The impassable gap between experiential and symbolic values

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Abstract

To choose between options of different natures, standard decision models presume that a single representational system ultimately indexes their subjective value on a common scale, regardless of how they are constructed. To challenge this assumption, we systematically investigated hybrid decisions between experiential options, whose value is built from past outcomes experience, and symbolic options which describe probabilistic outcomes. We show that participants' choices exhibited a pattern consistent with a systematic neglect of the experiential values. This normatively irrational decision strategy held after accounting for alternative explanations, and persisted when it bore an economics cost. Overall, our results demonstrate that experiential and symbolic values are not symmetrically considered in hybrid decisions, suggesting that they are not commensurable and recruit different representational systems which may be assigned different priority levels in the decision process. These findings challenge the dominant models commonly used in value-based decision-making research.

Introduction

Standard models of economic decision-making generally assume a two-step decision process, where individuals identify and assign values to available options, and ultimately pick the option with the highest subjective value (1–3). The values attributed to individual options can derive from different sources. On the one hand, a priori neutral stimuli acquire positive or negative experiential values after association with past outcomes (rewards and punishments) (4–6). On the other hand, the explicit description of an option's possible outcomes and their probabilities are combined to form a subjective expected value (7–10). Such explicit descriptions may take many different forms, including written language (from simple vignettes to fully specified numerical variables), a symbolic code communicating the decision variables (payoffs and probability) in an unambiguous manner, or a combination of the two (11).

In the standard two-step model, the way option values are built (via experience or description) is only peripheral to the decision process itself, meaning that experiential and symbolic values converge to a central valuation and decision-making system (3, 12–16). Thereby, choices *between* experiential and symbolic options should present no particular challenge, because their values are translated into an internal common currency, allowing an unbiased comparison between these differently generated option values. This normative point of view is indirectly supported by the fact that the neural correlates of experiential and symbolic values largely overlap in the so-called brain valuation system (17–20).

However, several lines of evidence in behavioral decision-making research question the idea of a central valuation system. In fact, it is now a very well established that, when studied separately, experience-based and description-based choices display different properties: a phenomenon referred to as the *description-experience gap* (21–24). This difference in the subjective valuation of experiential and symbolic options poses a direct, theoretical challenge to the idea of a central valuation system (25). This rather suggests the existence of modality-specific valuation systems, relying on distinct cognitive representations, which would hinder, if not impede, the comparison between experiential and symbolic options

Strikingly, this key prediction has not been directly assessed, because studies usually consider separate sets of decision problems for experiential and symbolic options (26, 23). Thereby, to date, very little experimental evidence has formally assessed the commensurability of experiential and symbolic option values, nor their mapping into a central or different valuation systems (27, 28). This is particularly problematic considering that hybrid choices seem to be the norm rather than the exception in our modern societies where descriptive information is omnipresent. For example, everyday situations like choosing between our favorite restaurant (experience) and a new one with good review (description) is a prototypical example of such a hybrid decision.

To fill this gap and challenge the commensurability of experiential and symbolic values, we designed a new behavioral protocol. The experiment started with a learning phase during which human participants repeatedly faced abstract cues paired with probabilistic outcomes, thereby learned to associate experiential expected-values to the originally neutral symbols. After this phase, participants were asked to make hybrid choices between the experienced symbols and described lotteries visualized as colored pie-charts (a standard way to represent value symbolically) (11). When making hybrid choices, participants treated the two kinds of options asymmetrically and, specifically, were neglecting experiential values. This asymmetry was robust across seven experiments, where we controlled for many possible alternative explanations, such as, insufficient learning, generalization issues or lack of incentives. Overall, the relative neglect of an option's value conditional on its source is consistent with the idea that different types of values – such as experiential and symbolic – may involve different representational systems, resulting in their incommensurability.

Results

We conducted a series of experiments structured in two main phases, one allowing the formation of subjective values from the experience of past outcomes, and a second where these experiential options (E-options) were presented against options whose subjective values were described by symbolic means (S-options) (Fig. 1A). During the first (or learning: LE) phase, E-options were materialized by abstract shapes that provided no explicit information concerning the expected value (EV) of the option. During the LE choices, E-option values could therefore only be inferred from the history of gains (+ 1 point) and losses (-1 point) associated to a specific cue. E-options were presented in four fixed pairs, each featuring an EV-maximizing and an EV-minimizing option. Subsequently, in the Experiential-Symbolic (ES) phase, subjects were asked to make choices between the very same E-options of the previous phase and pie-charts explicitly describing the associated probabilities of gain and loss. As these ES, "hybrid" choices are the main focus of this paper, we thereafter delineate three plausible hypotheses concerning the behavioral output of this phase.

First, assuming that the subjective values of the E- and S-options are mapped into a common scale (*common currency* hypothesis), subjects should make *unbiased* decisions in the ES phase. Accordingly, the probability of choosing, say, the E-option, will be jointly determined by the EV of the E- and the S-option (Fig. 1B: left). In other terms, for a given E-option the inferred *indifference point* will precisely correspond to S-options with equal EV.

Alternatively, the possibility that subjective values are constructed and represented in a modality-specific way (*representational gap* hypothesis) entails that E- and S-options are not readily commensurable. This situation could lead to two possible scenarios. In one of them, participants make random choices in the ES-phase. In the other scenario participants could prioritize one of the two sources of information. Within this scenario, participants could resolve the tension between E- and S-options basing their choices primarily on the explicit symbolic values provided by the lotteries. In other terms, subjects would pick the lottery, when positive, and reject it when negative, as if the E-option values were neglected and regressed to zero (*experiential value neglect*, Fig. 1B: mid). In the other case, subjects would present an over-reliance on experiential values and would display the opposite pattern: accept or reject an E-option without considering the S-option value (*symbolic value neglect*, Fig. 1B: right). Crucially, the ES phase of our experiments allows to tease apart these different scenarios by analyzing the probability of choosing an E-option as a function of the S-option being presented. More precisely, taking each E-option separately and uncovering the S-option (value) at which a preference shifts from the former to the latter provides us with an estimate of how much a participant values an E-option. Quantifying the relation between E-options and S-options boils down to inferring indifference points (i.e., when the probability of choosing one option over the other is 50%) which acts as proxies of subject E-option values (Fig. 1B: insets).

First evidence for the experiential value neglect scenario

In the LE phase of the first experiment (N = 76), we presented pairs of E-options in an *interleaved* manner (i.e., E-option pairs are distributed randomly in the sequence of trials) and we displayed only the outcome of the chosen option (*partial feedback*) **(**Fig. 2A, **Exp. 1).** Apart from the most difficult learning context (60/40), choice accuracy was above chance level for all E-option pairs ($T(75) = 1.5$, $P > .05$; $T(75) = 10.98$, $P < 0.001$), thus indicating that subjects aimed at (and managed to) maximize expected value. Furthermore, accuracy was modulated by the difference in expected value (i.e., the *decision value*) of the E-option pair. Choice accuracy increased as a function of the decision value ($\beta = 0.077$, $T(300) = 2.16$, $P < 0.05$; $\beta = 0.08$, $T(300) = 2.35$, $P < 0.05$; $\beta = 0.21$, $T(300) = 5.94$, $P < 0.001$), thus indicating that subjects' behavior was sensitive to the specific EV of E-options involved in a given pair.

