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Are choices based on conditional or conjunctive probabilities in a sequential risk-taking task?

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Abstract

In this study, we examined participants' choice behavior in a sequential risk-taking task. We were especially interested in the extent to which participants focus on the immediate next choice or consider the entire choice sequence. To do so, we inspected whether decisions were either based on conditional probabilities (e.g., being successful on the immediate next trial) or on conjunctive probabilities (of being successful several times in a row). The results of five experiments with a simplified nine-card Columbia Card Task and a CPT-model analysis show that participants' choice behavior can be described best by a mixture of the two probability types. Specifically, for their first choice, the participants relied on conditional probabilities, whereas subsequent choices were based on conjunctive probabilities. This strategy occurred across different start conditions in which more or less cards were already presented face up. Consequently, the proportion of risky choices was substantially higher when participants started from a state with some cards facing up, compared with when they arrived at that state starting from the very beginning. The results, alternative accounts, and implications are discussed.

KEYWORDS

Columbia Card Task (CCT), conditional probability, conjunctive probability, dependent events, sequential risk-taking

1 | INTRODUCTION

Imagine you are visiting a street fair and you pass a performer playing a card game. Sitting on a wooden table are three cards showing face up, two jokers and a number card, the latter you are supposed to avoid. You witness the performer turning the cards face down and then swiftly shuffling all of them. Once done, he asks you to pick a card. Of the three, you pick the middle one. Luckily, you found a joker. Now there are two cards left and the performer challenges you to take yet another card. Would you try? Which card do you choose? Setting aside the (typically one-sided) flow of cash in such games and the likely event that the last card is whatever the performer wants it to be, how do people conceptualize those types of sequential risks? Is the decision for picking another card evaluated in isolation or do people evaluate consecutively choosing cards as part of a series of actions?

Many actions in our daily life, some of which are risky in nature, involve probabilistic rather than deterministic outcomes. Actions such as texting while driving, taking a sunbath without sunscreen, smoking a cigarette, or having one too many drinks *can* lead to negative outcomes but do not have to. Interestingly, people appear to have

Data and scripts are stored on the Open Science Framework (OSF) website: https://osf.io/x2j4r/.

difficulties properly judging long-term risks or the likelihood of effects related to repeated exposures, often referred to as cumulative risk (e.g., Renner & Schupp, 2011; Slovic, 2000). And much like the risky decisions we face in our daily life, gambles like the above mentioned card game are typically characterized by an increased reward with every action that is taken, yet the potential reward comes at the cost of an increased risk to lose something or even cause greater harm. Behavioral experiments of such structure are often referred to as sequential risk-taking tasks. The most prominent representatives are the Balloon Analogue Risk Task (BART; Lejuez, Aklin, Zvolensky, & Pedulla, 2003), the Columbia Card Task (CCT; Figner, Mackinlay, Wilkening, & Weber, 2009; Figner & Voelki, 2004), or the Angling Risk Task (ART; Pleskac, 2008). The BART score has been shown to correlate with self-reported health and addictive behavior (Hopko et al., 2006; Lejuez et al., 2002), risky sexual behavior (Lejuez, Simmons, Aklin, Daughters, & Dvir, 2004), and the test could even differentiate between smokers and non-smokers (Lejuez et al., 2003).

For the CCT, it is not entirely clear at this point how well it reflects naturalistic, risky decision-making. Although the task captures age differences (Figner et al., 2009; van Duijvenvoorde et al., 2015), or effects of social stress (Jamieson & Mendes, 2016), and other affective processes (e.g., Baumann & DeSteno, 2012; Figner et al., 2009), its associations with personality (Buelow, 2015), or risk-taking in general (Frey, Pedroni, Mata, Rieskamp, & Hertwig, 2017) are absent or at least unclear. In support of the CCT's potential for capturing naturalistic risk-taking, Schonberg, Fox, and Poldrack (2011) have argued that the task possesses the properties required for a computational decomposition of the involved cognitive components. In addition, we believe that the CCT has the necessary level of transparency and flexibility for studying how people conceptualize sequential decisions and the probabilities involved in dependent events. For instance, do you take another dose of painkillers after already having taken two? Is the second cigarette judged as equally risky compared with smoking two cigarettes in a row? Do you think that the next drink is too much, or do you think that three drinks were enough? How risky is taking a second card to you compared with taking two cards in a row? Understanding those subtle differences may help us gain a better understanding of how people evaluate similar dependent risks, thereby advancing our comprehension of naturalistic risk-taking and risk perception.

Before we show that, in a simplified version of the CCT, participants show interesting choice patterns that appear to be largely based on conjunctive probabilities (of doing something a couple of times in a row), we introduce relevant concepts and related research on the perception of cumulative risk and sequential risk-taking behavior.

1.1 | Probabilities in sequential risk-taking

When judging sequences of actions, it is important to differentiate between dependent and independent events. Independent events are those in which previous actions do not affect the outcome of subsequent ones (i.e., sky diving). A prominent example of independent events is drawing marbles from an urn *with* replacement. However, let us reconsider the card game with three cards (two jokers and one number card) mentioned at the beginning. The chance of drawing a joker is $p = .66$, whereas the chance of drawing a number card and lose the round is $p = .33$. If the successfully chosen joker card is turned face down and the deck is shuffled again, the first draw has no influence on the second draw; there still is a 66% probability of getting a joker. On the other hand, the conjunctive probability of drawing a joker twice in a row is .66 × .66, or 44%. For dependent events (e.g., drawing marbles *without* replacement), previous actions do have an influence on subsequent ones (e.g., getting alcohol poisoning from too many drinks). Imagine our drawn cards remain open and the deck is not shuffled again. Drawing a joker card on the first try (two out of three, or $p = .66$) changes the likelihood of drawing another one on the second try. The conditional probability of a joker on the second trial, given the first one was also a joker, is reduced to $p = .5$ (i.e., one out of two). The conjunctive probability of drawing two jokers in row therefore is .66 × .50, or 33%.

One approach towards an understanding of how people conceptualize the sequential (or cumulative) nature of events and their outcomes is an assessment of their actual risk perception. One could present people with descriptions of risky scenarios and ask them to provide estimates (outcome frequencies or risk probabilities) for successive states of the respective scenario (e.g., Doyle, 1997; McCloy, Byrne, & Johnson-Laird, 2010). Apparently, people have difficulties assigning correct numbers to the various states of those cumulative risk scenarios (McCloy et al., 2010). One reason might be the computational complexity. Accordingly, McCloy et al. (2010) suggested that estimates should improve when problems are framed in a way that people can iteratively focus on the appropriate subset. Doyle (1997) could show that participants, when asked to judge cumulative health risks, used various strategies that yielded inaccurate results for conjunctive probabilities. Generally, though, this line of research focuses on independent events, as cumulative risks for dependent ones are supposedly even more complicated to understand.

Another approach is using behavioral paradigms, that is, presenting participants with actual urns from which they have to draw marbles, or using other game-like tasks. Bar-Hillel (1973), for example, had participants choose between an elementary gamble (draw from an urn once) and a compound gamble (draw from an urn a couple of times). In one of her experiments, urns were designed in a way that winning probabilities of compound gambles were similar to those of elementary gambles. Participants preferred compound gambles to elementary gambles, indicating that conjunctive probabilities were overestimated. Bar-Hillel's study is an excellent example of the potential of using choice paradigms to make inferences about participants' perceptions without explicitly asking for probability estimates.

