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Article *in* Journal of Experimental Psychology General · March 2009

DOI: 10.1037/a0014585 · Source: PubMed

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Journal of Experimental Psychology: General
2009, Vol. 138, No. 1, 22–38

0096-3445/09/$12.00 DOI: 10.1037/a0014585

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Causal considerations must be relevant for those making decisions. Whether to bring an umbrella or leave it at home depends on the causal consequences of these options. However, most current decision theories do not address causal reasoning. Here, the authors propose a causal model theory of choice based on causal Bayes nets. The critical ideas are (a) that people decide using causal models of the decision situation and (b) that people conceive of their own choice as an intervention. Four corroborating experiments are reported. The first 2 experiments showed that participants chose on the basis of the causal structure underlying a choice scenario rather than the statistical relation among actions and outcomes. Experiments 3 and 4 showed that participants treated choices and interventions similarly. They also suggest that decision makers use causal models to derive inferences about expected outcomes. Boundary conditions on causal decision making and examples of faulty causal inferences in choice (e.g., self-deception) are discussed.

Keywords: causal models, decision making, choice, intervention

People who buy running shoes frequently are in better shape than those who do not. If you wanted to get in shape, would you therefore buy new shoes every month? Probably not. Purchasing running shoes frequently would make sense if it improved your physical fitness. But the reason that buying shoes frequently and being in good shape are correlated is presumably not that one is a cause of the other; rather, both are effects of a common cause having to do with your workout regime. Buying shoes on a monthly basis would deplete your budget without changing the target effect (i.e., getting in better shape). Thus, the crucial question for a decision maker is not whether an action is related to the desired outcome. It is whether an action has the causal power to produce the desired outcome. Causal reasoning is necessary for answering the latter question.

In this article we explore whether and how decision makers derive causal inferences while they make a choice. First, we briefly review how current consequentialist theories of decision making deal with causality. Second, we show that causal Bayes nets (see, e.g., Glymour, 2001; Pearl, 2000; Sloman, 2005; Spirtes, Glymour, & Scheines, 1993) provide the means to model reasoning and decision making in a way that is sensitive to causal structure. Third, we outline our own descriptive model of decision making, the causal model theory of choice, which posits that decision makers derive and use causal knowledge (Sloman & Hagmayer, 2006). Fourth, we present four experiments that tested critical predictions of the theory. Finally, boundary conditions of the theory are outlined.

Causal Considerations in Decision-Making Theories

Expected utility theory remains the gold standard for good decision making. The theory is built on the gambling metaphor. The rational decision maker is conceived of as playing a game, such as roulette, that has a set of possible outcomes, each of which has some probability of occurring and some value, payoff, or utility for the decision maker. The best options, which have the highest probability of getting the most value, are those with the highest expected utility. If and how these probabilities reflect causal relations in the world is not part of the theory. In fact, in games of pure chance, the probability of any specific outcome is independent of the choice made. The probabilities are fixed by the setup and rules of the game. For example, the probability of red in roulette is determined by the number of red, black, and green fields. It is (unfortunately) not affected by the bettor's choice of color. Therefore, causal considerations do not provide much help to the bettor in games of pure chance.

But the probabilities of most events relevant to decision makers do depend on chosen actions in a way determined by causal structure. A statistical relation between an option and an outcome may reflect a direct or indirect causal relation (e.g., take the stairs → be in good shape) or a noncausal correlation due to a common cause (e.g., the relation between buying shoes frequently and being in good shape). Although direct and indirect causal relations allow for active manipulation of an event, mere correlations do not.

Along with many philosophers (e.g., Joyce, 1999; Lewis, 1981; Meek & Glymour, 1994; Nozick, 1969, 1993; Skyrms, 1980), we consider the distinction between causal relations and merely evidential correlations to be critical for good decision making (not all philosophers agree; see Levi, 2000). The option with the highest

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This work was funded by National Science Foundation Award 0518147. We thank Emanuel Robinson for his contributions to this research and Iris Risse and Katharina Müller for collecting most of the data. Adam Darlow, Phil Fernbach, and Ju-Hwa Park made helpful comments on earlier drafts of this article.

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evidential value may not be the option that increases utility the most. Buying new running shoes frequently is diagnostic of being in good shape, because runners need to do so more often than others. In contrast, taking the stairs is not good evidence of being in good shape, because many people take the stairs in the absence of elevators. Yet it is an effective way to get in shape. Expected utility theory in its original form (Savage, 1954; von Neumann & Morgenstern, 1947) neglects the distinction between noncausal correlations and causal relations. The original framing was in terms of probabilities or subjective probabilities without specification of whether those probabilities reflect causal structure or noncausal correlations. Therefore, expected utility theories must be based on the assumption that probabilities reflect the right, causally relevant relations.

In an effort to be explicit about the determinants of choice, decision theorists have developed causal decision theories (e.g., Joyce, 1999; Lewis, 1981; Nozick, 1969, 1993; Skyrms, 1980). For example, Nozick (1993) distinguished evidential from causal expected utilities on the basis of the probabilities that are used to determine outcomes. Although evidential expected utilities are computed with probabilities that reflect statistical relations, causal expected utilities use only probabilities that reflect causal relations. The problem that Nozick and others encountered was how to represent the distinction between probabilistic relations that refer to causal mechanisms and those that do not. Until recently, there was no good, principled way to do so. Causal Bayes nets have provided a solution (see Glymour & Cooper, 1999; Pearl, 2000). These theories are outlined in the next section.

Descriptive decision theories belonging to the family of consequentialist likelihood-value theories likewise do not deal with the causal underpinnings of the probabilities considered crucial for choice. For example, prospect theory (Kahneman & Tversky, 1979) remains silent about the provenance of the probabilities being transformed into decision weights, even though Tversky and Kahneman (1980) demonstrated the influence of causal considerations on judgment and choice. Other researchers have provided evidence about the role of causal knowledge. Pennington and Hastie (1993) found that causal narratives influenced jurors' decision making. Fischhoff and colleagues showed that causal assumptions affect risk assessment (e.g., Morgan, Fischoff, Bostrom, & Atman, 2001). Research on problem solving shows that causal knowledge improves performance in system control tasks (see Frensch & Funke, 1995; Funke, 2006). Finally, causal knowledge seems to be necessary for understanding positive and negative feedback loops in control systems (Sterman, 2006).

Causal Bayes Net Theories

Causal Bayes nets theories (e.g., Glymour, 2001; Pearl, 2000; Sloman, 2005) offer a formal framework for representing and reasoning about causal systems using causal models, a form of graphical representation of both deterministic and probabilistic causal systems. Such models distinguish probabilities that reflect causal relations from those that reflect noncausal correlations by explicitly representing causal structure (Glymour, 2001; Pearl, 2000; Spirtes, Glymour, & Scheines, 1993; Woodward, 2003). Noncausal correlations between two events are not due to a direct causal connection but could be due to a common cause. The model in the upper left-hand corner of Figure 1 depicts the causal model that explains the correlation between buying running shoes frequently and being in good shape. Noncausal relations do not support interventions (i.e., a manipulation of one variable would have no impact on the other and vice versa). For example, your waistline will not be reduced if you are provided with new shoes every month (external intervention). The upper right-hand side of Figure 1 shows the causal model of the direct causal relation between taking the stairs and being in good shape. This causal relation allows a manipulation of waistline by means of an intervention. If you force a person to take the stairs instead of the elevator, this may have an impact on his or her tummy.

A precise definition of the notion of intervention within the causal Bayes net framework allows formal representation of interventions and their consequences (Pearl, 2000; Spirtes, Glymour, & Scheines, 1993). Interventions are exogenous (i.e., they are independent of all variables in the causal system other than their consequences) and render their immediate effects independent of all other causes. The two models depicted in the lower half of Figure 1 depict interventions on the corresponding causal models

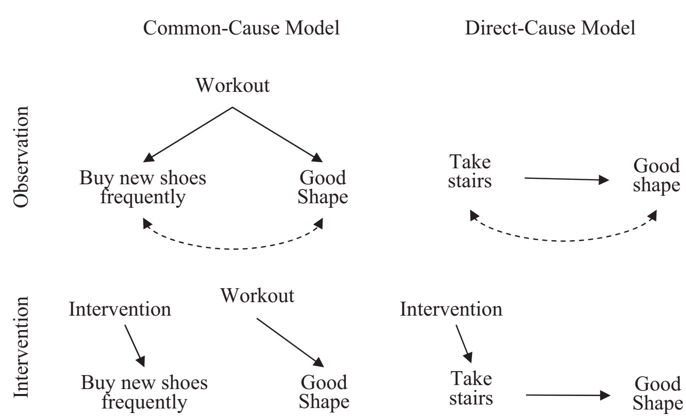

Figure 1. Observations of and interventions on causal models that explain a statistical relation between an action and an outcome. Causal relations are represented by continuous one-headed arrows; observable statistical relations are represented by dashed arrows.

in the upper half. Interventions are represented as separate nodes connected only to the intervened-on variable (i.e., they are exogenous). Furthermore, the intervention on buying deletes the causal influence of working out, because it is the intervention and not the normal cause that is now determining the buying scheme. As a result, purchasing shoes becomes independent of working out. The elimination of causal influences of other variables due to interventions has been called undoing (Sloman, 2005). Undoing reflects that the event intervened on is no longer diagnostic of its usual causes. If a person is forced to buy new running shoes, the action is the result of an intervention and does not change the probability that he works out or is in shape. By contrast, an intervention on taking the stairs (e.g., turning off the elevator) increases the probability of being in good shape. That is, an intervention instantiates the causal relations originating in the variable intervened on.