Regarding analysis of the ES phase, the probability of choosing an E-option in an ES decision was largely determined by the S-option EV-value and the preference shift abruptly occurred around S-option EV equal to zero (i.e., $P(+1) = P(-1) = 0.5$). Despite clear proofs of successful value learning and encoding during the LE phase, ES phase-choice pattern was clearly consistent with the *experiential value neglect* scenario. (Fig. 2B: left).

To quantify and statistically compare the differences in preferences observed in the LE and the ES phase, we first estimated the theoretical subjective value of each E-option separately for the two choice types, proxied by its probability of winning a point: p(win) (remind that the outcomes are fixed, so the expected value of different options only depend on their probabilities to win). Concerning the LE phase, we leveraged on a classical associative learning approach, where we assumed p(win) to be iteratively updated as a function of a prediction error-minimizing learning rule (30, 31, 6). We were able to infer p(win) attributed to each E-option at the end of the learning process by fitting this, rather parsimonious and standard, model.

Concerning the ES phase, subjective p(win) estimates were inferred using the following method: the probability of choosing a specific E-option over a S-option of various expected values was assumed to take the form of a logistic sigmoid function. We fitted those logistic functions to each E-option and subject, and used them to extrapolate the indifference points indexing E-options' subjective p(win).

Finally, to compare the overall valuation of the E-options in the LE and the ES phases, we computed a measure of how well the subjective p(win) estimates from each phase matched the objective underlying probabilities, using slopes estimates from linear regressions.

At this aggregate level, a slope equal to 1 corresponds to an unbiased representation of E-options' p(win), whereas a slope equal to 0 corresponds to random representations. In our data, the slopes estimated from the LE phase were significantly higher and closer to 1 compared to those estimated from ES-choices ($T(75) = 6.53$, $P < .001$) (Fig. 2C: left). Thus, ES decision problems feature a specific neglect of E-option values, as if hybrid choices prioritized the value of the symbolic options over an unbiased comparison of experiential and symbolic values, thereby confirming the *experiential neglect* hypothesis.

We ruled out a first trivial interpretation for this result, by only including in the analyses subjects that performed at 100% of correct response in catch trials (i.e. trials involving choices between two S-options; see **Supplementary Materials**), disseminated across the ES phase to ensure the subjects' capacity to understand the symbolic representation of the probabilities.

In the following sections of the paper, we provide additional evidence in favor of the experiential neglect hypothesis by progressively ruling out alternative interpretations via additional measures and experiments.

Ruling out insufficient learning and forgetting

While the *experiential neglect* pattern observed in the ES phase is consistent with the idea that E-options and S-options are not equally considered in the decision process, it is also consistent with a much more trivial hypothesis: insufficient learning. Despite reinforcement learning model fitting suggesting otherwise (see Fig. 2C: left), it is indeed possible that the neglect of E-option in the decision is caused by an imperfect and noisy E-option value representations at the end of the learning phase. To rule out this alternative interpretation, we devised a series of experiments where we changed the LE phase in order to improve learning, while keeping the (average) option values the same. In a second experiment (Exp.2; N = 71), we therefore presented decision problems as blocks (rather than interleaved as in Exp.1), so as to improve performance and option identification by preventing the saturation of working memory (32). In a third experiment (Exp.3; N = 83), we additionally provided the information concerning the unchosen option (complete feedback – a manipulation known for increasing accuracy (Palminteri et al., 2015; Bavard, 2021). Finally, on top of these variations, in a fourth experiment (Exp.4; N = 88) we also reduced the number of decision problems of the LE phase to two, such that each decision problem was presented for twice as many trials as in experiments 1–3, thereby reducing the uncertainty about the options' outcomes. These manipulations were successful in significantly increasing decision accuracy in the LE phase (**Exp1**: 0.66 ± 0.01; **Exp2**: 0.71 ± 0.01, β = 0.05, T(314) = 2.28, P < 0.05; **Exp3**: 0.82 ± 0.01, β = 0.16, T(314) = 7.17, P < 0.001; **Exp4**: 0.79 ± 0.01; β = 0.13, T(314) = 5.8, P < 0.001), while avoiding ceiling performance issues. Indeed, even in the easiest experiments, accuracy was still significantly modulated by the decision values; for instance, the accuracy in the more difficult decision problem (60/40) was always lower compared to the easiest one ('90/10') (T = 5.81, P < 0.001; T = 8.81, P < 0.001).

Crucially, the remarkable increase in the LE phase accuracy of the new experiments (107% − 124% of Exp.1) was not paralleled by detectable qualitative differences in ES phase choice patterns (Fig. 2B**)**. In other terms, the *experiential value neglect* persists despite the uncertainty concerning the E-options' values being considerably reduced (via blocked design, complete feedback and increasing the number of trials per decision problem).

To quantitatively characterize this claim, we estimated the subjective p(win) for each E-option separately for the LE and the ES phases and fitted a linear regression between the estimated subjective p(win) and their true values (as described above). Confirming the efficiency of our manipulations in increasing learning performance, the LE-inferred slopes increased significantly across experiments (**Exp. 2**: β = 0.11, T(942) = 5.98, P = 0.055; **Exp. 3**: β = 0.28, T(942) = 6.5, P < 0.001; ; **Exp. 4**: β = 0.31, T(942) = 7.27, P < 0.001). Critically, the ES slopes were not modulated across experiments aside from Exp. 4 (**Exp. 2**: β=-0.1, T(942)=-1.76, P = 0.07; **Exp. 3**: β = 0.02, T(942) = 6.5, P = 0.67; ; **Exp. 4**: β = 0.11, T(942) = 2.06, P < 0.05) (Fig. 2D). Overall, LE-inferred slopes were significantly higher than the ES slopes in all experiments (**Exp. 2**: T(70) = 11.74, P < 0.001; **Exp. 3**: T(82) = 15.8, P < 0.001; **Exp. 4**: T(87) = 11.64, P < 0.001; Fig. 2E), and the asymmetric effects of the manipulations on the LE versus ES phases translated into a significant interaction between the choice modality (ES and LE) and the experiment number (**Exp. 2**: β=-0.21, T(942)=-2.58, P < 0.05; **Exp. 3**: β=-0.26, T(942)=-3.29, P < 0.01; ; **Exp. 4**: β = 0.2, T(942) = 2.57, P < 0.05).

The comparison between the first four experiments suggests that *experiential value neglect* is not a mere effect of insufficient learning. We indeed observe that an improved performance in the learning phase does not translate into a similar decrease of the *experiential value neglect* effect. However, independently of the quality of learning, it is also theoretically possible that subjects forgot the E-option values when entering the ES hybrid choice phase, although the fact that the ES phase directly succeeded the LE phases within a matter of seconds makes it improbable. To rule out this possibility, in Exp. 1–4, we asked subjects to evaluate the E-options' p(win) just after the ES phase, by implementing a fully incentivized stated probability (SP) procedure (35). More precisely, subjects were explicitly asked to rate the probability of winning a point they attribute to an E-option, by means of a numerical rating scale (Fig. 1D).

