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Circumventing Spatio-Numeric Biases Through Non-Numeric Assessments of Perceived Causal Strength

Daniel William Czarnowski
daniel.czarnowski@student.shu.edu

CIRCUMVENTING SPATIO-NUMERIC BIASES THROUGH NON-NUMERIC ASSESSMENTS OF PERCEIVED CAUSAL STRENGTH
by
Daniel William Czarnowski

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APPROVAL FOR SUCCESSFUL DEFENSE

Master's candidate, Daniel William Czarnowski, has successfully defended and made the required modifications to the text of the master's thesis for M.S. during this Fall 2018.

THESIS COMMITTEE

Mentor:
Kelly M. Goedert, PhD: ______________________

Committee Member:
Marianne Lloyd, PhD: ______________________

Committee Member:
Michael Vigorito, PhD: ______________________

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Abstract

Knowledge of cause and effect allows individuals to meaningfully interpret the events they perceive in the world, and the understanding of causality is thought to be grounded in the understanding of forces (Wolf, Ritter, & Holmes, 2014). Previous research has linked handedness with both the ability to exert force (e.g., Linkenauger et al., 2005) and causal learning (e.g., Goedert & Czarnowski, 2017). Historically, number lines have been used to assess causality, but because handedness has a strong spatial element, SNARC effects may influence judgments (Fias, 1996). The current experiment replicates previous work by Goedert and Czarnowski (2017) but changes the assessment measure used to capture causal judgments. Right-handed participants underwent a trial-by-trial learning task where they were instructed to discern how effective various plant liquids were on plant blooming. Instead of using a number line, I created a color selector that reduces the impact of spatio-numeric biases by instructing participants to choose a color they feel accurately captures their causal judgment. Bayesian analyses found that individuals were able to use the color selector to appropriately discern between moderately contingent and non-contingent plant liquids. More importantly, no strong evidence for the presence of spatial biases was found.

Introduction

Causal Inference.

Each day, we are faced with situations that rely on our understanding of causal relationships. To effectively navigate the world around us, individuals must be able to make inferences about causes and effects so that they can react appropriately to events and make informed judgments. For example, if someone was experiencing digestive trouble after eating certain foods, being able to make causal inferences may allow them to recognize the potential offender based on their recent meals.

In some instances, causation can be directly observed. For example, if two billiard balls collide with one another, one can recognize that it is the momentum of one ball being transferred to the next that facilitates movement (Michotte, 1963). The contact between the two balls is the component from which belief in the causal nature of the event is derived. This contact, thus, serves as a causal mechanism, an element of the event that is thought to be necessary for a causal relationship to be present (Woo-kyoung, Kalish, Medin, & Gelman, 1995). If the two balls never made contact, but the cue ball stopped suddenly and the other ball began moving as if it was struck, the event would violate our knowledge of physics and seem non-causal.

In other instances, causal mechanisms are not directly observable, such as when a switch is flipped and a light turns on, or when nausea is experienced after eating shell fish. While empirical and theoretical work has examined when and how people make causal inferences for both observable and non-observable causal events (e.g., White, 2007, 2012; Wolff & Shepard, 2013), very little work has addressed how people acquire a conceptual understanding of causation, especially in situations for which the causal mechanism is not directly observed. Some researchers, however, have theorized that the understanding of causation may be grounded in the understanding of physical forces via the sensorimotor systems (e.g., Wolff & Shepard, 2013;

White, 2006). From this perspective, the inputs and outputs of the sensorimotor systems, as receivers and producers of forces, influence our understanding of causal events. As such, our understanding of causality may be grounded in our knowledge of forces, whether we are experiencing them from an external source, or if we are exerting them upon the world around us.

Grounding Causation in Sensorimotor Experience

Historically, philosophers have suggested that causation is, perhaps, rooted in the ability to produce change. Aristotle thus offered a "force-based" account of causation which held that causation involves the transference of a "form" from an agent to a patient (Marmodoro, 2007). While a critique of the force-based approach was that forces could not be directly observed (i.e., Hume, 1748/1975), advocates argued that forces can be detected through the sensorimotor system (Reid, 1788).

Force-based approaches of grounding causal inference take one of two forms, either that our causal understanding is grounded in our experience as patients receiving the forces, or that it is grounded in experience as agents executing forces. As agents of forces, our notions of force, power, and causation may be derived from our execution of physical actions. Additionally, the kinesthetic stimulations from our actions (i.e., muscle movements) provide input that further informs our concept of forces (Jammer, 1957). When we make voluntary movements, we are both producing effects on the world, as well as receiving feedback based on the actions we perform. We can thus combine these elements into a schema that explains a necessary pattern of force to appropriately execute a particular action (Piaget 1927, as cited in Hazlitt, 2012). Therefore, when we see a pattern of motion, the pre-formed schemas that match those patterns of force are activated (White, 1999). This may inform our understanding of causality because the events we perceive visually are directly informed by the experience we have interacting with the world (White, 2012).