The notion of intervention allows causal Bayes nets to distinguish observational probabilities that reflect the statistical relations among events from interventional probabilities that represent the probabilities of events resulting from manipulation or action. The latter probabilities can be inferred only with knowledge of causal structure. Consider the two causal models depicted in Figure 1. Given a direct cause model, the observed probability of good shape conditional on taking the stairs and the interventional probability of good shape conditional on being forced to take the stairs coincide. By contrast, given a common cause model, the probabilities diverge. The probability of being in good shape is higher for someone who is observed to buy new running shows frequently (observational probability) than for someone who buys new running shoes due to an intervention by a spouse (interventional probability). See Hagmayer, Sloman, Lagnado, and Waldmann (2007) for further details.

Modeling Decision Making

The notion of intervention offers a way to model decision making in causal Bayes nets. In this article we focus on deliberate decision making (i.e., willful actions that are assumed to be a product of thought). First, let us construct a causal model of a person deliberating whether to bike to work to get in better shape. Thus we are looking for a causal model of the person's decision-making process. A possible causal model is shown in the left side of Figure 2. In this model, the decision maker's choice (i.e., whether to bike or take the car) is assumed to be causally affected by her own decision-making process (e.g., her deliberations about getting in better shape vs. getting home early). Some other external factors the person may or may not be aware of may also affect the decision (e.g., the current gas prices). The decision-making process is also assumed to be affected by external factors (e.g., pressure by the significant other).

The outcome of this decision-making process is a choice, an intended action. We represent choice as a separate node in Figure 2, because it is an element of the cognitive process that is distinct both from decision making and from action. To distinguish choice from decision making, one could describe a decision-making process that does not end in a choice ("Although I've spent much time making the decision, I still haven't chosen whether or not to bike to work"). To distinguish choice from action, one could make a choice but never take the chosen action ("I chose to bike, but I ended up taking the car as usual"). Choice (e.g., the decision

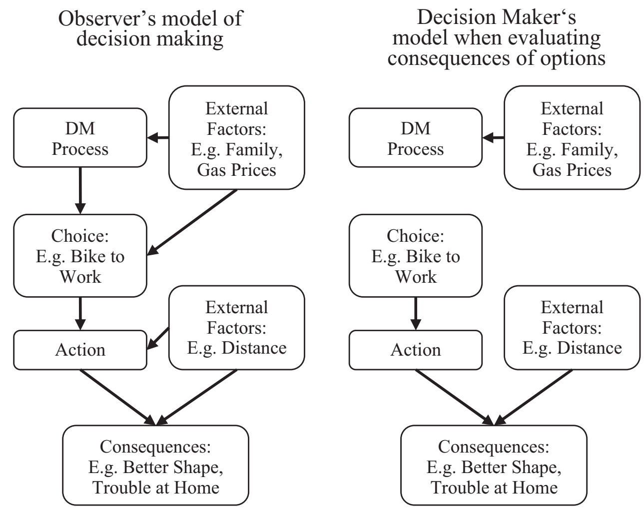

Figure 2. Modeling deliberate choice from the perspective of an outside observer (left) and the decision maker (right). Example describes the decision of whether to bike to work. DM = decision making.

to bike) influences which action is taken, and the action together with other causal variables in the world (e.g., whether you have a flat tire) result in outcomes (e.g., an increase in fitness and a later arrival time). This causal model allows the integration of many theoretical accounts (e.g., the theory of reasoned action; Ajzen & Fishbein, 1980) and empirical findings that show how external factors shape decision processes (e.g., frames, anchors; see Ariely, 2008; Hastie & Dawes, 2001, for overviews). Note that, according to this model, neither the action resulting from choice nor choice itself qualifies as an intervention in the sense of causal Bayes nets. If they were interventions, they would have to be independent of other causes.

Using Causal Models to Make Decisions

So far, we have considered decision making from an observer's perspective. Now we want to look at decision making from an agent's own perspective. Imagine you have to decide whether to bike to work. There are many ways to make that decision, such as habits ("I always bike during the summer"), external forces ("If you do not pick up the kids after school, there will be no dinner"), and spontaneous intuitions ("Currently I do not feel like biking"). Here, we focus instead on deliberate decisions based on consideration of the consequences of choice.

We hypothesized that decision makers use a causal model to envision the consequences resulting from the options before them. Such a model is depicted in the right side of Figure 2. This model is similar to the causal model an observer may use, but there is a crucial difference: Decision makers conceive of their own deliberate choice as an intervention on their actions in order to predict the consequences of the action. That is, we hypothesized that decision makers, in order to determine potential consequences, assume that their choices are made by an independent agent and that their choice determines their action. Thus, while thinking about the effects of each option, they treat their choice as independent of everything else and potential actions as independent of everything but choice. Therefore, we should see undoing: The diagnostic links from choice to its causes should be removed. For example, when you are thinking about what will happen if you bike to work rather than take the car, you focus only on outcomes (better shape, improved fitness, late dinner) and do not change your beliefs about the other factors that may have affected your choice.

Before we report our empirical justification, we offer three conceptual reasons for this assumption. First, it feels like choices that are made deliberatively are made freely, as if they are exogenous variables. We certainly consider the external constraints on our choices, but in the end, we deliberate to arrive at a final choice that we ourselves deliver; we do not see ourselves as conduits of external forces. In those cases in which we do feel like conduits, as in cases of addiction or compulsive behavior, choices are not deliberative. Even researchers who deny free will (e.g., Wegener, 2002) concede that most people believe themselves to be free agents.[1]

Second, people believe that their choices cause their actions and that those actions cause consequences. What this belief requires is the assumption that our choices and our actions are not confounded with other variables that influence the consequences. Otherwise we would always have to wonder whether the relation between our actions and their outcomes is spurious. For example, if a woman walks every night on the basis of her doctor's advice and later gets a good evaluation on an annual checkup, she infers that walking has improved her health. She does not infer that walking and getting a good evaluation are merely correlated and that the physician has acted as a common cause. The independence of choice and action from other causally relevant factors follows from the assumption that choice is an intervention. Hence, the assumption of intervention permits us to learn the relation between choice, action, and consequence.[2]

Empirical evidence supports the claim that decision makers treat action as independent of factors outside of those that govern their choices. For example, decision makers deny that their judgments are affected by arbitrary anchors (see Ariely, 2008, for many examples). Moreover, decision makers overestimate the influence they have upon their own actions. They tend to neglect factors outside of their control, and this tendency frequently leads them, for example, to underestimate the time required to complete a project (Buehler, Griffin, & Ross, 2002).

Third, we rarely draw inferences from our deliberate choices about other factors. These factors either are known in advance and may be considered in the decision-making process or are unknown and remain unknown. If I decide to bike to work, I do not learn by virtue of the choice that I consider getting in shape more important than my partner's being upset because I no longer drive the kids home from school. I presumably knew that already when I decided to bike. Also, I do not learn from my choice about the dangers of biking. If I did not know it at the time of decision, choice itself would not reveal it. Note that observers of my choice (who may include myself at a later time) may derive inferences from observing what I choose to do ("Looking back at my life, there was a time when I ignored the dangers of biking during rush hour").

For these reasons, we assume that decision makers model their own choices as interventions while they are thinking about the consequences that may arise from their different options.

A Causal Model Theory of Choice

We applied the notion of intervention from causal Bayes nets to decision making and proposed a descriptive theory of decision making, the causal model theory of choice (Sloman & Hagmayer, 2006). The key idea is that at least some deliberate decision making uses simplified causal models of the decision problem and imaginary choices. The theory makes two claims: (a) decision makers consider the outcomes of causal processes rather than statistical relations and (b) decision makers conceive of their choice as an intervention. We assume that people go through three phases of decision while they make a decision.

Phase 1. Representation of the Decision Problem: World Model Construction

The decision problem is represented as a causal model. This is done by determining the causal consequences to be considered (e.g., physical fitness) and then identifying factors that are causally relevant to those consequences (e.g., workout and diet). Information about these factors might be directly available or might be inferred from background knowledge. Research on causal attribution (e.g., Ahn, Kalish, Medin, & Gelman, 1995) has shown that people can easily come up with factors that do (or could) causally affect an outcome. In general, only a small number of factors are consciously considered (Fischhoff, Slovic, & Lichtenstein, 1978), even in complex, naturalistic situations (Klein, 1998; Zsambok & Klein, 1997). Next, a causal model of the decision problem that describes how the selected factors bring about the causal consequences is constructed.

Phase 2. Representation of Options = Choice Model Construction

Before a decision maker can evaluate the consequences of a potential action, a new model that represents the consequences that would result from each option considered must be constructed. We call this the choice model. To represent choice, one adds a node to the world model for the intervention that choice entails. Because choice is conceived of as an intervention, the choice node is not connected to any causal variable apart from the chosen action. In addition, undoing is implemented (i.e., the action is rendered independent of other causes; see right side of Figure 2). When reasoning, people apparently understand that interventions result in undoing (Rehder & Burnett, 2005; Sloman & Lagnado, 2005; Waldmann & Hagmayer, 2005).

Next, the action is taken in imagination and the consequences are simulated with the choice model. That is, the interventional probabilities of the outcomes resulting from the chosen action are

[1] Note that our analysis is agnostic about whether people actually have free will and whether interventions have a real, metaphysical existence. We claim, however, that people act as if both of these possibilities are true in the sense that they represent some choices as interventions in the course of their decision making.

[2] Glymour (2004) even argued that the assumption of independent choice is a necessary prerequisite for instrumental causal learning, because we can never rule out the possibility that all relations we observe among our actions and outcomes are due to unknown common causes.

inferred. We do not claim that people can infer interventional probabilities precisely but rather that judgments will be consistent with undoing. Note, however, that some studies have shown that people are able to compute interventional probabilities from observed statistical relations and causal models quite accurately for generative interventions (Meder, Hagmayer, & Waldmann, 2008; Waldmann & Hagmayer, 2005).