We then evaluated the quality of the E-option memory retention by regression these stated probabilities against their true values. Note that because this elicitation happens *after* the ES phase, this SP-inferred slopes constitutes a lower bound of how well E-option values are learned and could be recovered during the ES phase. Yet, the SP-inferred slopes were systematically higher than the ES-inferred slopes and significantly so in Exp. 2, 3, 4 (**Exp. 1**: $T(75) = 2.62$, $P > 0.05$; **Exp. 2**: $T(70) = 3.42$, $P < 0.05$; **Exp. 3**: $T(82) = 4.38$, $P < 0.001$, **Exp. 4**: $T(87) = 4.87$, $P < 0.001$). Therefore, E-options' values elicited during the SP phase were more accurate than those elicited in the preceding ES-phase. This observation rules out forgetting as a plausible interpretation of the apparent *experiential value neglect* pattern observed in the ES phase.

Ruling out generalization issues and assessing the robustness to practice

The above-reported results from 4 experiments and 3 preference elicitation methods indicate that the *experiential value neglect* phenomenon cannot be accounted for by insufficient learning nor by mere forgetting. In the present section we rule out two additional alternative explanations. First, it should be noted that the ES phase involves a generalization process, because the E-options are extrapolated from the decision context where their subjective values are originally learned. It is therefore conceivable that the apparent *experiential value neglect* is spuriously created by a generalization problem. Second, in the previously reported experiments, subjects went through the different phases (LE, ES and SP) only once: perhaps subjects were somehow taken by surprise by the ES phase. In that case, presenting them different phases of the experiment twice will possibly allow them to improve their decisions by anticipating the ES-phase (36).

To control for generalization and practice, we run two additional experiments. In experiment 5 and experiment 6 ($N = 71$ and $N = 66$), after the learning phase, we interleaved the ES-choices with choices involving E-options presented in all possible combinations (referred to as EE-choices). Thus, in all cases except one, EE-choices required being able to generalize their value to new decision problems. As in ES-choices, we plotted the probability of choosing a given E-option as a function of the alternative E-option (Fig. 3B). To check whether *experiential value neglect* disappears if participants are given the opportunity to learn how to make ES decisions, Exp. 6 included a second session where we repeated all phases (LE, ES, ES and SP). Of note, E-options in the second sessions were materialized by a new set of symbols.

EE-choices curves revealed that subjects were capable of successfully extrapolating the value of the E-options to new decision problems involving other E-options. On the other side, the ES-choices were consistent with experiential values neglect, thus replicating the previous experiments (of note, the LE-phase of Exp. 5 and Exp. 6 presented the same characteristics as that of Exp.3: complete feedback and block design) (Fig. 3A).

To formally assess the difference between EE- and ES-choices, we calculated for each subject their option-specific indifference points, following the same procedure used for ES-choices and we compared the inferred slopes across decision modalities. EE-inferred slopes were consistently significantly higher than ES slopes in both Exp.5 and Exp.6 (**Exp. 5**: $T(70) = 4.5$, $P < 0.001$; Exp 6.1: $T(65) = 4.08$, $P < 0.001$).

Being presented with the whole experiment a second time had no detectable effect in choice behavior in neither the EE- or the ES-phase. Indeed, we observe no significant increase in the slopes in neither ES- (β = 0.04, $T(260) = 0.84$, $P = 0.4$) nor EE- choices (β = 0.1, $T(260) = 1.59$, $P = 0.11$) and the ES-inferred slopes were still significantly smaller compared to EE- ones (Exp. 6.2: $T(65) = 5$, $P < 0.001$). This suggests that being exposed with the whole experiment one time and, by doing so giving participants the possibility to adjust the decision strategy does not affect the main results.

Experiential value neglect persists even when it bears an economic cost

Analysis of choice behavior in the ES show that learned values of the E-options are largely neglected, as if subjects were deciding on the basis of the value of the S-options only, and this despite the fact performance in the LE, SP and EE-choices indicate that E-option values are well learned and memorized. Neglecting experiential values seems, at least *prima facie*, suboptimal for the decision process, as taking into account all relevant information is considered a hallmark of normative behavior (37, 38). However, if E-option information processing (e.g. memory access/retrieval) is costly or if neglecting E-options does not hinders decision performance dramatically, it may become rational to do so (39–41).

To evaluate this possibility, we simulated choices based on an extreme version of the experiential neglect rule: if an S-option has positive expected value, choose it, otherwise choose the E-option. These simulations show that, applied to the decision problems of the ES phase from experiments 1-to-6, extreme experiential neglect still generates 77% of expected-value maximizing choices. This result is actually not as counterintuitive as it initially appears: by design, a positive lottery is the most advantageous option in ≥ 50% of the decision problems in which it appears, and the converse is true for the negative expected value lotteries. These considerations suggest that, instead of representing an intrinsic cognitive limitation of value-based decision-making, the *experiential value neglect* is a rational heuristic strategy deployed by efficient (or lazy) decision-makers maximizing an accuracy-effort trade-off (42–45).

In order to test this new interpretation of the results, we designed a new experiment (Exp. 7) where we reorganized E- and S-options probabilities in a way that makes neglecting experiential values economically disadvantageous **(**Fig. 4A**)**. In this new configuration, the narrower range of S-option values are nested within the broader E-option values, so that any given S-option has a higher expected value compared to the 4 negative E-options, and a lower expected value compared to the 4 positive E-options. Such configuration guarantees that subjects neglecting E-option values in the ES-phase will exhibit a chance-level choice accuracy (50% of expected value maximizing choices). Except for the modification of the lotteries, Exp 6 present the exact number of trials.

Despite this stronger economic incentive, the behavioral pattern in ES-phase remained consistent with the *experiential value neglect* scenario (Fig. 4B**).** The significant difference between ES and EE slopes persisted in Exp. 7 ($T(70) = 5.12$, $P < 0.001$), suggesting that despite the reorganization of probabilities, we were still able to elicit more accurate E-option values from EE-choices (Fig. 4F, Fig. 4G). As a consequence, compared to Exp. 6, the accuracy in the ES-choices significantly dropped in Exp 7 by approximately 20% ($T(94.97) = 11.01$, $P < .001$, Fig. 4C). Of note, the accuracy in the EE-choices remained the same (Fig. 4D, Fig. 4E), with no significant difference between the two experiments ($T(131.77) = 0.38$, $P = 1$, BF^{1} =0.19).

These findings indicate that experience values are neglected even when it involves an (economic) cost. Therefore, the results are consistent with the idea that the experiential value neglect reflects a hard-coded feature of hybrid choices between experiential and symbolic option, rather than being strategically deployed by the relative lack of incentive in Exp1-6.

Controlling for ambiguity aversion

E-options may be deemed more ambiguous, because their outcome probability distributions are inferred from finite samples and cannot been known with absolute precision or certainty. Experiential value neglect cannot be accounted by a simple form of ambiguity aversion (46–48), because E-options are generally preferred compared to negative expected value S-options (i.e., there is no systematic bias *against* E-options). Nonetheless, to assess whether the participant's attitude toward ambiguous lotteries differed between experiential and symbolic options in a final experiment we included choices with ambiguous lotteries (i.e., lotteries, whose value was hidden). The results (presented in the **Supplementary Materials** and **Figure S1**) indicate that ambiguity aversion was not detectable in our set up and that it could therefore not contribute to explain the observed pattern of behavior. The results of Exp 8 also replicate all previously reported findings.

