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Maximizing as satisficing: On pattern matching and probability maximizing in groups and individuals

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ABSTRACT

Distinguishing meaningful structure from unpredictable randomness is a key challenge in many domains of life. We examined whether collaborating three-person groups (n = 81) outperform individuals (n = 81) in facing this challenge with a two-part repeated choice task, where outcomes were either serially independent (probabilistic part) or fixed in a particular sequence (pattern part). Groups performed as well as the best individuals in the probabilistic part but groups' accuracy did not credibly exceed that of the average individual in the pattern part. Qualitative coding of group discussion data revealed that failures to identify existing patterns were related to groups accepting probability maximizing as a "good enough" strategy rather than expending effort to search for patterns. These results suggest that probability maximizing can arise via two routes: recognizing that probabilistic processes cannot be outdone (maximizing as optimizing) or settling for an imperfect but easily implementable strategy (maximizing as satisficing).

1. Introduction

> To live on a day-to-day basis is insufficient for human beings; we need to transcend, transport, escape; we need meaning, understanding, and explanation; we need to see overall patterns in our lives.
> Oliver Sacks (2012, p. 90)

The ability to perceive structure, detect rules, and extract associations is a hallmark feature of human cognition, vital for understanding and navigating the complex world people live in. Yet people often perceive patterns where there are none—in random sequences or unconnected events (Bar-Hillel & Wagenaar, 1991; Oskarsson et al., 2009). This well-documented misperception of randomness has been thought to give rise to striking violations of rational choice in simple repeated decisions under uncertainty (e.g., Gaissmaier & Schooler, 2008). When asked to repeatedly predict the next of two possible outcomes (e.g., whether a colored square will appear above or below a fixation cross) people often *probability match* by selecting available choice options in proportion to the options' relative rates of success. In random sequences of events, however, prediction accuracy is best achieved by *probability maximizing*: Exclusively selecting the option with the higher outcome probability. This is because the expected accuracy from selecting the infrequent event never exceeds that of selecting the frequent event. Although probability matching violates the principle of stochastic dominance, a cornerstone of rational choice theory, it has been demonstrated in numerous studies of human decision making, attracting broad theoretic interest in psychology and economics (for reviews see, e.g., Koehler & James, 2014; Newell & Schulze, 2017; Vulkan, 2000).

Why do people probability match in decision making under uncertainty? The classic, economic perspective dismisses probability matching as a simple mistake revealing that imperfect cognitive processes underlie human decision making (e.g., Koehler & James, 2009; Vulkan, 2000; West & Stanovich, 2003). Supporting this view, probability matching has been found to be less prevalent in individuals with high cognitive abilities (West & Stanovich, 2003), and markedly reduced when sufficient experience and incentives are provided (Newell & Rakow, 2007; Shanks et al., 2002) or when applicable choice strategies are described before the task (Koehler & James, 2010). Moreover, when groups rather than individuals repeatedly predicted the outcome of the roll of a die with a known color configuration, probability matching was nearly eradicated by the greater cognitive resources of a small group of people (Schulze & Newell, 2016a). This last finding

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suggests that the erroneous nature of probability matching can be demonstrated and overridden in small group discussions—even if a large portion of a group's members initially hold different beliefs.

Yet probability matching may not always be due to faulty cognition. Under some circumstances, it may instead result from cognitively well-adapted strategies that map onto the structure of complex choice environments (e.g., Gaissmaier & Schooler, 2008; Green et al., 2010; Plonsky et al., 2015; Schulze et al., 2015, 2017). For instance, people may probability match because they do not realize or believe that a sequence of events is random and thus attempt to outperform probability maximizing by finding a predictable pattern (Gaissmaier & Schooler, 2008; Peterson & Ulehla, 1965; Unturbe & Corominas, 2007; Wolford et al., 2004). Because any predictable pattern must match the outcome frequencies, at the outcome level, this exploratory search would result in probability matching. Supporting this notion, Gaissmaier and Schooler (2008) showed that individuals who probability matched in the absence of patterns were more likely to detect regularities introduced later on than individuals who maximized. Moreover, assuming a cognitive process that exploits environmental regularities by focusing on contingencies in past experiences has been shown to account for probability matching behavior and other behavioral phenomena in experience-based decisions (Plonsky et al., 2015; see also Szollosi et al., 2019).

Here, we bridge research on probability matching and group decision making, which allows us to (i) identify whether small groups can harness effective probability maximizing without missing important regularities and (ii) use qualitative group discussion data to gain insight into prevalent causes underlying both probability matching and probability maximizing. Distinguishing meaningful structure from unpredictable randomness is a key challenge of daily life—for example, when evaluating health outcomes or the validity of evidence. Our study tests whether collaborating three-person groups outperform independent individuals in facing this challenge with a repeated choice task that consisted of two parts (in counterbalanced order; adapted from Gaissmaier & Schooler, 2008). In the probabilistic part, outcomes were serially independent and probability maximizing was the optimal strategy; in the pattern part, a randomly generated sequence was repeated many times and choice optimality was reflected in participants' pattern accuracy.

1.1. Group choice in a patterned environment

How will groups perform compared to individuals in this partly patterned choice environment? Previous research supports diverging predictions. One possibility is that groups' augmented cognitive resources help them to adopt a maximizing strategy when outcomes are random (as has been shown in repeated choice without probability learning; see Schulze & Newell, 2016a) and to engage in more effective rule-searching and pattern-memorization when a pattern exists. This prediction is consistent with research on group multiple-cue judgment, in which groups surpassed their members' performance due to better encoding and storage of exemplars in memory (Olsson et al., 2006). A second possibility is that group performance is superior in the first, but not the second part of the task. If the group identified an existing pattern in the first part, individual group members may be more reluctant to abandon search efforts later on; if the group experienced (and demonstrated) probability maximizing as the optimal solution in the first part, subsequent pattern search efforts may be undermined. Supporting this prediction, groups have been found to lose their advantage over individuals in risky choice when the environment changes unexpectedly (Lejarraga et al., 2014, but see Kämmer et al., 2013). A final possibility is that groups show a general bias toward a static maximizing strategy, which may be easier to coordinate and negotiate between the group members. That is, to implement a mixed strategy such as probability matching, the group members need to work out trial-by-trial when to switch between the options. Probability maximizing, by contrast, involves simply repeating responses to the same option. In other words, the previously observed group advantage in repeated risky choice (Schulze & Newell, 2016a) may simply be due to the lower coordination costs of probability maximizing compared to a mixed strategy such as probability matching (similar to coordination losses in other group tasks; see Steiner, 1972).

1.2. Maximizing as optimizing versus satisficing

This conceptualization of probability maximizing as a suboptimal response in group decision making casts new light on a strategy that is typically considered superior in standard repeated choice. In fact, previous research has almost uniformly regarded probability maximizing as an optimizing response that may result from either a deliberative "top-down" process culminating in the understanding that a random process cannot be outdone (e.g., Koehler & James, 2010) or a learning-driven, "bottom-up" process that reinforces maximizing as the more profitable strategy (e.g., Newell et al., 2013; Newell & Rakow, 2007). A possibility that has not been widely considered is that probability maximizing may, in some contexts, instead serve as a shortcut aimed at keeping processing costs low (but see Koehler & James, 2014, for a discussion of "dumb maximizing"). Here, we suggest that there are two routes that lead people to maximize probability in repeated choice: (1) they understand that the choice task involves a random process that cannot be outdone—*maximizing as optimizing*—or (2) they suspect that patterns exist in the outcome sequence but believe these regularities would be too difficult or effortful to identify, and adopt probability maximizing as a "good enough" strategy—*maximizing as satisficing* (see Simon, 1956). The notion of maximizing as satisficing may be notably more prevalent in groups than individuals because it provides the group with a justification for evading a diligent but laborious search for a perfect solution that individuals might be more willing to undertake (see Steiner, 1972).

In sum, our approach extends an ongoing debate in cognitive psychology on the adaptive merits versus faulty perils of probability matching by providing an integrative perspective on the cognitive strategies underpinning both pattern matching and probability maximizing in groups as well as individuals.

2. Method

2.1. Participants

A total of 162 participants (91 female) were recruited via the subject pool of the Max Planck Institute for Human Development. The sample size was determined via power calculation (using G*Power software) such that we would achieve sufficient statistical power to detect a medium between-subjects effect of group versus individual choice across all blocks of the choice task. The majority of participants (69.75%) self-identified as students and the average age was 25.72 years (SD = 3.98, range 18–35 years). Participants earned a performance-contingent payment (earnings ranged from 5.38 EUR to 9.30 EUR) and an additional flat fee of 10 EUR. The experiment was reviewed and approved by the institutional review board (IRB) of the Max Planck Institute for Human Development and all participants gave informed consent to take part in the study.

2.2. Design and procedure

We invited groups of three people to the lab. Twenty-seven groups of three participants each were assigned to one of two conditions based on simultaneous (or consecutive) attendance: individual choice (n = 81) or group choice (n = 81). Participants in the individual choice condition were seated at separate computers and completed the task independently; participants in the group choice condition were seated at the same computer in a larger space and worked together on the task.