Phase 3: Decision

The choice model allows for qualitative and quantitative decision making. Whenever one's choice renders the chosen action independent of the desired consequences, the default choice is not to act, because any action incurs some cost in time, effort, or assumption of responsibility. This is the case when the action is related to the outcome via a common cause (see Figure 1, left side). By contrast, if choice increases the probability of the effect, it should be accepted, as long as costs do not outweigh the resulting benefits. This is possible when the action is a direct cause of the outcome (see Figure 1, right side). In both cases, a merely qualitative assessment of the resulting interventional probabilities is sufficient for making a choice. We focus on these cases in this article.

An option may also be immediately accepted without consideration of further options if it increases the probability of a desired outcome sufficiently. This strategy constitutes satisficing (Simon, 1957). Research on naturalistic decision making has shown that people under high pressure tend to take the first option that they consider to be causally efficacious (Klein, 1998; Zsambok & Klein, 1997).

Finally, if more than one option has the power to increase the likelihood of the outcome, interventional probabilities for each option have to be inferred. Quantitative decision making thus becomes necessary. To make a final decision, one must somehow integrate these interventional probabilities with assessments of the outcome's value. Several schemes for integrating likelihoods and values have been proposed (e.g., Hernstein, 1961; Kahneman & Tversky, 1979). Our crucial claim is that, whatever the precise choice rule used by a decision maker for a particular decision problem, interventional and not observational probabilities are used.

Rebuttals

Here, we consider counterarguments to our claim that people conceive of their choices as interventions on actions. The first argument is that choices are obviously influenced by a number of factors (e.g., external factors and the decision maker's deliberations). Hence, choices are not independent of these factors and therefore cannot be interventions. This argument is correct when one looks at decisions from an observer's perspective (see Figure 2, left side). People's choices are indeed affected by a multitude of factors, many of which we are unaware (e.g., Fitzsimons & Bargh, 2003). Phase 1 of our theory identifies how external factors are taken into account. Our claim is only that decision makers model their own deliberate choices as interventions when they think about the possible outcomes resulting from implementation of each option. At that point, the values of external factors should already have been identified and incorporated into the world model. Nothing can be learned about those factors by considering the effects of each option. At the point at which consequences are being considered, everything has been learned that can be learned about variables and events that are upstream of choice. So the choice reveals nothing that decision makers do not already know; it is nondiagnostic of the causes of choice. In that sense, decision makers treat their choice as an intervention on action.

The second counterargument is that if choices were interventions, people would ignore other factors that influence choice in decision making. But they do not. Indeed, deliberating decision makers must consider factors that include their own preferences and assets, other agents, the expected consequences of their actions, and their goals. If they didn't, choice would be random. Our claim is not that people ignore these factors but rather that inferences are not made about them in the model people use to determine the effects of options (see Figure 2, right side).

A third counterargument identifies an alternative theoretical account of how people consider causal structure in decision making. It proposes that people base their decisions on beliefs about the causal efficacy of different actions. If an action produces a desired consequence, it is considered. Otherwise, it is not. On this view, mere correlations among actions and outcomes are discounted, because such correlations are not on the causal path from action to consequence. The notion of choice as intervention is therefore irrelevant. Undoing is unnecessary, because it merely serves to block diagnostic reasoning that is not important to decision making. We call this account the causal path hypothesis. Indirect evidence for this approach comes from Koslowski (1996), who showed that the same statistical relation is judged to be less causal if no plausible causal mechanism can be inferred.

By contrast, we hypothesized that participants' sensitivity to causal structure would be due to inferences based on assumptions about the underlying causal processes and the equation of choices and interventions. The causal path hypothesis identifies which paths are considered in decision making by distinguishing when actions cause outcomes and when they do not. The causal model theory, by contrast, assumes that knowledge about causal structure is used for inferring interventional probabilities from the observed probabilities. Hence, it distinguishes observational from interventional probabilities. The causal path hypothesis does not make this distinction. Therefore, to distinguish the theories, we manipulated causal structure and obtained both observational and interventional probability judgments in Experiments 3 and 4.

In summary, a causal model theory of choice makes two crucial claims: (a) decision makers consider the outcomes of causal processes rather than merely statistical relations and (b) decision makers conceive of their choice as an intervention when they identify the consequences of that choice. Both claims can be tested empirically and distinguished from other accounts. The main alternative account is that people pay attention only to whether outcomes are on a causal path downstream of the actions being considered.

Experiment 1

Our goal in Experiment 1 was to provide evidence that participants used causal knowledge rather than merely statistical relations among actions and outcomes to make decisions. Therefore, participants received six scenarios that described a statistical relation between an action and a desirable outcome. In addition, they were provided a causal model that explained the relation as originating either from a common cause structure or from a direct cause structure. If participants took this information into account when making their choice, they should recommend acting to a friend only if they believed the statistical relation reflected a direct causal relation and not a common cause.[3] To show that participants relied on causal beliefs regardless of the way the statistical relation was presented, we manipulated the format of the presentation of evidence (frequencies vs. percentage increase vs. qualitative).

Method

Participants and design. The study was run online. Participants were recruited at various psychology websites around the world and through advertisements in the Brown University newspaper. Most of the 41 participants were Brown University students. They were rewarded for participation with a small chance (1/41) to win $50. Each participant received six different scenarios, each of which had either a common cause model or a direct cause model. Thus, for each scenario, causal model was manipulated between participants, whereas overall it was manipulated within subjects. As a second factor, the presentation format (frequencies, probabilities, qualitative) was manipulated across participants.

Materials and procedure. The six scenarios described familiar, everyday activities and their statistical relation to desired outcomes. All scenarios had the same basic outline and were roughly the same length. The order of the scenarios was counterbalanced across participants. The relations in all scenarios were very strong. We will describe only one scenario in detail here; the other five can be found in Appendix A. In the chores scenario, participants read the following story:

> Recent research has shown that of 100 men who help with the chores, 82 are in good health whereas only 32 of 100 men who do not help with the chores are. Imagine a friend of yours is married and is concerned about his health. He read about the research and asks for your advice on whether he should start to do chores or not to improve his health. What is your recommendation? Should he start to do the chores or not?

In two experimental conditions we added a causal explanation for the statistical relation in the scenario. Participants were informed either that the research has found that the cause was that "doing the chores is an additional exercise every day" (direct-cause condition) or that "men who are concerned about equality issues are also concerned about health issues and therefore both help to do the chores and eat healthier food" (common cause condition). After they had read the scenario, participants were given a forced choice to recommend either acting or not acting. No feedback was provided. We expected participants to recommend action given a direct cause model but not given a common cause model.

We also manipulated the presentation format of the statistical relation between participants. As outlined earlier, reasoning about causal models requires Bayesian reasoning for updating the values of variables. Although some researchers have found that Bayesian reasoning is impaired with probabilities relative to natural frequencies (Gigerenzer & Hoffrage, 1995; but see Barbey & Sloman, 2007), others have found that such inferences are possible on the basis of qualitative information alone (Sloman & Lagnado, 2005). Therefore participants (a) received information about conditional frequencies, as in the example above; (b) were presented with a percentage increase ("men who do the chores are 50% more likely to be in good health than men who do not"); or (c) were informed that there was a statistical relation without mention of any specific numbers ("men who do the chores are substantially more likely to be in good health than men who do not"). We expected sensitivity to causal models regardless of the format of the statistical relation.

Results and Discussion

The 41 participants made a total of 244 decisions. Overall, only 23% of the participants in the common cause condition recommended acting; in comparison, 69% of the participants who assumed a causal link made a recommendation to act. The difference between causal models turned out to be significant for five of the six scenarios ($p < .05$); the difference for one scenario (clothing) was almost significant ($p = .06$). As all six scenarios showed the expected effect, we combined the results for further analyses. Table 1 shows the percentages of recommendations of action conditional on presentation formats. Differences between causal models turned out to be significant for each presentation format: for frequencies, $\chi^2(1, N = 81) = 18.8$, $p < .01$; for percentage, $\chi^2(1, N = 82) = 16.3$, $p < .01$; and for qualitative description, $\chi^2(1, N = 81) = 16.9$, $p < .01$. To test whether there was a difference between presentation formats, we conducted an overall chi-square test for which we computed the expected frequencies separately for each causal model condition. No difference resulted, $\chi^2(5, N = 244) = 1.71$, *ns.*

These results suggest that participants took causal structure into account when they made their decisions. Choices were not based solely on statistical relations; rather, options were declined that had no impact upon the desired outcome according to a causal model. Counter to our expectations, 23% of participants recommended action even though the common cause model identified the statistical relation as being merely correlational. This result might have been due to participants' own beliefs about the underlying causal relations. Others may have ignored the causal structure information and considered only statistics. Nevertheless, the results clearly support our first hypothesis in that most people used causal assumptions to make decisions.

Experiment 2

In the first experiment we directly manipulated participants' assumptions about the causal structure underlying the statistical relation between action and outcome. One may object that informing participants about causal structure drew their attention to the relevance of causal considerations. This could explain why they took causal structure into account. Therefore, in Experiment 2 we obtained recommendations from participants without giving them causal information. Thus they were informed only that people taking an action had a higher probability of achieving the outcome than did people not taking the action. In case the plausibility of

[3] We asked for recommendations to a friend, because most scenarios had high self-relevance (e.g., drug usage, academic achievement). This may have biased participants' choices. A pretest confirmed this hunch.

Table 1
Results of Experiment 1: Percentages of Recommendations to Act Conditional on Presentation Format

	Assumed causal model	
Format	Common cause	Direct cause
Frequencies	22.0	70.0
Percentage	19.5	63.4
Qualitative description	27.5	73.2

the statistical relation affected participants' recommendations, we manipulated plausibility in this experiment. We also evaluated causal beliefs but only after participants had provided recommendations. In particular, participants were asked to provide a causal explanation for the statistical relation. If causal beliefs mediated their recommendations, these explanations should be predictive of their recommendations regardless of whether or not the statistical relation was plausible. Again, we expected that participants who assumed a common cause model would not recommend action and that those who assumed a direct causal model would recommend it.