1.2 | CCT probabilities and solutions

Of the sequential risk-taking tasks introduced earlier, the CCT offers a sufficient level of transparency to be used for our purpose, which is, studying how sequential risks are mentally represented. There are

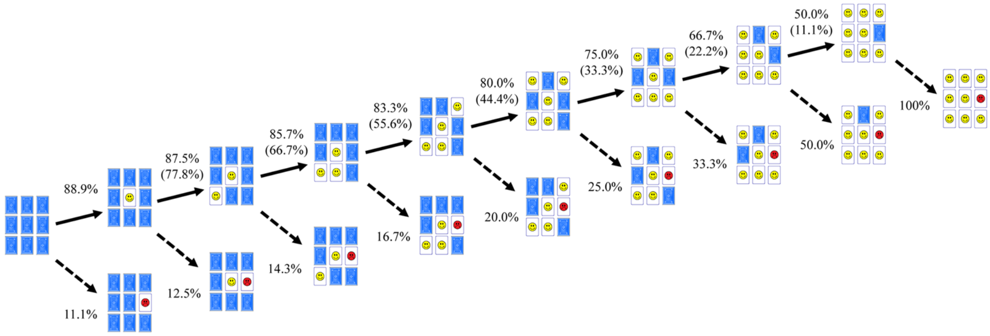

FIGURE 1 Probability tree for a simplified nine-card Columbia Card Task that starts with one open gain card. Numbers without brackets assigned to the solid line indicate the conditional probability that the next card is a gain card. The numbers in brackets indicate conjunctive probabilities of turning a series of gain cards in row. The numbers assigned to the dashed lines indicate the conditional probability that the next card is a loss card [Colour figure can be viewed at wileyonlinelibrary.com]

two versions of the CCT. The *hot* version is supposed to trigger affective processes, whereas the involvement of affective processes is supposed to be minimized in the *cold* version (Figner et al., 2009). In the *hot* version, participants see a certain number of mixed gain and loss cards shown face down that they can sequentially turn over. Turning a gain card adds a certain amount of money to a temporary account. In each step of a trial, participants have to decide whether to turn a card or to stop and transfer the collected money to a permanent account. If they continue and turn a loss card, a high fixed amount of money is deducted, the trial is over, and a new trial begins. Here, we consider a simplified version of this game with only nine cards (see Figure 1) and no negative payoffs.

First, we were interested in whether participants evaluate the choice to take another card separately for each action or whether they consider the entire choice sequence. Second, we were interested in how participants perform when they already start with an advanced state of a choice sequence.

One possibility of addressing those questions is to inspect how the involved probabilities are perceived. We know from the BART that participants treat the probabilities as if they do not change during the trial (Wallsten, Pleskac, & Lejuez, 2005) or that ratings of bursting probabilities differ from those predicted by an otherwise successful cognitive model (Schürmann, Frey, & Pleskac, 2019). Because BART players have no information about the underlying task structure, how the task is mentally represented may vary strongly between early and late task experiences (Koscielniak, Rydzewska, & Sedek, 2016; Schürmann et al., 2019; Walasek, Wright, & Rakow, 2014). In contrast, the CCT provides a well-defined environment in which all information is readily available (gain amount, number of loss cards, total number of cards, etc.). Importantly, though, there is some evidence that participants focus only on the probability of winning or losing in the hot version of the CCT (Markiewicz & Kubińska, 2015). Moreover, with no negative outcomes, all that matters are the probabilities, at least if one attempts to maximize the expected payoff. Yet, there is more than one possibility of how the involved probabilities might be subjectively represented, that is, either as conditional or as conjunctive probabilities.

To provide an example, let us consider the simplified nine-card CCT used in this study. Assume that each trial starts with state S_1, which means that one gain card is already shown face up[1]. Now imagine a player A, who intuitively captures the *conditional probability* of successfully turning a gain card on the next trial (for an illustration, see Figure 2a, solid line). Accordingly, the chance of turning a gain card at, for instance, S_3, that is, after having turned two further gain cards, would be 83.3% (five out of six remaining cards are gain cards). Thus, player A is likely to turn a card at S_3. At state S_5, the conditional probability would drop to 75% (i.e., 3/4). It is still high, but player A's propensity to turn another card should slightly decline. In fact, player A might be very optimistic until there is only a 50:50 chance of success at state S_7. Overall, player A is expected to turn relatively many cards and is inclined to do so even at later states. Importantly, conditional probabilities are the basis for understanding and modeling many sequential risk-taking tasks.

In contrast, another player B might intuitively capture the *conjunctive probability* of turning a series of gain cards in a row (see Figure 2a, dashed line). At state S_3, the probability of getting three gain cards in a row is about 62.5% (e.g., 7/8 × 6/7 × 5/6). At state S_5, the number drops to 37.5%. Compared with player A, player B should be generally less likely to turn another card and is expected to quit more frequently at earlier states of the CCT.

In a series of five experiments, we examined the extent to which the hypothetical task representations of player A and player B account for the behavior observed in our experiments. In the first part, we show that participants risk-taking (i.e., choosing the option to turn a card) declines the more they advance within a choice sequence and that they take more risks when they start with a later state as compared with when they arrive at the same state through a series of decisions. In the second part, we use computational modeling to corroborate whether the use of conditional or conjunctive probabilities accounts best for the behavioral pattern.

2 | EXPERIMENT 1

The first experiment should serve as baseline for choice behavior in a simple, sequential risk-taking task, in which participants start with one

[1]Please note that the numbers are different with no open gain cards at trial start.

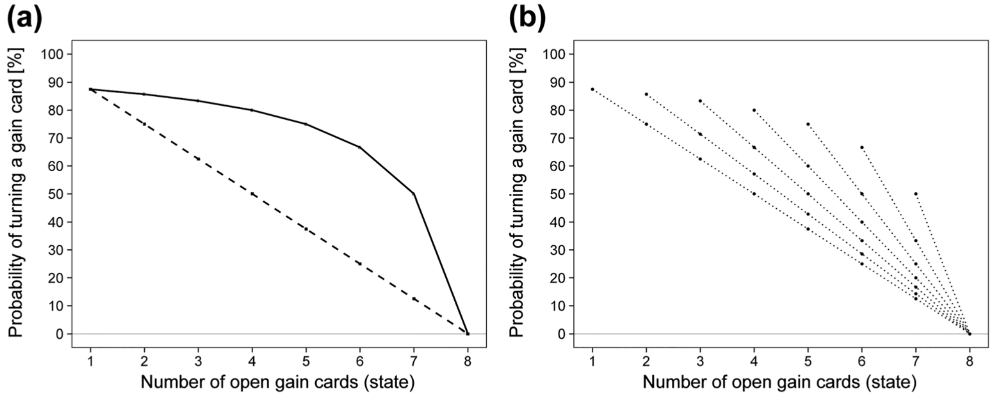

FIGURE 2 Possible conceptions of the probabilities to turn another card (depending on the number of already open gain cards) involved in the present version of a nine-card CCT. (a), Conditional probabilities (solid line) that the next card at a certain state is a gain card and the conjunctive probabilities (dashed line) of finding the gain card the corresponding times in a row. (b), Top data point of each dotted line represents conditional probabilities; subsequent data points indicate the conjunctive probability from that point onwards

open gain card[2]. In the analysis, we inspected how often participants chose another card after each subsequent successful step (i.e., number of open gain cards). By doing so, we expected to obtain first insights into the extent to which participants represented the risk by either conditional or conjunctive probabilities.

2.1 | Methods

All experiments were programmed using the software Presentation® (Version 14.7 Build 11.10.10, www.neurobs.com). We used R (R Development Core Team, 2019), the *afex* package (version 0.25-1; Singmann, Bolker, Westfall, Aust, & Ben-Shachar, 2019) to perform a generalized linear mixed effects regression (GLMER) analysis, and the *ez* package (Lawrence, 2016) to run repeated-measures analyses of variance (ANOVAs). The data were visualized using the *ggplot2* package (Wickham, 2009).

2.1.1 | Participants

Twenty-two participants (16 female) between 18 and 39 years (M = 22.8, SD = 4.9) from the University of Konstanz were recruited via our online participant database (Greiner, 2015). All participants received a base payment (i.e., show-up fee) of €3 or half a course credit point for completing the study. In addition, the outcome of five randomly selected trials, resulting in rewards between from €0 to €4.50 (mean: €2.30), was added to the base payment.

