

Marbles in Inaction: Counterfactual Simulation and Causation by Omission

Simon Stephan¹ (sstepha1@gwdg.de) Pascale Willemsen² (pascale.willemsen@rub.de)
Tobias Gerstenberg³ (tger@mit.edu)

¹Department of Psychology, Georg-August-University Göttingen and Leibniz ScienceCampus Primate Cognition

²Institute for Philosophy II, Ruhr-University Bochum

³Department of Brain and Cognitive Sciences, Massachusetts Institute of Technology

Abstract

Consider the following causal explanation: The ball went through the goal because the defender didn't block it. There are at least two problems with citing omissions as causal explanations. First, how do we choose the relevant candidate omission (e.g. why the defender and not the goalkeeper). Second, how do we determine what would have happened in the relevant counterfactual situation (i.e. maybe the shot would still have gone through the goal even if it had been blocked). In this paper, we extend the counterfactual simulation model (CSM) of causal judgment (Gerstenberg, Goodman, Lagnado, & Tenenbaum, 2014) to handle the second problem. In two experiments, we show how people's causal model of the situation affects their causal judgments via influencing what counterfactuals they consider. Omissions are considered causes to the extent that the outcome in the relevant counterfactual situation would have been different from what it actually was.

Keywords: causality; counterfactuals; causation by omission; causal attribution; mental simulation

Introduction

Billy is on his way home. He is driving on a lonely country road, when he notices a damaged car next to the road. The car seems to have collided with a tree next to the road, and the driver appears unconscious. Billy decides not to stop and keeps driving home. A few days later, Billy reads in a local newspaper that the driver died because he had not received any medical attention.

Many people would concur that Billy's not having stopped was causally relevant for the driver's death. However, there are two fundamental problems with citing omissions (i.e., events that did not happen) as causes. First, there is the *problem of causal selection*. Why cite Billy's not stopping as causally relevant for the driver's death? Why not cite the Queen of England? Second, there is the *problem of underspecification*. Assuming that Billy would have stopped to check on the driver, what would he have done? Would Billy's acting have prevented the driver's death, or would she have died anyway?

In this paper, we show how the counterfactual simulation model (CSM) of causal judgment developed in Gerstenberg, Goodman, Lagnado, and Tenenbaum (2012) (see also Gerstenberg et al., 2014; Gerstenberg, Goodman, Lagnado, & Tenenbaum, 2015) provides a natural solution to the underspecification problem. The CSM predicts that an omission is a cause when the positive event that is chosen as its replacement would have changed the outcome of interest. More specifically, we show how people's causal model of a situation guides their selection of the relevant counterfactual which subsequently determines their judgment about whether the omission made a difference to the outcome.

The paper is organized as follows: we first discuss the causal selection problem and the underspecification problem in more detail, and we then propose an extension to the CSM intended to deal with the latter. Thereafter, we present and discuss the results of two experiments which test the CSM. The results show that people's counterfactual simulations in the context of omissions are constrained by prior expectations about the physical features of the environment. The results further show how participants' counterfactual selections are shaped by statistical norms and prescriptive norms, both subsequently affecting causal judgments.

The Causal Selection Problem

Many philosophers argue that counterfactual approaches to causation are too inclusive when it comes to omissions (e.g. McGrath, 2005). If Billy had stopped and checked on the unconscious driver, the driver would not have died. Consequently, the driver died because Billy did not stop. However, following this logic, the same counterfactual seems to be true for the Queen of England. If the Queen of England had stopped, the driver would not have died either. Nevertheless, it is certainly Billy's omission that was causally relevant. This problem of causal selection has been intensively discussed in both philosophy and empirical studies (e.g. Hesslow, 1988). Interestingly, while the causal selection problem seems to be a challenge for philosophers, laypeople do not have any difficulty in selecting the cause of the driver's death. Based on evidence from research on causal cognition, it has been suggested that the concept of causation is not a purely descriptive one, but that it depends on reasoners' expectations (Willemsen, 2016).