All instructions and discussions were in German. The group discussions of participants in the group choice condition were video-recorded during the experiment and each participant in this condition gave explicit consent to the recordings being used for data analysis.[2] The choice task was adapted from Gaissmaier and Schooler (2008) and involved repeated binary decisions over 576 trials. In each trial, participants (groups or individuals) were asked to predict whether a colored square would appear above or below a fixation cross on a computer screen by using the arrow keys on the keyboard. The square appeared in one location with a probability of $p = .67$ and in the other with $1 - p = .33$. To aid discriminability, squares that appeared above the fixation cross were in a different color than squares that appeared below the fixation cross: the squares were either red or green (counterbalanced across participants for red/green positions and for upper/lower majority outcome locations). Participants were informed that one outcome may occur more often than the other but had to learn the outcome frequencies from repeated choice experience. They received no information on whether a pattern was present or absent in the sequence of outcomes. Participants in the group choice condition were encouraged to discuss before making a decision on each trial but were free to make their decisions as they saw fit, that is, we did not impose a predefined decision rule. Group members were also asked to take turns occasionally at using the keyboard and, when coding the group discussion data, we confirmed that the large majority of groups complied with this instruction. In one group, a single member implemented all joint decisions; in two further groups, two members implemented all decisions. Excluding these groups from the behavioral analyses did not affect the pattern of effects we observed. The verbatim instructions given to groups and individuals are provided in Appendix A. Following each choice, a colored square appeared at the top or bottom of the screen and correct predictions were rewarded with two cents for each person, irrespective of whether participants completed the task as part of a group or individually. Choice trials were self-paced and participants pressed the space bar to advance to the next trial after observing outcome feedback. Each person's ensuing payoff was updated continuously on the screen and participants were encouraged to earn as much money as possible. Before the start of the choice task, participants were given 10 training trials that were not incentivized in order to familiarize them with the controls of the task.

The choice task was split into two parts with 288 trials each: a probabilistic half and a pattern half. The order of the halves was counterbalanced. In the probabilistic half, the sequence of outcomes was serially independent and the primary dependent measure was participants' proportion of choices to the more probable outcome (maximizing rate). In the pattern half, a randomly generated outcome sequence of length 12 (with constraint $p = .67$) was repeated 24 times and the primary dependent measure was participants' proportion of correct predictions (pattern accuracy). For example, the pattern might follow the form 110100111011, where the probability of the majority outcome was $p = .67$ (i.e., 8/12); we analyzed how often participants correctly predicted each outcome. Patterns were yoked between conditions such that the same number of participants in both conditions were exposed to exactly the same randomly generated patterns to ensure similar overall detectability. During a self-paced break between the two parts, participants were reminded that the second half could be different. The more common outcome of the first half was reversed in the second half in order to make it easier for participants to detect potential changes in the outcome structure (see Gaissmaier & Schooler, 2008). In addition to analyzing choice data, we also recorded response times and participants' overall completion times for all parts of the experiment. Because groups were encouraged to discuss in each trial, which choice to make, and to take turns occasionally at using the keyboard, we expected the interacting groups to need more time for completing the choice task (cf. Schulze & Newell, 2016a). Indeed this is what we found; groups completed both the probabilistic and pattern half of the task considerably slower than individuals. These findings are summarized and discussed in Appendix B.

Following the choice task, each participant completed a short questionnaire on a computer by themselves. Participants were asked to provide demographic data and to answer questions about the underlying probabilistic structure, their strategy use, and, if applicable, their group's decision process during the choice task. The data from the post-task questionnaire indicated that groups and individuals did not systematically differ in how they perceived the probabilistic structure of the task nor in the prevalence with which they indicated noticing regularities in the outcome sequence; these findings are summarized in Appendix C.

2.3. Coding of group discussion data

The group discussions that participants engaged in during the experiment were video-recorded and transcribed for analysis. A total of 18,007 statements were made by the groups during the experiment ($M = 666.93$, $SD = 384.47$, range 130–1360); statements were defined as any verbal expression made by a group member that was confined either by a pause or a switch of the speaker. We developed a coding scheme for analyzing the content of the expressed statements based on theoretical consideration of cognitive processes previously proposed to underlie people's decisions in probability learning paradigms—such as win-stay, lose-shift (e.g., Gaissmaier & Schooler, 2008; Otto et al., 2011)—and with the aim of differentiating between strategies that conceptualize maximizing as satisficing and strategies that conceptualize maximizing as optimizing. We hypothesized that an optimizing maximization strategy might, for instance, include explicit reference to the randomness of the process, speculation about the absence of patterns in the outcome sequence, or the realization that the optimal response in a probabilistic choice task entails accepting the losses associated with implementing it. By contrast, if groups maximized with the goal of finding a “good enough” strategy, they might highlight the relative payment and time effectiveness of maximizing or speculate about potential patterns being too complex to identify or pattern search too effortful to be practical. Note that these concepts of maximizing as satisficing and maximizing as optimizing need not be considered as mutually exclusive and that verbalizations indicative of either strategy may, at least to some extent, overlap. For instance, highlighting the randomness of the generating process may entail some level of satisficing in the sense that, in theory, the laws of physics determine each outcome unambiguously but, in practice, these outcomes cannot be predicted based on the available information. Nonetheless, people have been shown to intuitively differentiate between the concepts of epistemic or “knowable” uncertainty (e.g., a pattern that has not yet been identified) and aleatory or “random” uncertainty (e.g., the roll of a dice) in both their use and interpretation of natural language (Ülkümen et al., 2016). The coding scheme was devised to test whether the concepts of maximizing as satisficing and optimizing are, in principle, distinguishable. The resulting coding scheme was then revised and refined by inspecting approximately 15% of the group discussion data (four of 27 groups). The final coding scheme was validated on another 15% of the group discussions by two independent raters. The inter-rater agreement for main and substrategy classifications was excellent

[2] We chose not to record the deliberations of individuals (e.g., via think-aloud instruction) because our focus is on the nature of group interactions and their influence on strategy development and selection. We acknowledge that certain types of concurrent verbal expressions can alter performance (see, e.g., Ericsson & Simon, 1980). In this specific task, however, earlier work suggests that giving individuals additional time to deliberate and reflect on their decisions did not confer the advantages that emerge from group discussion (see Schulze & Newell, 2016a). Moreover, our findings suggest that an important factor in determining group performance was how the group reached consensus when making decisions rather than how the group members perceived the task relative to independent individuals (see also Appendix C).

Table 1
Coding scheme for analyzing group discussion data, number of statements made for each coded category, and number of groups making at least one statement in a category.

Category	Description	Example statement(s)	Number of statements	Number of groups
Probability maximizing				
Accept loss	Accepting losses associated with probability maximizing	It's more likely that the outcome appears at the top. That's why it makes sense to always press the up button. Then we forgo the 40% that we lose.	24	14
Explicit maximizing	Explicit suggestion to maximize probability	We try to figure out whether up or down is more likely and then we stick with where it is more likely.	222	24
Pattern absent	Patterns are likely absent or no patterns could be identified	I don't think that there is a pattern.	93	25
Pattern difficult	Patterns are too complex or pattern search is too effortful	There might have been a pattern over, say 50 outcomes, but we couldn't have figured that out anyway.	25	9
Pattern trivial	There must be more to the task than identifying a simple pattern/rule	I think it would be too trivial if it was just a simple series.	9	7
Pay effectiveness	Reference to the relative payment effectiveness of maximizing	We can win at least half of the pay if we simply stick with red. I think we should stick with red, because I think we won't win anything from starting to guess a lot. We have more than 50% correct, which means this strategy has proven to be successful.	113	20
Random	Reference to the randomness of the sequence/process	It's chance. It's like throwing a coin—a loaded coin. It's a game of chance, like throwing a die.	67	20
Time effectiveness	Reference to the relative time/effort effectiveness of maximizing	Always press red. Then we'll be finished quickly.	11	7
Probability matching				
Avoid loss	Avoiding losses associated with maximizing	This way [by maximizing] we always let some money slip through our fingers.	8	6
Explicit matching	An explicit suggestion to match the frequency of outcomes	Now we do 70/30 and if we observe that it becomes 60/40 again, we reduce our responses.	54	1
Gambler's fallacy	Statement indicates that the gambler's fallacy was committed	The more often we predict red, the more likely it becomes that it will be green eventually. Now we can almost bet on it being up, because it can't stay down forever.	55	19
Maximizing trivial	There must be more to the task than maximizing	If we only pressed one button that would be too simple, right?	5	4
Memorize	Explicit suggestion to memorize patterns or technique to memorize sequences	I think each of us should memorize part of the sequence. We can split up and each of us memorizes 10 [outcomes] at a time.	59	12
Pattern analysis	A previous or recalled sequence of outcomes is analyzed for its structure in order to identify a pattern	Maybe it always adds up to five, so that it's green three times and red twice and then green four times and red once. Green never occurs more than twice in a row.	829	27
Pattern ID	Identification of a distinctive run or “sub-pattern”	Exactly this rhythm: Twice up, once down, three times up, once down, I think. Now comes the six streak again.	997	25
Pattern reference	Reference to the possibility of the existence of patterns	Maybe there is some kind of pattern. Shall we look for a system again? Do you get the sense that there's a pattern behind this?	131	25
WSLS	A win-stay, lose-shift rule is applied	For a while, always repeat the outcome that was just correct.	64	20
Other				
Alternating outcomes	Outcomes are likely to alternate	Right now it's going back and forth, back and forth.	103	21
Clarify	Clarification of (part of) the instructions/task	There are more than 200 decisions that we need to make, right? Two hundred and eighty-eight I think.	222	27
Count	Participants are counting out loud or express/suggest a counting rule	One of us can count how often it is up, one counts how often it is down, and one counts the total number of trials. Then, after 20 trials, we know which side is more probable. We need to count how often it goes back and forth; so far we had red once, green once.	1258	27
Evaluate	Evaluation of past predictions	We have twice as many correct predictions as we have wrong ones.	239	27
Hypothesis	(Meta-)hypothesis about the structure/point of the task above and beyond the use of matching and maximizing	Maybe the computer program is reacting to us. The more we choose down, the more it does up and maybe this has to do with how we press the buttons. I think one of us is a mole. I wonder why there are two parts. Maybe in the second part something will be different.	331	26
Probabilities	Probability or frequency judgment	In 80% of the cases it is up. Now it's almost 50/50, right? Or is it still down more often?	512	27

(Cohen's $\kappa = 0.94$–0.95, Krippendorf's $\alpha = 0.94$–0.95; Cohen, 1960; Krippendorff, 1970) and the remaining discussion data were coded by a single rater.

