kahneman, 2003; Sloman, 1996; Stanovich & West, 2000). While much of these works have pointed out the shortcomings of non-deliberative, intuitive thinking (producing approximate solutions that may deviate from rationality; e.g., Dhami, 2003; Gigerenzer & Goldstein, 1996; Kahneman, 2003; Simon, 1997; Simon et al., 1992), there is also a substantial body of research documenting its advantages. For example, human decisions are more accurate in nonlinear cue environments when relying on configural learning rather than rule abstraction (Juslin et al., 2008; Olsson et al., 2006) and people sometimes make better decisions in the absence of attentive deliberation (Dijksterhuis et al., 2006; Enkvist et al., 2006; Olsson et al., 2006). Similarly, it has been argued that high-level cognitive decisions can be sub-optimal, as evidenced by deviations from the predictions of expected utility theory, while performance is more aligned with expected utility theory in many perceptual or motor decision tasks, which are more reliant on implicit processes (Wu et al., 2009; for a counter argument see Jarvstad et al., 2013). Further, implicit processes may also be faster and more economical (Dane & Pratt, 2007; Gigerenzer & Goldstein, 1996; Simon, 1997). Finally, past work has shown that intuitive decision-making often leads to better outcomes in real world scenarios when the decider can rely on acquired expertise (Klein, 2015; Simon, 1992; Simon & Chase, 1973). Due to its reliance on pattern recognition, intuition has been characterized as holistic, thereby enabling the effortless integration of complex information (Dane & Pratt, 2007; Shapiro & Spence, 1997). This notion of intuition is closely related to the idea of configural learning, which emphasizes the importance of pattern recognition, exemplar memory, and implicit, intuitive processes (Juslin et al., 2003, 2008; Olsson et al., 2006).

Prior work suggests that configural learning and intuition play an important role in sensory substitution. For example, research shows that the sensory decoding in sensory substitution tasks can be learned intuitively and that familiarization with sensory substitution devices leads to a progressively automatic decoding of information. This progressively automatic decoding - a key characteristic of intuition (Adam & Dempsey, 2020; Hogarth, 2001) - is manifested in a lack of conscious attention or effort when completing sensory substitution tasks (Deroy & Auvray, 2012). Similarly, after sufficient familiarization with tactile sensory substitution devices, users have reported that they no longer perceive the proximal stimulation on their skin, but instead directly attribute it to a distant object (Bach-y-Rita et al., 1969; Bach-y-Rita & Kercel, 2003; Deroy & Auvray, 2012; Lenay et al., 2003). This shift to distal attribution has, in turn, been linked to implicit perceptual strategies as opposed to explicit cognitive strategies (Siegle & Warren, 2013).

Taken together, these examples suggest that sensory substitution taps into implicit, intuitive, learning processes similar to those underlying configural learning. Consequently, by enabling people to experience abstract information more directly (i.e., through their bodies), sensory substitution may encourage configural learning and facilitate intuitive, perceptual decision-making. This shift to configural learning might lead to improved performance when decision-makers are required to integrate complex (and interactive) information from multiple sources.

1.2. *Current research*

Integrating the literature on sensory substitution and configural learning, we argue that sensory substitution can enable people to experience abstract information more holistically, thereby encouraging configural learning and intuitive decision-making. Specifically, employing a multiple-cue learning task (Enkvist et al., 2006; Juslin et al., 2008; Olsson et al., 2006), we investigate two complementary research questions pertaining to the effect of sensory substitution on decision-making and its underlying mechanism:

Research Question 1: Can sensory substitution improve decision-making? We hypothesize that displaying data in the form of tactile information (i.e., sensory substitution), rather than in numerical form, will result in higher decision-making accuracy.

Research Question 2: Which underlying mechanism explains the effect? We hypothesize that the benefit of sensory substitution is the result of a shift from (deliberate) explicit rule abstraction to (intuitive) configural learning.