Throughout these experiences, however, we are not simply an agent that exerts its influence on the environment. Instead, we are also the recipient of forces. When we are the recipient of a force, we are the patient to it. Meaning, we are being acted upon by an external power (Fales, 2002). For example, you may be walking down the street when suddenly a gust of wind knocks you off balance. Here, you are receiving the force of the wind. Nevertheless, you resist being blown over. A combination of information from your vestibular system (balance) and tactile perceptions (strength of wind against the body) enable you to compensate for the force by activating your muscles in a way that allows you to regain your balance. Once again, this direct experience of force is what allows you to conclude that the wind *caused* you to lose your balance.

The most contemporary force-based theory of causal understanding claims that we understand causation from our role as patients of forces, and in particular, through the sensory experience of touch (Wolff & Shepard, 2013). By conceptualizing causation in terms of force, a force-based approach to causation would allow us to "make sense" of the phenomena that surround causal relationships (Wolff & Shepard, 2013). When we observe a causal event, Wolff & Shepard (2013) suggest that we simultaneously infer the forces needed to execute that event. For example, during a collision event, such as with billiard balls, we infer the transfer of momentum via contact. As such, this inferring of kinetic force at the point of contact lets us empathize with the patient object. We are aware of how it is affected because we are aware of the pattern of forces that are used to facilitate the collision event. Thus, we infer the relevant forces when we observe the event take place, thereby grounding our knowledge of causation in terms we can understand – that of force.

Evidence for Force-Based Approaches

Recent research provides evidence for both the patient and agent versions of the force-based understanding of causation (Wolff, Ritter, & Holmes, 2014; Rakison & Krogh, 2012). Consistent with a patient-based account, in a series of experiments Wolff et al. (2014) demonstrated that observing causal events primed the detection of a mild force applied to the hands. In their research, they employed the use of a haptic controller; a mechanical arm that is capable of exerting a force on a participant. Across their work, they showed participants various animations of either causal or non-causal events. The causal events varied from physical causation to social causation. To elicit physical causation Wolff et al. (2014) used the Michotte Launch Task, which consists of a simple animation that contains two balls. The way these balls interact with one another varies, but a simple "launching" event is demonstrated by one of the balls moving towards, and making contact with, another ball, which subsequently causes the second ball to travel away from the first one (Michotte, 1963).

At the conclusion of each animation, participants were to respond as quickly as possible upon detecting a stimulus: participants in the auditory condition heard a tone, participants in the visual condition saw a light flash above the final frame of the animation, and participants in the haptic condition felt the haptic controller exert a force on their hand. Seeing a causal event (i.e., collision event) should prime the participants to feel a force, which would present as shorter reaction times for the individuals in the haptic response condition. Wolff et al. (2014) found that participants responded faster to the haptic stimulus, but not the auditory or visual, after viewing the causal versus non-causal animations. This suggests that watching a causal event has a specific interaction with the detection of force.

While it might seem straight forward for a collision event to prime the detection of a force, critically, Wolff et al. (2014) demonstrated that the detection of a force was primed even when the causal mechanisms were not directly observable. For example, in one animation, participants observed social causation, where the causal mechanism was simply a person waving their hand to redirect another person's walking path. Even here, in the absence of physical forces, participants were sensitized to the feeling of force by perceiving a causal event.

In a final experiment, Wolff et al. (2014) demonstrated that haptic priming was present when making causal inferences from contingency information, but only when participants were provided with a causal mechanism for the contingency. In the experiment, participants saw animations consisting of two circles, one on the left and one on the right. Each trial consisted of one of three animations (e.g., the left circle turns solid followed by right circle turning solid). Participants in the mechanism condition were told that there was an underlying mechanism (causal narrative) that connected the two circles. In the non-mechanism condition, the participants were only told that they would see a series of animations. Participants in the mechanism condition were more likely to endorse the statement that the "cause" circle caused the "effect" circle to change. Additionally, participants responded faster to the haptic force in the mechanism condition versus the non-mechanism condition. This pattern of results suggests that when we conceptually represent causal mechanisms, regardless of how abstract, we may be recruiting a notion of force to help us ground our understanding. And, as their results suggest, this is not limited to perceiving instances of physical causation. Instead, it seems to apply to inferences of causation from covariation as well.

Overall, the Wolff et al. (2014) work suggests that causal events, whether the mechanisms are observable or unobservable, prime an expectation of force. Meaning, when we observe a causal event, we infer a force, which thus sensitizes us to feeling a force. Therefore, people may be perceiving forces from the visual stimuli and somehow “empathizing” with each patient object in the animations, which thus sensitizes their sense of touch, making them more susceptible to feeling forces.

These results are consistent with Fales’ (1990) patient-oriented account of force perception, which suggests that when we perceive a force, we adopt the perspective of the patient object. Thus, we identify with the inactive entity and empathize, thereby “feeling” the force being acted upon it. Wolff et al.’s (2014) work suggests that there is a relationship between the perception of causation and the *feeling* of force. This work supports a patient-oriented view of causation. However, in our experiences, we do not only act as patients to forces. When exerting our influence on the world, we often assume the role of agents. Even though Wolff et al. (2013) did not find general reaction time improvements associated with causal versus non-causal events, Rakison and Krogh (2012) demonstrated that the ability to exert force upon the world is critical to the understanding of causal relationships.