The final coding scheme is summarized in Table 1 and consists of 23 strategies that can be attributed to (1) a probability maximizing scheme, (2) a probability matching approach, or (3) neither (both) of these approaches. The table also lists the total number of statements categorized as indicative of each strategy (each statement was coded to be indicative of at most one strategy) and the number of groups that expressed at least one statement belonging to a particular category; on average, 33.76% ($SD = 11.97\%$, range 14.99%–62.50%) of a group's expressions were coded as strategy statements. In addition to coding strategy use, we also identified statements referring to a particular group process (e.g., a majority rule or an explicit suggestion to discuss the next decision). These statements accounted for a rather small fraction of all expressions ($M = 5.13\%$, $SD = 2.60\%$, range 1.37%–15.38%), however, and were not notably related to any of the behavioral measures; therefore, these data were not considered further (see also Appendix C for the role of self-reported group processes in accounting for the behavioral data). Finally, we also coded what prediction group members verbalized and whether a statement indicated a particular level of confidence in this prediction or a proposed strategy; these data were not considered further.

2.4. Data analysis

All data are available via the Open Science Framework and can be accessed at https://osf.io/pmaby/. In addition to using conventional methods of null hypothesis significance testing, we conducted Bayesian inference, for which we report Bayes factors that quantify how much more likely it is for the data to have occurred under one hypothesis than another. All Bayes factors were estimated in JASP (v.0.11.1; JASP Team, 2019) using the default priors. For Bayesian ANOVAs, JASP provides inclusion Bayes factors (denoted as $BF_{\text{Inclusion}}$) that quantify the strength of evidence for the presence of a particular effect averaged across models that include that effect (see, e.g., Wagenmakers et al., 2018). For all remaining Bayesian analyses, we report Bayes factors that quantify the strength of evidence in favor of the alternative hypothesis (denoted as BF_{10}), where $BF_{10} > 1$ indicates support for the alternative hypothesis and $BF_{10} < 1$ indicates support for the null hypothesis. For all conventional ANOVAs in which the sphericity assumption was violated, the degrees of freedom were corrected using the Greenhouse and Geisser coefficient.

3. Results

We first examine the behavioral choice data of groups and individuals, then relate the qualitative group-discussion data to the behavioral findings.

3.1. Behavioral choice data

3.1.1. How do groups compare to individuals?

We compared the performance of the collaborating three-person groups to that of the best, second-best, and third-best of three randomly selected independent individuals, separately for each half of the choice task (see, e.g., Laughlin et al., 1991; Schulze & Newell, 2016a). In the probabilistic half, individual ranks were assigned based on the proportion of participants' choices of the more probable outcome (maximizing rate) within each set of three independent individuals. In the pattern half, individual ranks were assigned based on the proportion of correct predictions (pattern accuracy). Where two or more individuals returned identical choice proportions/accuracies, we assigned rank positions randomly. The proportions of groups' and individuals' maximizing rates in the probabilistic half, shown in Fig. 1a, were subjected to a mixed model ANOVA with the within-subjects factor block (three blocks of 96 trials each) and two between-subjects factors, choice condition (groups, best, second-best, and third-best independent individuals) and order of presentation (probabilistic vs. pattern half first). Groups' and individuals' proportions of probability maximizing choices significantly increased across blocks of the probabilistic part, $F(1.89, 188.78) = 58.74$, $p < .001$, $\eta_p^2 = 0.370$, $BF_{\text{Inclusion}} = 2.30 \times 10^{14}$, and we found significant differences in the maximizing rate between groups and individuals at different rank levels, $F(3, 100) = 24.13$, $p < .001$, $\eta_p^2 = 0.420$, $BF_{\text{Inclusion}} = 1.11 \times 10^9$. Comparing group choice proportions to individual choice at each rank level, Tukey's HSD test-based conventional post-hoc analyses and follow-up Bayesian *t*-tests showed that groups performed as well as the best individuals ($p = .963$, $BF_{10} = 0.29$), but selected the more probable outcome significantly more often than the second-best ($p = .009$, $BF_{10} = 9.21$) and third-best individuals ($p < .001$, $BF_{10} = 81{,}564.29$). Moreover, groups' maximizing rate was credibly higher than that of the average individual, $t(106) = 3.16$, $p = .002$, $d = 0.70$, 95% CI = 0.26–1.15, $BF_{10} = 16.32$. Additionally, participants who completed the probabilistic half second showed higher maximizing choice proportions than those who completed the probabilistic half first, $F(1, 100) = 13.37$, $p < .001$, $\eta_p^2 = 0.118$, $BF_{\text{Inclusion}} = 30.48$—possibly because they had already learned that the outcome probabilities were uneven. Groups and individuals in different ranks did not differ in this effect of presentation order; that is, there was no interaction between presentation order and choice condition, $F(3, 100) = 0.08$, $p = .969$, $\eta_p^2 = 0.002$, $BF_{\text{Inclusion}} = 0.21$. No other effects in this analysis were statistically significant (all $ps \geq .207$ and all $BF_{\text{Inclusion}} \leq 0.32$).

The proportions of groups' and individuals' accurate predictions in the pattern half, shown in Fig. 1b, were subjected to a 4 (choice condition) × 2 (presentation order) × 3 (blocks of 96 trials each) mixed model ANOVA. Groups' and individuals' pattern accuracy increased across blocks of the pattern half, $F(1.65, 164.84) = 250.57$, $p < .001$, $\eta_p^2 = 0.715$, $BF_{\text{Inclusion}} = 2.87 \times 10^{13}$, and we again found significant differences in pattern accuracy between groups and individuals at different rank levels, $F(3, 100) = 14.24$, $p < .001$, $\eta_p^2 = 0.299$, $BF_{\text{Inclusion}} = 4.26 \times 10^7$. Comparing groups' pattern accuracy to that of individuals at each rank level, Tukey's HSD test-based conventional post-hoc analyses and follow-up Bayesian *t*-tests showed that groups identified patterns slightly but not significantly *less* accurately than the best individuals ($p = .873$, $BF_{10} = 0.34$), no better than the second-best individuals ($p = .098$, $BF_{10} = 1.75$), and significantly more accurately than the third-best individuals ($p < .001$, $BF_{10} = 3165.56$). In fact, group pattern accuracy was not credibly higher than that of the average individual, $t(106) = 2.42$, $p = .017$, $d = 0.54$, 95% CI = 0.10–0.98, $BF_{10} = 2.88$. Moreover, individuals' pattern accuracy increased more continuously across blocks than that of groups, as evidenced by a significant interaction between choice condition and trial block, $F(4.95, 164.84) = 5.16$, $p < .001$, $\eta_p^2 = 0.134$, $BF_{\text{Inclusion}} = 900.29$. There was no effect of presentation order, $F(1, 100) = 2.93$, $p = .090$, $\eta_p^2 = 0.029$, $BF_{\text{Inclusion}} = 0.66$, no interaction of this factor with choice condition, $F(3, 100) = 0.20$, $p = .896$, $\eta_p^2 = 0.006$, $BF_{\text{Inclusion}} = 0.28$, and no other statistically significant effects in this analysis (all $ps \geq .078$ and all $BF_{\text{Inclusion}} \leq 0.78$). Thus, *on average*, groups were better at maximizing than the average individual, but not better at pattern matching.