Method

Pretest. To construct the scenarios, we conducted an extensive pretest in which we asked 34 undergraduates to rate the plausibility of statistical relations among various actions and outcomes. Plausibility was defined as the likelihood of a relation regardless of the underlying causal processes. Ratings were given on a scale ranging from 0 (*not plausible at all*) to 100 (*very plausible*). To run Experiment 2, we selected a relation rated as highly plausible ("people who watch movies in their original language speak better English"; $M = 76.5$, $SE = 4.36$) and a relation rated as implausible ("people who use sunscreen with a low protective factor have a darker tan"; $M = 39.7$, $SE = 4.62$). We chose these extremes in order to disentangle causal assumptions and plausibility.

Participants and design. Sixty-one students from the University of Göttingen participated to satisfy a course requirement. Participants were randomly presented with either a plausible or an implausible scenario.

Materials and procedure. In the plausible condition, participants received the following scenario (translated from German):

> Recent research has found that people who watch movies in their original language speak better English than people who do not. Imagine a friend of yours wants to improve his English. What is your recommendation? Should he start to watch movies that are not dubbed?

In the implausible condition, they read the following scenario:

> Recent research has found that people who use sunscreen with a low protective factor have a darker tan than people who do not. Imagine a friend of yours wants to get a darker tan. What is your recommendation? Should he start to use sunscreen with a low SPF?

Ratings were given on a 6-point rating scale ranging from 1 (*no, definitely not*) to 6 (*yes, for sure*). After they made their recommendation, participants were asked whether the relation between the action and the outcome was due to (a) the action that directly affected the outcome or (b) some other factor that influenced both the action and the outcome while the action itself had no impact on the outcome. Thus, they were asked whether they believed in a direct cause model or a common cause model.

Results and Discussion

Participants in both conditions were grouped according to the causal model they chose after making their recommendation. Roughly two thirds of participants assumed an underlying common cause model in both conditions. Exact numbers and mean recommendations for the resulting groups are shown in Table 2. An analysis of variance (ANOVA) with plausibility and causal model as between-participants variables and recommendation as the dependent variable yielded two significant main effects and no interaction: causal model, $F(1, 57) = 35.6$; $p < .01$; plausibility, $F(1, 57) = 10.3$, $p < .01$, $MSE = 1.82$. As Table 2 shows, recommendations were generally lower for the implausible scenario, but a strong effect of the assumed causal model obtained for both the plausible and implausible scenarios. Thus, the effect of the assumed causal model turned out to be independent of the plausibility of the given statistical relation.

The results of Experiments 1 and 2 complement each other. Whereas assumptions about the causal structure were directly manipulated in Experiment 1, they were collected after the recommendation in Experiment 2. Nevertheless, both experiments showed that the same statistical relation between action and outcome led to differential recommended actions conditional on the assumed causal model. Thus, the findings of both experiments support our first claim that assumptions about causal structure guide decision making.

Experiment 3

The finding that participants take causal structure into account when they recommend actions or making choices raises the question of how they do so. We have focused on two possible accounts.

Table 2
Results of Experiment 2: Recommendations Made by Participants

	Assumed causal model	
Recommendation	Common cause	Direct cause
Plausible relation: movies ↔ English		
N	20	11
M	2.75	5.46
SE	0.32	0.28
Implausible relation: sunscreen ↔ tan		
N	21	9
M	2.05	3.78
SE	0.26	0.62

Note. Assumptions about causal models were assessed after recommendations were made. Recommendations were given on a 6-point scale ranging from 1 (*no, definitely not;* coded as 1) to 6 (*yes, for sure*).

The first is the causal path hypothesis that assumes that participants choose only actions that are on a causal path that leads, directly or indirectly, to the desired outcome. People do not recommend or take actions they believe not to have an impact on the outcome, and they choose actions they believe will bring about desired consequences. According to this account, a causal model is just a structured representation of a set of direct causal relations that can be used to discount statistical relations that have no underlying causal path from action to outcome. For example, when deciding whether to bike to work to get in better shape, decision makers activate their beliefs about the causal impact of biking upon being in shape. If there is a causal link, they have reason to choose to do so.

We propose a different account, one that assumes that people are sensitive to causal structure and conceive of their choice as an intervention. Treating choice as an intervention on action guarantees that only outcomes on a causal path, leading from the set of choice options, will be considered. Choices are assumed to trigger all causal pathways that are causally downstream of the chosen action and to eliminate the impact of alternative causes upstream of the action (see Figure 2, right side). In consequence, only those statistical relations that indicate direct causal relations are relevant; mere correlations are eliminated. Hence, both accounts predict that people consider causal structure and prefer actions that have a causal impact over actions that are merely correlated to an outcome. But the causal path hypothesis holds that this preference is due only to an assessment of whether the cause leads to the outcome, whereas the causal model hypothesis holds that it is due to choice being treated as an intervention.

We had two goals in Experiment 3. The first was to show that people's sensitivity to causal structure is not limited to an assessment of a causal path. The second was to accumulate evidence showing that people treat choices and interventions similarly and thus treat choice as an intervention. In particular, we predicted, if choices are conceived of as interventions, probabilities inferred from deliberate choices should equal probabilities inferred from external interventions (i.e., from forcing somebody to take action), because both would constitute interventions.[4] This prediction presupposes that the resulting actions are the same, and this assumption might not be plausible whenever agents resisted the external pressure and took the action unwillingly.

According to the causal model theory, people should assume that the probability of a causally related outcome rises after both deliberate choice and enforced action. But the outcome probabilities should not be affected by actions that are related to an outcome by a common cause. It is crucial that these inferences should differ from inferences drawn on the basis of an observation of the same action. Observing somebody take an action not only entails that the causal effects of the action should be present but also provides diagnostic evidence that events correlated with the action for other reasons should be present. Therefore, participants should infer a high probability of the outcome regardless of the assumed causal model. A simple causal path model cannot differentiate between observations on one hand and interventions and choices on the other. If action and outcome are assumed not to be causally related, the judged probability should remain the same, no matter whether the action is observed, chosen, or enforced. Conversely, the probability should be elevated if there is a direct causal relation.

Method

Participants and design. A sample of 146 students from the University of Göttingen participated. Most did so to satisfy course requirements, although some ($n = 45$) were paid a small amount of money for participating in this and various unrelated experiments. They were randomly assigned to one of six conditions resulting from the manipulation of causal model assumptions (common cause vs. direct cause) and type of inference (based on deliberate choice, external intervention, or observation). Both factors were manipulated between participants.

Materials and procedure. Participants responded to one of four scenarios. Scenarios were similar to the scenarios used in Experiment 1 (see Appendix B for details). To cover a broader range of choices, we used two types of scenarios. Two scenarios pertained to actions we generally engage in consciously. One was the chores scenario described in Experiment 1; the second scenario (exercise) described a relation between doing sports and consuming fewer calories from fat. The second pair of scenarios pertained to behaviors we usually do not choose but do reflexively. For example, in the beard scenario, participants read the following story (in German): "Recent research has shown that of 100 bearded men who frequently scratch their chins, 65 have skin irritations, whereas only 10 of 100 men who do not have the same problem."

Thus, as in Experiment 1, participants first learned about a strong statistical relation between an action and an outcome. They were then informed about the underlying causal structure: "The research also indicated that the cause of this fact is beard growth. Men who have strong growth tend to scratch their chin frequently and to have more skin problems (common cause condition); or "The research also indicated that the cause of this fact is impurities. Frequently scratching the chin rubs dust and dirt into the skin, which in turn causes skin problems (direct cause condition)."

The other scenario was similar and described the relation between touching one's nose and problems with breathing through the nose. We did not expect to find any differences between the two types of scenarios (actions vs. behaviors), because deliberately choosing actions or behaviors should eliminate the causal impact of other factors upon the action in both cases.

After participants had read the scenario, we asked them to summarize the scenario to check their understanding. In case of misunderstandings, they were requested to reread the scenario. In the choice condition, participants were asked to imagine engaging in the action occasionally and experiencing the outcome from time to time. They were asked whether they would stop the action in scenarios in which the action was related to an undesired outcome (e.g., skin problems in the beard scenario) or if they would intensify the action when it was related to a desired outcome (e.g., being healthy in the chores scenario). They gave their answer on a rating scale ranging from 1 (*definitely not*) to 4 (*definitely yes*). Next they were asked to imagine choosing to engage in the action frequently

[4] We do not claim that people fail to distinguish between enforced and deliberate actions. We claim only that the two are functionally equivalent when it comes to inferences. Both types of action are conceived of as interventions on actions.

and to infer the resulting probability of the outcome. Then they were asked to imagine stopping the action completely and to predict the probability of the outcome on the same scale. That means they estimated the probability of the outcome conditional on deliberately chosen actions, P(outcome|action) and P(outcome|$\sim$action). In all cases, outcomes were framed positively (i.e., negative events were absent and positive events were present). This framing allowed us to use the same rating scale for all scenarios. Probability ratings were given on a scale from 0 (*the outcome will not occur for sure*) to 100 (*the outcome will occur for sure*). Anchors were adapted to the specific scenario.

In the intervention condition, participants were asked to imagine a friend being forced to (a) engage in the action frequently and (b) stop the action completely. The force was exerted either by a technical device, for those behaviors normally not consciously chosen, or by another person. Again, participants had to infer the probability of the outcome using the same rating scale as before. That is, they estimated the probability of the outcome conditional on forced actions.

In the observation condition, participants were requested to imagine observing a friend (a) engage in the action frequently and (b) not engage in the action at all. As in the other two conditions, they were asked to infer the resulting probability of the outcome. That is, they estimated the probability of the outcomes conditional on observed actions. In all three conditions, the order of the last two questions was counterbalanced.