The current research aims to make three main contributions. First, it adds to the literature on sensory substitution by studying the concept in a novel context: decision-making. Second, it tests a novel theoretical prediction derived from the decision-making literature, namely the idea that configural learning may be responsible for improved decision-making performance associated with sensory substitution. Third, it provides a starting point for a novel research program at the intersection of cognitive science and human-computer interaction (HCI) that could lead to a wide range of theoretical contributions and practical applications.

2. Method

2.1. *Participants*

We collected data from 48 participants (22.04 $\pm$ 2.71 years old, 66.66% female). The targeted sample size was based on pilot data suggesting large effects of the treatment conditions. All participants were students at Columbia University, recruited through the university's

Behavioral Research Lab. Data collection was covered under the IRB at Columbia University (protocol number: AAAS9184-M00Y01). All experiments were performed in accordance with relevant guidelines and regulations, and informed consent was obtained from all participants before data collection.

2.2. Experimental design

The study employed a one-factorial within-person design with three randomly ordered counterbalanced conditions. Participants were presented with a multiple-cue prediction task (Enkvist et al., 2006; Juslin et al., 2008; Olsson et al., 2006), in which they repeatedly had to make binary decisions. In the three conditions, participants' decisions were based on: 1) abstract numerical information (three integer numbers predictive of a single binary outcome), 2) abstract visual exemplars (shapes that represent those same three integers), or 3) sensory substitution (vibrations administered through a vibro-tactile interface representing those same three integers). In each condition, participants were asked to make a prediction regarding the value of the unknown outcome variable by pressing either the left or the right arrow key on a computer keyboard. After the answer was recorded, participants received feedback on whether their decision was correct or not. Each condition involved 100 trials during which the participant had to infer the underlying relationships between the predictors and the outcome. The data were constructed such that the task could be solved perfectly if participants had full knowledge of the data generating process (i.e., the two outcome classes were fully separable using a configural strategy). In practice, since participants had to learn the underlying rules gradually, performance was expected to be much lower. Specifically, the dataset was generated using the Scikit-Learn (Pedregosa et al., 2011) "make_classification" method, which is a standardized procedure to generate random n-class classification problems, based on an algorithm adapted from Guyon (2003). We chose to generate 6 fully separable gaussian clusters across the three feature dimensions, half of which were randomly mapped to each of the two classes of the target variable. This resulted in a classification task that is moderately difficult to solve for human learners but can be solved perfectly by a statistical classifier that is able to represent a sufficiently complex decision boundary. The full dataset alongside a visual representation and descriptive statistics of the feature distributions, as well as the code that was used to generate the data can be found on the authors' OSF page. An overview of the experimental design can be found in Fig. 1.

Condition 1: Numerical baseline. Participants were presented with three numbers on a computer screen. Each of the numbers represented one of three variables from a synthetic dataset generated for the task. The variables were scaled to a range of [0, 1000] (Fig. 1).

Condition 2: Visual exemplar. This control condition was implemented to test whether configural learning is part of the cognitive mechanism leading to improved performance. Exemplars are prototypical representations of objects stored in memory that allow for the classification of novel objects based on similarity (Medin & Schaffer, 1978; Nosofsky, 2011) and have been shown to play a critical role in configural learning (Juslin et al., 2003, 2008). Exemplar learning is typically studied using distinguishable visual shapes. Accordingly, the three numbers shown in the baseline condition were transformed into a single shape with three equally spaced vertical axes. The shapes were constructed such that the length of the three vertical axes mapped proportionally onto the three numbers presented in the baseline condition, and the area spanned by the axes was filled to create the impression of a single shape. Simply, the shapes captured exactly the same relative information as the numbers in the baseline condition, but presented them in a single coherent configuration in order to evoke configural learning rather than explicit rule abstraction (Fig. 1). While the presentation of shapes may be regarded as an instance of sensory substitution itself, in the sense of translating information from a "number sense" (Dehaene, 2011) to the visual modality, its primary purpose in the given study was to act as a control condition where configural learning was guaranteed to occur. Comparing its results to those produced by tactile sensory substitution would then indicate whether configural learning played a role in tactile sensory substitution (see below).