Examining pattern accuracy at the level of individual groups and participants, however, suggests a somewhat different conclusion. Fig. 2 displays the distributions of groups' and individuals' maximizing rate (panel a) and pattern accuracy (panel b) toward the end of learning in the final trial block of each half. The distributions of groups' and best individuals' maximizing rate, as shown in Fig. 2a, were highly similar and nine groups and eight best individuals maximized during the final block of the probabilistic half (probability maximizing was defined as selecting the more probable option on no less than 95% of trials; see, e.g., Newell & Rakow, 2007). By contrast, the distribution of groups' pattern accuracy in the final trial block, as shown in Fig. 2b, was more

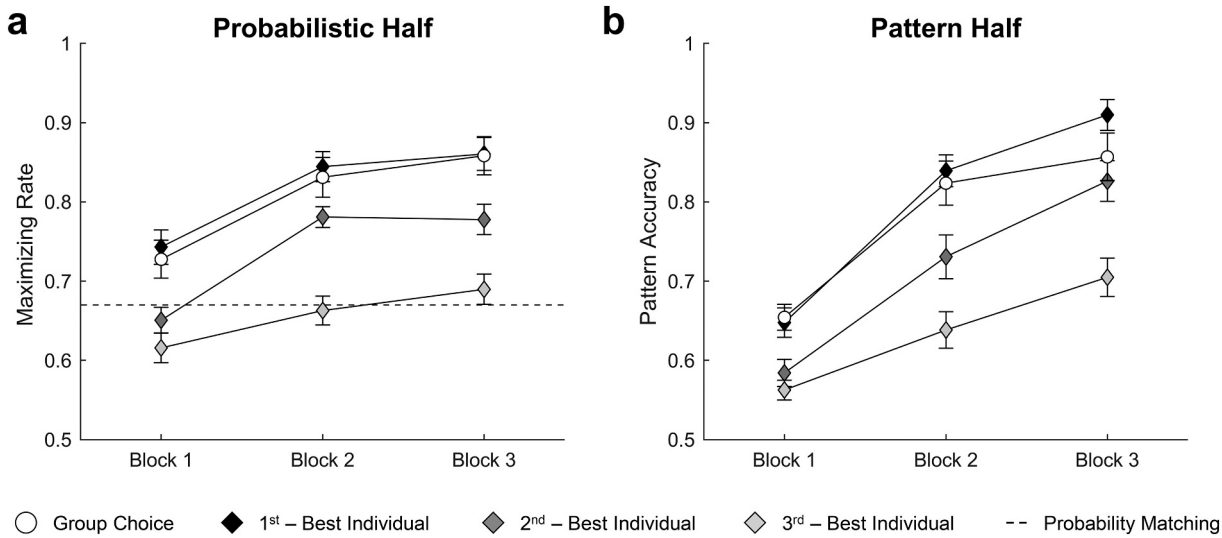

Fig. 1. Groups' and individuals' mean (± SEM) proportion of choices of the more probable option in the probabilistic half (a) and proportion of correct predictions in the pattern half (b) for three blocks of 96 trials each. For the probabilistic half, probability matching is indicated by the dashed line at 0.67.

bimodal than the distributions of individuals' pattern accuracy at each rank level. Specifically, the majority of groups accurately identified the pattern but other groups selected the more probable option exclusively (peak at 0.67). That is, although similar numbers of groups and best individuals (14 groups vs. 16 individuals) identified the pattern during the final block—defined as predicting the correct outcome on no less than 95% of trials—a substantial number of groups (26%) performed systematically worse than the best individuals because they attempted to maximize probability instead of searching for a predictable pattern. This propensity toward probability maximizing when a pattern was present was more prevalent when groups experienced the probabilistic half first (five of seven groups that maximized toward the end of the pattern half experienced this part second), although there was no overall effect of presentation order (see above).

3.1.2. What is the relationship between probability matching and pattern accuracy?

Fig. 3 shows the full distribution of groups' and individuals' performance toward the end of learning in each part of the task by plotting participants' pattern accuracy in the final block as a function of their maximizing rate in the final block. We subdivided groups and individuals into four subclasses: participants who identified the pattern with at least 80% accuracy in the final block of the pattern half but did not reach a maximizing rate of at least 80% in the probabilistic half (pattern matchers); participants whose maximizing rate in the final probabilistic block was at least 80% but who did not identify the pattern with at least 80% accuracy (probability maximizers); participants who achieved at least 80% on both pattern accuracy and maximizing rate (smart responders), and participants who did not achieve 80% or more on either. Fig. 3 shows that both groups and individuals who accurately identified the pattern were widely distributed across

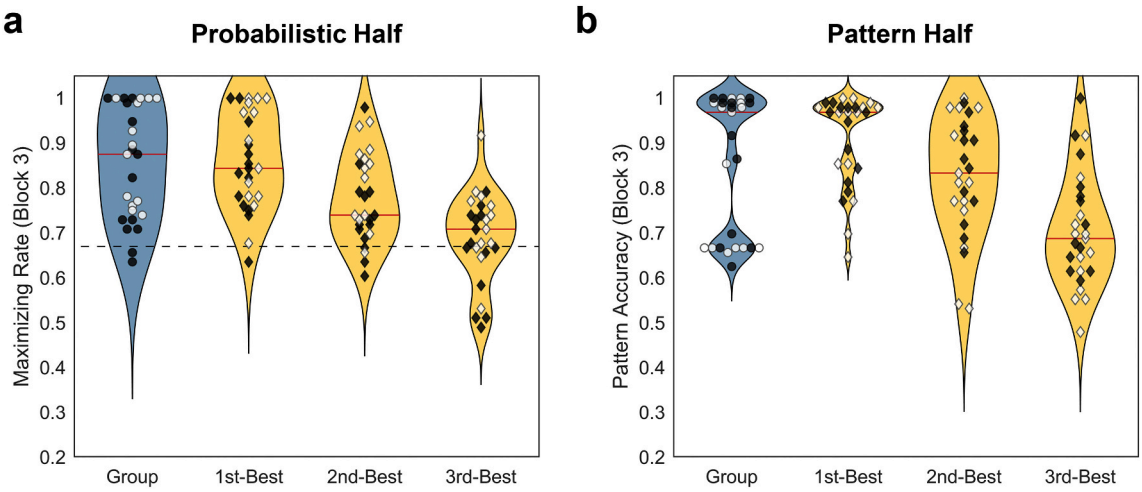

Fig. 2. Distributions and medians (red lines) of the proportion of choices of the more probable option in the final block of the probabilistic half (a) and the proportion of correct predictions in the final block of the pattern half (b) for groups and the best, second-best, and third-best individuals. Colors indicate whether groups and individuals completed a particular half first (black circles/diamonds) or second (white circles/diamonds). For the probabilistic half, probability matching is indicated by the dashed line at 0.67. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

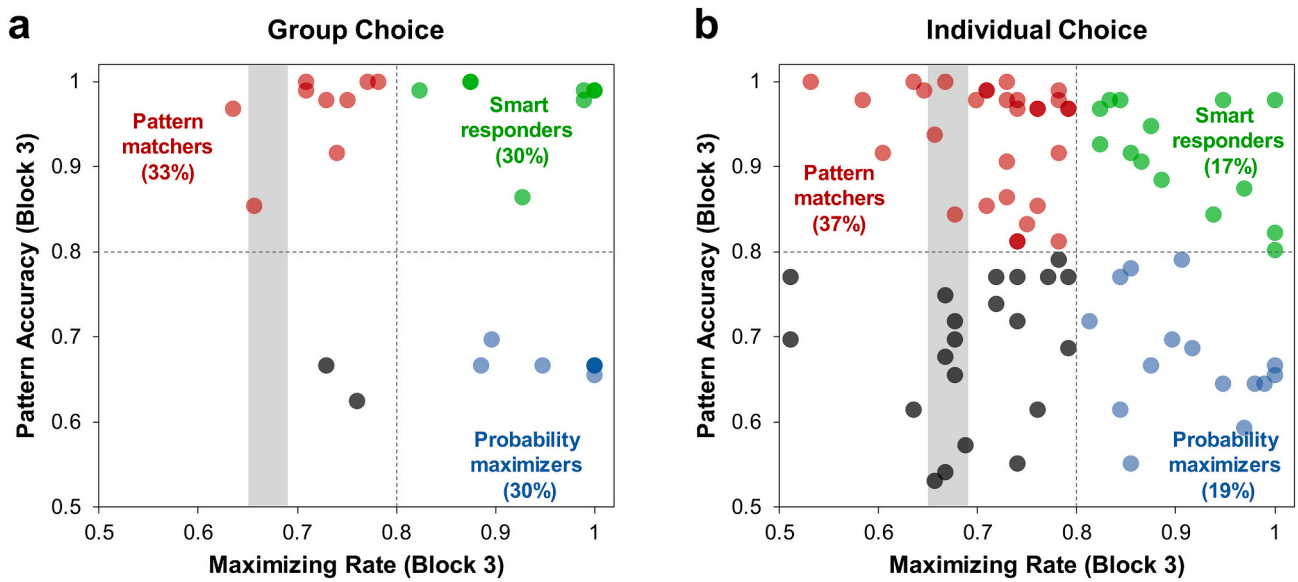

Fig. 3. Relationship between maximizing rate toward the end of the probabilistic half (block 3) and pattern accuracy toward the end of the pattern half (block 3) for groups (a) and individuals (b). Probability matching in the probabilistic half is indicated by the grey shaded area around 0.67. Participants are categorized into four subclasses: pattern matchers (upper left quadrant, shown in red), probability maximizers (lower right quadrant, shown in blue), smart responders (upper right quadrant, shown in green), and neither (lower left quadrant, shown in grey; see main text). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

performance levels in the final block of the probabilistic half. Yet, overall, pattern matching appeared to be mainly driven by "intermediate" performance in the probabilistic half (choice proportions between 0.70 and 0.90) rather than strict matching (but see Gaissmaier & Schooler, 2008).[3]

We therefore examined the curvilinear relationship between choice in the probabilistic half and accuracy toward the end of the pattern half; we expected that, compared to random responding or maximizing, some form of choice diversification in the probabilistic half would lead to superior pattern accuracy (see Gaissmaier & Schooler, 2008). Such a curvilinear trend is shown in Fig. 4 and was reflected in a quadratic regression with the proportion of maximizing responses in the probabilistic half as independent variable and accuracy in the last block of the pattern half as dependent variable, $F(2, 105) = 5.07$, $p = .008$, $R^2 = 0.088$, $BF_{10} = 4.38$. Similarly, the improvement in prediction accuracy between the first and last block of the pattern half was found to be a quadratic function of the maximizing rate in the probabilistic half, $F(2, 105) = 5.53$, $p = .005$, $R^2 = 0.095$, $BF_{10} = 6.38$.