The Underspecification Problem

The causal selection problem is not the only problem that makes omissions challenging. Another fundamental problem is how to define the relevant counterfactual contrast (cf. Schaffer, 2005). For positive events ("something happened"), the counterfactual contrast ("it didn't happen") is often well-defined. However, replacing a negative event with a positive event is more problematic. There are an infinitely many ways in which events can come about. If Billy stopped and helped the driver in the actual situation, it's pretty clear what would have happened if he hadn't helped (he would just have continued to drive on). However, if Billy didn't help, it's unclear what would have happened if he had helped (would he have helped in a competent manner that would have prevented the driver's death, or would he have been too nervous and screwed things up?).

The causal selection problem has received much attention in the literature (e.g., Henne, Pinillos, & De Brigard, 2015; Livengood & Machery, 2007), the underspecification problem less so. Wolff, Barbey, and Hausknecht (2010) suggested a model of causal judgment that addresses both problems. Wolff et al. (2010) argues that causation by omission is linked to the removal of an actual (or anticipated) force that previously prevented a certain outcome from occurring. For example, imagine a person pushing aside the jack that is holding up a car, whereupon the car falls to the ground. According to the force theory of Wolff et al. (2010), the proposition that “the lack of a jack caused the car to fall to the ground” is linked to the removal of the jack’s force that had previously held up the car. Thus, the absence of the jack is an omission in the causally relevant sense. Wolff et al. (2010) avoids both the *causal selection* and the *underspecification problem*, since we know what omission is causally relevant (the jack’s) and what the relevant counterfactual contrast is (the jack staying in its previous position). However, this account appears too restrictive in that it cannot account for cases in which no force is removed. Imagine, for instance, sentences like “The lack of rain caused the drought in Somalia”. Here, it would be a stretch to think of a the lack of rain as the removal of a force.

The extension of the CSM that we propose in this paper provides a solution to the *underspecification problem* without the need for force removal. The CSM’s solution is rather in line with a counterfactual account proposed by Petrocelli, Percy, Sherman, and Tormala (2011). According to their account, the impact that a counterfactual has on a causal judgments depends on the multiplicative combination of two probabilities: the first is the probability of the antecedent condition to occur, and the second is the probability of the antecedent to lead to an outcome different from the actual one. Even though Petrocelli et al. (2011) have shown that both probabilities seem to influence people’s causal judgments, it remains unclear how people typically derive the probability with which the counterfactual antecedent leads to a different outcome. We will show how we can use the CSM to determine this probability.

Counterfactual Simulation and Omission

The *counterfactual simulation model* (CSM) predicts that people make causal judgments by comparing what actually happened with the outcome of a counterfactual simulation. So far, the model has been applied to capturing participants’ judgments about events that actually happened (Gerstenberg et al., 2012, 2014, 2015). Consider the example shown in Figure 1b (bottom) indicated as the *ideal path*. Here, A collides with B and B subsequently goes through the gate. The CSM says that ball A caused ball B to go through the gate in this case, since ball B would have missed the gate if ball A hadn’t been present in the scene. More generally, the CSM predicts that causal judgments are a function of the reasoner’s subjective degree of belief that the candidate cause made a difference to the outcome. More formally, we can express the

probability $P(x \triangleright y)$ that x caused y as

$$P(x \triangleright y) = P(y' \neq y | \mathcal{S}, \text{do}(x')), \quad (1)$$

where x denotes the event of ball A hitting ball B, and the outcome y captures the event of ball B going through the gate. We first condition on what actually happened \mathcal{S} (i.e. the motion paths of each ball, the position of the walls, etc.). We then intervene to set the candidate cause event x to be different from what it was in the actual situation, $\text{do}(x')$. Finally, we evaluate the probability that the outcome in this counterfactual situation y' would have been different from the outcome y that actually happened. The results of several experiments have shown that there is indeed a very close relationship between the counterfactual judgments of one group of participants (about what would have happened if the candidate cause had been absent), and the causal judgments of another group of participants (cf. Gerstenberg et al., 2012, 2014, 2015).

