



# Statistical numeracy as a moderator of (pseudo)contingency effects on decision behavior



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## ABSTRACT

Pseudocontingencies denote contingency estimates inferred from base rates rather than from cell frequencies. We examined the role of statistical numeracy for effects of such fallible but adaptive inferences on choice behavior. In Experiment 1, we provided information on single observations as well as on base rates and tracked participants' eye movements. In Experiment 2, we manipulated the availability of information on cell frequencies and base rates between conditions. Our results demonstrate that a focus on base rates rather than cell frequencies benefits pseudocontingency effects. Learners who are more proficient in (conditional) probability calculation prefer to rely on cell frequencies in order to judge contingencies, though, as was evident from their gaze behavior. If cell frequencies are available in summarized format, they may infer the true contingency between options and outcomes. Otherwise, however, even highly numerate learners are susceptible to pseudocontingency effects.

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## 1. Introduction

Contingency learning undoubtedly plays a crucial role in everyday life. It “enables individuals to explain the past, control the present, and predict the future” (Crocker, 1981, p. 272). However, there seems to be a growing body of evidence that “the criteria by which people judge [contingencies] do not agree with statistical convention” (Yates & Curley, 1986, p. 294). The contingency between two binary variables  $X$  (cues) and  $Y$  (outcomes) can be expressed by  $\Delta p$  (e.g., Allan, 1980), which is the difference between the conditional probabilities  $P(Y1|X1)$ —the probability of outcome  $Y1$  in the presence of cue  $X1$ —and  $P(Y1|\sim X1)$ —the probability of outcome  $Y1$  in the absence of cue  $X1$ .  $\Delta p$  takes all four (equally weighted) cell frequencies of a  $2 \times 2$  contingency table into account. If more simplistic strategies are used in order to determine the sign and size of a contingency, contingency judgments can be severely biased. Such biases have frequently been explained in terms of unequal weighting of cell frequencies (e.g., Arkes & Rothbart, 1985; Chapman & Chapman, 1969; Crocker, 1982; Einhorn & Hogarth, 1978; Hamilton & Gifford, 1976; Mandel & Lehman, 1998; McKenzie & Mikkelsen, 2007; Schustack & Sternberg, 1981; Wasserman, Dorner, & Kao, 1990). In contrast, a more recent approach stresses the role of base rates for contingency judgments and proposes that a focus on marginal rather than cell frequencies gives rise to *pseudocontingencies* (Fiedler, 2000).

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A pseudocontingency is a potentially biased estimate of the contingency between two variables  $X$  and  $Y$ , which is inferred not from cell frequencies but from skewed base rates of  $X$  and  $Y$ , or from pairwise correlations of both  $X$  and  $Y$  with a third variable  $C$  (e.g., Fiedler, Freytag, & Meiser, 2009). The following example illustrates the latter case where two variables  $X$  (cues) and  $Y$  (outcomes) are observed in two or more contexts  $C_i$  (see Table 1). Imagine you move into a new apartment with two roommates (contexts  $C1$  and  $C2$ ). As you get to know each other, you notice that one of your roommates often stays up late (cue  $X1$ ) and tends to be a bit grumpy in the morning (outcome  $Y1$ ), whereas the other one usually has an early night (cue  $X2$ ) and is mostly quite good-humored even before his first cup of coffee (outcome  $Y2$ ). Thus,  $C$  is correlated with both  $X$  and  $Y$ , and  $X$  and  $Y$  are correlated at the level of contexts: Your evidence suggests that people who typically go to bed late are more likely to be typically bad-tempered in the morning than people who typically go to bed early. Importantly, this relationship between someone's typical bedtime and their typical mood in the morning does not imply that a late (early) night corresponds with bad (good) mood in the morning at the level of individual occasions. In fact,  $X$  and  $Y$  can still be uncorrelated or even correlated in the opposite direction at the level of individual observations (see Table 1; cf., e.g., Robinson, 1950). If you looked more closely at your roommates' behavior on single occasions, you might find that your first roommate is actually just as (or even more) likely to be grumpy at breakfast after one of his few early nights, and that your second roommate is actually just as (or even more) likely to be cheerful in the morning after he stayed up half the night. Still, the ecological correlation between  $X$  and  $Y$  at the level of contexts might tempt you to infer a similar relationship

**Table 1**

Frequency table suggesting a positive pseudocontingency between options *X* and outcomes *Y* in contexts *C1* and *C2* despite a negative true contingency.

	C1		C2	
	X1	X2	X1	X2
Y1	12	6	0	6
Y2	6	0	6	12

between the time people went to sleep the night before and their mood in the next morning. That is, you might fall for a pseudocontingency between *X* and *Y* at the level of individual observations and conclude that people are more likely to be good-humored in the morning if they went to bed early than if they went to bed late.

Although such pseudocontingency inferences can be deceptive, they are both subjectively valid and adaptive (e.g., Fiedler & Freytag, 2004; Fiedler et al., 2009; Kutzner, Vogel, Freytag, & Fiedler, 2011): Cell frequencies, or contingency estimates based on the whole set of cell frequencies, often cannot be obtained due to cognitive constraints or constraints in the learning environment. Under these circumstances, it is efficient and adaptive to rely on base rates instead. Skewed base rates of *X* and *Y*, or *CX* and *CY* contingencies, constrain the range of possible coefficients of the *XY* contingency (see, e.g., Duncan & Davis, 1953; Meiser, 2006), are likely to yield contingency estimates of the correct sign if there is a contingency in the population (see, e.g., Kutzner et al., 2011), and permit above chance accuracy in prediction tasks even if the (true) contingency is ignored (see, e.g., Kareev, Avrahami, & Fiedler, 2009). Last but not least, contingency inferences on the basis of skewed base rates conform with the implications of a normative Bayesian learning algorithm (Klauer, 2015) and can thus be regarded as rational when facing complex probabilistic environments. In short, using skewed base rates of variables *X* and *Y*, or contingencies *CX* and *CY* with a context variable, for inferences on the relation between *X* and *Y* provides an adaptive strategy of human bounded rationality.