In this study, a group of 4½ -month old infants were able to interact with a set of balls by wearing Velcro mittens, while another group of infants were given no such action experience. The Velcro mittens facilitated the infants’ ability to pick up the balls and manipulate them, which would otherwise be impossible due to a lack of fine motor skills. After a designated action experience period, the two groups were exposed to Michotte launch task animations. The investigators used a habituation in looking-time paradigm and found that the infants who were given the Velcro mittens, that is, the infants who were able to exert force on the balls, better discriminated between the causal and non-causal animations in terms of visual fixation when compared to the group of infants that had no action experience. By being able to exert force on the balls, the infants were better able to recognize the causal events. This result exemplifies the importance that the role of the agent plays in developing accurate representations of causality.

Agent-Based Causal Grounding and Judgments of Causal Strength

If our ability to understand causation relies at least in part on our ability to exert force, it is possible that a person may perceive causes to be of different strengths when using their dominant versus non-dominant hands. For example, right-handed individuals interact with the world more efficiently when using their dominant hand, and thus, they believe that their right arm is longer and better able to reach for objects than is their left (Linkenauger, Witt, Stefanucci, Bakdash, & Proffitt, 2009). Additionally, right-handed individuals are able to produce a 10% greater force with their dominant hand than they are their non-dominant (left) hand, while left-handed individuals exhibit no such disparity (Petersen, Petrick, Connor, & Conklin, 1989). In these examples, actions like reaching and gripping are tied to the physical execution of movements where the dominant hand is the causal mechanism producing a change. If handedness is associated with the ability to act and produce force, and force informs our understanding of causation, handedness may be a relevant factor in our perception of causal strength. While these results suggest that handedness affects physical, observable acts (i.e., reaching, gripping), does it play a role in the formation of causal inferences when causal mechanisms are unobservable? Perhaps. If we extend the qualities of our dominant hands to the sides of space they reside in, we may interpret information that is presented in those respective sides of space in different ways.

When causal mechanisms are unobservable, we can potentially use covariation information to make causal inferences (Cheng, 1997). For example, if we want to assess the effectiveness of a headache medication, we may attend to whether administration of the medicine covaries with the presence of a headache. A scenario that employed covariation information was explored by Goedert & Czarnowski (2017) during a causal learning task. A trial-by-trial learning task posed participants with two bottles of plant-treatment liquids (fertilizers), which participants observed being applied in various combinations (one, neither, or both) to a plant. Here, each bottle represented a potential cause, one of which, the target, had a causal power of .49, and the other was non-effective, having a causal power of 0.[1] During the trials, a centrally located plant was flanked on both sides by the bottles. Each trial presented a combination of the bottles being applied to the plant, after which the participants predicted whether the plant would bloom. Therefore, throughout the trials, participants had to synthesize the presented covariation information to accurately discern how powerful each of the liquids was in plant blooming. After every 12 trials, participants rated how causal they believed each of the liquids to be using a number line that spanned from 0 (completely ineffective) to 100 (completely effective).

Participants consistently rated the target cause as being more causal when it was presented on the right versus the left side of the screen (Goedert & Czarnowski, 2017). One explanation for this pattern of results is that right-handers expected a stronger cause to be on the right side of space because they exert greater force with their dominant (right) hand. It's also possible, however, that participants rated the cause as being more effective when it was on the right side of space because the number line that they used to make their judgments presented a spatial layout that was consistent with higher values on the right (100) and lower values on the left (0). The latter explanation may be a function of a cognitive transformation that occurs when a causal judgment is translated into a numerical estimate (i.e., on a number line).

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[1] Equation for generative causal power (Cheng, 1997) $Causal\ Power = \frac{P(e|i)-P(e|\sim i)}{1-p(e|\sim i)}$, where $P(e \mid i)$ is the probability of the outcome in the *presence* of the cause and $P(e|\sim i)$ is the probability of the outcome in the *absence* of the cause.

Spatial-Numeric Associations

The mental number line is a form of cognitive architecture that serves as the basis for our accessing numeric information. Being a projection of the understanding of a left-right number system where values increase in the rightward direction and decrease in the leftward, the mental number line is mapped to the left-right nature of our external spatial field (Zebian, 2005). As a result, we are exposed to the biases that coincide with this representation; small numbers are routinely associated with the left side of space, and large numbers with the right (Wood, Willmes, Nuerk, & Fischer, 2008). These biases often manifest in the form of SNARC effects (Spatial-Numerical Association of Response Codes), which are influences that attribute spatial characteristics to numerical values (Dehaene, Bossini, & Giraux, 1993). For example, Fias (1996) showed how the left and right sides of our body are differentially sensitive to numerical values. In this experiment, participants were given a judgment task in which they had to determine whether two values were equal. Fias (1996) found that left-hand responses were faster with smaller values while right-hand responses were faster with higher values. This is consistent with our understanding of the number line, where values increase towards the right and decrease towards the left.