To model causal judgments about positive events, the CSM considers counterfactuals in which the positive event (ball A colliding with B) is simply removed from the scene. Things become more intricate, however, when we want to model omissions as causes. As discussed above, it is often straightforward to replace an event with a non-event (e.g., a collision with no collision), but less clear how to replace a non-event with an event. Consider the situation shown in Figure 1a. Did ball B go through the gate because ball A did not hit it? The problem is that there are infinitely many ways for ball A to collide with ball B. Which of these events are we to consider? The collision event is severely underspecified. We will now show how the CSM can be extended to yield predictions about omissions as causes, and thereby provide a solution to the underspecification problem.

Modeling Omissions

We assume that people solve the underspecification problem by sampling counterfactual possibilities based on their intuitive understanding of the situation (Kahneman & Tversky, 1982). The extent to which the omission is viewed as a cause of the outcome is a function of the proportion of samples in which the outcome would have been different from what actually happened, assuming that the counterfactual event of interest was realized. Let us illustrate how the model works by example of the situation depicted in Figure 1a. In the actual situation, ball A did not move and ball B went right through the middle of the gate. We want to determine to what extent A’s not hitting ball B was a cause of B’s going through the gate. To do so, we simulate what would have happened if ball A had moved instead of remaining still. More specifically, we need to determine the time t at which A would have started to move, the direction d in which ball A would have moved, and the velocity v . Once we have determined these quantities, we can simulate what would have happened. For many combinations of values for t , d , and v ball A would not collide with ball B. We can discard all such situations since we are interested in evaluating what would have happened if ball A had hit ball B. For each situation

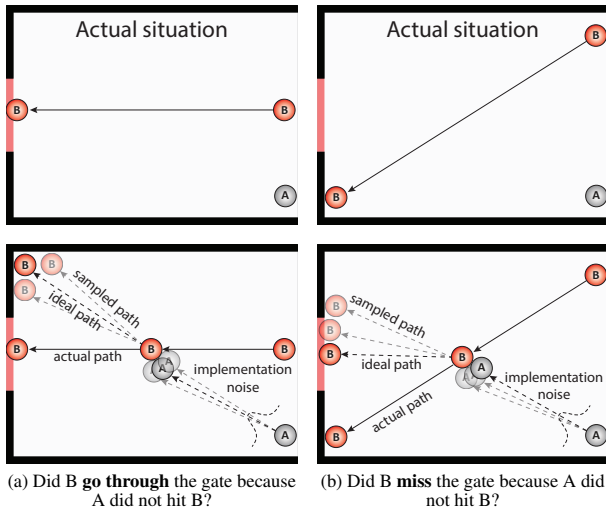


Figure 1: Illustration of what actually happened (top) and the counterfactual simulation model (bottom). The diagrams illustrate the actual path that ball B took, as well as an ideal path for (a) A preventing B from going through the gate, or (b) A causing B to go through the gate. The sampled paths show example simulations that result from applying implementation noise to the ideal path. *Note:* In (a), A would have prevented B from going through the gate in one sample but not so in the other in which B would still have missed even though A hit B.

in which the two balls collide, we record what the outcome would have been – would B have missed the gate, or would it still have gone through the gate? We can now obtain the probability that ball A’s not hitting ball B was a cause of ball B’s going through the gate (cf. Equation 1) by looking at the proportion of samples in which B would have missed the gate instead of going through.

But how do we determine what values to take for t , d , and v which jointly determine what counterfactual situation we consider? We predict that prior expectations guide the counterfactuals we consider. In Experiment 1 below, we contrast situations in which participants don’t have any strong expectations about what normally happens, with situations in which participants have statistical, or normative expectations. We will now discuss how the model incorporates these expectations.