Results and Discussion

First we analyzed participants' choices in the choice condition. As in Experiment 1, causal model assumptions clearly affected participants' choices (see Table 3). Note that here, in contrast to the first two experiments, participants decided for themselves rather than gave advice to somebody else. When they assumed a direct causal relation between action and outcome, they decided to stop actions leading to undesired outcomes but to intensify actions leading to a desired outcome. When they assumed an underlying common cause model, they preferred not to change their actions, despite being confronted with the very same statistical relation. As expected, no differences were found for the two types of scenarios. An ANOVA with causal model and type of scenario (mere behavior vs. deliberate decision) as between-participants factors yielded no interaction, $F(1, 44) = .171$, $p = .62$, but a significant main effect for causal model, $F(1, 44) = 20.6$, $p < .01$. Therefore, to increase statistical power we decided to analyze all scenarios together.

Table 3
Results of Experiment 3: Means and Standard Errors of Choice Ratings

Scenario	Assumed causal model: Common cause	Direct cause
Mere behavior	2.17 (0.24)	3.00 (0.21)
Deliberate decision	1.92 (0.15)	2.92 (0.19)

Note. Data in parentheses are standard errors. Choices were made on a scale ranging from 1 (*definitely not*) to 4 (*definitely yes*).

Results for participants' inferences for the probability of the outcome conditional on taking the action frequently and stopping the action completely are given in Table 4. Overall, participants clearly differentiated between choice and intervention on one hand and observation on the other. In both the choice and intervention conditions, the probabilities of the outcome for taking the action frequently, P(outcome|action), and stopping the action completely, P(outcome|$\sim$action), differed strongly when a direct cause model was assumed. The probabilities differed less when a common cause model was assumed. As expected, no differences between the two causal models resulted when participants based their inferences on observations of behavior. These descriptive analyses were confirmed by statistical analyses. An initial overall ANOVA with causal model and type of inference (based on choice, intervention, or observation) as between-participants factors and outcome (conditional on action vs. conditional on no action) as a within-participant factor resulted in a significant three-way interaction, $F(2, 140) = 6.0$, $p < .01$, $MSE = 260.0$, which we followed up with more focused analyses.

First we conducted the same ANOVAs but included only the choice and intervention conditions. There was no effect of type of inference, $F(1, 92) = 1.02$, $p = .31$, $MSE = 338.0$, and no interaction of Type of Inference $\times$ Outcome, $F(1, 92) = 0$, $p = 1$, $MSE = 326.6$, and Type of Inference $\times$ Causal Model $\times$ Outcome, $F(1, 92) = .01$, $p = .94$, $MSE = 326.6$. This finding indicates that participants did not differentiate between interventions and choice. By contrast, the assumed causal model interacted with the difference of the two inferred outcome probabilities, $F(1, 92) = 30.4$, $p < .01$, $MSE = 326.6$. As the means shown in Table 4 indicate, the probabilities differed more in the direct cause condition. This finding confirms the prediction that participants take the structure of the causal model into account. The difference between the two probabilities also turned out to be significant, $F(1, 92) = 98.1$, $p < .01$, $MSE = 326.6$. Finally, we conducted an ANOVA for the observation condition only, with outcome as a within-participants variable and model as a between-participants variable. In line with our predictions, no effect of causal model was observed, $F(1, 48) = .16$, $p = .69$, $MSE = 158.3$, but participants inferred a higher probability of the outcome when the action was observed to be frequent than when it was never taken, $F(1, 48) = 506.3$, $p < .01$, $MSE = 132.5$. Overall, these findings conformed closely to our hypotheses. Moreover, a regression analysis revealed that the inferred probabilities in the choice condition were highly predictive of the choices made by participants, $F(2, 45) = 14.6$, $p < .001$, $MSE = .43$, $R^2 = .39$.

Contrary to our prediction for the choice and intervention conditions, the probabilities of the outcome given action and no action did differ by a small amount even when a common cause model was assumed (see Table 4, left side, upper and middle rows). According to causal model theory, choices and interventions delete (undo) the relation between the action and the outcome; therefore, the probability of the outcome should be the same regardless of action. A closer analysis of the data revealed that our predictions were correct for the two scenarios that involved conscious actions. No difference between P(outcome|action) and P(outcome|$\sim$action) resulted for these scenarios, $F(1, 24) = .14$, $p = .71$. However, a difference did obtain for scenarios concerning behaviors that people perform reflexively, $F(1, 24) = 19.2$, $p < .01$. Perhaps undoing is limited to factors of which people are

Table 4
Results of Experiment 3: Mean Judged Probabilities and Standard Errors of Outcomes

	Assumed causal model			
	Common cause		Direct cause	
Inference task	*P*(outcome∣action)	*P*(outcome∣~action)	*P*(outcome∣action)	*P*(outcome∣~action)
Choice	59.2 (4.17)	47.9 (5.48)	68.3 (2.67)	27.9 (2.76)
Intervention	50.4 (4.28)	38.8 (3.15)	71.7 (2.38)	31.7 (3.84)
Observation	73.6 (2.35)	22.4 (2.45)	75.2 (2.76)	22.8 (2.02)

Note. Data in parentheses are standard errors.

aware. Some participants may have been unable or unwilling to undo the unconscious factor that allegedly influenced their behavior. Some other participants may have assumed an additional direct causal influence of the action upon the outcome because such a link was highly plausible. Comments from a few participants support this post hoc hypothesis (e.g., "scratching always causes skin irritations"). Others might have been confused because the outcomes for the inference questions were framed in terms of absence of a negative effect. For example, in the beard scenario they were asked, "Imagine you have deliberately chosen to scratch your chin more often. What is the likelihood that you have fewer skin problems?" Some might have forgotten about causal structure while they dealt with this complicated question. In any case, participants did distinguish common cause and direct cause models in the choice and intervention conditions, given the mere behavior scenarios. As predicted, the difference between judged probabilities given action and no action differed more for the direct cause model than for the common cause model. A post hoc ANOVA that included causal model as a between-participants factor and probability as a within-participant variable again resulted in a significant interaction of causal model and probability for these two conditions, $F(1, 46) = 8.06$, $p < .01$, $MSE = 297.8$.

In summary, the results of Experiment 3 show three things. First, they replicate the findings of the previous experiments that people take causal structure into account when making a decision. They also show that the effect occurs for both actions we are normally aware of choosing (doing the chores, doing sports) and behaviors we are normally not tracking consciously (scratching our chin, touching our nose). Second, the findings show that this effect is not merely due to participants' causal beliefs about whether or not the action is on a causal path with the outcome. Participants clearly derived different inferences for the probability of the outcome conditional on the causal model and on whether the action was chosen, enforced, or observed. The causal path hypothesis implies no differences between observed and chosen actions. Finally, as predicted by the causal model hypothesis, inferences in the context of choice behaved like inferences in the context of intervention. Therefore, the findings corroborate our claim that people conceive of their own choices as interventions.

Experiment 4

Our goal in Experiment 4 was to provide further evidence for our claim that people equate choices with interventions. If choice is treated as an intervention on action, a deliberately chosen action should be rendered independent of other causes (see Figure 1), such that the action is no longer diagnostic of these causes. Consider our initial example. If I choose to buy running shoes on a monthly basis from now on, my purchasing behavior is not diagnostic of my workout regime. In contrast, buying shoes frequently does support inferences about the effects of that action (e.g., an overstuffed closet). The causal path hypothesis does not differentiate between deliberately chosen actions and actions being caused by some other factors. If an action is caused or affected by another factor, the action should be diagnostic of this factor. To test these differential predictions, we again investigated participants' inferences derived from deliberately chosen actions, enforced actions, and observations of actions.

Method

Participants and design. Forty-eight students from the University of Göttingen and 36 students from Brown University participated. German students participated to fulfill a course requirement (50%) or for a small amount of money. All Brown students were paid. All participants responded to two scenarios describing either a common cause or a causal chain model. In the common cause model, action and outcome were introduced as being effects of the same causal factor; in the causal chain model, the action was the cause of an intermediate event (identical to the common cause) that in turn led to the outcome. Students drew inferences on the basis of chosen actions, enforced actions, or observed actions. Both factors (causal model and type of inference) were manipulated between participants. The order of scenarios was kept constant at Brown but was counterbalanced at Göttingen.

Materials and procedure. Participants responded to two of the scenarios used in Experiments 1 and 3 (chores and exercise). Both scenarios were slightly modified to be compatible with both a common cause and a causal chain model (see Appendix C for details). In each scenario, the same event was framed as either the common cause or the intermediate event in the causal chain. For example, in the exercise scenario, participants read the following:

> Recent research has discovered that of 100 people who exercise, 65 consume less than the average number of calories whereas of 100 people who do not exercise, only 25 consume less than the average number of calories. The research also indicated that the cause of this fact is the presence of the neurotransmitter CNA. *The neurotransmitter causes people to exercise more and to eat less* (common cause condition). *Exercise causes the release of the neurotransmitter, which in turn causes people to eat less* (causal chain condition).

In the chores scenario, we used having a positive attitude both as the common cause of doing the chores and being healthy and as the intermediate variable in a chain going from doing the chores to being healthy.

After they had read the scenario, participants summarized it so we could check their understanding. Then they were asked to infer the probability of the common cause or the intermediate event. In the choice condition they were told to imagine that a friend read about the research and thereupon deliberately decided to act. In the intervention condition they were told to imagine forcing a friend to act. Finally, in the observation condition they were told to imagine a friend being engaged in the action. In all three conditions they were asked what they could infer about the presence of a common cause or intermediate variable. For example, in the exercise scenario they were asked, 'What can you infer from that about the presence of the neurotransmitter CNA in your friend's brain?' Answers were given on a scale ranging from 0 (*the neurotransmitter is not present*) to 50 (*nothing can be inferred, the transmitter might be present or not*) to 100 (*the neurotransmitter is present*). Descriptors were appropriate for each scenario. Finally confidence ratings were obtained from participants. The scale ranged from 0 (*not confident at all*) to 100 (*extremely confident*).