Considering these SNARC effects and the existence of the mental number line, it's possible that Goedert & Czarnowski's (2017) findings are the result of response effects derived from the number lines that were employed in the study. That is, judgments of the target may have been artificially inflated or diminished based on the number line that was used to base judgments on. When the target cause was presented on the right side of the screen, SNARC effects may have seemingly inflated the target's causal power, since it coincided with the side of space associated with greater values.

Additionally, when participants were using their right hands to respond, they may have been subject to the SNARC effect, and subsequently applying the bias to their responses, resulting in stronger causal judgments. If the SNARC effect is interfering with the production of a judgment that accurately captures a causal belief, perhaps numbers are not the most effective means of evaluating causal relations.

Current Experiment

The current work seeks to circumvent these numeric-spatial associations. Goedert and Czarnowski's (2017) work is replicated, save for one crucial change. Instead of producing value judgments based on a number line, participants were brought to a screen with a circle that contains a gradient-presentation of the color green, with pure green (0,255,0) on the perimeter gradually darkening to dark green (0,55,0) in the center. Participants responded by using a Logitech game controller that had the cursor mapped to one of two control sticks, either on the right or left of the controller. Prior to the trial-by-trial causal learning task, participants learned that a darker, more saturated color (i.e., those towards the center of the circle) indicated greater causal effectiveness. They were instructed to choose a color that best represents their belief in the causal power of the particular plant liquid in question. Once their color was selected, they clicked down on the control stick to record their choice. Additionally, the starting position of the cursor that participants used to select their color was placed on the upper left of the circle or the upper right of the circle to counterbalance potential spatial effects of the cursor starting location.

My reasoning for this change to the previous work lies in the way that we transform a causal attitude to a value judgment. When we use number lines, we are forced to convert an abstract attitude (causal belief) to a tangible form (numeric judgment). Unfortunately, when value judgments contain numbers, they are inherently subject to the spatial biases that coincide with the mental number line (e.g., SNARC effect). As such, the saturation of a color's hue is being used as an alternative to absolve the response process of spatial biases in the hopes of achieving more accurate causal judgments.

Participants' color selections were assessed by the percent saturation of the chosen color. As such, the dependent variable was the participant's causal judgments in the form of a percent saturation of green. Higher saturations (approaching black) represented stronger judgments (approaching 100% causal). The variables that were manipulated were similar to those of the previous work; the response hand used (right vs. left), the strength of the cause (moderately contingent vs. non-contingent) and the location of the target cause (right side of screen vs. left side of screen) (Goedert & Czarnowski, 2017). I hypothesized that participants would be sensitive to the strengths of the causes. In contrast to the previous Goedert and Czarnowski (2017) work, participants did not have direct access to the numeric information of their causal judgments. Therefore, they should not be mapping numeric information to the spatial properties of the color selector. By removing the influence of numbers and the number line, the current work seeks to explain how spatial information contributes to the formation of causal judgments. If no pattern of spatial effects arises, that would suggest that individuals are able to able to circumvent spatial biases (that are otherwise present when considering numbers) when evaluating the strength of causal agents. If spatial effects do arise, however, this would suggest that, even in the absence of numeric information, spatial elements are considered when forming causal judgments.

Methods

Participants

One hundred-seven right-handed Seton Hall University undergraduate students participated in exchange for course credit. An a-priori power analysis yielded a sample size of 84 for a mixed design ANOVA sensitive to a within-between interaction. Using the Goedert & Czarnowski (2017) data, I generated an effect size for a partial eta squared of .05. Using G-Power 3, I calculated a sample size that would achieve .95 power with an expected correlation of 0 among repeated measures (to be conservative).

Design

The design was a 2 (response hand: right or left) by 2 (location of target: right side of screen or left side of screen) by 2 (causal power of cause: .49 or 0) by 2 (starting location of cursor: right or left) by 3 (block: 1, 2, or 3) mixed design. Response hand was manipulated between-groups and location of target, strength of cause, and cursor starting location was manipulated within-groups so that each participant completed two conditions of the experiment (one with the target on the left side of the screen and one with it on the right). While the presentation of the stimuli was randomized within each block of trials, the ratio of the effect (plant blooming) in the presence and absence of the cause (fertilizer being used/not used, respectively) remained constant across blocks to preserve the strength of the target cause (causal power = .49).

Materials

Cover Story. Participants were read a cover story upon beginning the experiment (See Appendix A for full text). Participants imagined that they had been recruited by their landlord to help her determine the strengths of the plant fertilizers she has in her garage. Amongst these fertilizers, however, are bottles of colored water that have no effect on plant growth. None of the bottles are labeled, so she has tasked the participant with testing out the various bottles to determine their effects. To do so, the participants evaluated the strength of each treatment liquid as they are poured in various combinations onto the plants.

Stimuli. In each trial, participants were presented with stimuli derived from Goedert and Czarnowski (2017). Figure 1 illustrates an example trial in which the red liquid is applied to the plant.

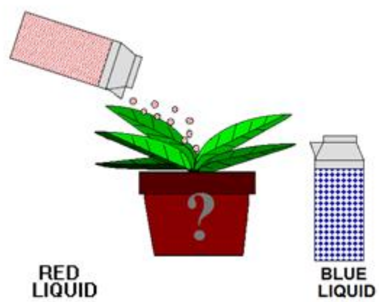

Figure 1. Example prediction screen in trial-by-trial learning task. The red liquid is being applied to plant in this trial. The blue liquid is not. Adapted from Goedert and Czarnowski (2017).