In sum, we found that groups performed as well as the best individuals in the probabilistic part of the task, but groups' pattern accuracy was not credibly higher than that of the average individual in the pattern half. Moreover, groups that did not identify an existing pattern systematically underperformed by attempting to maximize probability and, for groups, poorer pattern accuracy was associated with higher maximizing rates in the probabilistic half. What explains this pattern of findings? The post-task questionnaire data summarized

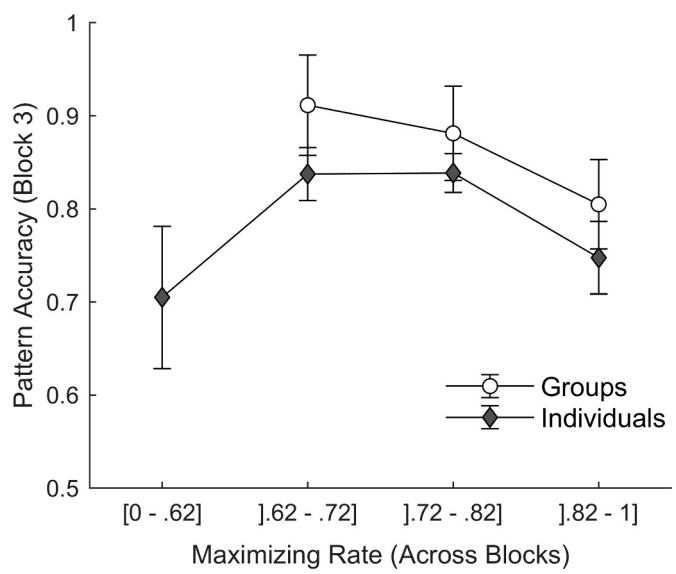

Fig. 4. Curvilinear relation between the mean proportion of maximizing responses in the probabilistic half and mean (± SEM) accuracy in the last block of the pattern half for groups and individuals.

in Appendix C suggest that the behavioral loss at the group level was not due to group members perceiving the task differently than independent individuals, but rather related to how groups gained consensus on a line of action. To further shed light on these results, we turn to the qualitative group discussion data with two main questions in mind. First, what strategies did groups discuss and which hypotheses about the task did they entertain? Second, how does the content of groups' discussions relate to the strategies they implemented, and can the distinction between maximizing as satisficing versus maximizing as optimizing explain groups' superior performance in the probabilistic half and more bimodal performance in the pattern half?

[3] To assess the extent to which pattern accuracy was predicted by probability matching in the probabilistic half, we also carried out median split analyses (see Gaissmaier & Schooler, 2008). Specifically, for each group and each individual, we computed the absolute difference between the proportion of maximizing choices across all trials of the probabilistic half and probability matching (i.e., 0.67) and then divided participants into matchers and non-matchers at the median of this measure, separately for groups and individuals. Although there was a trend toward probability matchers being more successful at pattern identification, a 2 (matchers vs. non-matchers) × 2 (groups vs. individuals) × 2 (order of presentation) × 3 (block) mixed model ANOVA indicated that pattern accuracy did not differ significantly between probability matchers and non-matchers, $F(1, 100) = 2.25$, $p = .137$, $\eta_p^2 = 0.022$, $BF_{\text{Inclusion}} = 0.20$.

3.2. Qualitative group discussion data

3.2.1. What do groups talk about?

Overall, groups expressed more statements indicative of a probability matching strategy (40.55% of all strategy statements) than of a probability maximizing strategy (10.38% of all strategy statements, see Table 1). To account for the considerable between-group variability in how much the groups discussed and how many of their expressions were strategy related (see Section 2.3. *Coding of group discussion data*), we analyzed, for each group, the proportions of statements categorized as each of the strategies listed in Table 1 relative to all strategy statements and across the entire experiment. Most frequently, groups talked about implementing a counting strategy ($M = 21.42\%$) and about analyzing or identifying patterns ($M = 13.74\%$ and $M = 16.57\%$, respectively). In fact, as Table 1 shows, all but two groups explicitly referred to the possibility that a pattern or system may determine the outcome sequence and all groups made some verbal attempt to analyze the outcome structure for a pattern (although they may not have explicitly stated that they suspected an underlying pattern). This was also the case during only the first half of the task for groups that experienced the probabilistic part first (i.e., the equivalent of a standard probability learning task): Here all but one group made at least one explicit suggestion that a pattern might underlie the outcome sequence, and all groups in this subset analyzed the structure for a pattern. In addition to discussing pattern searching, most groups made at least one statement in line with probability-matching behavior driven by either a simple win-stay, lose-shift strategy (20 of 27 groups) or based on a prominent misperception of randomness, the gambler's fallacy (19 of 27 groups); however, these statements combined accounted for less than 3% of all strategy statements the groups made (see Table 1).

Overall, groups made far fewer references to strategies that were indicative of probability maximizing than of probability matching, and when groups did talk about maximizing, it was most often an explicit suggestion to follow this approach ($M = 5.67\%$). Nonetheless, we found evidence in groups' discussions for conceptualizations of probability maximizing as both optimizing and satisficing. We had hypothesized that maximizing as optimizing would include an explicit reference to the randomness of the process—mentioned by 20 of 27 groups—or the absence of patterns in the outcome sequence—mentioned by 25 of 27 groups. Additionally, approximately half of the groups made at least one statement suggesting that the optimal response in a probabilistic choice task entails accepting the losses associated with implementing it (see Table 1). Many groups also discussed maximizing with the goal of finding a "good enough" strategy. Of 27 groups, 20 highlighted the relative pay-effectiveness of maximizing, while fewer groups speculated that potential patterns would be too difficult and effortful to identify (nine groups) or that implementing a maximizing strategy would save them time (seven groups; see Table 1).

3.2.2. What is the relationship between discussion content and choice behavior?

The overall proportion of maximizing statements was positively related to groups' maximizing rate in the final trial block, $r(25) = 0.546$, $p = .003$, $BF_{10} = 14.65$, but negatively related to their pattern accuracy in the final trial block, $r(25) = -0.631$, $p < .001$, $BF_{10} = 86.91$; conversely, the proportion of probability matching statements was positively related to groups' pattern accuracy in the last block, $r(25) = 0.631$, $p < .001$, $BF_{10} = 86.93$, and negatively related to their maximizing rate in the last block, $r(25) = -0.465$, $p = .015$, $BF_{10} = 4.06$. In other words, the content of groups' discussions mirrored the strategies they used, thus broadly validating our coding scheme. Turning to the more specific strategies and motives potentially underlying probability matching and maximizing, Table 2 summarizes the associations between behavioral measures and voiced strategies. We did not consider the relationship between choice behavior and statements labelled as "other" in Table 1 for these analyses because these expressions cannot unambiguously be attributed to either a probability matching or a probability maximizing approach. Pattern accuracy in the final trial block was most strongly related to groups *not* discussing the relative payment effectiveness of a maximizing strategy. That is, the availability of maximizing as a profitable (enough) strategy in groups' discussions may have prevented some groups from searching for and identifying an existing pattern in the outcome sequence. Perhaps unsurprisingly, groups' pattern accuracy in the final trial block was positively related to them voicing the patterns they identified and negatively related to explicit suggestions to maximize probability. By contrast, groups' maximizing rate toward the end of learning in the probabilistic half was most strongly related to statements accepting the guaranteed losses associated with probability maximizing (see Table 2). Additionally, groups' maximizing rate in the final block was positively related to explicit suggestions to maximize and to statements highlighting the payment effectiveness of maximizing, but negatively related to statements that identified patterns in the sequence.[4]

Fig. 5 further illustrates these results by relating the contents of groups' discussions to the classification of groups based on behavioral data to three (approximately equally sized) subclasses of participants: pattern matchers, probability maximizers, and smart responders (see Section 3.1. *Behavioral choice data*). The figure provides further support for the notion that groups that failed to identify the pattern differed from the other two subclasses of groups mainly in that they discussed maximizing as a pay-effective strategy (and did not analyze or identify the pattern). Moreover, Fig. 5 reveals that statements hinting at a misconception of randomness, the gambler's fallacy, were more prevalent in pattern matcher groups. Interestingly, statements referring to the possibility that a pattern may exist in the outcome sequence were made approximately equally often by all subclasses of groups.[5]

4. Discussion

The need to distinguish meaningful structure from unpredictable randomness poses an important individual and societal challenge in many domains of life. Could that lump be cancerous or is it just a lump? Does that song's popularity indicate a musician's talent or will they be a one-hit wonder? Are those statements intentionally misleading or are they based on an innocent mistake? In dealing with this challenge,

[4] To evaluate the robustness of these findings, we also correlated the proportion of strategy statements made during only one part of the task with groups' performance in the final block of that part (i.e., the proportion of strategy statements in the pattern half with groups' pattern accuracy, and the proportion of strategy statements in the probabilistic half with their maximizing rate). In these analyses, all credible associations with pattern accuracy and maximizing rate summarized in Table 2 remained credible. Additionally, the Bayesian evidence for a negative relationship between maximizing rate and statements supporting the gambler's fallacy was positive for the probabilistic half, and we found that groups made more verbal attempts to analyze the outcome structure for a pattern when one existed, if the pattern half was experienced first, $r(25) = 0.556$, $p = .003$, $BF_{10} = 17.59$.