Reaction times analysis: a tale of two systems?

Choice behavior differ across the ES- and the EE-choices. In the ES-phase, participants neglect the experiential option value and to make choices only based on the symbolic option value, so that, if the S-option is positive, it is chosen, otherwise it is rejected (Fig. 5A). On the other hand, EE-choices are based on the retrieval from memory of the experiential values of both options. Thus, one decision process (ES-choices) seems to involve the processing and representation of only one option value (the lottery), while the other process (EE-choices) seems to involve the processing and the representation of two option values. We hypothesized that these different processes translate into different reaction times between the two choice modalities. To test this prediction, we compared the reaction times in EE and ES-choices, while including only decisions with similar objective value difference (49). Indeed, we found that ES decisions were faster compared to EE decisions, both when the S-option is chosen – (ES_s) and when the E-option is chosen –(ES_e) ($T(136) = 6.02$, $P < 0.001$; $T(136) = 3.98$, $P < 0.001$; Fig. 5B and Fig. 5C). Of note, within ES decisions, ES_e choices were also slightly but significantly slower the ES_s choices (~ 50ms; $T(136) = 4.35$, $P < 0.001$), which may indicate that choosing the E-option requires additional processing to retrieve and represent the value of the E-option. To confirm this intuition, we considered two categories of ES-choices: choices exclusively consistent with the subject choosing using the estimates inferred from the LE phase, on one side, and choices consistent with a full experiential value neglect, on the other side (**Fig. S5)**. We observed that, in conformity with previous results, ES-choices that are consistent with a full experiential value neglect are significantly faster than choices that can only be explained taking into account the E-option values estimated from the LE-phase ($T(386) = 2.27$, $P < 0.05$) (Fig. 5D). Overall, the RT analyses support the idea that choices based on the S-values of the lotteries required reduced cognitive processing compared to those involving the retrieving from memory. Thus, E-values inferred from ES-choices are consistent with the dual process model of Fig. 5A.

Discussion

Our results clearly indicate that the experiential and symbolic option values are not treated symmetrically when making hybrid choices and speak against the idea of a central valuation system that encodes option values in a common currency, regardless of the way they are built (3, 12). The key finding supporting this claim is provided by the analysis of hybrid decision problems between experiential and symbolic cues, where choices appeared to be made by largely neglecting value information acquired during the learning phase. Crucially, by running several experiments and including multiple control measures, we ruled out several alternative explanations for of the experiential value neglect: this decision-making pattern is not due to insufficient learning, forgetting, generalization issue, or a lack of incentive. Finally, reaction time analyses are consistent with different processing of experiential and symbolic values and with the idea of an additional cognitive cost associated with the memory retrieval of learned values. It seems that past experiences and symbolic descriptions of possible outcomes ultimately generate value representations different enough to make them largely incommensurable and that the tension between the two is resolved by overweighting (or prioritizing) symbolic information. In the following paragraphs we try to provide plausible reasons why these values representations radically differ, why symbolic information is favored in hybrid choices and which cognitive mechanisms could underly the behavioral pattern observed.

Symbolic descriptions of lotteries in our task (and in general) involve separate information about at least two different features of outcomes: payoffs (i.e., the amount of reward to be won or lost) and their probability (50). Models of decision-making designed to explain behavior in this kind of paradigms frequently assume that probability and payoffs are processed individually. For instance, in prospect theory and its extensions, different subjective weighting functions are supposed to apply to these variables (51–53, 14, 54). A separate representation of payoffs and probabilities is also assumed by models that do not suppose the calculation of a multiplicative expected utility (55) and by models supposing that decisions are underpinned by feature-by-feature comparisons (56–60). On the contrary, experience-based choices, as instantiated by simple reinforcement learning tasks, are usually modeled assuming that the decision-makers represents a unique numeric value for each state-action pair. The decision-maker can ‘look-up’ in this value matrix before making their choice and, once an outcome is obtained it partially overwrites the ‘cached’ values previously stored in memory, so that they approximate the average outcome (61). Option value representation is therefore structurally very different from that of description-based choices, because the relevant features (payoffs and probabilities) are never explicitly represented as separate attributes of the outcomes. Furthermore, some authors even suggest that reinforcement-based choices may bypass the calculation of reward-based option-specific values, and is underpinned by what is called direct policy learning (62–65). Our results seem to reject an extremely orthodox interpretation of direct policy learning (accuracy in the learning phase was sensitive to the value difference between options and experiential values were successfully generalized to new combinations). It is nonetheless plausible to conceive that - at least to some extent - reinforcement-based decisions involve a value-free (policy-based) component that can be hardly compared with the subjective extracted from explicit payoffs and probabilities. Functional neuroimaging investigations of experiential and symbolic decision-making may also shed light on the debate about value representation across modalities. While functional meta-analyses identified overlapping correlates of experiential and symbolic values (17–20), the putative neural mechanisms of reinforcement-based and description-based decisions differ in many crucial respects. First of all, the most influential and consensual neural models of reinforcement-based leaning and decision-making give a preponderant role to dopamine-induced neural plasticity circuits (66–68). More specifically dopamine-dependent plasticity is supposed to drive action selection by shaping the strength of the synapses between the frontal cortex and the basal ganglia (69, 70). Current neural models do not attribute to dopamine-driven processes and the basal ganglia a prominent role in description-based choices. Rather, they suppose that the decision process is solved by cortical circuits (71–74), following an evidence accumulation process similar to that observed for perceptual decisions (75, 76). Thus, structural differences in the neural mechanisms of choices across modalities may represent a biologically grounded bases of the representational difference between experiential and symbolic values.

The representational tension of hybrid choices is solved by subjects by neglecting the experiential values and basing their choices on the symbolic value. Several control analyses allowed us to formally exclude the possibility that this effect merely arise from insufficient knowledge of the experiential values. Why is the symbolic information preferred? We suggest two not-mutually exclusive explanations. One possibility is that experiential value estimates are perceived as less precise. Note here that precision represents the uncertainty about the value estimate itself (48). Indeed, assuming imperfect memory storage and retrieval, it is conceivable that experiential values are less precise compared to symbolic ones that can be perfectly calculated (77). According to this interpretation, subjects would quasi-systemically prioritize the more precise source of information for their choices (47, 48, 78). Another possibility is that subjects prefer discarding experiential information not to incur the cost associated with the cost of memory retrieval (79, 80). Reaction times analysis was overall consistent with this idea, because choices involving the processing of the experiential values were generally slower compared to those involving symbolic ones, even if balanced in objective difficulty (49). This latter interpretation leaves open the possibility that if one makes memory retrieval less costly, the behavioral pattern could be reversed (i.e., we would witness symbolic value neglect). This could be possible for example after extensive training, once experience-based choices are routinized (81) or, conversely, by making symbolic information harder to decode. These are interesting possibilities to be explored by future studies.