Figure 2 illustrates the potential outcomes of the trial: either this combination of liquids is followed by plant blooming or not.

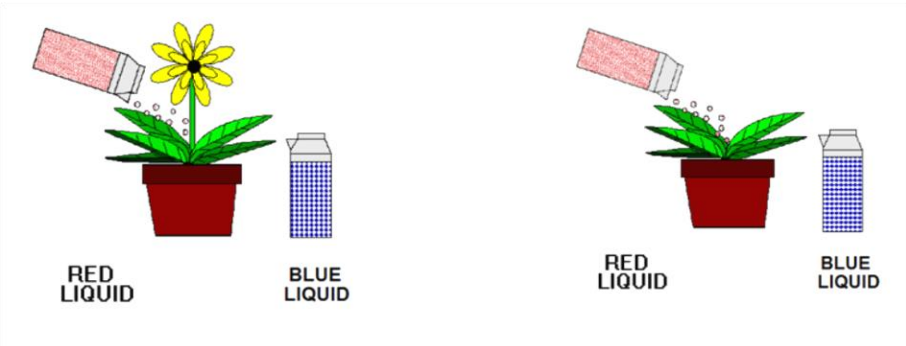

Figure 2. Potential feedback screens in trial-by-trial learning task. Picture on the left indicates that this combination of plant liquids made the plant bloom. The picture on the left indicates that this combination of plant liquids did not make the plant bloom. Adapted from Goedert and Czarnowski (2017).

At the conclusion of each twelve-trial block, the color selector I created was presented to participants so they could make their causal judgments for each of the plant liquids (see Figure 3). The choice of green as the color to be used on the selector was driven by the stimuli used in the trial-by-trial learning task. In each of the six conditions (e.g., Figure 1), colored bottles of plant liquid are depicted being applied to the plant. If the color on the color selector matched one of the colors used for the plant liquids, participants may form an association between the two concepts and return biased judgments. Therefore, green was chosen because none of the colored liquids used in the stimuli were green in nature. Each of the twelve bands on the color selector represent a discrete shade of green, and participants were free to choose their color anywhere on the selector. When presented, participants used the game controller to navigate the cursor to the color they felt accurately represented their causal judgment of either the target or the alternate cause and then confirm their selection using a button press.

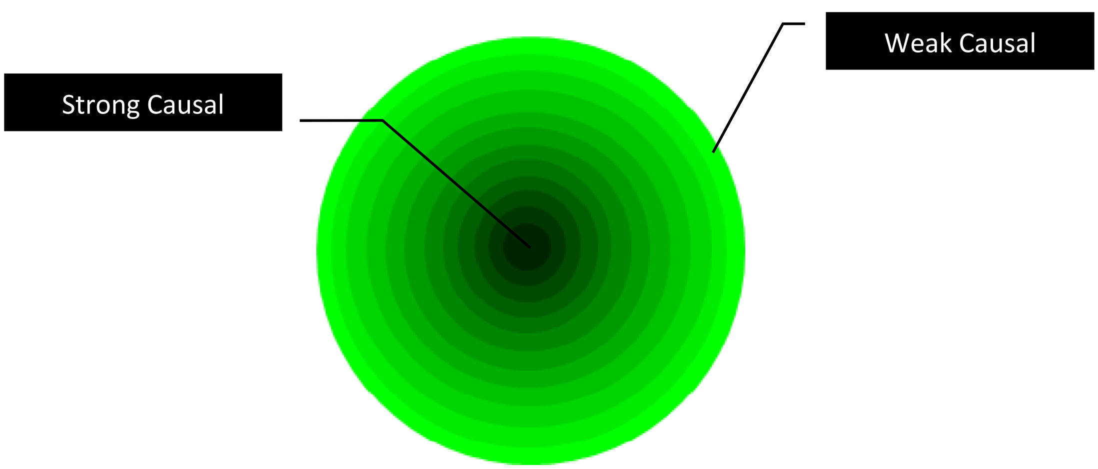

Figure 3. Color selector utilized as the assessment measure to capture causal judgments. Callouts indicate examples of strengths of judgments but were not present during the experiment.

Comprehension Check. Two practice trials preceded the beginning of the causal learning task. Participants were presented with the color selector and then trained on how to choose their judgments. They were then given practice by being instructed to select a color that represents a weak causal judgment and a color that represents a strong causal judgment.

Procedure

The experimenter read the cover story to the participants. Prior to the beginning of the task, participants underwent a series of two practice trials to ensure that they accurately selected between the "yes" and "no" response buttons. In these trials, participants saw written prompts that instructed them to select either the "yes" or "no" response button on the controller, based on the hand they were assigned to use. The "yes" and "no" responses were mapped to either the right or left trigger buttons of the controller, depending on which condition they were assigned to (left response hand or right response hand).