Results and Discussion

A first ANOVA showed the same pattern of results for Brown and Göttingen students (location did not yield a main effect, nor did it interact with inference task or causal model). Therefore, we combined the data for subsequent analyses. Table 5 depicts the results both for participants' estimated probabilities and participants' confidence averaged over both scenarios. Participants' confidence was rather high in all six conditions, and the conditions differed only slightly (see Table 5, right side). An ANOVA with causal model and inference task as between-participants variables and scenario as a within-participant variable yielded no significant effects except for a tendency to be more confident about inferences drawn on the basis of causal chains, $F(1, 78) = 3.31$, $p = .07$, $MSE = 332.5$.

Clear differences were found, however, for the estimated probabilities. An overall ANOVA with the same three variables yielded significant main effects for causal model, $F(1, 78) = 31.6$, $p < .01$, and inference task, $F(2, 78) = 28.9$, $p < .01$, as well as a significant interaction between the two, $F(2, 78) = 7.50$, $p < .01$, $MSE = 280.2$. Participants inferred a higher probability in the causal chain condition than in the common cause condition if the action was either deliberately chosen or enforced externally. Recall that the variable asked about was the same in both models. No differences between causal models resulted if the action was merely observed. This pattern was confirmed by separate analyses of the effect of causal model within each condition: choice, $F(1, 26) = 32.8$, $p < .01$, $MSE = 281.9$; intervention, $F(1, 26) = 12.1$, $p < .01$, $MSE = 311.8$; and observation ($F < 1$).

Against expectation, the ANOVA for the intervention condition resulted in a significant interaction of scenario and causal model, $F(1, 26) = 9.11$, $p < .01$, $MSE = 200.8$. The respective means in the chores scenario were $M_{CC} = 43.6$ versus $M_{Chain} = 48.6$, and $M_{CC} = 47.1$ versus $M_{Chain} = 75.8$ in the exercise scenario. Post hoc ANOVAs for the intervention condition with causal model as a between-participants variable yielded a significant effect for the exercise scenario, $F(1, 26)$. $p < .01$, $MSE = 309.1$, but no effect for the chores scenario ($F < 1$). Recall, in the exercise scenario the intermediate variable/common cause was a neurotransmitter, and in the chores scenario it was an attitude. It seems that participants assumed forced actions do not lead to an attitude change but do affect biological variables.

In summary, Experiment 4 provided a second test of our claim that people conceive of choice as an intervention. In line with predictions derived from this hypothesis, participants again differentiated forced and deliberately chosen actions on one hand and observed actions on the other. These findings complement the results of Experiment 3. Although participants derived diverging inferences about the probability of the outcome in Experiment 3, they estimated different probabilities with respect to a common cause and an intermediate event in Experiment 4. Neither finding could be predicted on the basis of the causal path hypothesis, which holds that people discount statistical relations they believe do not reflect a direct causal path from action to outcome. The findings therefore support a causal model theory of choice that holds that people use causal models and the notion that choice is an intervention to infer the probability of outcomes that would result from choice.

General Discussion

The results of previous research on causal learning and reasoning have shown that participants distinguish among causal models and their implications (e.g., Waldmann, 1996; Waldmann & Hagmayer, 2001). People also differentiate noncausal correlations from causal relations, understand how an intervention alters the structure of a causal model (e.g., Sloman & Lagnado, 2005), and are capable of inferring the probabilities that would result from an intervention (e.g., Waldmann & Hagmayer, 2005). These insights build the foundation

Table 5
Results of Experiment 4: Mean Judged Probability and Confidence of Common Cause in a Common Cause Model and of Intermediate Variable in a Causal Chain Model

	Probability		Confidence	
Inference task	Common cause model	Causal chain model	Common cause model	Causal chain model
Choice	50.7 (3.59)	76.1 (3.27)	76.1 (4.55)	79.6 (4.67)
Intervention	45.4 (2.93)	61.8 (3.95)	76.4 (3.65)	76.1 (4.09)
Observation	76.8 (2.67)	78.2 (3.57)	68.2 (3.67)	80.4 (3.06)

Note. Data in parentheses are standard errors. Confidence ratings were made on a scale ranging from 0 (*not confident at all*) to 100 (*extremely confident*).

of the causal model theory of choice. Its central claim is that people make decisions based on causal models they have used to infer the probability of consequences of choice options.

The findings of the four experiments presented in this article support this claim. The first two experiments showed that participants did not simply base their decisions on statistical relations among actions and outcomes but considered the underlying causal model. Experiment 2 showed that they did so even when they were not provided with a causal model. For both plausible and implausible statistical relations, participants derived causal hypotheses themselves and used these hypotheses to recommend choices. Experiments 3 and 4 directly inquired about participants' inferences and tested the hypothesis that participants conceive of choice as an intervention. The results of both experiments show that participants drew the same inferences about the outcome (Experiment 3) and other causally relevant variables (Experiment 4) from choices and external interventions and that those inferences differed when actions were observed.

Causal Path Hypothesis Versus Causal Model Theory of Choice

The results of the first two experiments and many other empirical studies provide compelling evidence that people take causal structure into account when making inferences and choices (see Hagmayer et al., 2007; Lagnado, Waldmann, Hagmayer, & Sloman, 2007). A critical question is how people do so. We compared two possible theoretical accounts. According to the first, a causal path hypothesis, people consider whether a statistical relation between a variable and an outcome is or is not due to a direct causal relation. If the relation is merely correlational, they discount it and therefore decline to take action. This model can explain the findings of our first two experiments and may provide a partial account of some decision making.

The causal model theory of choice is an alternative that proposes that people make quite sophisticated inferences on the basis of their assumed causal model. Thinking of their choice as an intervention, people infer the probability of the outcome that would result if they deliberately decided to act. This account makes the same predictions as the causal path hypothesis with respect to people's choices, but it predicts that people can infer interventional probabilities from the observed data and the assumed model. It predicts that people differentiate between actions that are merely observed and actions that are either enforced or deliberately chosen. In contrast, the causal path hypothesis predicts that people will only differentiate actions that have a causal impact on the outcome from actions that do not. The results of Experiments 3 and 4 clearly support the causal model theory over the causal path hypothesis. Participants derived different inferences for choice, intervention, and observation.

Choices That Are Not Interventions

The findings reported here indicate that people conceive of their choices as interventions that render chosen actions independent of other factors that may be involved in the decision-making process. We argued that this is the way people normally understand decision making. However, violations of the logic of intervention do exist. In one such violation, self-deception, people choose actions but assert that the action is determined by something else. For example, Quattrone and Tversky's (1984) participants unconsciously changed their tolerance for cold water in a way that indicated a healthy type of heart. Although the participants manipulated how long to hold their hand in cold water, many did not admit to this manipulation; they believed their actions were not determined by their choice. As participants deceived themselves, their actions became diagnostic of their heart type and they generated evidence of their own healthiness. Deliberate choice of the duration should have deleted the diagnostic relation (cf. Experiment 4). Only by virtue of believing that their level of tolerance was caused by the condition of their hearts and filtering out of consciousness the impact of their own choice did they retain the belief that their actions were diagnostic.

Self-handicapping follows a similar logic. In such cases, people create hardships for themselves while they suppress awareness that doing so will produce bad outcomes. This behavior allows them to attribute any negative consequences to factors they are not responsible for because they have avoided any conscious choices. Surveys suggest that up to 90% of college students admit to resorting to self-handicapping strategies at one time or another (e.g., oversleeping on exam day; Covington & Roberts, 1994). Self-handicapping separates performance from competence, because the performance is assumed to be determined by the handicap. Therefore, bad performance is no longer diagnostic of low competence. This assumption permits the maintenance of self-esteem regardless of success or failure.

There are also cases in which people believe they have made a choice and have thereby influenced outcomes, although in fact they have not. The vast literature on the illusion of control provides many examples (e.g., Langer, 1975; Langer & Roth, 1975; see also Wilson & Dunn, 2004). The most prominent are gamblers' fallacies. Superstitious behavior follows the same logic, although here people claim that they know their choice makes no difference.

Sometimes people choose not to base their choice on their own free will but to give in to some external force. In these cases they admit that their choice is not made freely. For example, they may base their choice on an advertisement or a craving or a request by a loved one.[5] If so, they allow their choice to be a consequence of these factors. Therefore, choice and the action resulting from it are diagnostic of these factors and other variables related to them. We cannot quantify how often actions result from external or internal pressure rather than deliberate decision making. We also cannot specify the conditions that promote deliberate choice. Our observation is merely that a particular kind of cognitive model is operative when deliberate choices are made.

People may also be reluctant to consider their choices as interventions with respect to factors they have not deliberately taken into account. For example, when walking down the hall to the soda machine we choose a certain speed without being aware of making a choice. In turn, we are willing to concede that our chosen speed tells us something about our mood. Thus, undoing may be limited to factors we are aware of influencing our decisions.

In sum, in a number of situations, people do not seem to conceive of their choices as interventions on their own actions. Nevertheless, we suspect that people frequently do so. We all believe that we usually determine what we do. This assumption appears to be crucial for mental health. A pivotal factor in cognitive behavioral therapy is for patients to recognize that they decide what they do and therefore can decide to change (e.g., self-management therapy; Karoly & Kanfer, 1982).

[5] We thank an anonymous reviewer for pointing this out.

Conditions Promoting Causal Decision Making

Research in decision making has revealed a multitude of strategies, including some that do not even take outcomes into account (reviewed in Hastie & Dawes, 2001). For example, it has been shown that people sometimes follow social or moral rules, such as "do not be greedy," or base their decisions upon convictions (e.g., "natural is better than artificial"; see Baron, 1994, for a review of nonconsequentialist decision making). Thus causal considerations do not always influence decisions.