Finally, we speculate on the possible cognitive mechanisms underlying the experiential value neglect phenomenon and we identify two plausible candidates. The first mechanism involves ‘bottom-up’ attentional processes. It is well-documented that attentional focus biases evidence accumulation in value based decision-making (82, 83). It is therefore conceivable that an attentional bias toward symbolic options may result in prioritizing described information and neglecting experiential one. The second possible mechanism involves a 'top-down' heuristic process, according to which the calculation of individual option values is highjacked by a deterministic decision rules (44). Of note, even if we managed to demonstrate experiential value neglect in situations where it is disadvantageous (experiment 7), it can nonetheless be argued that this decision rule is overall adaptive, because computationally cheap and satisfying in most situations (see experiments 1–6).

To conclude, our results add to the collection of behavioral anomalies showing that values representations are inherently dependent on the way they are built, as it is postulated by the 'construction of preference' framework (84, 14, 85). More specifically, our findings pose serious challenges to the default assumption that values representations are shared across different decision-making modalities, traditionally referred to as experience- and description-based. The incommensurability between experiential and symbolic values results in behaving as if discarding acquired information and consequently entails suboptimal decisions. These findings are worth exploring outside the experimental setting because many real-life decisions involve a tension between an experiential and a symbolic component.

Declarations

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Figures

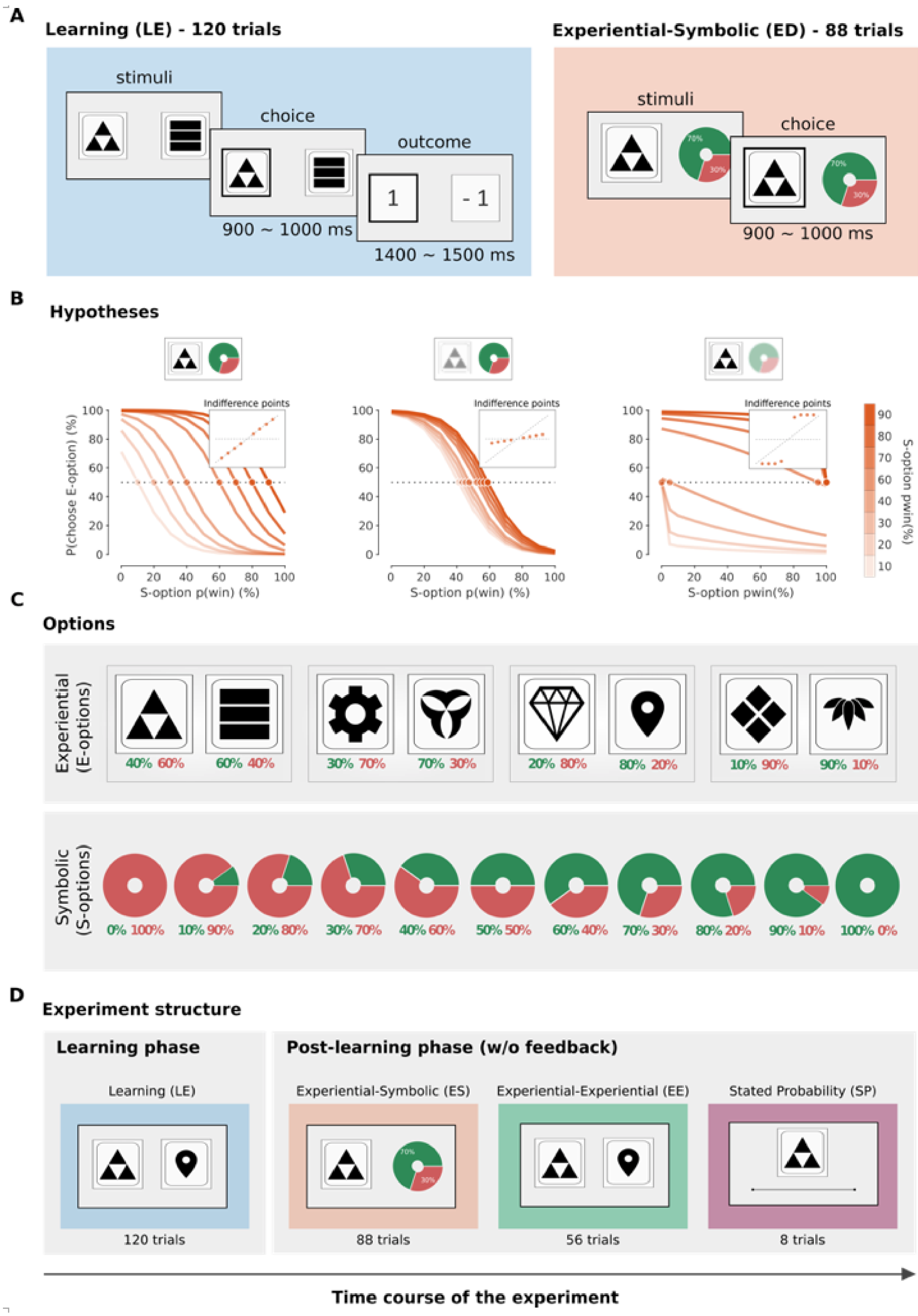

Figure 1

Behavioral tasks, hypotheses, option values and experimental protocol. (A) The leftmost panel displays successive screens of a typical trials in the learning phase (LE). The LE-phase consists in a two-armed bandit task with fixed (4 or 2 – in experiment 4) pairs of abstract cues (E-options) and contained 120 trials. The rightmost panel displays successive screens of a typical trials in the Experiential-Symbolic choice phase (ES). The ES-phase consists in binary choices between a lottery (standardly materialized as a pie-chart) and a symbol previously presented in LE-phase. In most experiments, the EE phase lasted 88 trials (8 E-options x 11 S-options). Durations are given in milliseconds. (B) The panels illustrate three possible hypotheses on how subjects could make choices in the ES-phase. In each panel the probability of chosen the E-option is plotted against the value of the S-option (expressed as probability of winning a point). The insets represent the indifference points (where the curves cross 50%; of not unbiased indifference points should lay on the diagonal). The color of the curves indicates the value of the E-option (lowest: light orange; highest: dark orange). The leftmost panel illustrate the default hypotheses according to which E-options and S-options are fully commensurable and therefore the curves cross 50% (indifference point) at exactly the value of the E-option. The central panel illustrates *experiential value neglect* scenario according to which ES-choices are determined (almost) uniquely by the value of the S-options. Finally, the rightmost panel illustrates the symbolic value neglect scenario, accordingly to which ES-choices are determined (almost) uniquely the value of the E-options. (C) The panel displays the options values. The topmost part shows how E-option were organized in learning contexts (in all experiment except Experiment 4 and 7; of note, the attribution of the value to the symbols was randomized across participants). The bottommost part shows the lotteries used in the ES phase (in all experiment except Experiment 7). (D) The experiments were structured as follows: they all started with a learning phase (LE), where subjects made choices between abstract symbols and received feedback information. After the LE phase, subjects were asked to make repeated choices between each E-option and several lotteries (see Fig. 1A and Fig. 1C). From Experiment 5 on, subjects were also asked to make choice between E-options that were not necessarily presented together. Finally, we assessed the stated probability (SP) of winning for each symbol by asking subjects to explicitly rate each E-option, following a probability matching procedure (*29*).