Expectations Shape Counterfactual Simulations

No Strong Expectations Let us first assume a situation in which an observer does not have strong expectations. When asked whether A’s not hitting B caused B to go through the gate, we have to generate situations in which A would have hit B. This already considerably constraints what kinds of situations we consider. For example, it would be futile to consider situations in which A only starts moving after B already went through the gate, or in which A moved toward the right.

We generated counterfactual samples in the following way: we first discretized the space for t , d , and v . For t , we considered all values from 0 to $t_{outcome}$ where $t_{outcome}$ corresponds to the time at which ball B went through the gate (or hit the wall). For d , we considered the full range from A going

straight to the left to A going straight up. For v , we considered a reasonable range from A moving slowly to A moving fast. For each generated world, we noted whether A and B collided, and whether B went through the gate or missed the gate. We then discarded all situations in which the two balls did not collide, and recorded the proportion of situations in which B would have gone through the gate if the balls had collided.

The model makes the following predictions: For the situation in which B is on a path toward the gate, the model predicts that there is a good chance that B would have missed the gate if ball A had hit it. In contrast, when B is on a path away from the gate, there is only a small chance that ball B would have gone through the gate if ball A had hit it. Thus, the model predicts that participants will be more likely to agree that ball B *went through* the gate because ball A did not hit it than they will be to agree that ball B *missed* the gate because ball A did not hit it in situation.

Normative Expectations Now imagine that you learn that two players play a game with marbles. Player B wants to get her marble into the goal, while Player A wants to make sure that this does not happen. On a particular trial, Player A did not pay attention and forgot to flick his marble. Did Player B’s marble go through the gate because Player A’s marble did not hit it?

We predict that the counterfactuals that observers consider are affected by their expectations. When it is a player’s job to prevent a marble from going through the gate, people may expect that this player would not have just flicked her marble randomly (if she had paid attention). Instead, she can be expected to try her best to make sure that the other marble does not go through the gate. Similarly, consider a situation in which Player A also wants that Player B’s marble passes the the gate. In that case, it seems likely that Player A will try to flick his marble so that it makes sure that B’s marble will go through the gate.

Figure 1 illustrates how these normative expectations influence the way in which counterfactual situations are sampled. We assume that the player would first determine a time t at which to flick her marble. For any given point t , the player then determines an optimal d and v given the player’s goals. For a player who wants to prevent ball B from going through the gate, the player’s goal is to maximize the distance between B’s position and the middle of the gate. For a player who wants to cause B to go through the gate, the player’s goal is to minimize the distance between B’s position and the middle of the gate (i.e., she wants B to go right through the middle of the gate). While we assume that players can plan their action optimally, they have some implementation noise. We model this implementation noise by applying a small perturbation to the direction in which A moves.

Figure 1 shows the actual path that ball B took, the ideal paths that player A “wanted” the marbles to take, and two examples for paths that ball B actually took after subjecting A’s ideal plan to some implementation noise. Notice that the

implementation noise has a larger effect in Figure 1b where it leads to a situation in which ball B would have missed the gate even though ball A hit it. In contrast, in Figure 1a the implementation noise has less of an effect. Here, ball B would reliably miss the gate even if we apply some implementation noise to player A’s intended plan. Accordingly, CSM predicts that it is more likely that A hitting B would have resulted in B missing the gate (when B actually went through, Figure 1a) than it would have resulted in B going through the gate (when B actually missed, Figure 1b). Since the sample of considered situations is biased toward optimal actions, CSM predicts that judgments will overall be higher than in the situation in which an observer does not have any normative expectations.

Statistical Expectations Imagine that instead of learning anything about agents playing a game, you get to see a few situations first that shape your expectations about what tends to happen. We incorporate such statistical expectations into the model in the same way in which we handled normative expectations. However, we allow for the implementation noise to be different between these situations. This parameter will depend on the kind of evidence that participants have seen. For example, if A always hit B in a way so that B went straight through the gate, this would suggest a small implementation noise parameter.