2.1.2 | Material and procedure

Participants played a simplified version of the CCT (Figner et al., 2009), that in its structure was highly similar to the task used by Slovic (1966). In particular, participants were playing with nine cards presented in a 3x3 arrangement (see Figure 1). The start-up composition consisted of eight gain cards (smiley face) and one loss card (frowny face), all but one gain card shown face down at trial start. Their task was to decide whether they want to (continue to) flip a randomly chosen card (left mouse click) or not (right mouse click). For each open gain card on the screen, participants received 30 points that were added to a temporary account. If participants decided to stop at a certain state, those points were added to a permanent store and the next trial began. If, however, a loss card was uncovered, all points in the temporary account were lost and the next trial began. Please note that we did not incorporate the original payoff scheme, in which a very large amount is subtracted from the temporary account after turning a loss card. This can lead to a negative final payment (which we did not want to claim from participants), and, consequently, to frustration on the participant's side. Participants played 300 trials of the game.

It is worth noting that there is a normative solution to the question of whether a participant should turn a card or not, by considering the maximization of the expected values (EVs) of the competing choice options based on conditional probabilities. Differences in the EVs could guide participants to the optimal choice, if the game is played repeatedly. For this specific task with no negative payoffs, irrespective of any gain amount, participants should not take another card when five or more cards have been turned (see Figure 3a)[3].

In our analyses, we focused on each possible state in which participant chose to take another card (vs. choosing to stop), that is, conditional on the number of already open (i.e., turned) gain cards. For convenience, in the remainder of the article, we will refer to the task state of one open gain card as S_1, that of two open gain cards as S_2, and so on, up to seven open gain cards (S_7).

[2]With all cards shown face down, doing nothing would result in winning nothing and taking a card would give the participants a chance of winning something (vs. nothing). In those cases, participants will always take the first card. Given the number of trials in our experiments, we thought it would be a good idea to save at least 300 clicks by starting the game with one open gain card, and therefore, a meaningful first choice.

[3]Given that five gain cards worth 150 points have been turned before, the conditional probability that the next card is a gain card (worth another 30 points), is p = .75 (three gain cards out of four remaining cards in total). Accordingly, EV(another card) = 180 × .75 = 135 points, whereas EV(stop) = 150 × 1.0 = 150 points. Participants should stop in this case. Please note that for four already turned gain cards, both actions have the same expected value, that is, 120 points. Participants should be indifferent between the choice options.

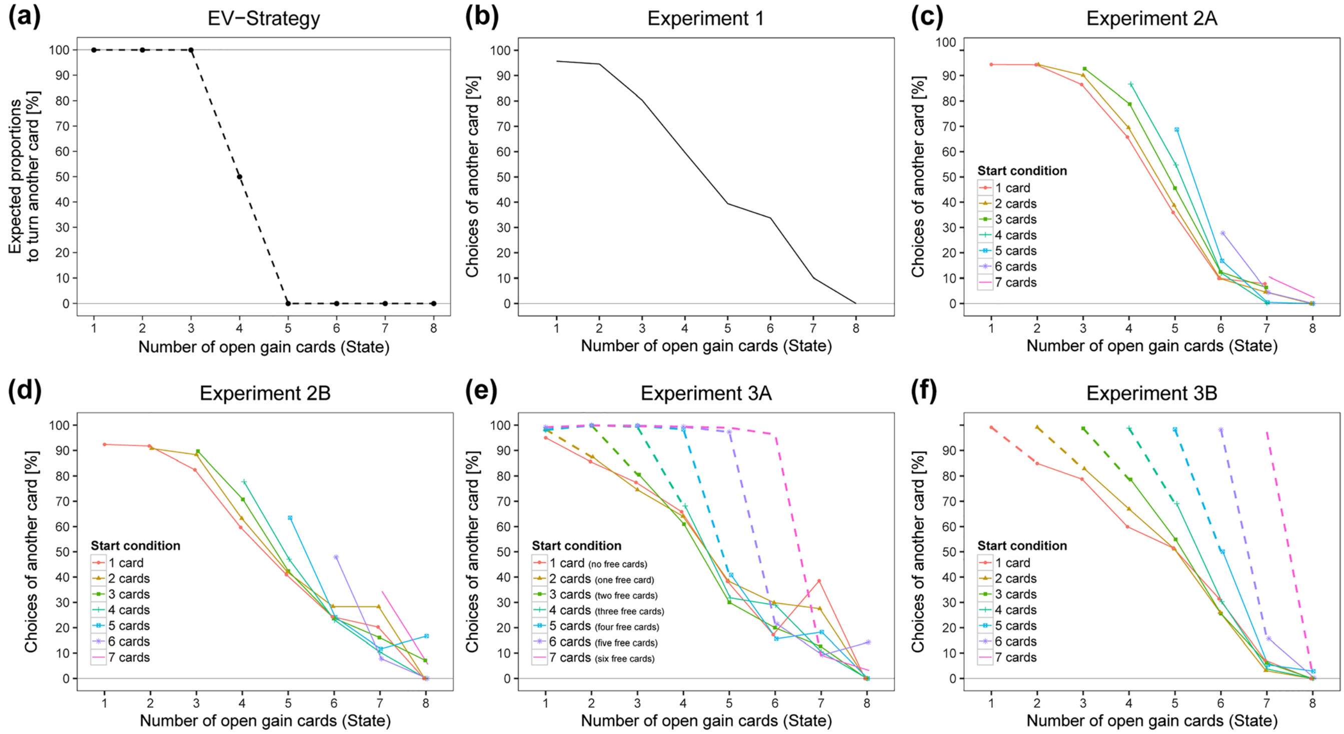

FIGURE 3 (a), Predicted choice proportions for turning a gain card for the different numbers of already turned gain cards (*states*) under the assumption that an expected value strategy was used. (b–f), Observed choice proportions for the five experiments. Exp. 1: Always starting with one open gain card. Exp. 2A: Starting with one to seven open gain cards. Exp. 2B: As before, but with adjusted frequencies. Exp. 3A: Starting with one open gain card and zero to six free cards upon trial start. The dashed lines indicate transitions from stages in which free cards were available. Exp. 3B: Starting with one to seven open gain cards and a single free card on the first choice (with dashed lines indicating transitions from stages in which a free card was available) [Colour figure can be viewed at wileyonlinelibrary.com]

2.2 | Results

Typically, the average number of turned cards on trials on which participants voluntarily stopped is computed as indicator of participants' risk taking. Here, an average of 4.10 cards (*SD* = 0.87) were turned. However, we were more interested in the proportion of taking another card as a function of how many cards have already been turned (see Figure 3b). To do so, we used all available data. If a participant turned a loss card at some point, previous decisions from the same trial were also included in the computation of the proportions of turning choices at the respective states.

For the statistical analysis of individual choices to turn another card, we used a generalized (logit) linear mixed effects model (GLMER), in which *states* (one to seven open gain cards) entered as fixed effects. As random effects, we had intercepts for every participant. As the GLMER analysis shows (see Table A1), with each card that is uncovered, the odds that another card is chosen steadily declined. In other words, the proportion of participants' choices to flip another card decreased with an increase in the number of already turned cards (see also Figure 3b). Participants exhibited an awareness of the increasing risk at later stages, acted accordingly, and did not follow a step-function pattern that the normative solution would suggest.

2.3 | Discussion

Based on the typical risk score, that is, the number of turned cards, one might conclude that people followed an EV-calculation. A more detailed inspection of the choice behavior revealed that participants did not act perfectly deterministic, although they may have had an optimal number of turns in mind. Much like in real life, their tendency to turn a card declined gradually, rather than abruptly, as the situation changed. Interestingly, if we compare the decreasing proportion of turns (Figure 3b) with the probabilities shown in Figure 2a, it is obvious that they neither align with conjunctive nor with conditional probabilities.

The results do not clearly show whether our participants based their choice on the one or on the other probability type. Because the conclusions drawn from visual inspection are very limited, we used computational modeling to obtain further insights, which will be presented in a later section. In any case, for later states with more open cards it appears that participants' choice behavior was less optimistic. This is surprising, because one could also have expected that participants focus on the actual composition of cards displayed to them, thereby showing higher propensity to take another card in line with the computationally less demanding conditional probabilities. The task structure of the hot CCT may foster such behavior. However, it also does not provide the choice environment that enables a researcher to disentangle the two probability conceptions. In order to address this issue, we further modified the task. Specifically, we introduced variable starting points in the next two experiments.