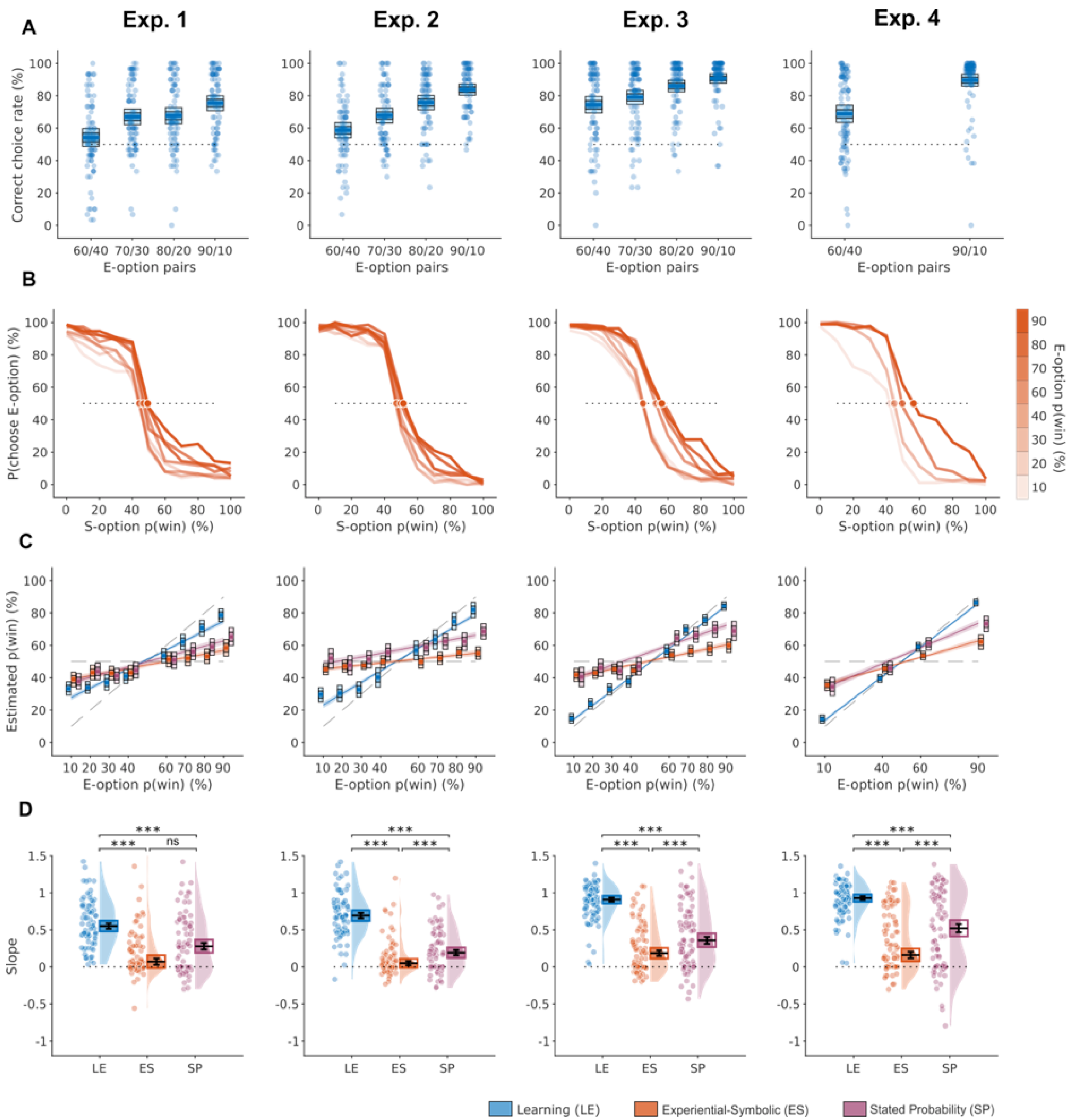

Figure 2

Raw behavioral results and inferred option values in Experiments 1-to-4. (A) Correct choice rate grouped per learning context in the LE phase, where '40/60' designated the hardest decision problem, '10/90' the easiest decision problem. The dark blue line indicates the mean, the mid-dark blue indicates the standard mean error, and the light blue indicates a 95% confidence interval. The dotted line indicates chance (or random) responding (50%). **(B)** Average probability of choosing an E-option over a S-option during ES phase. The color of the curves indicates the value of the E-option (lowest: light orange; highest: dark orange). Dots represent the empirical indifference points, the value of a lottery that corresponds to a probability of choosing the symbol 50% of the times. **(C)** The panels represent for each symbol the inferred value (as expressed by the probability of winning; p(win)) as a function of the actual value. ES estimates are represented in orange, LE estimates in blue and SP estimates in pink. In the data-boxes, the dark tone line represents the mean, mid-dark tone the standard mean error, light tone a 95% confidence interval. The lines represent linear regression (dark tone), and the average standard mean error (light tone). **(D)** Comparison of individual inferred slopes obtained from linear fit (see **Fig. 2C**) in the three modalities (LE, ES and SP in blue, orange and pink, respectively). The black lines represent mean and standard error of the mean. The colored boxes represent 95% confidence interval. The shaded area probability represents density functions. ***$p<0.001$ paired sample t-tests.