Experiment 1

Experiment 1 tests whether the CSM accurately predicts people’s causal judgments for omissions in dynamic physical scenes. We look at causal judgments about situations in which ball A failed to hit ball B, and ball B either went through or missed the gate (see Figure 1). In line with the CSM, we predict that the degree to which people judge ball A’s not hitting ball B as causally relevant to the outcome would be tightly coupled with the results of a mental simulation about what would have happened if a collision had occurred. Furthermore, we test the hypothesis that different types of expectations (normative or statistical) influence what counterfactual situations people consider.

Methods

Participants and Materials 476 participants (239 female, $M_{Age} = 33.83$ years, $SD_{Age} = 12.03$ years) were recruited via Prolific Academic (www.prolific.ac) and participated in this experiment for a monetary compensation of £0.25. The clips were created in Adobe Flash CS5 using the physics engine Box2D.

Design and Procedure The experiment had a mixed design. We manipulated what actually happened (*actual outcome*: missed vs. went through), and the expectations that participants have about what will happen (*expectation*: no expectations, statistical expectation, social expectation). Between participants, we manipulated what question participants were asked (*question*: causation vs. probability).

In the “no expectations” condition, subjects simply read that they will see a couple of short animations in which a stage with solid walls, two balls A and B, and a gate will be

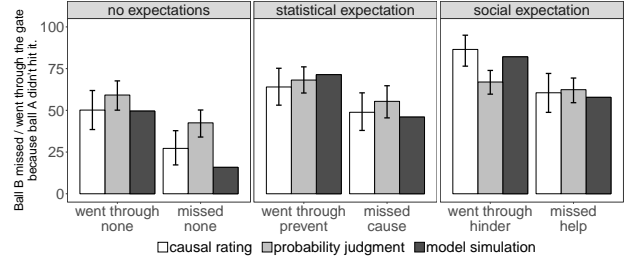


Figure 2: **Experiment 1.** Mean causal and probability judgments together with the predictions of the CSM. *Note:* Error bars indicate 95% bootstrapped CIs.

displayed. All subjects were shown a graphical illustration of the stimuli. Participants in the “statistical expectation” condition were presented four primer clips in which ball B actually collided with A. One group of subjects saw that the collision always *caused* B to go through the gate, while the other half always saw that A *prevented* B from going through the gate (see Figure 1). In the “social expectation” condition, subjects were instructed that the video clips show different rounds of a game of marbles played by two agents, Andy and Ben. We manipulated whether subjects believed that Andy wants to *help* Ben to flip his marble through the gate or whether he wants to *hinder* Ben from doing so.

Participants in the “causation” condition indicated how much they agreed with the claim that B *missed* the gate because A did not hit it, or that B *went through* the gate because A did not hit it, depending on the outcome. Participants in the “probability” condition gave a corresponding probability judgment: they indicated what they thought the chances are that B would have gone through/ missed the gate if ball A had hit ball B. Participants provided their ratings via a displayed slider. Importantly, which outcome participants saw depended on the expectation condition: in the *help* condition, B actually missed the gate, while in the *hinder* condition B went through the gate; in the “statistical expectation” conditions, participants who had seen the *causation* clips saw that B missed the gate, whereas who had seen the *prevention* clips saw that B went through the gate. We used this combination of expectation and outcome to see whether the expectation increases participants’ causal as well as their probability ratings.

Results

Figure 2 shows participants’ mean causal ratings (white bars), probability ratings (gray bars), as well as the predictions of the CSM (black bars). The CSM correctly predicts a difference in agreement ratings for both the causal and probability condition as a function of the outcome. A global 2 (question) \times 6 (combination of expectation and outcome) factorial ANOVA shows a main effect of outcome, $F(5,464) = 14.51$, $p < .001$, $\eta_G^2 = .61$ but no main effect of question, $F(1,464) < 1$. The interaction between question and expectation was significant, $F(5,464) = 2.74$, $p < .05$ but the effect size small, $\eta_G^2 = .03$.