3 | EXPERIMENTS 2A AND 2B

In the previous CCT, it was not entirely clear whether participants based their choices on conditional or on conjunctive probabilities. Therefore, similar to approaches in risk perception research, we provided participants with subsets of the choice problem, that is, they started the card game not only from the beginning (one card open), but also from progressed states of the game. This manipulation can provide insights in the extent to which participants evaluate their choices within a sequence and allows a better differentiation between the involved probabilities. The question therefore was, whether participants show the same choice pattern as in Experiment 1, or exhibit a choice behavior that is entirely different.

Specifically, we asked: do participants turn cards equally often when starting at state S_5 as compared with when they arrived at the same state after starting from S_1? Doing so would indicate that they actually focus on the composition of cards that is presented to them (i.e., on the conditional probabilities). In addition, there should be no difference in risk taking as function of the starting state and an overall relatively high proportion of choices to turn another card if the focus is on conditional probabilities. On the other hand, if participants were indeed considering conjunctive probabilities, it would require the consideration of past choices within a choice sequence. Earlier starting states should then lead to fewer card turns as they advance within a trial. However, our variation of starting states increased the number of actual conjunctive probabilities compared with Experiment 1. Each starting state yields its own branch of conjunctive probabilities resulting in a complex pattern shown in Figure 2b. Accordingly, it is conceivable that participants perform in line with a mixture of conjunctive and conditional probabilities. Indeed, as we will see, it appears as if participants conceive the initial probabilities as conditional probabilities, yet proceed by considering conjunctive probabilities.

3.1 | Methods

3.1.1 | Participants

For Experiment 2A, 27 participants (18 female) between the age of 18 and 33 years (M = 21.9, SD = 3.2) from the University of Konstanz played another modification of the nine-card CCT[4]. A base payment of €3 or half a course credit point were offered as compensation for the completion of the study, to which the reward of five randomly selected trials was added (ranging from €1.80 to €9.30; mean: €6.40).

Twenty-four participants (17 female) between the age of 18 and 35 years (M = 21.6, SD = 3.7) participated in Experiment 2B. Additional rewards for this group ranged between €0 and €6.90 (mean: €4.20).

3.1.2 | Material and procedure

This version of the nine-card CCT was similar to the previous one, except that between one to seven gain cards were already face up upon start of a trial, after which participants could continue to choose another card or decide to stop. In order words, participants' first choice on each trial varied in terms of risk throughout the experiment. For example, when five gain cards were shown face up at trial start, participants faced a decision between a sure gain of 150 points (five times 30 points) if they decided to stop the round, or a potential reward of 180 points (in three out of four cards), otherwise nothing, if they choose to take another card.

If participants started with a lower number of already turned gain cards, they might either encounter a loss card or stop voluntarily before they arrive at a higher state. For Experiment 2A, we therefore increased the number of trials to 840, that is, each starting state (1 to 7 open cards) was presented 120 times, in order to ensure that sufficient data points were obtained[5].

For Experiment 2b, however, we accounted for the fact that Exp. 2A inflated the instances on which participants encounter higher numbers of open gain cards. Accordingly, we adjusted the number of trials with which each starting state appeared. Of the total of 770 trials, 200 started with one gain card (i.e., at S_1), 170 with two, 140 with three, 110 with four, 80 with five, 50 with six and 20 trials started with seven gain cards already turned face up upon trial start. This selection was arbitrary, but we aimed for at least 20 trials for S_7 to ensure meaningful mean choice proportions.

3.2 | Results

3.2.1 | Experiment 2A

Does the propensity to choose another card differ on instances in which, for example, S_5 was a start condition or in which a participants had to "arrive" at S_5 after starting from the very beginning? For our analysis, we focused on the S_5. A participant can arrive at this state in five ways. The most obvious case is that participants (a) started directly with five open gain cards. They could also arrive at that state when they started with (b) four, (c) three, (d) two, or (e) one card, and consecutively turned one, two, three, or four cards, respectively. To avoid multiple testing and to avoid obtaining empty cells by considering the later states (i.e., S_6 and S_7), state S_5 was considered as most interesting case for this and the following experiments. This subset is also interesting, because it is the state with the highest expected differences in choice behavior depending on the probabilities used. For

[4]We made sure to exclude participants from invitations to the lab who took part in other versions of the experiment, limiting the number of participants to 20 to 30 participants per experiment.

[5]An increased number of trials also ensured that the experiment would take around 30 minutes, which is usually more attractive to our student population than very short experiments.

all earlier or later states (e.g., S_1 *or* S_7), on the other hand, participants' choice behavior is expected to be more similar.

Considering all trials on which participants voluntarily stopped, an average of 5.62 cards (*SD* = 0.53) were turned in Experiment 2A, suggesting overall higher risk-taking in this version of the task, compared with the previous experiment. Figure 3c indicates a higher proportion of decisions to turn another card on participants' initial choices in the various starting states. Conversely, having arrived at the same state after several successful card turns, this proportion is reduced.

We performed a GLMER analysis on S_5-choices, in which *start conditions* (i.e., one to five open cards) entered as fixed effect and participants as random effects. The analysis showed that the odds of taking another card increased with a smaller number of previously turned cards (see Table A2). Specifically, for a later start condition, the odds of taking other card were significantly higher compared with the intercept (i.e., starting with one open card); bs > 0.33, zs > 3.16, ps < .002. Expressed in choice proportions: when participants started at S_5, they chose another card in 68.8% of the cases, whereas this proportion decreased to 54.7%, 45.6%, 38.7% and 35.9% when they began at S_4, S_3, S_2, and S_1, respectively. This declining pattern of risky choices as a function of start condition was also consistent for inspection of S_3 to S_6 (see also Figure 3c).

3.2.2 | Experiment 2B

The lower frequency of high numbers of open gain cards upon trial start resulted in an overall smaller number of turned 4.89 cards (*SD* = 0.73). Figure 3d shows that the general pattern was similar to that of Experiment 2A, though not as perfectly ordered. The GLMER analysis of S_5-choices revealed the same pattern as in Exp. 2A (see Table A2), that is, with more open cards as start condition, the odds of taking other card were significantly higher compared with starting with one open card; bs > 0.25, zs > 2.77, ps < .006. On instances in which participants started at S_5, they chose another card most frequently (63.5%), as compared with when they arrived at the same state after beginning the trial with four (47.1%), three (42.4%), two (42.0%), and one (40.9%) card.

3.3 | Discussion

Different from Experiment 1, choice behavior did not follow a simple, single pattern in Experiment 2A. Rather, the introduction of varying starting states had differential effects. For instance, when participants started from S_1, choice behavior resembled that in Experiment 1. However, when starting from late states, choices to turn a further card were more frequent compared with when arriving at the same state. This result is consistent with the idea that the participants considered conditional as well as conjunctive probabilities, depending on the state. The hypothesis is further supported by the strong resemblance of the choice proportions to the probabilities shown in Figure 2b. Although the overall propensity to turn a card slightly declined in Experiment 2B, the pattern of a higher propensity on the first decision remained even after reducing the frequency with which the later start conditions occurred.

The difficulty lies in disentangling the extent to which participants' actions reflect a more or less accurate understanding of the involved probabilities or whether they were guided by a different mechanism. A higher propensity for taking risk on the first choice is also consistent with the idea of a so-called action bias. This term refers to a tendency to do something rather than doing nothing, which may lead to more risky choices (e.g., Bar-Eli, Azar, Ritov, Keidar-Levin, & Schein, 2007; Patt & Zeckhauser, 2000). Experiments 3A and 3B were conducted to test the idea of an action bias by introducing free cards.

Generally, though, participants' choices were in line with the notion of an increased risk as the trial progressed, thereby indicating that the entire choice sequence was considered rather than that their actions are guided by the relatively high winning probabilities for the immediate next choice.