Condition 3: Sensory substitution. Haptic information was delivered via a vibro-tactile interface that projected the numerical data into vibrations of varying intensity. The interface consisted of an Arduino board and three vibration motors attached to participants' fingertips (index, middle and ring finger) with straps (Fig. 1). The vibrations were administered through 10 × 2.7 mm button-type motors commonly used in smartphones. The vibration amplitude exerted by each motor was independently controlled by varying the voltage in the circuit. The numerical inputs were mapped to vibration intensities by regulating the voltage between 0 and 5 V, proportional to the underlying numeric values used in the numerical baseline condition. The motors were controlled using a Matlab interface. The stimulus was interrupted while participants received feedback for each trial in order to prevent habituation of the sensory tactile threshold (Kaczmarek et al., 1991).

Participants were briefed on the study design, expected time, and instructions for each condition prior to the study initiation. Participants provided basic information concerning their age, gender, and handedness. Following, participants were fitted with the sensory substitution apparatus to ensure ease of transition to the sensory substitution condition. Participants sat approximately 60 cm from a 24-inch monitor. The visual content was presented on the screen within roughly 25° of visual angle. The lab setting (noise, luminance, temperature, etc.) were fixed across participants. Participants had no opportunity to practice the task before the experiment, because the goal of the experiment was to capture the learning process starting at baseline. However, participants received detailed instructions for each sub-task and were familiarized with the stimuli and the arrow keys used to indicate their decision. After

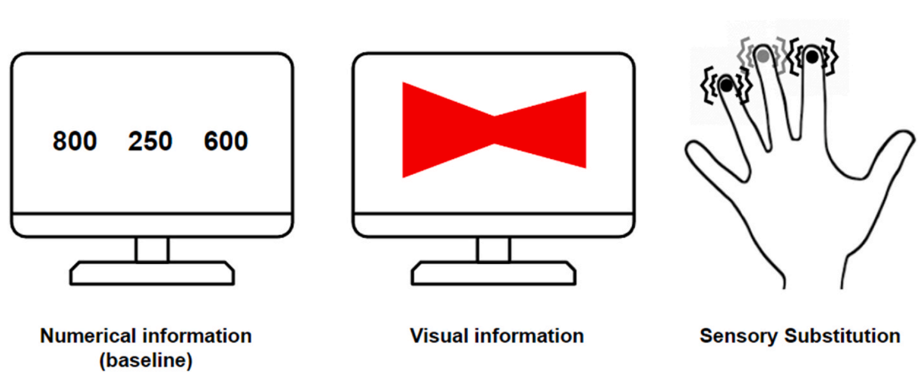

Fig. 1. Overview of the experimental conditions. For the same three numbers, we represent the data in three conditions: numerical (left), sensory (right), and visual (center).

the participants had finished all multiple-cue learning tasks, they were asked to rate each of the conditions on two 5-point Likert scales ("How intuitive was the task?", "How enjoyable was the task?"). Participants were also asked to provide some qualitative description of their approach to each task. Finally, participants were debriefed about the purpose of the study and were paid. A minimum payment of $5 for participation was guaranteed. Additionally, each correct answer above chance performance was rewarded with a bonus of 20¢.

Exclusion criteria included low response variance (SD < 0.3, decision class ratio >90/10) and consistently low response times (mean < 0.2 s) per person per condition, as this would indicate a lack of engagement with the task. If a person met one of these criteria in any condition they would have been excluded from the dataset, but none of the participants met the exclusion criteria. Generally, non-compliance was not a major concern as the experiment was conducted in person under the supervision of a research assistant and correct responses were incentivized.

2.3. Outcome measures and statistical hypotheses

The main outcome measure of interest was the percentage of correct trials in each of the three conditions. In addition, the performance on the decision-making task over time (i.e., learning curves; Fig. 2) was operationalized as the cumulative score corrected for chance performance, using the formula:

$$P_t = 0.01\left[\left(\sum_0^t C_t\right) - tp\right] + p \tag{1}$$

where P_t denotes the learning state in trial t, C_t denotes the value of the participant's response in trial t, and p denotes the chance of guessing the correct answer (i.e., the expected value of the target variable). The .01 constant was chosen to ensure a [0, 1] range for P across the 100 trials. A final value of 0 reflects a participant who made the wrong prediction in every single trial and a final value of 1 reflects perfect predictions across all trials. A final value of 0.5 reflects chance performance.