In line with this reasoning, previous research concerned with base rate effects on contingency learning and causal judgments confirms that learners are sensitive to skewed base rates of cues and outcomes (e.g., Allan & Jenkins, 1983; Estes, 1976; Reips & Waldmann, 2008; White, 2004; see Perales & Shanks, 2007, for an overview on cause and outcome density effects). For example, they give higher estimates for the contingency between cues and outcomes, and in prediction tasks rely more strongly on base rates of outcomes rather than their probabilities conditional on cue, the more highly skewed a learning sample's marginal frequencies are (e.g., Blanco, Matute, & Vadillo, 2013; Kareev et al., 2009; Kutzner, Freytag, Vogel, & Fiedler, 2008). Furthermore, estimates of the contingency between *X* and *Y* have been shown to be biased according to the contingencies learners perceive between *C* and *X* on the one hand and between *C* and *Y* on the other hand if skewed base rates of *X* and *Y* covary across contexts (Meiser & Hewstone, 2004). Indeed, jointly skewed base rates of *X* and *Y* can be sufficient to make learners perceive a (pseudo)contingency between *X* and *Y*. Several studies, in which cell frequencies were not revealed and, consequently, the true contingency between *X* and *Y* was not defined in the learning sample, have already provided evidence for pseudocontingency effects (e.g., Fiedler & Freytag, 2004; McGarty, Haslam, Turner, & Oakes, 1993; Meiser, 2006). However, pseudocontingency effects have also been observed although information on cell frequencies was provided (e.g., Fiedler, 2010; Fiedler & Freytag, 2004; Meiser & Hewstone, 2004). Moreover, they are reflected even in actual decision behavior with immediate and personally relevant consequences (Meiser, Rummel, & Fleig, 2016; see also Chapman & Chapman, 1967; Kutzner et al., 2008). These findings suggest that learners might rely on base rates despite other, more valid cues, because they overestimate their validity for contingency judgments at the level

of individual observations. Apparently, learners tend to not distinguish between information on the contingency between *X* and *Y* at the aggregate level and evidence for a contingency between *X* and *Y* at the lower level of individual data (Fiedler, Freytag, & Unkelbach, 2007). They seem to find it difficult to understand that contingencies may vary considerably, even in their signs, between these different levels of analysis (Fiedler, Walther, Freytag, & Nickel, 2003). In this respect, statistical expertise with regard to contingencies and conditional probabilities could play an important role, as interventions designed to foster learners' understanding of these concepts have been shown to improve contingency judgments and normative use of base rate information (e.g., Shaklee & Tucker, 1980; Stanovich & West, 1999). More specifically, in environments in which contingencies at the aggregate level are incompatible with contingencies at the individual level, pseudocontingency effects could be negatively related to the learner's proficiency with regard to probabilities in general and conditional probabilities in particular—a statistical concept crucial for ( $\Delta p$ ) contingency judgments.

On the other hand, even learners who know how to calculate an unbiased contingency estimate at the level of individual data and are aware of the drawbacks of other strategies might not always be able to keep track of cell frequencies and integrate them—according to the  $\Delta p$  rule, for example—due to limited cognitive capacity. Even if frequency information could be encoded automatically and effortlessly (e.g., Hasher & Zacks, 1984), cognitive capacity should determine if and to what extent learners are able to process these cell frequencies and combine them into a measure of the *XY* contingency within contexts (cf., e.g., Eder, Fiedler, & Hamm-Eder, 2011). Research demonstrates that although learners may not give unbiased contingency estimates if cell frequencies are readily available (e.g., Shaklee & Mims, 1982; Wasserman et al., 1990), their performance typically deteriorates as cognitive demands of contingency learning increase (Arkes & Harkness, 1983; Kao & Wasserman, 1993; Shaklee & Mims, 1982; Ward & Jenkins, 1965). In a similar vein, correlational research confirms a positive relationship between contingency learning and individual differences in working memory capacity, fluid intelligence, and reasoning skills (e.g., Rakow, Newell, & Zougkou, 2010; Stanovich & West, 1998). Furthermore, Eder et al. (2011) found that participants were more susceptible to an illusory correlation, which may be regarded as a specific type of pseudocontingency (see, e.g., Meiser & Hewstone, 2010), if their cognitive capacity was low or cognitive load was high. Thus, task difficulty could moderate the relationship between statistical numeracy and pseudocontingency effects. Because learners need to adapt to cognitive limitations as well as requirements and restrictions of the learning situation, even highly numerate learners might have to fall back on pseudocontingencies if cell frequencies prove (too) difficult to process. Consequently, beneficial effects of statistical numeracy could decrease, as cognitive demands of cell frequency processing increase.

## 2. The present research

Following this line of reasoning, the present study addressed the role of statistical numeracy for pseudocontingency effects on decision behavior with immediate and personally relevant consequences. The experimental procedure, an adapted version of the gambling machine task by Barron and Erev (2003), was adopted from an earlier study on pseudocontingencies (Meiser et al., 2016). First, participants observed a gambling machine that had been set up in two casinos (contexts *C1* and *C2*) over a series of learning trials. This gambling machine had two buttons (options *X1* and *X2*). On each trial, one of the two buttons of the gambling machine in one of the two casinos was pressed, leading to either a win (outcome *Y1*) or a loss (outcome *Y2*). In the second part of the gambling machine task, participants played for real money at the gambling machine in the two casinos. Afterwards, they estimated the

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