When do people consider causal structure? At this point, we can offer only informed guesses. Causal reasoning and decision making demand both cognitive capacity and effort. Therefore, a high level of motivation is needed. Personal involvement and high stakes create such motivation (Petty & Cacioppo, 1986). Moreover, stress has been shown to reduce available cognitive capacity (Driskell & Salas, 1996) and should therefore lead to less causal decision making.

General knowledge about possible causal mechanisms underlying a decision problem should promote causal decision making, because a model allows pinpointing of successful interventions. For example, the generation of patient-specific causal models has been shown to improve treatment planning and subsequent interventions in psychotherapy (Morton, 2004). Research on naturalistic decision making has shown that experts use causal models when they cannot identify the best solution right away. By contrast, if experts have specific knowledge about successful actions under the prevailing circumstances, they start to act without considering various options or possible consequences (Klein, 1998).

Thus, causal decision making may be most likely for novel decision problems for which decision makers have some background knowledge and whose consequences are important enough that decision makers will expend the time and effort required to think through the consequences of making a choice. We propose that whenever a causal model is used, people will treat their own choice as an intervention.

References

Ahn, W.-K., Kalish, C. W., Medin, D. L., & Gelman, S. A. (1995). The role of covariation versus mechanism information in causal attribution. *Cognition, 54,* 299–352.

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior.* Englewood Cliffs, NJ: Prentice-Hall.

Ariely, D. (2008). *Predictably irrational.* New York: HarperCollins.

Barbey, A. K., & Sloman, S. A. (2007). *Base-rate respect: From ecological rationality to dual processes.* Manuscript submitted for publication.

Baron, J. (1994). Nonconsequentialist decisions. *Behavioral and Brain Sciences, 17,* 1–42.

Buehler, R., Griffin, D., & Ross, M. (2002). Inside the planning fallacy: The causes and consequences of optimistic time predictions. In T. Gilovich, D. Griffin, & D. Kahneman (Eds.), *Heuristics and biases: The psychology of intuitive judgment* (pp. 250–270). Cambridge, England: Cambridge University Press.

Covington, M. V., & Roberts, B. W. (1994). Self-worth and college achievement: Motivational and personality correlates. In P. R. Pintrich, D. R. Brown, & C. E. Weinstein (Eds.), *Student motivation, cognition, and learning: Essays in honor of Wilbert J. McKeachie* (pp. 157–187). Hillsdale, NJ: Erlbaum.

Driskell, J. E., & Salas, E. (1996). *Stress and human performance.* Hillsdale, NJ: Erlbaum.

Fischhoff, B., Slovic, P., & Lichtenstein, S. (1978). Fault trees: Sensitivity of estimated failure probabilities to problem representations. *Journal of Experimental Psychology: Human Perception and Performance, 4,* 330–344.

Fitzsimons, G. M., & Bargh, J. A. (2003). Thinking of you: Nonconscious pursuit of interpersonal goals associated with relationship partners. *Journal of Personality and Social Psychology, 84,* 148–164.

Frensch, P. A., & Funke, J. (1995). *Complex problem solving: The European perspective.* Hillsdale, NJ: Erlbaum.

Funke, J. (2006). Komplexes Problemlösen [Solving complex problems]. In F. Funke (Ed.), *Enzyklopädie der Psychologie: Band 8, Denken und Problemlösen.* Göttingen, Germany: Hogrefe.

Gigerenzer, G., & Hoffrage, U. (1995). How to improve Bayesian reasoning without instruction: Frequency formats. *Psychological Review, 102,* 684–704.

Glymour, C. (2001). *The mind's arrows.* Cambridge, MA: MIT Press.

Glymour, C. (2004). We believe in freedom of the will so that we can learn. *Behavioral and Brain Sciences, 27,* 661–662.

Glymour, C., & Cooper, G. F. (Eds.). (1999). *Computation, causation, and discovery.* Cambridge, MA: MIT Press.

Hagmayer, Y., Sloman, S. A., Lagnado, D. A., & Waldmann, M. R. (2007). Causal reasoning through intervention. In A. Gopnik & L. E. Schultz (Eds.), *Causal learning: Psychology, philosophy, and computation* (pp. 86–100). New York: Oxford University Press.

Hastie, R., & Dawes, R. M. (2001). *Rational choice in an uncertain world.* Thousand Oaks, CA: Sage.

Hernstein, R. J. (1961). Relative and absolute strength of response as a function of frequency of reinforcement. *Journal of the Experimental Analysis of Behavior, 4,* 267–272.

Joyce, J. M. (1999). *The foundations of causal decision theory.* Cambridge, England: Cambridge University Press.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47,* 263–291.

Karoly, P., & Kanfer, F. H. (1982). *Self-management and behavior change: From theory to practice.* New York: Pergamon.

Klein, G. (1998). *Sources of power: How people make decisions.* Cambridge, MA: MIT Press.

Koslowski, B. (1996). *Theory and evidence: The development of scientific reasoning.* Cambridge, MA: MIT Press.

Lagnado, D. A., Waldmann, M. A., Hagmayer, Y., & Sloman, S. A. (2007). Beyond covariation: Cues to causal structure. In A. Gopnik & L. E. Schultz (Eds.), *Causal learning: Psychology, philosophy, and computation* (pp. 154–172). New York: Oxford University Press.

Langer, E. J. (1975). The illusion of control. *Journal of Personality and Social Psychology, 32,* 311–328.

Langer, E. J., & Roth, J. (1975). Heads I win, tails it's chance: The illusion of control as a function of the sequence of outcomes in a purely chance task. *Journal of Personality and Social Psychology, 32,* 951–955.

Levi, I. (2000). Review of "The Foundations of Causal Decision Theory" by James M. Joyce. *Journal of Philosophy, 97,* 387–402.

Lewis, D. (1981). Causal decision theory. *Australasian Journal of Philosophy, 59,* 5–30.

Meder, B., Hagmayer, Y., & Waldmann, M. R. (2008). Inferring interventional predictions from observational learning data. *Psychonomic Bulletin & Review, 15,* 75–80.

Meek, C., & Glymour, C. (1994). Conditioning and intervening. *British Journal for the Philosophy of Science, 45,* 1001–1021.

Morgan, M. G., Fischoff, B., Bostrom, A., & Atman, C. J. (2001). *Risk communication. A mental model approach.* New York: Cambridge University Press.

Morton, J. (2004). *Understanding developmental disorders.* Malden, MA: Blackwell.

Nozick, R. (1969). Newcomb's Problem and two principles of choice. In N. Rescher (Ed.), *Essays in honor of C. G. Hempel.* Dordrecht, the Netherlands: Reidl.

Nozick, R. (1993). *The nature of rationality.* Princeton, NJ: Princeton University Press.

Pearl, J. (2000). *Causality.* New York: Cambridge University Press.

Pennington, N., & Hastie, R. (1993). Reasoning in explanation-based decision making. *Cognition, 49,* 123–163.

Petty, R. E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. In L. Berkowitz (Ed.), *Advances in experimental social psychology* (Vol. 19, pp. 123–205). New York: Academic Press.

Quattrone, G., & Tversky, A. (1984). Causal versus diagnostic contingencies: On self-deception and on the voter's illusion. *Journal of Personality and Social Psychology, 46,* 237–248.

Rehder, B., & Burnett, R. (2005). Feature inference and the causal structure of categories. *Cognitive Psychology, 50,* 264–314.

Savage, L. J. (1954). *The foundations of statistics.* New York: Wiley.

Simon, H. (1957). *Models of man: Social and rational.* New York: Wiley.

Skyrms, B. (1980). *Causal necessity.* New Haven, CT: Yale University Press.

Sloman, S. A. (2005). *Causal models: How we think about the world and its alternatives.* Cambridge, MA: Oxford University Press.

Sloman, S. A., & Hagmayer, Y. (2006). The causal logic of choice. *Trends in Cognitive Science, 10,* 407–412.

Sloman, S. A., & Lagnado, D. A. (2005). Do we "do"? *Cognitive Science, 29,* 5–39.

Spirtes, P., Glymour, C., & Scheines, R. (1993). *Causation, prediction, and search.* New York: Springer.

Sterman, J. D. (2006). *Business dynamics.* Boston: McGraw Hill.

Tversky, A., & Kahneman, D. (1980). Causal schemas in judgments under uncertainty. In M. Fishbein (Ed.), *Progress in social psychology.* Hillsdale, NJ: Erlbaum.

von Neumann, J., & Morgenstern, O. (1947). *Theory of games and economic behavior* (2nd ed.). Princeton, NJ: Princeton University Press.

Waldmann, M. R. (1996). Knowledge-based causal induction. In D. R. Shanks, K. J. Holyoak, & D. L. Medin (Eds.), *The psychology of learning and motivation* (Vol. 34, pp. 47–88). San Diego, CA: Academic Press.

Waldmann, M. R., & Hagmayer, Y. (2001). Estimating causal strength: The role of structural knowledge and processing effort. *Cognition, 82,* 27–58.

Waldmann, M. R., & Hagmayer, Y. (2005). Seeing versus doing: Two modes of accessing causal knowledge. *Journal of Experimental Psychology: Learning, Motivation, and Cognition, 31,* 216–227.

Wegener, D. M. (2002). *The illusion of conscious will.* Cambridge, MA: MIT Press.

Wilson, T., & Dunn, E. W. (2004). Self-knowledge. Its limits, value, and potential for improvement. *Annual Review of Psychology, 55,* 493–518.

Woodward, J. (2003). *Making things happen. A theory of causal explanation.* Oxford, England: Oxford University Press.

Zsambok, C. E., & Klein, G. (1997). *Naturalistic decision making.* Mahwah, NJ: Earlbaum.