4 | EXPERIMENT 3A AND 3B

In the previous two experiments, we could show that participants took a further card more frequently on their first choices. Unfortunately, in addition to the probability hypothesis, the finding is also consistent with the tendency to do something rather than doing nothing, that is, with a so-called action bias (e.g., Bar-Eli et al., 2007; Patt & Zeckhauser, 2000). Action bias as well as following conditional probabilities at trial start, predict a high tendency to take another card. Therefore, the present two experiments were designed to test the action-bias account. In order to prevent the impulse of doing something at the very beginning of a trial from affecting choice behavior, we provided free cards, that is, occasions on which the choice to turn a further card led to a sure gain. We assumed that safe choices leading to a certain state should reduce the impulse to turn a further card, compared with when the trial directly starts at that state.

In order to influence the relative strength of the action bias, we introduced multiple free cards (Exp. 3A) as well as a single free card (Exp. 3B). Under strict application of an action bias, if a single free card reduces the proportion of flipping choices, then this would speak in favor of an action bias. If, other the hand, the different numbers of free cards produce differential effects, then the consideration of the available probability information should have been involved more strongly.

4.1 | Methods

4.1.1 | Participants

In Experiment 3A, 22 participants (19 female) between the age of 18 and 29 years (*M* = 22.0 years, *SD* = 3.1) from the University of Konstanz took part. The payment scheme was the same as in the other experiments. Additional rewards ranged from €2.70 to €9.30 (mean: €6.50).

Twenty-three participants (21 female) between 18 and 23 years (*M* = 20.0 years, *SD* = 1.2) participated in Experiment 3B. They managed to gain between from €4.50 to €10.20 (mean: €7.10) as additional reward.

4.1.2 | Material and procedure

In Experiment 3A, participants played a nine-card CCT in which every trial started at S_1. However, they received a varying number of free cards, ranging from zero (which is equivalent to a start condition at S_1) to six (mimicking S_7 as start condition for probabilistic choices). The number of free cards was displayed on the screen at any time. Participants were told that as long as free cards were available, the next click would uncover a gain card worth 30 points with certainty. Once the counter dropped to zero, the outcome was probabilistic. Of course, they could also decide to stop and cash-in the accumulated reward before all free cards were used. Experiment 3A was highly similar to Experiment 2A, except for the additional activity (i.e., clicks) participants had to exert before arriving at later states within a trial. As before, start conditions (regarding instances after which outcomes were random) did range from one to seven cards and each condition was presented 120 times resulting in 840 trials in total.

In Experiment 3B, start conditions remained the same, but the number of free cards was reduced to one. For instance, participants started at S_4 and could (but did not have to) click once to obtain a gain card with its additional 30 cents for sure (vs. stopping to cash-in 120 points). Afterwards, that is at S_5, the outcomes were probabilistic again (with three gain cards out of four, in this case).

4.2 | Results

4.2.1 | Experiment 3A

With the introduction of free cards, the average number of turned card was $M = 5.19$ ($SD = 0.67$). As before, we submitted participants' choices at S_5 to a GLMER analysis with *start condition* as fixed effect and participants as random factor. Please note that we included only those cases, in which all free cards were consumed. The analysis shows that compared with starting with one open gain card, the odds that participants take another card are statistically no different to when they started with two ($b = 0.13$, $z = 1.06$, $p = .291$) or three open gain cards ($b = 0.03$, $z = 0.29$, $p = .776$), yet the odds increased when four ($b = 0.23$, $z = 2.10$, $p = .036$) and five open gain cards ($b = 1.01$, $z = 9.50$, $p < .001$) were presented at trial start (see also Table A2). Visually, when participants still had free cards left (see dashed lines in Figure 3e), they chose another card in most cases. For all other cases, this proportion was reduced to between 30.0% and 40.9% (and no turning choices when only one loss card was left). More generally, after having consumed all free cards, choice proportions did not diverge as much as compared with Experiments 2A and 2B.

4.2.2 | Experiment 3B

In Experiment 3B, the average number of turned cards was $M = 6.06$ ($SD = 0.54$). When participants started at S_5, their first choice resulted in a sure turn of a gain card. Accordingly, participants turned another card in 98.4% of the cases. This condition was excluded from the GLMER analysis, as it would have artificially increased the magnitude of the differences. Similar to the Experiments 2A/B, with a later start condition, the odds of taking other card were significantly higher compared with starting with one open gain card; $bs > 0.38$, $zs > 2.84$, $ps < .005$ (see also Table A2). Had participants arrived at S_5 from four, three, two and one open gain cards as start condition, their proportion of turning another card was, 69.0%, 54.9%, 51.1%, and 51.5%, respectively (see Figure 3f).

4.3 | Discussion

Providing only one or a series of free cards had differential effects on our participants' choice behavior. If participants started with free cards from the very beginning until the state was reached from which onwards their choice was risky again (Exp. 3A), choice behavior was similar to that in Experiment 1. Specifically, it was in line with the idea that participants were aware of the declining conjunctive probability of successfully turning a series of gain cards as the sequence progressed. Apparently, safe decisions (i.e., turning a free card) and risky decisions contribute equally to the experience of a within-trial sequence, which lead to a gradual decrease in choices to turn a card.

With a single free card (Exp. 3B), though, choice behavior was similar to the experiments in which participants *did not* start from the very beginning but from later states of the card game. Obviously, one card severely limits the extent to which participants can experience the number of actions required for arriving at the specific state from which they started their risky choices. Yet, one action could have been sufficient to diminish the urge to take another action rather than doing nothing, if that was solely driven by an action bias. This was not the case. Accordingly, the action bias account does not contribute substantially to explaining the observed behavior. Rather, experiencing a sequence of actions, risky or not, appears to be the main influential factor to explain the differences across our experiments.

5 | COMPUTATIONAL MODELING

So far, we have considered a behavioral account of the choice patterns in our simplified CCT modification. We could show that it matters whether one starts a choice sequence from the very beginning or from an advanced state. Our findings support the notion that participants' choices were largely based on some kind of conjunctive probability. To corroborate the claim that participants relied more on conjunctive than on conditional probabilities, we fit a Prospect Theory model (e.g., Tversky & Kahneman, 1992) to the data. We varied the involved objective probabilities fed to the probability weighting function. As will be shown, conjunctive probabilities allow a better fit to the data than conditional ones.

5.1 | Modeling procedure

A Cumulative Prospect Theory (CPT; Tversky & Kahneman, 1992) model with four parameters was used as basis for modeling the choice behavior in the CCT (see also Pedroni et al., 2018). Three models were

TABLE 1 Averages of the fit indices and the best fitting CPT-parameters for the three tested models

	Model 1 (conditional)						Model 2 (simple conjunctive)						Model 3 (complex conjunctive)					
	G^2	α	δ	η	θ	n_{best}	G^2	α	δ	η	θ	n_{best}	G^2	α	δ	η	θ	n_{best}
Exp. 1	645.2	1.089	1.561	1.197	9.926	2	**622.7**	1.085	0.285	0.925	9.926	20	·	·	·	·	·	·
Exp. 2A	1,992.0	1.328	0.204	0.012	9.682	0	1,981.3	1.075	0.149	0.216	9.855	0	**1,801.0**	1.030	0.246	1.017	9.683	27
Exp. 2B	1,798.0	1.215	0.253	0.219	9.671	1	1,768.1	1.064	0.164	0.420	9.671	0	**1,617.2**	1.148	0.274	0.718	9.605	23
Exp. 3A	1,553.7	1.395	0.658	0.411	9.804	8	1,536.8	1.519	0.387	0.253	9.804	14	·	·	·	·	·	·
Exp. 3B	1,282.0	1.390	0.503	0.286	9.928	2	1,273.2	1.366	0.311	0.363	9.930	4	**1,205.8**	1.428	0.398	0.376	9.930	17

Note. For the task structure of Experiments 1 and 3A, Model 2 is a specific case of Model 3 and therefore resulted in the same predictions. Values in bold print indicate that the corresponding model had a significantly lower G^2-value than the competitors did. n_{best} indicates the number of participants, for whom the respective model emerged as best fitting one.

fit to individual data for all experiments. The resulting goodness-of-fit measures (G^2) were then subjected to an ANOVA for comparison. The parameters of the best fitting model with the smallest G^2 were examined in more detail.