Complementing the performance metrics, we examined two additional outcome measures. First, we recorded participants' response times for each trial. Second, we considered participants' self-reported intuitiveness ratings.

Based on the hypothesis that configural learning induced by sensory substitution leads to improved decision-making performance, we expected decision accuracy to be higher in the sensory substitution condition compared to the numerical condition. Similarly, we expected performance in the visual exemplar condition, which was specifically designed to induce configural learning, to be higher than in the numerical baseline condition.

To test whether the effects were indeed the result of configural learning, we formulated four additional hypotheses.

1) We expected no statistical difference in accuracy between the sensory substitution condition and the visual exemplar condition since both were presumably driven by configural learning (Juslin et al., 2003, 2008).
2) We expected response times in the sensory substitution condition and the visual exemplar condition to be significantly shorter than in the numerical condition, since the intuitive, perceptual decision process associated with configural learning should be less time intensive than the deliberative decision process associated with explicit rule abstraction (Dane & Pratt, 2007).
3) We expected participants to report higher degrees of intuitive decision-making in the sensory substitution condition and the visual exemplar condition compared to the numerical baseline condition.
4) Based on the idea that configural learning is well suited for nonlinear cue environments (Juslin et al., 2008), we predicted that participants' responses in the sensory substitution condition were better explained by a nonlinear cognitive model compared to a linear one (Brehmer & Brehmer, 1988).

3. Results

3.1. Research question 1: Can sensory substitution improve decision-making?

To test whether the sensory substitution condition resulted in higher performance than in the baseline condition, we compared the decision accuracy (proportion of correct trials) across conditions using pairwise dependent sample t-tests. As expected, participants performed significantly better in the sensory substitution condition (0.636 ± 0.087; t (47) = 6.01, p < .001, d = 0.87; Fig. 2) and the visual exemplar condition (0.649 ± 0.087; t (47) = 7.32, p < .001, d = 1.06) compared to the numerical baseline condition (0.535 ± 0.061). Participants in all three conditions performed better than chance (all p < .001).

As learning is a function of the feedback received during the task, we evaluated the performance curves over time across the three conditions. Participants in the sensory substitution condition and the visual exemplar condition learned faster and showed higher cumulative performance compared to the numerical baseline condition (Fig. 2). To formally characterize the learning process, we compared the