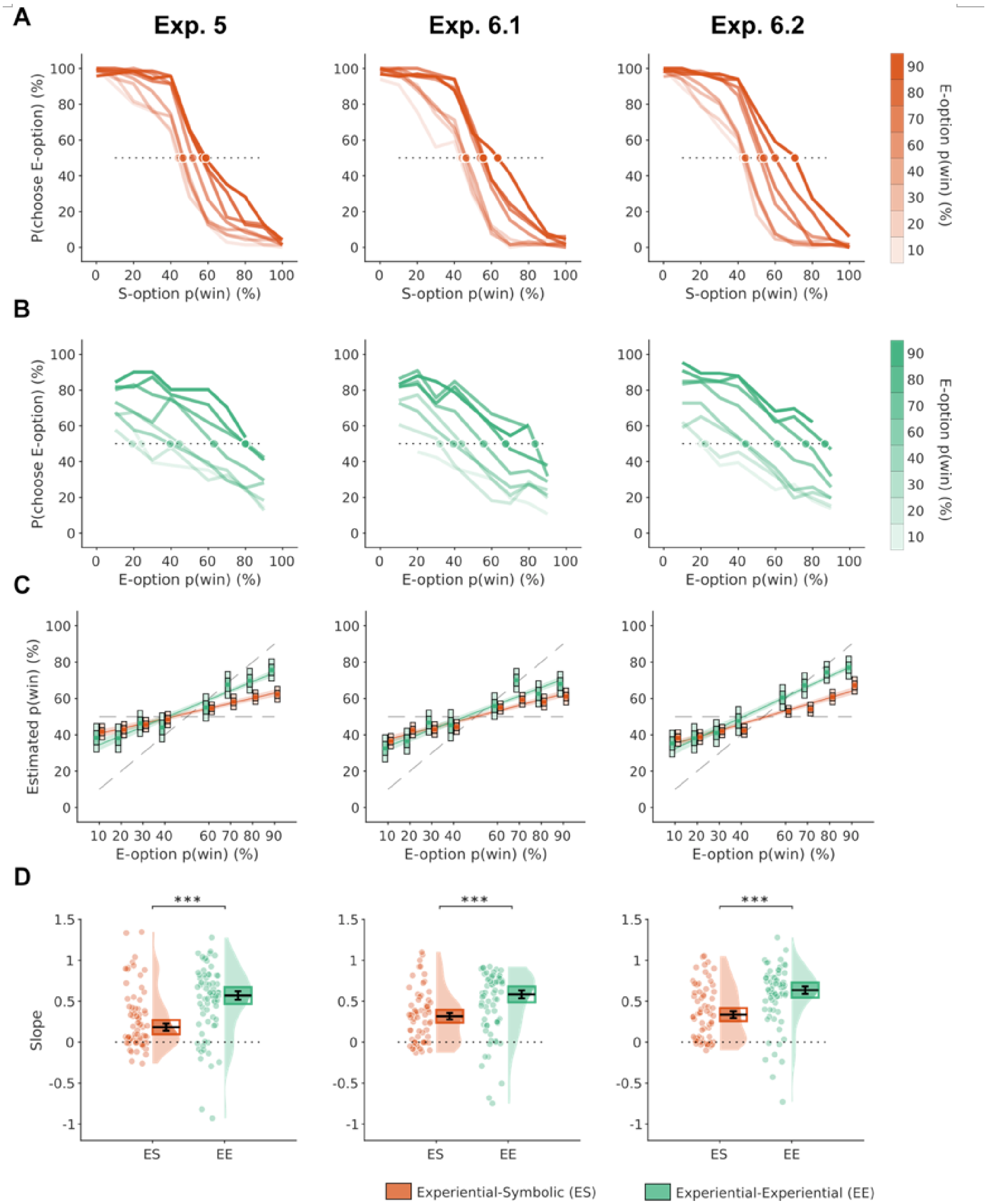

Figure 3

Raw behavioral results and inferred option values in Experiments 5-to-6. (A) Average probability of choosing an E-option over a S-option during ES phase. The color of the curves indicates the value of the E-option (lowest: light orange; highest: dark orange). Dots represent the empirical indifference points, the value of a lottery that correspond to a probability of choosing the symbol 50% of the times. Experiment 6.1 and Experiment 6.2 refers to the first and the second session, respectively **(B)** Average probability of choosing an E-option over another E-option during EE phase. The color of the curves indicates the value of the E-option (lowest: light green; highest: dark green). Dots represent the empirical indifference points, the value of a lottery that corresponds to a probability of choosing the symbol 50% of the times. **(C)** The panels represent for each symbol the inferred value (as expressed by the probability of winning; p(win)) as a function of the actual value. ES estimates are represented in orange and EE estimates in green. In the data-boxes, the dark tone line represents the mean, mid-dark tone the standard mean error, light tone a 95% confidence interval. The lines represent linear regression (dark tone), and the average standard mean error (light tone). **(D)** Comparison of individual inferred slopes obtained from linear fit (see **Fig. 3C**) in two modalities (ES and EE in orange and green, respectively). The black lines represent mean and standard error of the mean. The colored boxes represent 95% confidence interval. The shaded area represents probability density functions. ***p<0.001 two sample t-test.