[5] The main conclusions drawn from the analyses summarized in Fig. 5 were robust against the specific criterion for categorizing groups as probability maximizers, pattern matchers, and smart responders. Specifically, we also categorized groups based on a stricter criterion: participants whose maximizing rate in the final probabilistic block was at least 90% (see, e.g., Green et al., 2010) but who did not identify the pattern with at least 90% accuracy (probability maximizers); participants who identified the pattern with at least 90% accuracy in the final block of the pattern half but did not reach a maximizing rate of at least 90% in the probabilistic half (pattern matchers); and participants who achieved at least 90% on both pattern accuracy and maximizing rate (smart responders). This additional analysis also provided support for the notion that groups that failed to identify the pattern differed from the other two subclasses of groups mainly in that they discussed maximizing as a pay-effective strategy, did not analyze or identify the pattern, and made explicit suggestions to maximize.

Table 2
Correlation matrix summarizing the associations between and among behavioral measures and voiced strategies.

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1.	Pattern accuracy block 3	–																	
2.	Maximizing rate block 3	−0.34	–																
3.	Accept loss	−0.40†	0.71***	–															
4.	Explicit maximizing	−0.50**	0.51**	0.53**	–														
5.	Pattern absent	−0.08	−0.03	−0.18	0.34	–													
6.	Pattern difficult	−0.00	0.18	0.05	−0.01	−0.10	–												
7.	Pattern trivial	−0.29	0.22	0.36	−0.03	−0.34	0.19	–											
8.	Pay effectiveness	−0.61***	0.52**	0.55**	0.47*	0.06	0.08	0.37	–										
9.	Random	−0.28	−0.09	−0.14	−0.02	0.24	0.52**	0.12	0.25	–									
10.	Time effectiveness	−0.22	0.20	0.45*	0.03	−0.21	−0.20	0.39†	0.60**	−0.12	–								
11.	Avoid loss	−0.37	0.16	−0.05	0.31	0.28	0.20	−0.01	0.42†	0.22	0.00	–							
12.	Explicit matching	−0.21	0.06	0.00	−0.14	−0.23	−0.11	−0.11	−0.13	−0.13	−0.09	0.07	–						
13.	Gambler's fallacy	0.39†	−0.44†	−0.27	−0.46*	−0.42†	−0.12	0.09	−0.34	−0.04	−0.04	−0.09	−0.05	–					
14.	Maximizing trivial	−0.35	0.35	0.44*	0.64***	0.13	0.30	0.07	0.43†	0.33	−0.07	0.21	−0.07	−0.26	–				
15.	Memorize	0.29	0.02	0.04	−0.14	−0.03	0.40†	−0.09	−0.2	−0.14	−0.14	−0.12	−0.06	−0.01	−0.10	–			
16.	Pattern analysis	0.37	0.00	−0.21	−0.32	0.28	−0.11	−0.11	−0.33	−0.04	−0.09	−0.32	−0.18	−0.11	−0.41†	0.27	–		
17.	Pattern ID	0.59**	−0.54**	−0.52**	−0.50**	−0.22	−0.09	0.01	−0.65***	−0.31	−0.31	−0.41†	−0.18	0.39†	−0.40†	0.00	0.18	–	
18.	Pattern reference	0.00	−0.21	−0.33	0.05	0.60**	0.30	−0.03	−0.06	0.28	−0.36	0.47*	−0.13	−0.07	0.05	0.38	−0.01	−0.06	–
19.	WSLS	−0.18	−0.02	−0.15	0.44*	0.50**	−0.14	−0.16	0.19	−0.10	−0.09	0.78***	−0.10	−0.10	−0.01	−0.11	−0.24	−0.19	0.57**

Note. WSLS denotes statements referring to a win-stay, lose-shift strategy. Variables 3–10 represent statements that indicate a probability maximizing strategy; variables 11–19 represent statements indicative of probability matching (see Table 1).

† $p < .05$ but $BF_{10} < 3$.

* $p < .05$ and $BF_{10} > 3$.

** $p < .01$ and $BF_{10} > 5$.

*** $p < .001$ and $BF_{10} > 50$.

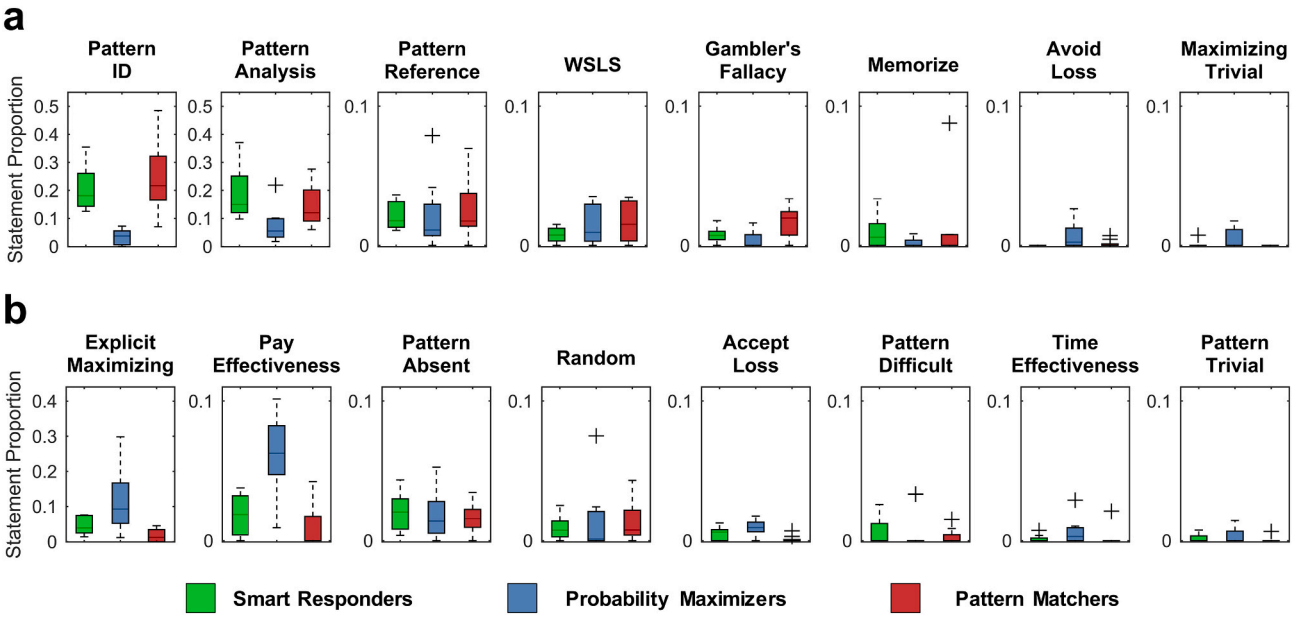

Fig. 5. Boxplots summarizing the proportions of different strategy statements indicative of (a) probability matching or (b) probability maximizing for three subsets of participating groups: probability maximizers, pattern matchers, and smart responders (see main text). Not shown are the data of two groups that achieved neither 80% accuracy in the pattern half nor a maximizing rate of 80% in the probabilistic half. Also not shown are statements categorized as an explicit suggestion to probability match because only a single group made statements suggesting this strategy (see Table 1). WSLS denotes statements referring to a win-stay, lose-shift strategy. In each plot, the center lines indicate medians; box limits indicate the 25th and 75th percentiles; whiskers extend to 1.5 times the interquartile ranges; + symbols mark outliers.

people's exceptional ability to identify structure in a disordered, uncertain world and their misgivings in understanding true randomness may represent two sides of the same coin. It is therefore important to consider both aspects for individual as well as groups of decision makers. In this article, we showed that interacting groups performed as well as the best individuals in a random environment with initially unknown outcome probabilities, thus extending previous findings demonstrating a group advantage in risky choice with known outcomes (Schulze & Newell, 2016a). Moreover, we found that similar numbers of groups and best-performing individuals identified and followed an existing pattern in the outcome sequence, suggesting some advantage of group decision making in a patterned environment as well. Yet when groups did not identify an existing pattern, they often systematically underperformed by attempting to maximize probability and, on average, groups' accuracy did not credibly exceed that of the average individual. More generally, there was a curvilinear relationship between participants' maximizing rate in the probabilistic half and their prediction accuracy in the pattern half: Compared to random responding or strict maximization, approximate (over-)matching was associated with better pattern identification (see also Gaissmaier & Schooler, 2008). Finally, groups and individuals responded comparably well to the change in the choice environment between the first and second half of the task. This result stands in contrast to previous findings from related risky choice tasks showing that groups lost their advantage over individuals when the environment changed unexpectedly (Lejarraga et al., 2014) and to findings from multi-attribute choice showing that dyads adapt their strategy use to environmental change more quickly than individuals (Kämmer et al., 2013).