In CPT, objective gains and their corresponding probabilities are transformed into their subjective representations, which are the basis for the evaluation of each options' subjective values and the corresponding choices. Here, we compared CPT-models that comprised either conditional or conjunctive probabilities. Specifically, the respective probabilities were used for the probability weighting function. Details regarding the modeling procedure can be found in Appendix A. In short, we used a parameter recovery procedure similar to the one in Wallsten et al. (2005) for modeling data of the BART. Our implementation corresponds to what Pedroni et al. (2018) referred to as RU-reference point model. For each of the five experiments, we fit a conditional probability model (Model 1), in which probabilities as outlined in Figure 2a (solid line) entered the probability weighting function. Furthermore, two conjunctive probability models were used, where applicable. Model 2 comprised conjunctive probabilities of when the game started from the very beginning, that is, with one open gain card (see Figure 2a, dashed line). With the introduction of different start conditions (e.g., in Exp. 2), it is reasonable to assume a more complex pattern that was tested with Model 3. According to this model, conditional probabilities are used for the first choice followed by conjunctive probabilities from that point onwards (see Figure 2b for a depiction). Accordingly, Model 2 is a subset of Model 3's probabilities. Please note that for Experiments 1 and 3A, the task structure yields the same probabilities for Model 2 and for Model 3. For simplicity, only the results of Model 2 will be reported.

5.2 | Modeling results

For Experiment 1, G^2 values of Model 2 were significantly smaller than those of Model 1, $F(1, 21) = 55.21$, $p < .001$, $\eta^2_G = 0.009$, although the effect size was relatively small[6]. This indicates that conjunctive probabilities were used by the majority of participants for their decisions (see n_{best} of Table 1).

[6]Assumptions for parametric tests of the G^2 statistic were met, except for Exp. 3B. For all cases, nonparametric tests yielded the same patterns as parametric tests.

With the introduction of open cards in Experiments 2A and 2B, three models had to be compared and their fit varied systemically; *Fs* > 70.40, *ps* < .001, $\eta^2_G > 0.076$. Specifically, Model 3 emerged as best fitting model with respect to mean G^2 and frequency of best fit. It is noteworthy, though, that the simpler conjunctive probability model (Model 2) also showed a significantly better fit to the data than the conditional probability competitor (Model 1); *ts* > 5.37, *ps* < .001, *ds* < 1.097.

In Experiment 3A, participants faced varying start conditions, but were given free cards (i.e., sure gains) to arrive at those conditions by clicking the mouse button several times (i.e., exert additional action). Overall, the modeling revealed that Model 1 and 2 fit similar to the data; $F(1, 21) = 0.37$, $p = .548$, $\eta^2_G = 0.001$. For about two thirds of the participants, however, Model 2 more often produced a better fit. When the number of free cards was reduced to one in Experiment 3B, differences in G^2 emerged as well; $F(2, 44) = 8.59$, $p < .001$, $\eta^2_G = 0.009$. Thus, similar to Exp. 2A/B, conjunctive probability models were superior to the conditional probability version; *ts* > 2.78, *ps* < .011, *ds* < 0.581.

Estimated parameter values for Experiment 1 indicate an underestimation of conditional probabilities ($\delta > 1$) as well as a strong overestimation of conjunctive probabilities ($\delta < 1$). As a result, dissimilar values of objective winning probabilities in the nine-card CCT converge to relatively similar subjective representations of the involved probabilities (see Figure 4, top row). Visually, subjective probabilities strongly resemble the objective conditional probabilities.

For the remaining experiments, a different pattern emerged. Values of $\delta < 1$ point to a general overestimation of the objective winning probabilities across the three models. As Figure 4 (rows 2–5) shows, subjective winning probabilities were relatively constant (i.e., between 80% and 90%) until there was only a 50:50 chance of obtaining a gain card at S_7. This was particularly true for the Models 2 and 3. For Model 3, the pattern was largely the same. Yet, due to a more nuanced composition of objective conditional and conjunctive probabilities, the subjective winning probabilities range between 65% and 95% (depending on start condition and state).

Regarding the CPT value function, we recovered values of $\alpha > 1$, indicating an increasing marginal utility of gains across all experiments and models. Values of α were particularly high in experiments in which free cards were introduced.

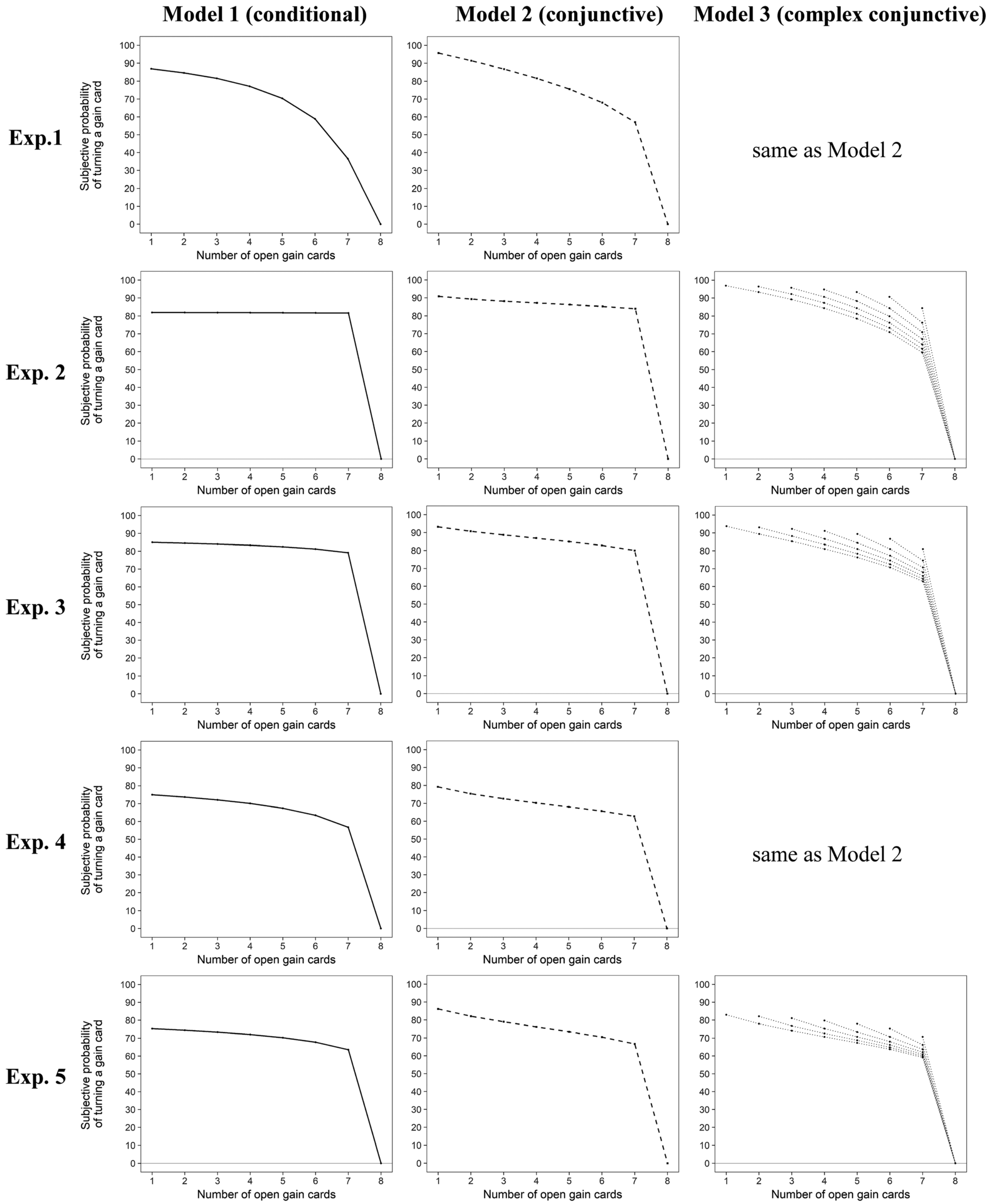

FIGURE 4 Subjective probabilities in the nine-card Columbia Card Task (CCT) for the five experiments (rows) and the three models (columns). Each plot represents the transformed objective probabilities produced by a two-parameter probability weighting function (Prelec, 1998) with the recovered parameters reported in Table 1

Choice consistency was comparable across experiments and models. Specifically, recovered θ-values close to the upper bound of 10, indicating a deterministic and consistent choice pattern across trails.