During each trial, participants saw two bottles of different colored liquids surrounding a potted plant and responded as to whether or not the plant would bloom. As seen in figure 1, if a bottle was in the air, it indicated that it was being used in that trial. Considering this, there were four combinations of how the liquids could be applied (left only, right only, both, or neither). After they made their selection, they were presented with a feedback screen for 2500ms that indicated if the plant bloomed during that trial. After twelve trials, the participants saw an assessment screen that prompted them to respond to how effective they thought each of the treatment liquids were on plant blooming. On each assessment screen, participants saw written instructions that reminded them how to use the color selector. Separate assessments were made for each liquid on sequentially-presented screens, and after they made their second assessment, the next block began. After the third block, the participants were informed that they were testing a new set of liquids (indicated by a different set of colored bottles), which was similarly completed across three blocks of twelve trials each. Each participant was thus exposed to 72 total trials across six blocks (three per condition). At the conclusion of the sixth block, participants were debriefed and then dismissed.

Test for Color Blindness. At the conclusion of the causal learning task, participants completed the 14-plate Ishihara Color Test (1936) to check for color-blindness, as the dependent measure in this experiment required discriminating different saturations of the color green.

Dependent Measures

Causal Judgments. Causal judgments were collected using the color-selector depicted in Figure 3. Participants selected their color by using the controller's joystick to navigate to their selection and then using a button input to confirm their selection. The button press instructed the program to log both the on-screen coordinates of their selection and the hexadecimal code of the selected color. To translate the selected colors to numerical data, I converted the hexadecimal color codes that participants selected to "percent saturation" values. Considering the range of greens between 0,55,0 (dark green) and 0,255,0 (light green), the percent saturation (x) of the selected color was evaluated via the following equation, where *y* equals the selected color value. To create a 0-point, I subtracted 35 from all selected values. That way, if the participant chose 235, then the equation evaluates out to 100% saturation. Conversely, if they chose 35, then the equation evaluates out to 0% saturation.

$$X = \frac{100(y-35)}{220} \tag{1}$$

Clicking Behavior. Clicking behavior was assessed by logging the coordinates of all on-screen clicking events. Therefore, each color selection was associated with a percent saturation value and a set of (X,Y) coordinates that corresponded to where on-screen each selection was made. The color selector was then divided into two regions of interest: a left half and a right half. In addition to determining whether there was a bias in the causal judgment, which was not mapped to a particular spatial location, I assessed for spatial biases in where on the screen participants clicked. For example, a weak causal judgment could be indicated by clicking on either the extreme right or extreme left of the color circle, but perhaps participants still exhibited a spatial bias by preferentially clicking on the right side of the color circle.

Results

Fourteen participants were excluded from analyses due to experimenter error (*N* = 6), technical difficulties (*N* = 3), or participant non-cooperation (*N* = 5), leaving *N* = 93 for analyses. No color-blind participants participated in the experiment. Hypotheses were tested using Bayes Factor Hypothesis testing, which reports a Bayes Factor for inclusion (BF) to compare how well the data supports the null versus alternative hypotheses (Wagenmakers et al., 2018). For a detailed description of Bayesian Hypothesis Testing, see appendix B. Throughout, Bayes Factors for inclusion greater than 3.2 are interpreted as evidence for the alternative hypothesis and those less than 0.313 as evidence for the null hypothesis. All Bayesian results reported here were qualitatively consistent with the frequentist analyses, which are reported in Appendix B.

Derived Causal Judgments

A preliminary Bayesian dependent samples t-test of the derived causal judgments revealed that participants were sensitive to the contingency information and able to use the color scale to discriminate between the target and the alternative causes. As expected, participants judged the target cause (M = 62.21, SD = 29.83) as more causal than the alternative (M = 25.68, SD = 28.91; d = 1.24, BF_{10} = 5.51e +81). This Bayes Factor suggests decisive evidence in favor of the alternative hypothesis (see Appendix Table B1 for interpretation of Bayes Factors) and the size of the effect is large given Cohen's (1988) conventions.

Target Cause (Causal Power = .49) Previous research using a numeric scale that increased from left to right found that participants rated the target more causal when it appeared on the right than left side of space, particularly when using their right hand (i.e., a side by hand interaction; Goedert & Czarnowski, 2017). I hypothesized that with the spatially non-linear color hue indicator of causal strength there would be no effects of target side nor of the hand used. The results are partially consistent with this prediction. Average derived causal judgments for the target cause appear in Figure 4. Inspection of the figure suggests that neither the hand that participants used, nor of the side of the screen on which the target appeared, influenced their estimates of its causal strength.