Qualitative coding of group discussions revealed that almost all groups explicitly considered the possibility that a predetermined system or pattern might control the outcome sequence and that a large portion of group discussions was spent analyzing the outcome structure for a predictable sequence. Many groups also made statements revealing inaccurate probabilistic concepts (e.g., the gambler's fallacy) or encouraging simplified strategies (e.g., win-stay, lose-shift). This finding is in line with verbal protocol analyses showing that participants asked to produce random sequences verbalized more incorrect than accurate perceptions of chance processes (Ladouceur et al., 1996). Moreover, these results confirm previous suggestions that not one, but multiple processes—some adaptive, others misguided—underlie probability matching in repeated choice (e.g., Gaissmaier & Schooler, 2008; Koehler & James, 2014; Otto et al., 2011) and provide a first account of *concurrently* elicited motives underlying probability matching. Our analyses thus extend findings from studies that have retrospectively probed participants' strategy use after the task (e.g., Ellerby & Tunney, 2017; Koehler & James, 2010; Schulze & Newell, 2016a; Unturbe & Corominas, 2007; Yellott, 1969). For instance, Yellott (1969) asked participants to report how they had made their predictions after completing a repeated choice task where, during the final block of trials, participants received positive feedback no matter which option they chose. In this situation, many participants reported having finally found the pattern once the feedback signaled they were always correct. Using a similar design with response-contingent feedback toward the end of a repeated choice task, Unturbe and Corominas (2007) showed that the complexity of rules that participants reported to have found was inversely related to them maximizing probability.

In addition to further illuminating the cognitive strategies underlying probability matching, our data suggest that also probability maximizing—which is typically regarded as optimal in repeated choice—may arise from more than one cognitive process. Some groups discussed maximizing as a shortcut aimed at keeping processing costs low; they highlighted its time- and pay-effectiveness or argued that potential patterns would be too difficult or effortful to identify. This approach to maximizing as satisficing (see Simon, 1956) was related to some groups systematically failing to identify an existing pattern. More generally, this finding highlights an imbalance in the effort associated with implementing different strategies in repeated choice under uncertainty: After an initial period of probability learning, maximizing involves simply repeating responses, whereas probability matching requires participants to track their choice proportions or possible regularities throughout the task. In individual choice, this imbalance in implementation effort between probability maximizing and probability

matching has been suggested to account for behavior when a concurrent task competes for cognitive resources under cognitive load (Koehler & James, 2014; Schulze & Newell, 2016b). That is, although there appears to be no uniform decrease in probability matching under cognitive load (Otto et al., 2011; Schulze et al., 2019; Schulze & Newell, 2016b), taxed cognitive resources reduce engagement in strategies that are difficult to implement (Schulze & Newell, 2016b) and decrease sensitivity to recent outcomes (Otto et al., 2011). Relatedly, lower short-term memory capacity has been shown to be associated with more maximizing, but also worse change detection (Gaissmaier et al., 2006). Finally, young children appear to be more prone to maximizing probability than older children or young adults (e.g., Derks & Paclisanu, 1967).

In our task, the differences in implementation effort between probability maximizing and probability matching may have weighted more heavily for groups than individuals because groups needed to coordinate their strategy use and find a consensus about how to approach the task. This need to coordinate and discuss decisions also led groups to take more time to complete the task than individuals (see Appendix B; but see Schulze & Newell, 2016a, where no differences in completion time emerged between groups and individuals, when the group discussion was frontloaded). A common finding in the group decision making literature is that groups often fall short of their ideal level of performance (Kerr & Tindale, 2004); they incur *process losses* because group members do not combine efforts effectively or are less motivated in a group setting (Steiner, 1972). However, this is not always the case—on rule induction problems, for instance, groups can perform as well as the best individuals (Laughlin et al., 1991). Similarly, we showed that groups probability maximized at the level of the best individuals when it was rational to do so (see also Schulze & Newell, 2016a). The appeal of this strategy for groups, even in a patterned environment, may be understood in terms of its robustness—a simple rule that is correct more often than not may not warrant the additional effort necessary to determine when it is inefficient. This notion of robust effectiveness across a range of environmental conditions has been used to explain the success of simple majority rules in group decision making (Hastie & Kameda, 2005) and may, more generally, account for the development of inexpensive, often effective group norms (Kerr & Tindale, 2004). In other words, "groups are *satisficing entities*—often it's not that groups cannot perform near their upper limits, it's that they simply don't need to" (Kerr & Tindale, 2004, p. 642, emphasis added). We have shown that the task of detecting meaningful structure in repeated choice under uncertainty represents one important domain in which groups' satisficing nature is apparent and can incur a loss.

Group decision making introduces several social aspects beyond the challenge of reaching a joint decision that are absent in individual choice. For instance, individuals who collaborate in groups that work together toward a common goal determine not only their own outcomes but also those of their fellow group members. This aspect of accountability for other people's resources and experiences has been examined in research on surrogate decision making, in which people make decisions on behalf of others. Several studies suggest that, in surrogate decision making under risk, people make different choices for others than they do for themselves (for a recent review see Polman & Wu, 2020). Medical doctors asked to make hypothetical treatment decisions for patients, for example, appear to make more risk-averse decisions for patients than they do for themselves (Garcia-Retamero & Galesic, 2012). Yet, at the same time, group contexts provide individual members with a means to diffuse blame or reduce regret for negative outcomes and it has been argued that individuals voluntarily join groups to share the potential burden of responsibility (El Zein et al., 2019). Indeed, in a kind of responsibility-aversion, people have been found to be more prone to delegating decisions to their groups' collective judgment when all group members' payoffs were affected compared to when only their own payoffs were at stake (Edelson et al., 2018). The extent to which people's engagement in probability matching and maximizing behavior is affected by their sense of accountability for other people's outcomes is currently an open question. One interesting avenue for future research is to investigate surrogate decisions in repeated choice under uncertainty.

In sum, our results suggest that there are two routes that lead groups and individuals to maximize probability in repeated choice under uncertainty: (1) recognizing that a probabilistic process cannot be outdone (maximizing as optimizing), and (2) contenting oneself with an imperfect but easily implementable strategy (maximizing as satisficing). This distinction extends a large literature in cognitive psychology that has contrasted the adaptive potential with the irrational inaccuracy of probability matching in repeated choice, and is relevant for understanding how people deal with the challenge of distinguishing meaningful structure from profound unpredictability in a range of social settings, from committees to board meetings to juries.

CRediT authorship contribution statement

Christin Schulze: Conceptualization, Methodology, Software, Data curation, Formal analysis, Visualization, Writing - original draft, Writing - review & editing. **Wolfgang Gaissmaier**: Conceptualization, Methodology, Data curation, Writing - review & editing. **Ben R. Newell**: Conceptualization, Methodology, Writing - review & editing.

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Declaration of competing interest

None.

Appendix A. Instructions

This appendix reproduces the translated verbatim instructions for the choice task given to independent individuals and collaborating groups. All instructions were in German. Where the instructions for individuals and groups differed, both versions of the wording are shown (separated by a slash); brackets summarize instructions given to only groups.

A.1. Instructions given to participants

Welcome! Thank you for participating in this experiment! This experiment is about decision making and depending on your [and other participants'] decisions you can earn a certain amount of money. It is therefore important that you read the following instructions carefully.

The choice task

Your job [, as a group,] will be to predict whether a colored square will appear above or below a fixation cross on the screen on many trials.

Squares may appear more often in one half of the screen than in the other. [On each trial, please discuss which choice you would like to make. Once you have agreed on the prediction you would like to make,] press the "up arrow" key if you think/your group thinks that the square will appear above the fixation cross, or press the "down arrow" key if you think/your group thinks that the square will appear below the fixation cross. [Take turns occasionally at using the keyboard!] Following each key press, you will be shown where the square actually appears. To help you tell the difference, squares that appear above the fixation cross will be a different color than squares that appear below the fixation cross: the squares are either red or green. Following the display of each square, please press the "return" key to proceed to the next trial. There is no time limit [, please discuss as much as you like]. The task consists of 2 times 288 trials.

Your earnings

Your [group's] decisions during the experiment will determine how much money you earn: For each correct prediction, you/each member of your group will earn 2 cents. For each incorrect prediction, you/each member of your group will earn 0 cents. During the experiment, all payoffs will be presented on the screen and, after each prediction, added to your/each group member's total score. At the end of the experiment, your/each group member's total payoff will be paid to you/them in cash. Additionally, you/each of your group's members will then be paid a show-up fee of 10 euros. Please try to earn as much money as possible [as a group]!

Appendix B. Task completion time

We recorded participants' overall completion times for all parts of the experiment. Because groups were encouraged to discuss, in each trial, which choice to make and to take turns occasionally at using the keyboard, we expected the interacting groups to need more time for completing the choice task. Indeed, groups and individuals at different rank levels differed significantly in the time they took to complete the probabilistic half of the experiment, $F(3, 104) = 38.29$, $p < .001$, $\eta_p^2 = 0.525$, $BF_{\text{Inclusion}} = 5.63 \times 10^{13}$, as well as the pattern half of the experiment, $F(3, 104) = 13.64$, $p < .001$, $\eta_p^2 = 0.282$, $BF_{\text{Inclusion}} = 1.02 \times 10^5$. Comparing groups' task completion times to those of individual participants at each rank level, Tukey's HSD test-based conventional post-hoc analyses and follow-up Bayesian *t*-tests showed that individuals at all rank levels needed less time than groups to complete the probabilistic half (all $ps < .001$, all $BF_{10} \geq 1.13 \times 10^5$) and the pattern half (all $ps < .001$, all $BF_{10} \geq 54.06$). On average, groups needed 1131 s to complete the probabilistic half whereas the best, second-best, and third-best of the independent individuals needed 335 s, 393 s, and 416 s, respectively, to complete this part of the experiment. For the pattern half, groups, best, second-best, and third-best individuals took, on average, 796 s, 381 s, 347 s, and 362 s, respectively.