6 | GENERAL DISCUSSION

In the present study, we investigated how participants deal with risky sequential decisions by examining choice behavior in a simplified version of the CCT (Figner et al., 2009). Specifically, we approached this question by analyzing the performance with respect to whether the involved probabilities were subjectively represented as either conditional or conjunctive. If participants focused on the immediate next chance of finding a gain card, choice behavior should be in line with conditional probabilities. With a focus on a sequence of choices, that is, on the chance of finding several gain cards in a row, behavior should be in line with a consideration of conjunctive probabilities. We aimed to show that the latter idea is the most appropriate. To do so, the analysis of five experiments was supplemented by computational modeling, specifically, by fitting a Cumulative Prospect Theory model (Tversky & Kahneman, 1992; see also Pedroni et al., 2018) to the data. Although it might appear simplistic to focus on probabilities in a task with monetary incentives, there is some evidence that in the hot version of the CCT participants indeed merely focus on the probabilities of winning or losing (see, for instance, Markiewicz & Kubińska, 2015).

In the first of five experiments, participants started the nine-card CCT with already one gain card turned. We examined the proportions with which participants turned a card at each state in the choice sequence. With trial progression, the propensity of turning a card decreased gradually and the majority of participants did not show perfectly deterministic choice behavior (i.e., turning choices up to a certain state only). However, the behavior analysis was inconclusive regarding the consideration of conditional or conjunctive probabilities. We then examined whether different starting points within a choice sequence affected the likelihood to turn a card at different states (i.e., either by starting from or by arriving at a certain state). Objectively, and under the application of conditional probabilities, it should make no difference. A focus on conjunctive probabilities, on the other hand, would result in different choice proportions as a function of starting states. Indeed, we observed the latter pattern in Experiments 2A and 2B. When participants started at a later state (e.g., five open gain cards), their propensity to turn a card was higher as compared with when they arrived at the same state from an earlier one. Critically, though, participants' tendency to take more risks on the initial choice might also be an indication of a so-called *action bias* (e.g., Bar-Eli et al., 2007; Patt & Zeckhauser, 2000), that is, the tendency to take action rather than doing nothing. Therefore, we introduced free cards in Experiment 3A and 3B to undermine the potential for excessive initial actions on probabilistic choices. One reviewer noted that participants might also treat risks as something rewarding. Turning a free card may not be considered rewarding and therefore would not alleviate the urge to turn yet another card. In this case, however, one would expect the same choice pattern irrespective of how many free card are provided. When participants had to exert additional activity by turning free cards before arriving at the various start conditions (Exp. 3A), the proportions to take a further card dropped substantially on their first choice. In fact, it resembled the pattern found in Experiment 1. However, a single free card in Experiment 3B should have been sufficient to reduce the tendency to take action, yet choice proportions on the second choice were still rather high. The results support neither an action-bias nor the idea of risk as rewards. More generally, though, it turned out to be difficult to disentangle purely psychological explanations from the different probability conceptions, because predictions are either overlapping or ill-defined for the purely psychological approaches. We therefore refrained from further inspecting purely psychological explanations (e.g., action bias, or sensation seeking) and turned to an alternative account suited for computational modeling. Specifically, our results support the idea that participants' initial choices were based on conditional probabilities, that is, according to the composition of gain and loss cards given at their first decision. From that state onward, they continued as if they considered conjunctive probabilities of being successful several times in a row.

Importantly, experiencing the choice sequence appears to be an important factor for the consideration of conjunctive probabilities – irrespective of being guided through a series of safe choices or by actually making risky sequential decisions. This aligns with observations by James and Koehler (2011), who could show that thinking about a sequence of decisions versus thinking about the individual decisions affected participants' choice behavior. Some of our manipulations may have put special emphasis on the sequence of choices (e.g., multiple free cards), fostering the consideration of conjunction, thereby reducing risk-taking. Other manipulations may have partly reduced the focus on a choice sequence (e.g., late starting conditions or a single free card), thus increased the tendency to take a card. Such results have implications for real-life risk-taking and its perception. For example, a continuation of risky behavior after a short break (e.g., the pause between two cigarettes) may be regarded as a "new round" and not as part of a chain of related actions. Accordingly, overall risk taking (e.g., the number of consumed cigarettes) is likely to increase. In future studies, it might be worthwhile to test whether raising awareness for the connectedness of one's actions can lead to a decrease in risk-taking, both in real-life and in the lab.

Admittedly, though, a purely behavioral analysis seems insufficient to determine the use of either probability representation. We therefore fit CPT models (Tversky & Kahneman, 1992; see also Pedroni et al., 2018) to the data. Specifically, we used conditional or conjunctive probabilities as basis for the probability weighting function, and identified the best fitting model across the five experiments. At this point, we would like to reemphasize that we do not claim that participants actually computed probabilities. Yet implementing reasonable probability representations led to quantitatively and qualitatively different models that could then be compared. Similar to the conclusions drawn from the behavioral analysis, the best fitting model was one that comprised conjunctive probabilities. Model 3 in particular – a combination of conditional followed by conjunctive probabilities – offered the best account for the systematic variation of choice proportions depending on the starting condition. Model 3 comprises several parameters that may explain the observed choice behavior. Parameter values for both value function and choice consistency were very similar across the three CPT models, and therefore should not be given too much weight. In addition, the magnitude of a potential reward is not affected by the starting position of a player or by how she or he arrives at a certain state. Accordingly, the objective gains only change for each state, and hence, values undergo the same subjective transformation irrespective of starting condition. The same principle holds, if one adopts a different reference point for the computation of the accumulated gains (e.g., decision-updated vs. round-updated reference point; Pedroni et al., 2018). It is noteworthy, though, that our estimated value-function parameters indicated an increasing rather than decreasing marginal utility. The latter was found in a variation of the 32-card CCT that included potential negative payoffs (Pedroni et al., 2017; Pedroni et al., 2018), which might have driven those differences.

The most likely influential factor is how the involved probabilities were represented. Only the implementation of both conditional and conjunctive probabilities allowed the CPT model to capture variations resulting from the combination of starting positions and the states at which the choices were made. Other probability conceptions do not account for the observed choice pattern to such a large degree. Parameter estimates for the probability weighting functions also suggest that objective probabilities underwent substantial distortions, resulting in an overestimation of the conjunctive probabilities. Our modeling results therefore complement studies from risk perception research that also show that conjunctive probabilities are typically overestimated (e.g., Bar-Hillel, 1973; Cohen, Chesnick, & Haran, 1971; Doyle, 1997; Slovic, 1969).

As mentioned earlier, Wallsten et al. (2005) found that, for the BART, the best fit was obtained with a model that assumed that participants treated the involved probabilities as not changing (i.e., stationary) during the trial. In addition, their results imply that participants severely underestimated their chance of success.[7] Similarly, Schürmann et al. (2019) found that probability ratings for the BART deviated strongly from the objective bursting probabilities of the virtual balloon. In particular, participants showed an overestimation of bursting probabilities (Schürmann et al., 2019), in other words, they also underestimated their chance of success. However, participants' probability estimates also indicated that they were aware of changes in probabilities as one advances within the trial. Our analysis of the nine-card CCT also supports the idea that participants are indeed sensitive to probability changes within a trial. This goes against the predominant notion that participants represent the involved probabilities as stationary (e.g., Wallsten et al., 2005), which most authors find surprising. The transparent task structure of the CCT may foster a more accurate, nonstationary probability representation. Similar to the catch'n'keep version of the Angling Risk Task, which was designed as a transparent equivalent of the BART, Pleskac (2008) showed that a nonstationary model outperformed the stationary version. Furthermore, the reported underweighting of high (conditional) probabilities may also indicate that participants relied on the lower conjunctive probabilities.