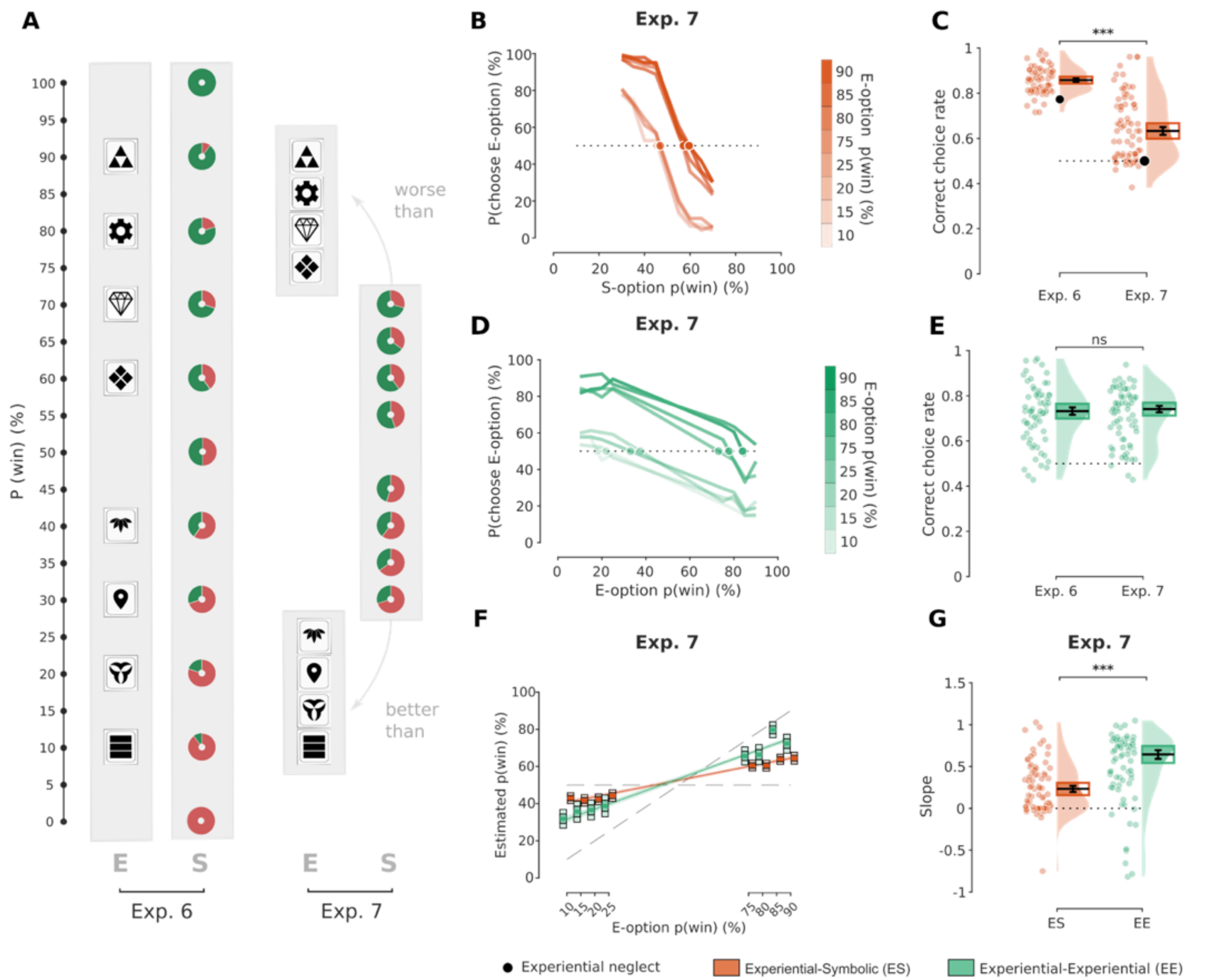

Figure 4

Option values and behavioral results in Experiment 7. (A) The panel shows and compare the options value in Exp .1-6 to that of Exp 7. In Exp. 7, we reorganized E-options and S-options values such that half of the E-options have higher expected-values than all S-options and, conversely the other half have lower expected-values. In such an arrangement, a subject fully neglecting the E-options values in the ES phase will end up with random choices in respect to utility maximization **(B)** Average probability of choosing an E-option over a S-option during ES phase. The color of the curves indicates the value of the E-option (lowest: light orange; highest: dark orange). Dots represent the empirical indifference points, the value of a lottery that correspond to a probability of choosing the symbol 50% of the times**. (C)** Expected value maximizing (i.e., correct) choices in the ES phase of Exp. 6 compared to Exp. 7. The black lines represent mean and standard error of the mean. The colored boxes represent 95% confidence interval. The shaded area probability represents density functions. ***$p<0.001$ two-sample t-test. **(D)** Average probability of choosing an E-option over another E-option during EE phase. The color of the curves indicates the value of the E-option (lowest: light green; highest: dark green). Dots represent the empirical indifference points, the value of a lottery that correspond to a probability of choosing the symbol 50% of the times. **(E)** Expected value maximizing (i.e., correct) choices in the EE phase of Exp. 6 compared to Exp. 7. The black lines represent mean and standard error of the mean. The colored boxes represent 95% confidence interval. The shaded area probability density functions. ***$p<0.001$ two-sample t-test. **(F)** The panel represents for each symbol the inferred value (as expressed by the probability of winning; p(win)) as a function of the actual value. ES estimates are represented in orange and EE estimates in green. In the data-boxes, the dark tone line represents the mean, mid-dark tone the standard mean error, light tone a 95% confidence interval. The lines represent linear regression (dark tone), and the average standard mean error (light tone). **(G)** Comparison of individual inferred slopes obtained from linear fit (see **Fig. 4F**) in two modalities (ES and EE; in orange and green, respectively). The black lines represent mean and standard error of the mean. The colored boxes represent 95% confidence interval. The shaded area probability represents density functions. ***$p<0.001$ paired two-sample t-test.

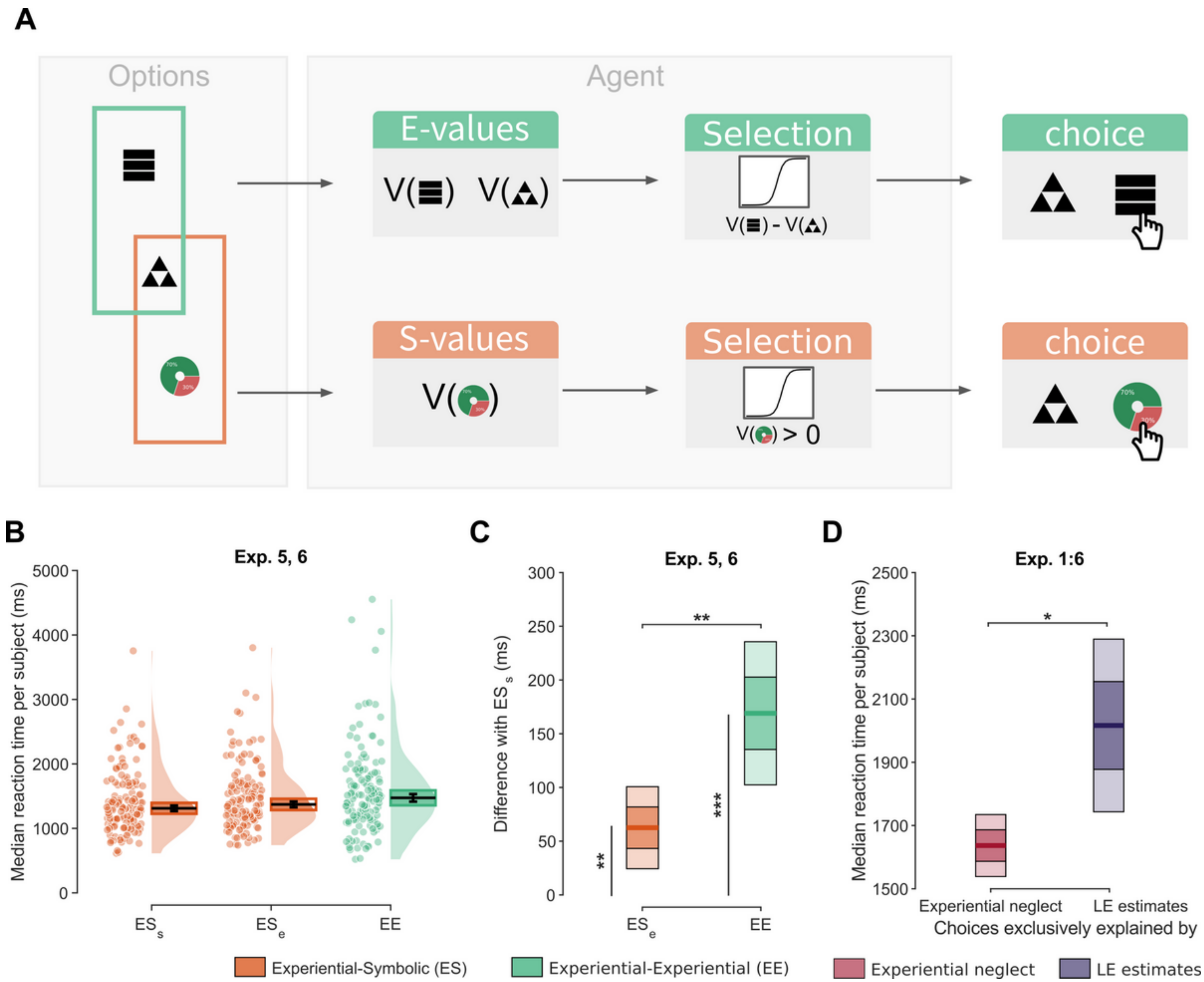

Figure 5

Hypothetical decision model and reaction times analyses (A) The panel presents a schematic representation of the decision process in the EE- and the ES- phases, respectively. The two processes differ in that in the former case (EE) the decision is based by retrieving the values of both options, while in the latter case (ES), under an extreme form of experiential value neglect, only the value of the lottery matters. **(B)** Median reaction times across modalities. EE decisions are significantly longer than ES decisions (regardless of the choice taken in ES). When comparing when an S-option is chosen (ES_s) and when an E-option is chosen (ES_e) we also observed a significant difference. The black lines represent mean and standard error of the mean. The colored boxes represent 95% confidence interval. The shaded area probability density functions. (**C**) Different in reaction times differences (ES_e – ES_s in orange; EE - ES_s in green). In the data-boxes, the dark tone line represents the mean, mid-dark tone the standard mean error, light tone a 95% confidence interval. **(D)** Reaction times as a function of whether the ES-choices could be only explained by a total neglect of the experiential value (red) or whether they could only be explained by experiential values estimated from the learning phase (dark blue). In the data-boxes, the dark tone line represents the mean, mid-dark tone the standard mean error, light tone a 95% confidence interval. *p<0.05, **p<0.01, ***p<0.001 paired two-sample t-test.

Supplementary Files

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