Participants saw A’s not hitting ball B as more causal in the

“went through” compared to the “missed condition”. This pattern indicates that participants’ counterfactual simulations and their causal inferences were sensitive to the constraints imposed by the virtual physical environment. Planned contrasts underlined that this difference was significant in the “no expectations” condition, $t(464) = 3.21, p < .01, r = .15$, in the “statistical expectation” condition, $t(464) = 2.13, p < .05, r = .10$, and also in the “social expectation” condition, $t(464) = 3.53, p < .001, r = .16$.

Besides the asymmetry between “went through” and “missed”, we also expected to see higher causality ratings in the “statistical” and the “social expectation” than in the “no strong expectation” condition. As Figure 2 shows, we did indeed observe this pattern. A planned contrast confirmed that this difference was significant, $t(464) = 5.98, p < .001, r = .27$.

As for the probability ratings, planned contrasts showed that the difference between “went through” and “missed” was significant in the “no expectations condition”, $t(464) = 2.33, p < .05, r = .11$, and the “statistical expectation” condition, $t(464) = 1.73, p < .05, r = .08$. However, in the “social expectation” ratings did not differ significantly, $t(464) < 1$. Concerning the predicted difference between the “no expectations” condition and the other two expectation conditions, Figure 2 shows that we obtained a similar pattern as for the causality judgments. In line with our expectations, the probability ratings for the “statistical expectation” and the “social expectation” condition were higher than the ratings for the “no strong expectation” condition, $t(464) = 2.82, p < .01$, though this effect was smaller than the effect for the causality judgments, $r = .13$.

Discussion

The results of Experiment 1 show that participants’ causal judgments are well accounted for by the CSM. What the results also imply is that participants’ causal inferences are sensitive to the physical constraints imposed by the environment, and that different forms of expectations can alter participants’ initial beliefs about these constraints.

A crucial finding in Experiment 1 is the asymmetry in participants’ causal judgments as a function of whether ball B went through the gate, or missed the gate. The CSM predicts this pattern because it is more likely that A’s hitting B would prevent B from going through the gate (cf. Figure 3a) than that it would cause B to go through (cf. Figure 3b). One possibility, however, that Experiment 1 cannot rule out is that people are in general more likely to regard omissions as causes when the relevant counterfactual involves preventing compared to causing. In Experiment 2, we investigate whether there is a general asymmetry between omissive causation and prevention.

Experiment 2

The goal of Experiment 2 was to rule out that the observed difference between “went through” and “missed” in Experiment 1 came about because people generally differentiate be-

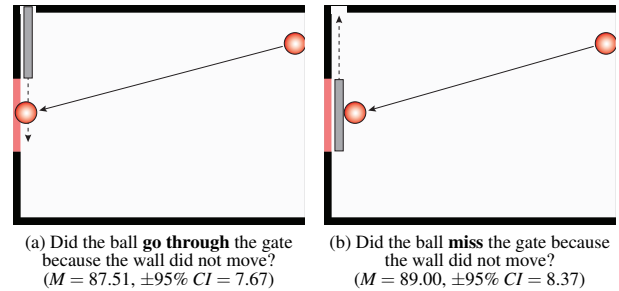


Figure 3: Illustration of the materials used in Experiment 2. Solid arrows indicate the actual path of the ball; dashed arrows show the hypothetical path of the wall. Graph (a) shows the “went through” and (b) the “missed” condition. The results for both conditions are included in brackets.

tween omissive causation and omissive prevention. Importantly, the CSM only predicts an asymmetry between the two situations to the extent that there is a difference in how likely it is that the positive event of interest would have made a difference to the outcome. Hence, if the above mentioned alternative explanation were correct, we should still see that participants treat “went through” and “missed” differently when the probability of an alternative than the actual outcome is kept at a fixed value. This was exactly the strategy that we applied in Experiment 2. To keep the probability of the counterfactual outcome constant, we simply replaced ball A with a wall that had exactly the size of the gate. To model “missed” and “went through”, we varied whether the wall blocked the gate or not, while a displayed ball always headed toward the gate (see Figure 3). Participants rated how much they agree that “the ball” missed/went through the gate because the wall did not move. There is no ambiguity about the relevant counterfactual in this case – it is clear that the outcome would have been different, had the wall moved. Accordingly, the CSM predicts that participants’ judgments should be high for both cases, no matter whether the omission caused to ball to go through or prevented it from doing so.