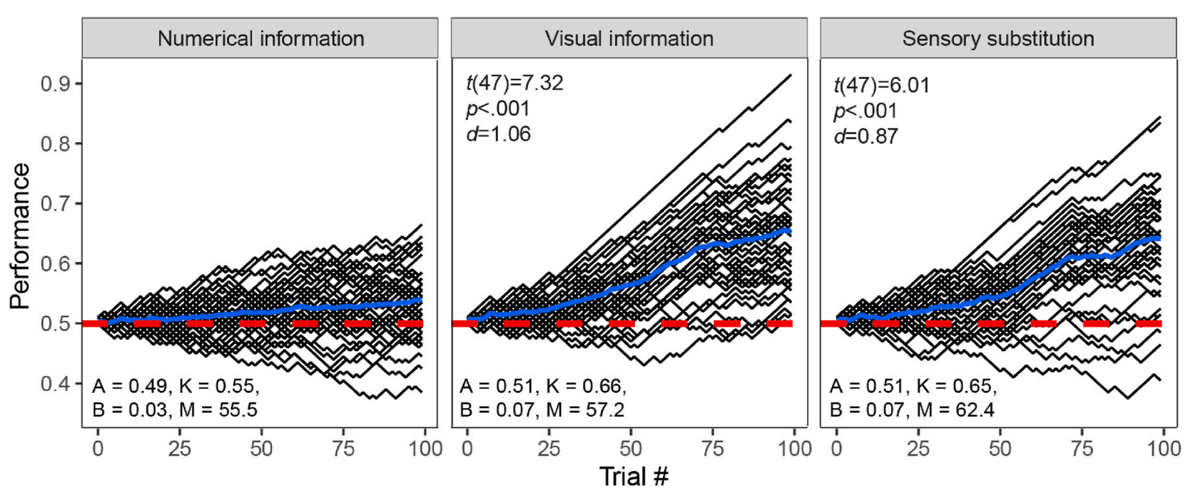

Fig. 2. Decision-making performance over time. Performance curves are depicted in gray (individual) and blue (mean) lines. Dashed red lines denote chance performance. The statistics in the upper left corner show the comparison of the visual exemplar and sensory substitution conditions with the numeric baseline condition. The parameters of the estimated generalized logistic function are shown on the bottom left.

performance curves to several plausible functions, including linear, quadratic, exponential, and generalized logistic. We found that the mean performance curves were best approximated by a generalized logistic function of the form:

$$P_t = A + \frac{K - A}{1 + e^{-B(t-M)}} \tag{2}$$

where P_t denotes performance in trial t, A the lower asymptote, K the upper asymptote, B the growth rate, and M the starting time (departure from the lower asymptote).

Whereas the lower asymptote (A) captures participants' initial random guesses (chance = 0.5) and the upper asymptote (K) acts as an approximation of the learning outcome (i.e., cumulative performance), a comparison of the remaining parameters allows us to statistically differentiate the learning mechanism across sensory modalities. Supporting the notion that translating data into abstract sensory experiences leads to a change in learning processes, the growth rates (B) of the sensory and visual performance curves were significantly different from those of the numeric condition (all $p < .001$; *t-test*; see parameters in Fig. 2).

3.2. Research question 2: Which underlying mechanism explains the effect?

To test whether the performance improvement could be explained by a shift towards configural learning, we offer converging evidence across four approaches: First, we analyze whether participants' performance and learning trajectories differ between the sensory substitution and visual exemplar condition. Second, we test whether participants' response times were faster in the sensory substitution and visual conditions compared to the numerical baseline. Third, we compare participants' self-reported intuitiveness ratings across conditions. Fourth, we employ a cognitive model using policy capturing techniques (Aiman--Smith et al., 2002; Brehmer & Brehmer, 1988) to assess whether higher levels of configural learning occurred in the sensory substitution and visual exemplar conditions compared to the numerical baseline condition.

3.2.1. Comparison of sensory substitution and visual exemplar condition

Aligned with our prediction that both the sensory substitution and the visual exemplar condition should be afforded the same configural learning benefits, we did not observe any differences in accuracy between the sensory substitution condition and the visual exemplar condition ($t\ (47) = -0.75$, $p = .457$, $d = -0.11$; Fig. 3). In addition, the analyses of learning trajectories showed that there was no difference in the growth rate between the sensory substitution and the visual exemplar condition ($p = .809$), indicating that the two conditions followed similar performance trajectories. Small differences were observed between the starting times (M, $p < .001$) as participants in the sensory substitution condition showed a slightly later pick-up in performance compared to the visual exemplar condition. While speculative, this difference might be explained by the fact that making decisions based on haptic feedback is less common than making decisions based on visual information, and hence might require a slightly longer adjustment period.

3.2.2. Response time

Participants in the sensory substitution condition (1.77 ± 0.648s) and the visual exemplar condition (1.40 ± 0.620s) were significantly faster in their response time compared to the numeric baseline condition (2.58 ± 1.51s; $t\ (47) = -4.05$, $p < .001$, $d = -0.58$ for the sensory-numerical comparison; $t\ (47) = -6.88$, $p < .001$, $d = -0.99$ for the visual-numerical comparison; Fig. 3). The shorter response times in the sensory substitution and visual exemplar conditions compared to the numerical baseline condition align with the suggestion that the intuitive, perceptual decision process associated with configural learning should be less time-intensive than the deliberative decision process associated with explicit rule abstraction (Dane & Pratt, 2007).