When interpreting these results, it is important to note that groups likely needed more time than individuals simply because they were asked to discuss their decisions in each trial. Indeed, in a similar repeated risky choice task, in which groups were given 10 min to discuss *before* making any decisions, Schulze and Newell (2016a) found, as did we, that groups outperformed the average individual. Yet, in this task, no differences in task completion time emerged between groups, individuals who started the task immediately, and individuals who were afforded an amount of "deliberation time" equivalent to the time the groups had available to discuss prior to the choice task. This finding suggests that the differences observed in task completion time in our task were likely due to the additional time groups needed to discuss—when the group discussion was frontloaded, no differences in completion time were found and nevertheless groups outperformed the average individual (Schulze & Newell, 2016a). Moreover, the results from Schulze and Newell (2016a) demonstrate that more time does not necessarily translate to better decisions; the decisions of individuals who started the choice task immediately and the decisions of individuals who were afforded solitary deliberation time were found to be virtually identical. Similarly, in our task, individual participants showed similar completion times across the individual performance ranks assigned within groups of three independent individuals during the probabilistic half (see above; all $ps \geq .783$, all $BF_{10} \leq 3.45$) and the pattern half (all $ps \geq .975$, all $BF_{10} \leq 0.60$). Finally, although groups took considerably longer than individuals to complete both the pattern and the probabilistic half, their pattern accuracy was not superior to that of the average individual. Thus, differences in task completion time between groups and individuals were likely not a main driver of the differences observed in choice behavior.

Appendix C. Post-task questionnaire data

Each participant completed a short post-task questionnaire after the choice task on the computer. For each part of the choice task, all participants (1) estimated the probability with which the two outcomes had occurred; (2) indicated whether they had noticed any predictable patterns or rules in the sequence of outcomes—if so, they were also asked to describe them—and (3) considered which of two strategies across 10 hypothetical choice trials—selecting the majority outcome on either all trials (probability maximizing) or two-thirds of trials (probability matching)—best described their choices, they thought would earn them more money, and they would use if they were to participate again (Koehler & James, 2010). Finally, an open-ended question asked all participants to give advice to a hypothetical future participant on how to earn as much money as possible in the experiment. Participants in the group choice condition additionally indicated (1) who had contributed to the group solution (one, two, or all group members), (2) by which process the group arrived at their decisions (forced choice between four decision schemes commonly assumed in group decision making research; see, e.g., Kerr et al., 1996), and (3) whether the group's strategy was the same as or different from the strategy that the participant would have used had they participated alone.

Participants' self-reports about their understanding of the underlying probabilistic structure, their strategy use, and their group decision process provide a measure of participants' insight into the nature of the problem and how they perceived their chosen line of action. We compared groups' and individuals' responses on the post-task questionnaire, then examined responses on the group-specific survey items. We found no differences between group members' and independent individuals' ability to estimate the outcome probabilities during each part of the task (for all *t*-tests, $ps \geq .735$ and $BF_{10} \leq 0.18$). In the probabilistic half, participants' probability estimates averaged at 69.42% and 30.60% for the two choice alternatives; in the pattern half, their estimates averaged at 62.48% and 37.56%. Next, we carried out chi-square tests to assess the association between choice condition and endorsements of maximizing in each part of task on three survey items—which strategy was used, which was expected to yield the highest payoff, and which would be used again (see Koehler & James, 2010)—as well as between choice condition and identification of patterns in the outcome sequence. More group members than independent individuals indicated they followed a maximizing strategy in both the probabilistic half, 55.56% of group members and 35.80% of individuals, $\chi^2(1) = 6.37$, $p = .012$, $BF_{10} = 4.59$, and the pattern half, 40.74% of group members and 14.81% of individuals, $\chi^2(1) = 13.57$, $p < .001$, $BF_{10} = 165.03$. However, group members were not more likely than independent individuals to endorse probability maximizing as the strategy that would earn them more money or say that they would use maximizing in the future for either part

of the task (for all chi-square tests, $ps \geq .063$ and $BF_{10} \leq 1.00$). Finally, we found no differences between group members and independent individuals in how frequently they reported noticing a pattern in either the pattern half, 79.01% of group members and 87.65% of individuals, $\chi^2(1) = 2.18$, $p = .140$, $BF_{10} = 0.42$, or the probabilistic half, 29.63% of group members and 34.57% of individuals, $\chi^2(1) = 0.45$, $p = .501$, $BF_{10} = 0.23$. Notably, 87.50% of the groups classified as "probability maximizers" (i.e., groups with a high maximizing rate in the probabilistic half that did not identify an existing pattern; see Section 3.1. *Behavioral choice data*) had at least one group member who claimed to have noticed a pattern when one existed; some even identified specific regularities that had occurred (e.g., "the green outcome occurred no more than twice in a row"). This result provides additional support for the notion that some groups may have settled for maximizing as a "good enough" strategy even though their members had detected specific regularities in the outcome sequence.

Table A1
Self-reported group choice processes for all 27 interacting three-person groups, sorted by overall group choice performance in both parts of the task (i.e., classification into smart responders, probability maximizers, pattern matchers, and neither strategy).

Classification	Maximizing rate (block 3)	Pattern accuracy (block 3)	Unanimity	Truth wins	Equiprobability	Majority
Smart responders	0.88	1	+	+Ø		
Smart responders	0.99	0.99	+ + +			
Smart responders	1	0.99	+ +Ø			
Smart responders	0.88	1	+ +			Ø
Smart responders	0.82	0.99		Ø	Ø	Ø
Smart responders	0.93	0.86	+	+ +		
Smart responders	0.99	0.98		+Ø	+	
Smart responders	1	0.99	+	+Ø		
Probability maximizers	1	0.67	+ +	+		
Probability maximizers	1	0.66	+ +		+	
Probability maximizers	1	0.67	+ +Ø			
Probability maximizers	1	0.67	+ +	Ø		
Probability maximizers	0.90	0.70		+ +Ø		
Probability maximizers	0.89	0.67	Ø		+ +	
Probability maximizers	1	0.67		+ +Ø		
Probability maximizers	0.95	0.67		Ø	+	+
Pattern matchers	0.75	0.98		+Ø	+	
Pattern matchers	0.71	1			+ +	+
Pattern matchers	0.71	0.99		+ +	+	
Pattern matchers	0.77	1	Ø	+ +		
Pattern matchers	0.73	0.98	+	+Ø		
Pattern matchers	0.64	0.97		Ø	Ø	Ø
Pattern matchers	0.66	0.85		Ø	Ø	+
Pattern matchers	0.78	1	+ +Ø			
Pattern matchers	0.74	0.92	+ +			Ø
Neither strategy	0.76	0.63	Ø		+ +	
Neither strategy	0.73	0.67	+		ØØ	
Count			30	28	16	7

Note. Participants self-identified group processes by selecting the statement that best described their group's decision process from the following options (see Schulze & Newell, 2016a): (a) The group members wanted to follow the same strategy, there was no need for discussion, and a consensus was found immediately (unanimity); or, the group members wanted to follow different strategies and (b) the majority opinion was followed after voting (majority), (c) the best strategy that was proposed by a group member was followed (truth wins), or (d) any proposed strategy was followed randomly or alternatingly (equiprobability). Symbols indicate the selected process of each person and whether a participant would have used the same (+) or a different strategy (Ø) had they completed the experiment alone.

Turning to the group-specific questionnaire items, Table A1 summarizes participants' responses and shows that, in most groups, two or more members agreed on the process through which a solution was reached (85.19%), and that two-thirds of group members would have followed the same strategy as their group had they participated alone. Overall, most group members indicated that their group made decisions unanimously (37.04%) or followed a "truth wins" procedure by implementing the most effective strategy proposed by one of the members (34.57%); fewer group members indicated their group followed proposals by different members with equal probability (19.75%) or by implementing a majority vote (8.64%). Looking at groups with different levels of performance in the two parts, however, showed that groups that systematically underperformed in the pattern half (probability maximizers) lacked insight into the loss they incurred: Like the smart responder groups, members of maximizer groups mainly indicated their group decisions had been unanimous (41.67% and 45.83% of maximizers and smart responders, respectively) or followed a truth-wins process (37.50% of both maximizers and smart responders). Pattern matchers indicated that their group was less unanimous (25.93%) but relied more on an equiprobability strategy (22.22%).

In sum, groups and individuals did not differ in how they perceived the probabilistic structure of the task nor in the prevalence with which they indicated noticing regularities in the outcome sequence. In fact, groups that did not identify an existing pattern were highly likely to have had at least one member who was convinced that there was predictability in the outcome structure. These findings suggest that the behavioral loss at the group level was not due to group members perceiving the task differently than independent individuals, but rather related to how groups gained consensus on a line of action.

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