Appendix A

Scenarios Used in Experiment 1 (Frequency Format Only)

Common cause version	Direct cause version
Exercise scenario	
Recent research has discovered that of 100 people who exercise, 65 consume less than the average number of calories, whereas of 100 people who do not exercise. only 25 consume less than the average number of calories. The research also indicated that the cause of this fact is that the desire to be healthy causes people to exercise and to eat less. Imagine a friend of yours wants to eat less. You have both read about the research and she asks you whether you would recommend starting an exercise program to achieve this goal. What would you recommend?	Recent research has discovered that of 100 people who exercise, 65 consume less than the average number of calories, whereas of 100 people who do not exercise, only 25 consume less than the average number of calories. The research also indicated that the cause of this fact is that exercise releases neurotransmitters that suppress appetite. Imagine a friend of yours wants to eat less. You have both read about the research and she asks you whether you would recommend starting an exercise program to achieve this goal. What would you recommend?
Used car scenario	
Recent research has discovered that of 100 people who drive used cars, 54 will have a car accident, whereas only 11 out of 100 people who drive new cars will. The research also showed that the cause for this fact is that young and inexperienced drivers tend to own used cars and cause more accidents than all other drivers. Imagine a friend of yours is driving a used car. She wants to avoid accidents and you have both heard about the new research finding. She asks you whether you would recommend buying a new car in order to lower her susceptibility for an accident. What would you recommend?	Recent research has discovered that of 100 people who drive used cars, 54 will have a car accident, whereas only 11 out of 100 people who drive new cars will. The research also showed that the cause for this fact is that used cars have worse brakes and worse tires than new cars, which are two of the most frequent causes of accidents. Imagine a friend of yours is driving a used car. She wants to avoid accidents and you have both heard about the new research finding. She asks you whether you would recommend buying a new car in order to lower her susceptibility for an accident. What would you recommend?

(*table continues*)

(*Appendixes continue*)

Table (*continued*)

Common cause version	Direct cause version
High-risk sports scenario	
Recent research has discovered that of 100 people who engage in high-risk sports, 56 are taking drugs, whereas of 100 people who do not engage in high-risk sports only 11 do. The findings also show that the cause for this fact is that the personality of the so-called sensation seekers makes them search for new thrills in all areas, including high-risk sports and drugs. Imagine a friend of yours engages in downhill racing and skydiving. But he is also concerned about developing a drug habit. You have both heard about the new findings and he wants to know whether you would recommend he stop his activities. What is your advice?	Recent research has discovered that of 100 people who engage in high-risk sports, 56 are taking drugs, whereas of 100 people who do not engage in high-risk sports only 11 do. The findings also show that the cause for this fact is that the thrill of high-risk sports releases neurotransmitters, which cause a strong craving for stimulating drugs like cocaine. Imagine a friend of yours engages in downhill racing and skydiving. But he is also concerned about developing a drug habit. You have both heard about the new findings and he wants to know whether you would recommend he stop his activities. What is your advice?
Chess scenario	
Recent research has discovered that of 100 students who play chess, 76 get above-average grades in college, whereas only 26 of 100 students who do not play chess do. The research also discovered that the cause for this fact is that a high IQ leads to a preference for chess and to better grades. Imagine a friend of yours wants to improve his grades in college and you have heard about the new findings. He wants your advice about whether he should start playing chess. What is your recommendation?	Recent research has discovered that of 100 students who play chess 76 get above-average grades in college, whereas only 26 of 100 students who do not play chess do. The research also discovered that the cause for this fact is that playing chess trains logical reasoning and strategic thinking, which leads to better grades in college. Imagine a friend of yours wants to improve his grades in college and you have heard about the new findings. He wants your advice about whether he should start playing chess. What is your recommendation?
Clothing scenario	
Recent research has discovered that of 100 women who spend more money on clothes, 65 have good skin, whereas of 100 women who spend less money only 25 have a good skin. The research also discovered the cause of this is that women with high socioeconomic status spend more money on clothes and beauty products and therefore have better skin. Imagine a friend of yours desperately wants to improve her skin. Right before she went out shopping for new clothes you both read about the research. Now she asks you for your recommendation on whether to buy cheap or more expensive clothes. What would you recommend?	Recent research has discovered that of 100 women who spend more money on clothes, 65 have good skin, whereas of 100 women who spend less money only 25 have a good skin. The research also discovered the cause of this is that expensive cloths contain less toxic colors and allergenic substances than cheap clothes and therefore do not affect the skin's health. Imagine a friend of yours desperately wants to improve her skin. Right before she went out shopping for new clothes you both read about the research. Now she asks you for your recommendation on whether to buy cheap or more expensive clothes. What would you recommend?

Appendix B

Scenarios Used in Experiment 3 Choice Condition

Common cause version	Direct cause version
Beard scenario	
Recent research has shown that of 100 bearded men who frequently scratch their chins, 65 have skin irritations, whereas only 10 of 100 men who do not have beards have the same problem. The research also indicated that the cause of this fact is beard growth. Men who have strong growth tend to scratch their chin frequently and to have more skin problems. Imagine that you scratch your chin occasionally, and you have skin irritations from time to time. Will you from now on pay attention and stop scratching your chin to avoid skin problems?	Recent research has shown that of 100 bearded men who frequently scratch their chins, 65 have skin irritations, whereas only 10 of 100 men who do not have beards have the same problem. The research also indicated that the cause of this fact is impurities. Frequently scratching the chin rubs dust and dirt into the skin, which in turn causes skin problems. Imagine that you scratch your chin occasionally, and you have skin irritations from time to time. Will you from now on pay attention and stop scratching your chin to avoid face problems?
Nose scenario	
Recent research has shown that of 100 people who frequently touch their noses, 70 have catarrh, whereas only 20 of 100 men who do not have the same problem. The research also indicated that the cause of this fact is allergies. People who have allergies tend to touch their noses frequently and to have catarrh more often. Imagine that you touch your nose occasionally, and you have catarrh from time to time. Will you from now on pay attention and stop touching your nose to avoid inflammations?	Recent research has shown that of 100 people who frequently touch their noses, 70 have catarrh, whereas only 20 of 100 men who do not have the same problem. The research also indicated that the cause of this fact is infections. People who touch their noses frequently transfer a multitude of bacteria into their noses causing catarrh. Imagine that you touch your nose occasionally, and you have catarrh from time to time. Will you from now on pay attention and stop touching your nose to avoid inflammations?
Chores scenario	
Recent research has shown that of 100 men who help with the chores, 82 are in good health, whereas only 32 of 100 men who do not help with the chores are. The research also discovered that the cause of this finding was that men who are concerned about equality issues are also concerned about health issues and therefore both help to do the chores and eat healthier food. Imagine that you are a man and you help doing the chores from time to time. Your current health is moderate. Will you from now on start to do the chores frequently to improve your health?	Recent research has shown that of 100 men who help with the chores, 82 are in good health, whereas only 32 of 100 men who do not help with the chores are. The research also discovered that the cause of this finding was that doing the chores is an additional exercise every day and therefore improves health. Imagine that you are a man and you help doing the chores from time to time. Your current health is moderate. Will you from now on start to do the chores frequently to improve your health?
Exercise scenario	
Recent research has discovered that of 100 people who exercise, 75 consume less than the average amount of fat, whereas of 100 people who do not exercise only 25 do. The research also indicated that the cause was an attitude. People who care about their health exercise more and eat less fat. Imagine that you exercise from time to time. You also like chocolate and other fatty foods. Will you from now on start to exercise frequently to minimize the amount of fat you consume?	Recent research has discovered that of 100 people who exercise, 75 consume less than the average amount of fat, whereas of 100 people who do not exercise only 25 do. The research also indicated that the cause of this fact is a neural mechanism. Exercise triggers this mechanism that suppresses appetite. Imagine that you exercise from time to time. You also like chocolate and other fatty foods. Will you from now on start to exercise frequently to minimize the amount of fat you consume?

Note. The scenarios in this table have been translated from German.

(*Appendixes continue*)

Appendix C

Scenarios Used in Experiment 4 Choice Condition

Common cause version	Causal chain version
Exercise scenario	
Recent research has discovered that of 100 people who exercise, 65 consume less than the average number of calories, whereas of 100 people who do not exercise only 25 consume less than the average number of calories. The research also indicated that the cause of this fact is that the presence of the neurotransmitter CNA causes people to exercise more and to eat less. Imagine that after reading about the research a friend of yours deliberately decides to start exercising and she does. What can you infer from that about the presence of the neurotransmitter CNA in her brain?	Recent research has discovered that of 100 people who exercise, 65 consume less than the average number of calories, whereas of 100 people who do not exercise only 25 consume less than the average number of calories. The research also indicated that the cause of this fact is that exercise causes the presence of the neurotransmitter CAN, which in turn causes people to eat less. Imagine that after reading about the research a friend of yours deliberately decides to start exercising and she does. What can you infer from that about the presence of the neurotransmitter CNA in her brain?
Chores scenario	
Recent research has shown that of 100 men who help with the chores, 82 are in good health, whereas only 32 of 100 men who do not help with the chores are. The research also discovered that the cause of this finding was the men's outlook on life. A positive outlook on life causes men to help to do the chores and it also causes them to be healthier. Imagine that after reading about the research a friend of yours deliberately decides to start doing the chores and he does. What can you infer from that about him having a positive outlook on life?	Recent research has shown that of 100 men who help with the chores, 82 are in good health, whereas only 32 of 100 men who do not help with the chores are. The research also discovered that the cause of this finding was that doing the chores creates a sense of achievement which leads to a positive outlook on life. The positive outlook on life in turn causes men to be healthier. Imagine that after reading about the research a friend of yours deliberately decides to start doing the chores and he does. What can you infer from that about him having a positive outlook on life?

Received January 7, 2007
Revision received October 1, 2008
Accepted October 1, 2008 ■