3.2.3. Intuitiveness ratings

In line with the more objective measure of response time, participants experienced the sensory substitution condition (3.14 ± 0.94, $t\ (47) = -4.26$, $p < .001$, $d = 0.62$; measured on a 1–5 scale) and visual exemplar condition (3.26 ± 1.01-, $t\ (47) = 4.43$, $p < .001$, $d = 0.61$) as more intuitive compared to the numerical baseline condition (2.39 ± 0.98). There was no difference in participants' subjective intuitiveness

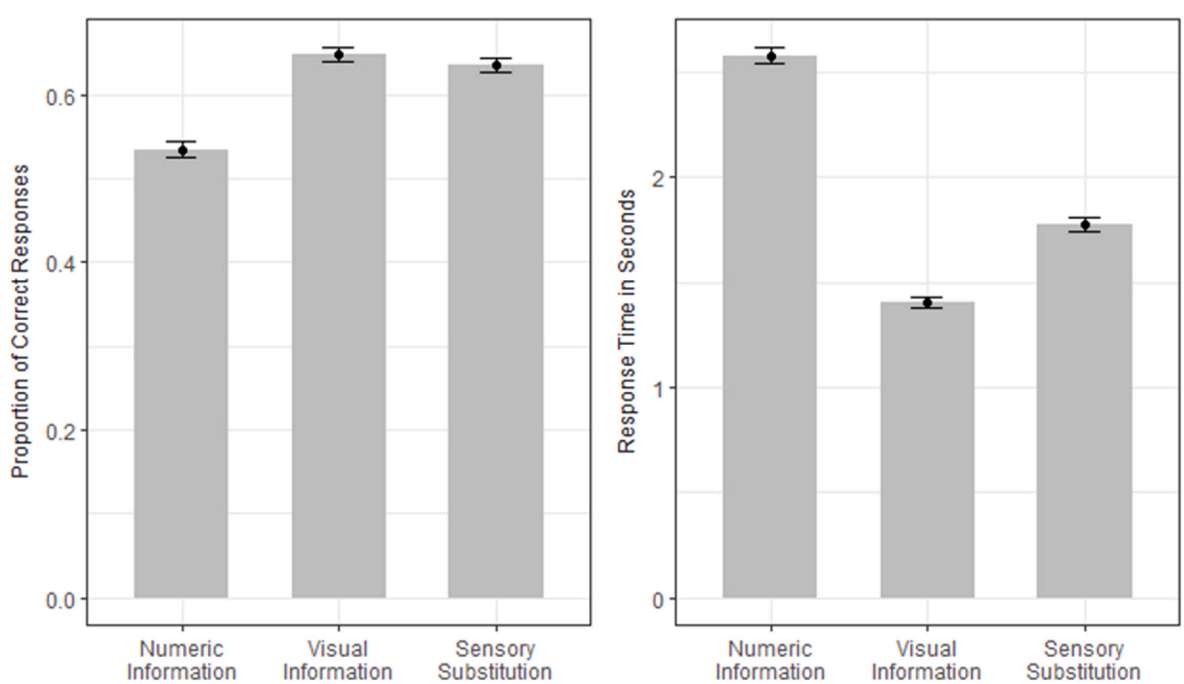

Fig. 3. Comparison of decision-making performance and response times across conditions. Mean proportion of correct responses per user across conditions (left). Mean response time in seconds across conditions (right). Error bars represent standard errors for repeated measures comparison.

ranking between the sensory substitution and visual exemplar conditions (t (47) = 0.706, p = .484, d = 0.10).

3.2.4. Cognitive model

Based on the notion that explicit rule abstraction is associated with linear solution strategies while configural learning is well suited for interactive cue environments (Juslin et al., 2008), we employed a computational cognitive modeling approach. Specifically, we used a linear additive regression model as a baseline to represent the strategy of explicit rule abstraction and a model containing interaction effects to represent configural learning (Brehmer & Brehmer, 1988; Castellan, 2013; Juslin et al., 2008). We identified the dominant cognitive strategy employed by each participant in each condition by comparing how well the models accounted for participant's responses (Brehmer & Brehmer, 1988). That is, we used the numeric values of the stimuli in each trial to predict participants' response in that trial. Intuitively, the bigger the gap between the performance of the nonlinear interaction model and the linear baseline model, the more likely it is that a participant engaged in configural learning (i.e., by taking interactions between the features into account when making their decision). On the contrary, a participant is less likely to have engaged in configural learning if the linear model and the interaction model were to explain the participant's responses equally well.