Method

Participants 65 participants (40 female, $M_{age} = 32.86, SD_{age} = 12.84$) who were again recruited via Prolific Academic completed this online experiment and received a monetary compensation of £ 0.25.

Design, Materials, and Procedure The final outcome, that is, whether the ball went through or missed the gate (see Figure 3) was manipulated between subjects. The instructions were similar those used in the “no expectations” condition in Experiment 1. Further, participants were presented an illustration showing the materials in which it was made clear that the wall can have only two different positions, either right in front of the gate or in the upper left corner of the stage (see Figure 3). Having read the instructions, participants were shown the respective video clip and provided the causality rating after the clip was finished.

Results

As expected, participants gave very high causal ratings for “went through” ($M = 87.51$, $SD = 21.62$) and “missed” ($M = 89.00$, $SD = 23.21$). Moreover, the ratings were not different from each other, $t(63) < 1$, which is in line with a counterfactual simulation that would reveal that the probability of a different than the observed outcome is maximal in both conditions.

Discussion

The results of Experiment 2 are in line with the CSM. Further, the fact that the causality ratings were both very high and not different from each other rules out the potential alternative explanation that people might generally differentiate between omissive causation and omissive prevention.

General Discussion

In this paper, we developed an extension of the *Counterfactual Simulation Model* to account for people’s reasoning about causation by omission. Based on previous research begun by Gerstenberg et al. (2014), we reasoned that people’s causal judgment are closely linked to their subjective degree of belief that the outcome would have been different, if the candidate cause had been replaced. We argued that this replacement by a counterfactual contrast is particularly difficult in cases of omissions. The counterfactual contrast to “did not hit” is clearly “had hit”, but it remains unclear what such a hitting would have looked like.

In two experiments we shed light on how the underspecification problem may be solved in human causal cognition. We predicted that prior expectations would constrain the number of counterfactual contrasts people consider relevant to the scenario. Two experiments tested this hypothesis. In Experiment 1, we found an asymmetry between “went through” and “missed”: A’s not hitting B was considered less causally relevant when B missed the gate. This pattern is exactly the one that is predicted by CSM, and thus lends support the hypothesis that causal judgments are grounded in counterfactually simulated probability estimations. We also saw that adding expectations increased both people’s causal judgments as well as their subjective degree of belief that a counterfactual collision would have led to a different outcome. Interestingly, this effect was particularly strong for social expectations. CSM explains this effect by assuming that knowledge about intentions of agents limits the range of counterfactuals relevant to consider. Our results thus add to previous research indicating that intentional compared to unintentional actions may signal higher causal stability (Lombrozo, 2010), and that causal stability is indeed a relevant dimension that influences causal reasoning (Nagel & Stephan, 2016).

It might be argued the asymmetry in causal attribution for “went through” and “missed” in Experiment 1 is not due to a difference in what would have happened in the relevant counterfactual simulations, but rather due to an inherent asymmetry between omissions that prevent and omissions that cause. Experiment 2 addressed this possible confound by looking at

situations in which the relevant counterfactual event was clear (a wall that could only move in one direction), as well as what would have happened in case that event had happened. Just as predicted, we found that causal ratings were equally high irrespective of whether the ball “went through” and “missed” in this case. Instead of a general asymmetry between prevention and causation, participants judge omissions to be causal the more certain they are that the omission made a difference to the outcome.

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