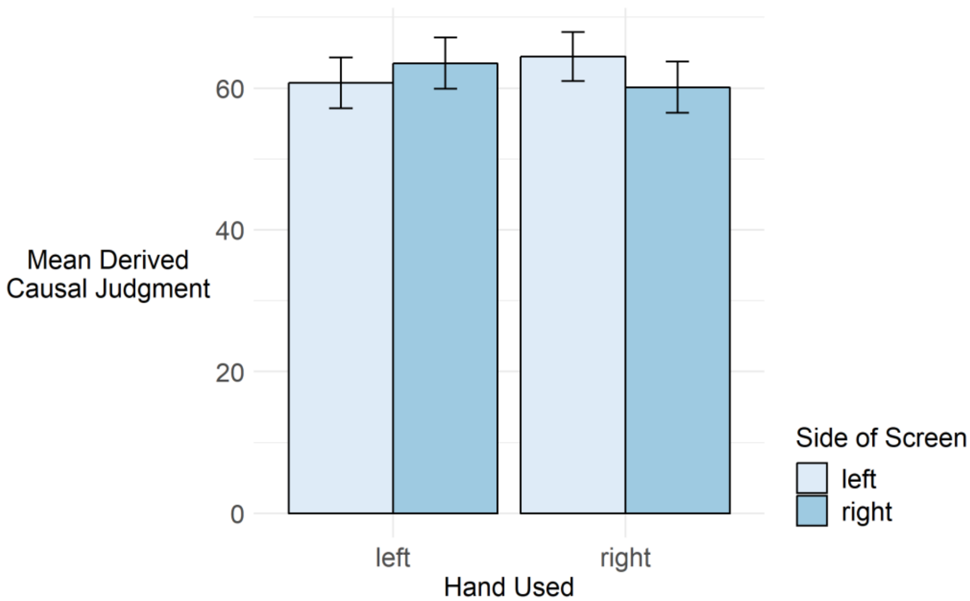

Figure 4. Mean causal judgments of target cause. Error bars are 1 *SE*.

These impressions were mostly supported by a 2 (hand used: left, right) X 2 (target side: left, right) X 2 (cursor start: left, right) x 3 (Block: 1, 2, 3) Bayesian repeated measures ANOVA. Table 1 presents the Bayes Factors for inclusion from this analysis. As can be seen in Table 1, the Bayesian analysis yielded clear evidence for an absence of an effect for most of the factors in this analysis. The one exception is the target side by hand used interaction, for which the Bayesian analysis did not yield clear evidence, neither for an effect, nor for an absence of an effect. Thus, there were clearly not main effects of the target side, nor of the hand used, as observed in previous studies (Goedert & Czarnowski, 2017).

Table 1

Bayesian Analysis of Effects on Target Only

Model	$BF_{inclusion}$	Interpretation
Block	.052	Strong Evidence for Null
Target Side	.096	Strong Evidence for Null
Hand Used	.166	Some Evidence for Null
Block x Target Side	.040	Strong Evidence for Null
Block x Hand Used	.050	Strong Evidence for Null
Target Side x Hand Used	.506	Inconclusive Evidence
Block x Target Side x Hand Used	.157	Some Evidence for Null

Note. Interpretations derived from Kass & Rafferty (1995) and Lepink et al. (2017).

Furthermore, the lack of clear evidence for the null on the target side by hand used interaction does not suggest that the effects observed in previous studies (i.e., Goedert & Czarnowski, 2017) are likely present here. As can be seen in Figure 4, the "inconclusive" interaction actually runs in the opposite direction of that previously observed, with participants rating the target as more causal when it appeared on the left side of the screen when they were using their right hand.

Previous research has suggested that right-handed participants are predisposed to a body-based expectation for a strong cause to occur in their right side of space (i.e., Goedert & Czarnowski, 2017). The current results suggest that this effect may have been exacerbated by, or even dependent on, how these causal judgments were previously assessed (i.e., number line activating spatial biases). In the current analysis of the target cause, no substantial evidence for hand used or target side arose. This suggests that even when assessing the relatively "strong" cause appearing on the right side, this body-based expectation did not influence judgments when using the color selector scale.

Alternative Cause (Causal Power = 0). Previous research has found that the body-based spatial-numeric association did not arise for non-causal events (Goedert & Czarnowski, 2017). When using a scale that doesn't activate spatio-numeric biases, I would further expect no spatial effects on causal judgments of the alternative cause. Once again, results are somewhat consistent with this prediction.