Formally, configural learning scores were operationalized as the difference in model fit between a linear model without interactions and a model with interactions, both of which predicted participants' responses from the cues presented in each condition of the experiment. Specifically, we used generalized linear models with a logit link function (logistic regression) to represent the relationships between cues and responses for each individual participant. The linear model contained only the three cues as linear predictors, whereas the interaction model contained the three linear predictors, as well as first order interaction terms (six terms in total). The model specifications were:

$$\text{Linear model}: logit(p_t) = \beta_0 + \beta_1 c_{1t} + \beta_2 c_{2t} + \beta_3 c_{3t} + e_t \quad (3)$$

$$\text{Interaction model}: logit(p_t) = \beta_0 + \beta_1 c_{1t} + \beta_2 c_{2t} + \beta_3 c_{3t} + \beta_4 c_{1t} c_{2t} + \beta_5 c_{1t} c_{3t} + \beta_6 c_{2t} c_{3t} + e_t \quad (4)$$

where p_t = E [R_t |c_{1t}, c_{2t}, c_{3t}] and R_t represents the binary response variable, while c_{1t}, c_{2t}, and c_{3t} represent the cues on which each decision was based. The intercept and the model coefficients of each predictor term are represented by β_i, and the error term is denoted by e_t. Both models were fitted for each participant and configural learning scores were computed by subtracting the deviance score of the interaction model from the deviance score of the linear model. Deviance is a commonly used measure of error in the context of generalized linear models, with lower values indicating better model fit (Pierce & Schafer, 1986). Configural learning scores were therefore higher when participants used nonlinear cue integration strategies (interaction model fit better than linear model fit) and lower when participants used linear cue integration strategies (interaction model did not fit better than linear model fit). Configural learning scores were computed separately for each individual and condition.

We used pairwise dependent sample t-tests to compare configural learning scores across conditions. The results show significantly higher configural learning scores in the sensory substitution condition (t (47) = -1.82, p = .038, d = 0.26) and the visual exemplar condition (t (47) = -3.51, p < .001, d = 0.51) compared to the baseline condition. Configural learning scores in the visual exemplar condition were also significantly higher than in the sensory substitution condition (t (47) = -2.66, p < .011, d = 0.38). Taken together, these results indicate that the performance difference between the sensory substitution condition and the numerical baseline condition was associated with a shift from explicit rule abstraction to configural learning.

4. Discussion

We tested whether sensory substitution improves decision-making by shifting cognitive processes from explicit rule abstraction to configural learning. Our findings show that sensory substitution was associated with a significant performance improvement compared to a numerical baseline condition. The same performance improvement was found with respect to the visual exemplar condition which was deliberately set to favor configural learning. No significant performance difference was found between the sensory substitution and the visual exemplar condition, pointing towards configural learning as the mechanism underlying the performance increase. The suggestion that configural learning drives the effect is further supported by the fact that participants in both the sensory substitution and visual exemplar conditions showed significantly lower response times compared to the numerical baseline condition. The latencies in each condition are consistent with the notion that intuitive and configural decision processes are quicker than deliberative, explicit, processes (Dane & Pratt, 2007). Additionally, both sensory substitution and visual exemplar tasks were rated by participants as significantly more intuitive compared to the numerical baseline task. In line with these findings, a cognitive modeling analysis indicates that participants relied more heavily on configural learning in the sensory substitution condition, compared to the numerical baseline condition.