In addition, the deviations from objective bursting probabilities in the BART, reported by Schürmann et al. (2019), may indeed appear striking, if the basis for comparison were conditional probabilities. If conjunctive probabilities were used for comparison, then their ratings would have aligned more strongly with the objective values.[8]

7 | CONCLUSION

It might be worthwhile to reconsider how probabilities are subjectively represented in sequential risk-taking tasks. The usual competition between stationary (constant) and nonstationary (conditional) probabilities now has a worthy third contender: nonstationary conjunctive probabilities. Ideally, its application will improve both the fit of cognitive models and the quality of the parameter estimates. Further investigations of the appropriateness of this approach to other tasks will at least advance our understanding of sequential risk-taking, which is a prerequisite for finding adequate, distinct cognitive components for properly representing the complexity of naturalistic risk-taking (Schonberg et al., 2011).

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[7]The chance of successfully inflating a balloon is higher than 95% for more than 100 pumps, and only drops to 50% on the 126th of 128 possible pumps within a trial.

[8]The probability of a success (obtaining a gain card, pumping a balloon without bursting) is more suitable for a comparison of conditional and conjunctive probabilities. The tasks simply do not allow for finding several loss cards in a row (CCT) or for further inflating an already exploded balloon (BART) within a single trail.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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APPENDIX A.

COMPUTATIONAL MODELING

According to Cumulative Prospect Theory (CPT; Tversky & Kahneman, 1992), the subjective value V of a lottery A is defined as

$$V(A) = v(x)\cdot\pi(p),$$

where the value function $v(x)$ characterizes the subjective value of a single option's gain x. As value function, we used the function proposed by Tversky and Kahneman (1992),

$$v(x) = x^{\alpha},$$

where α determines the curvature of the value function. A value of α = 1 would indicate that subjective and objective values are identical, whereas $\alpha < 1$ indicates decreasing subjective values (and increasing subjective values for $\alpha > 1$) as objective values increase. The probability weighting function $\pi(p)$ describes the transformation of the corresponding objective probability p into its subjective representation. Here, we used a two-parameter probability weighting function proposed by Prelec (1998) that was also used in Pedroni et al. (2018) for modeling CCT data,

$$\pi(p) = e^{-\delta(-\ln(p))^{\eta}},$$

where $\eta < 1$ produces an inverse s-shape. The δ parameter determines the elevation of the weighting function, thereby accounting for a general overestimation (if $\delta < 1$) or an underestimation (if $\delta > 1$) of the objective probabilities. For the present experiments that included free cards (Exps. 3A and 3B), objective probabilities were set to 1 as long as free cards were available during a trial. The exact numbers for every experiment and state are provided in the supporting information.

In the present study, to calculate the probability that a card is turned, we first computed the respective subjective value V_n of turning a card at the respective state S_n,

$$V_n(\text{take card}) = v(x_{n+1})\cdot\pi(p_n),$$

where the potential reward is determined by $x_{n+1} = (n + 1) \times 30$ points in our CCT version; and p_n refers to the (either conditional or conjunctive) probability p of obtaining a gain card at the respective state S_n. For instance, S_3 refers to the state of three open gain cards. The subjective value of the choice to stop at state S_n was determined as follows,

$$V_n(\text{stop}) = v(x_n).$$

The probability P that a participant turns a card at state S_n was calculated using an exponential choice rule:

$$P_n(\text{take card}) = \frac{1}{1 + e^{\theta(V_n(\text{take card}) - V_n(\text{stop}))}},$$

where θ is a choice consistency (or stochasticity) parameter. High values of θ reflect a higher consistency of choices across trials, whereas low θ-values indicate more stochastic choices and therefore a larger variation of choices across trials.

The parameter space was restricted as follows: $0 < \alpha < 3$, $0 < \delta < 3$, $0 < \eta < 3$, $0 < \theta < 10$. We used a model fit procedure similar to that in Wallsten et al. (2005; Appendix D). For each parameter, the parameter space was divided into quarters (e.g., in steps of 0.75 for α) and random numbers were computed for each section. The computer than randomly selected one of the four sections from each parameter space to obtain a set of starting values. If those starting values satisfied a criterion[9], they were fed to the Nelder-Mead method to further optimize parameters, and thereby minimize G^2. This process (i.e., finding and optimizing starting values) was repeated 500 times. The best fitting set of parameters was used for further analysis

[9]The criteria (G^2) for the five experiments were as follows. Exp. 1: 1000. Exp. 2A/B: 3000. Exp. 3A/B: 5000.

APPENDIX B.

REGRESSION TABLES

TABLE A1 Regression table for the generalized mixed effect model analysis of Experiment 1

Predictor	β	SE(β)	95% CI	z	p
Intercept	3.800	0.262	[3.268, 4.338]	14.50	.001
2opencards	−0.246	0.091	[−0.425, −0.067]	−2.69	.007
3opencards	−2.003	0.081	[−2.163, −1.846]	−24.81	.001
4opencards	−3.480	0.086	[−3.651, −3.312]	−40.31	.001
5opencards	−4.848	0.096	[−5.039, −4.661]	−50.31	.001
6opencards	−5.174	0.126	[−5.423, −4.929]	−41.04	.001
7opencards	−6.554	0.273	[−7.118, −6.043]	−24.05	.001

Note. Participants always started with one open gain card. The predictor variable was treatment coded, with the condition of "one open card" as baseline to which all other conditions are compared. Confidence intervals were derived using a profile-based method.

TABLE A2 Regression table for the generalized mixed effect model analysis of Experiments 2A, 2B, 3A, and 3B

Predictor	β	SE(β)	95% CI	z	p
Experiment 2A					
Intercept	−0.921	0.337	[−1.606, −0.239]	−2.73	.006
StartCondition2	0.328	0.104	[0.125, 0.532]	3.16	.002
StartCondition3	0.727	0.099	[0.534, 0.922]	7.35	.001
StartCondition4	1.223	0.096	[1.036, 1.412]	12.75	.001
StartCondition5	2.129	0.096	[1.941, 2.318]	22.11	.001
Experiment 2B					
Intercept	−1.272	0.374	[−2.043, −0.514]	−3.40	.001
StartCondition2	0.249	0.090	[0.073, 0.425]	2.77	.006
StartCondition3	0.432	0.088	[0.260, 0.605]	4.91	.001
StartCondition4	0.812	0.088	[0.640, 0.985]	9.23	.001
StartCondition5	1.873	0.097	[1.684, 2.064]	19.32	.001
Experiment 3A					
Intercept	−1.477	0.288	[−2.070, −0.895]	−5.13	.001
StartCondition2	0.132	0.125	[−0.113, 0.377]	1.06	.291
StartCondition3	0.034	0.118	[−0.198, 0.266]	0.29	.776
StartCondition4	0.232	0.111	[0.016, 0.450]	2.10	.036
StartCondition5	1.009	0.106	[0.802, 1.218]	9.50	.001
Experiment 3B					
Intercept	−0.894	0.464	[−1.878, 0.043]	−1.93	.054
StartCondition2	0.297	0.105	[0.092, 0.502]	2.84	.005
StartCondition3	0.551	0.099	[0.356, 0.746]	5.55	.001
StartCondition4	1.816	0.103	[1.615, 2.019]	17.66	.001

Note. Only data from the state of five open cards entered the analysis. The predictor variable was treatment coded. The intercept (i.e., starting with one open card) served as baseline to which all other conditions are compared. Please note that in Exp. 3A, start conditions imply that, except for the first one, free cards had to be consumed to arrive at the state of interest (here: five open cards). In Exp. 3B, the start condition of five cards was omitted, as this was an uninformative condition with a free card (i.e., sure gains). Confidence intervals were derived using a profile-based method.