Taken together, our findings provide the first empirical evidence that: 1) sensory substitution can aid decision-making (with large effect sizes between d = 0.87–1.06), and 2) the benefits afforded by sensory substitution are the result of a shift from (deliberate) explicit rule abstraction to (intuitive) configural learning. Our findings also extend prior work investigating the distinction between explicit rule abstraction and configural learning. While previous research has established the ability of holistic visual stimuli to encourage configural learning over explicit rule abstraction (Juslin et al., 2003), the projection of data to the tactile sensory modality provides an extended layer of abstraction that could be used in contexts where processing visual information is impractical (Luzhnica et al., 2018) or impossible (e.g., in situations where visual attention is required elsewhere, like driving). By involving new modalities that capitalize on the brain's ability to rapidly process information and adapt to new sensory settings (Rauschecker, 1995; Sharma et al., 2000) it might become possible for people to learn how to truly "feel" the solutions to complex problems rather than inferring them cognitively. For example, the same way humans experience "cold" as a holistic sensation that does not require them to deliberately integrate information about air temperature, radiant temperature, humidity and wind across multiple locations of their body, professional traders could gradually learn to *feel* the "temperature" of the stock market.

4.1. Limitations and future directions

As this is the first work to test the effects of sensory substitution in the context of decision-making, we note several limitations and avenues for future research. First, while the present study provides initial evidence for the proposed role of configural learning in sensory-based decisions, future work should further investigate the mechanism underlying the performance improvement. Specifically, we suggest studying the neural underpinnings of the effect using brain readouts such as EEG data to try to distinguish the neural pathways associated with explicit rule abstraction and configural learning.

Second, the present results call for an investigation of the generalizability of the findings. While our study demonstrates a strong positive effect of sensory substitution in a well-controlled context, it remains unclear how the results generalize to more complex use-cases beyond artificially generated data with specific properties (i.e., only three features, moderate correlations, interactions). Past work (e.g., Auvray & Harris, 2014) has pointed out the difficulties of using traditional sensory substitution devices in real-world settings when trying to preserve the complexity of the forwarded signal. Here, we propose a simpler version of a sensory device that can be used without extensive training. This simplicity can be achieved by limiting the amount of information forwarded to the human user, which in turn means that the developer pre-determined the functionality of the sensory augmentation device and its use case. This also imposes bounds on the generalizability of our findings to more complex use cases. To study the boundary conditions of the effect more rigorously, future work should also explore the moderating role of specific properties of the data, such as the number of features, or the specific kinds of interactions and nonlinearities in the inputs, as well as the effects of more extensive training.

Third, while the contribution of this paper is primarily theoretical, it has not escaped our notice that future research should identify real-world use cases and study how a system like the vibro-tactile interface can be turned into practical applications in ecological settings. For example, one could investigate how sensory substitution interacts with existing knowledge in a decision domain: would the effect persist when people interpret the predictors in meaningful ways and build on prior knowledge when making decisions? Further, would continuously wearing sensory substitution devices allow people to seamlessly integrate new information into their experience of the world (e.g., tracking the mood or productivity of an organization via a bracelet)? Indeed, it has been shown that after prolonged exposure, the data streams from sensory devices (such as cochlear and retinal implants, but also sensory substitution devices) are not experienced as external information projected to the ear/eye/skin, but as true sensory experiences (Bach-y-Rita et al., 1969; Bach-y-Rita & Kercel, 2003; Deroy & Auvray, 2012; Lenay et al., 2003; Rauschecker, 1995; Sharma et al., 2000).

4.2. Conclusion

Taken together, our findings provide the first empirical evidence for the effectiveness of sensory substitution in decision-making. In addition, the findings also offer a starting point for a broader cross-disciplinary research program that can investigate the mechanisms underlying the effectiveness of sensory substitution, its boundary conditions, and its potential to inform the design of real-world decision aides.

Credit author statement

Heinrich Peters: Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Data Curation, Writing - Original Draft, Visualization; **Sandra Matz**: Conceptualization, Methodology, Investigation, Resources, Writing - Original Draft, Supervision, Funding Acquisition; **Moran Cerf**: Initial Research Idea, Conceptualization, Methodology, Investigation, Resources, Writing - Original Draft, Supervision.

Declaration of competing interest

None.

Data availability

Anonymized data and code are available on the authors' OSF page.

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