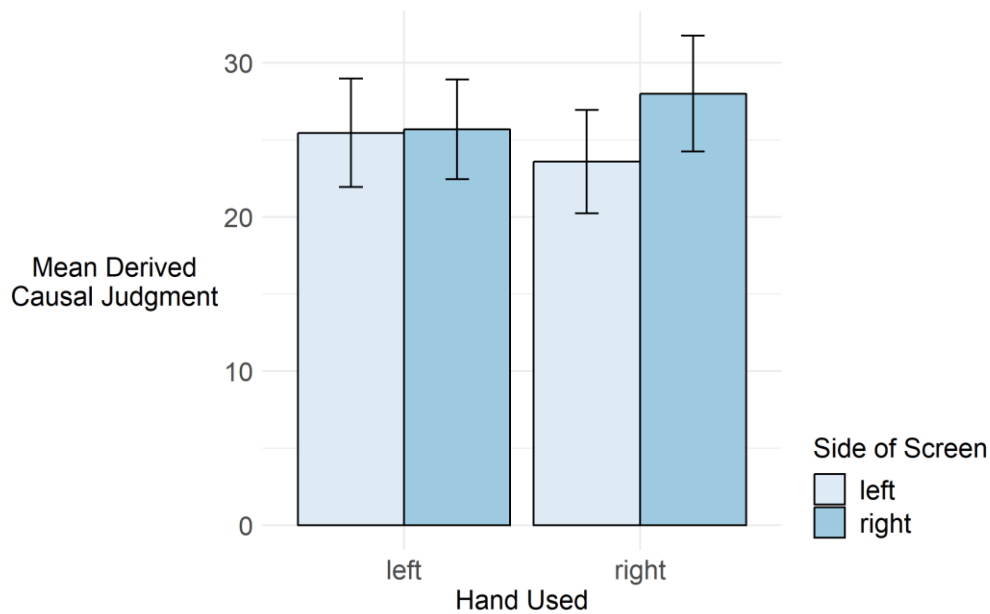

Figure 5. Mean causal judgments of alternative cause. Error bars are 1 *SE*.

Figure 5 depicts mean derived causal judgments of the alternative cause. Examination of figure 5 suggests that estimates of causal strength were not influenced by hand used nor the side of space the alternative cause appeared.

A 2 (hand used: left, right) X 2 (target side: left, right) X 2 (cursor start: left, right) x 3 (block: 1, 2, 3) Bayesian repeated measures ANOVA supported this impression. Table 2 presents the Bayes Factors for inclusion from this analysis. As can be seen in Table 2, the Bayesian analysis yielded some evidence for the absence of effects for most of the factors in this analysis. Two interactions yielded strong evidence for the null, block by hand used and block by target side by hand used. One factor, block, yielded very strong evidence for the null. Taken together, the analysis of effects in Table 2 suggests that no main effects of hand used or side of space arose, once again deviating from previous findings (i.e., Goedert & Czarnowski, 2017).

Table 2

Bayesian Analysis of Effects on Alternative Only

Model	$BF_{inclusion}$	Interpretation
Block	.026	Very Strong Evidence for Null
Target Side	.177	Some Evidence for Null
Hand Used	.199	Some Evidence for Null
Block x Target Side	.250	Some Evidence for Null
Block x Hand Used	.039	Strong Evidence for Null
Target Side x Hand Used	.216	Some Evidence for Null
Block x Target Side x Hand Used	.058	Strong Evidence for Null

Note. Interpretations derived from Kass & Rafferty (1995) and Lepink et al. (2017)

As can be seen in figure 5, participants using their left hand exhibited practically no differences in mean derived causal judgments of the alternative, regardless of the side of the screen it appeared on. Interestingly, when using their right hands, the interaction between target side and hand used seems to be consistent with what we would have expected for causal judgments of the target cause. Participants made weaker judgments when the alternative was presented on the left side and stronger judgments when the alternative was presented on the right side, but there is large variability around the observed means and the Bayesian analysis suggests some evidence for the null on the target side by hand used interaction.

Clicking Behavior

No effects were found for the variables of hand used and target side on causal judgments. Does this mean that participants were completely unbiased in their responses? Not necessarily. Because participants could use either the left or the right sides of the color selector for high and low causal judgments, it is possible that biases arose in participants' clicking behavior, as they were free to make their selections anywhere on the figure. Additionally, participants' cursor was randomly placed on the left or right side of the screen prior to viewing the color selector. It is possible that participants' whose cursors began on the left side of the screen favor the left side of the color selector and vice versa (Garza, Eslinger, & Barrett, 2008).

Figure 6 once again depicts the color selector I created for the task, with the addition of a vertical line that represents the middle of the color selector, x-coordinate 227. To assess clicking behavior, the coordinates of color selections were captured when participants made their causal judgments. If an x-coordinate less than 227 is selected, that means that selection was made on the left half of the color selector. If an x-coordinate greater than 227 is selected, that means that selection was made on the right half of the color selector.

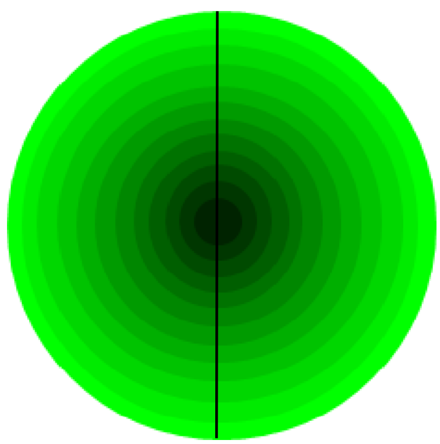

Figure 6. Color selector used when making causal judgments. The vertical line bisects the selector into left and right halves (X-Coordinate = 227).

Figure 7 depicts the mean x-coordinates chosen by participants across all conditions when making judgments. Horizontal lines indicate the cutoff point (x-coordinate = 227) that divides the color selector into left and right halves. Examination of Figure 7 suggests that when when the cursor began on the right side of the screen, on average, participants made their selection on the right side of the color selector. Similarly, when the cursor began on the left side of the screen, on average, participants tended to make their selection on the left side of the screen, or just beyond the midway point of the color selector. People who responded with their left hands, whose cursor began on the left side of the screen, however, seemed to exhibit a stronger leftward bias when making their causal judgments for the alternative cause when it was presented on the left side of the screen.

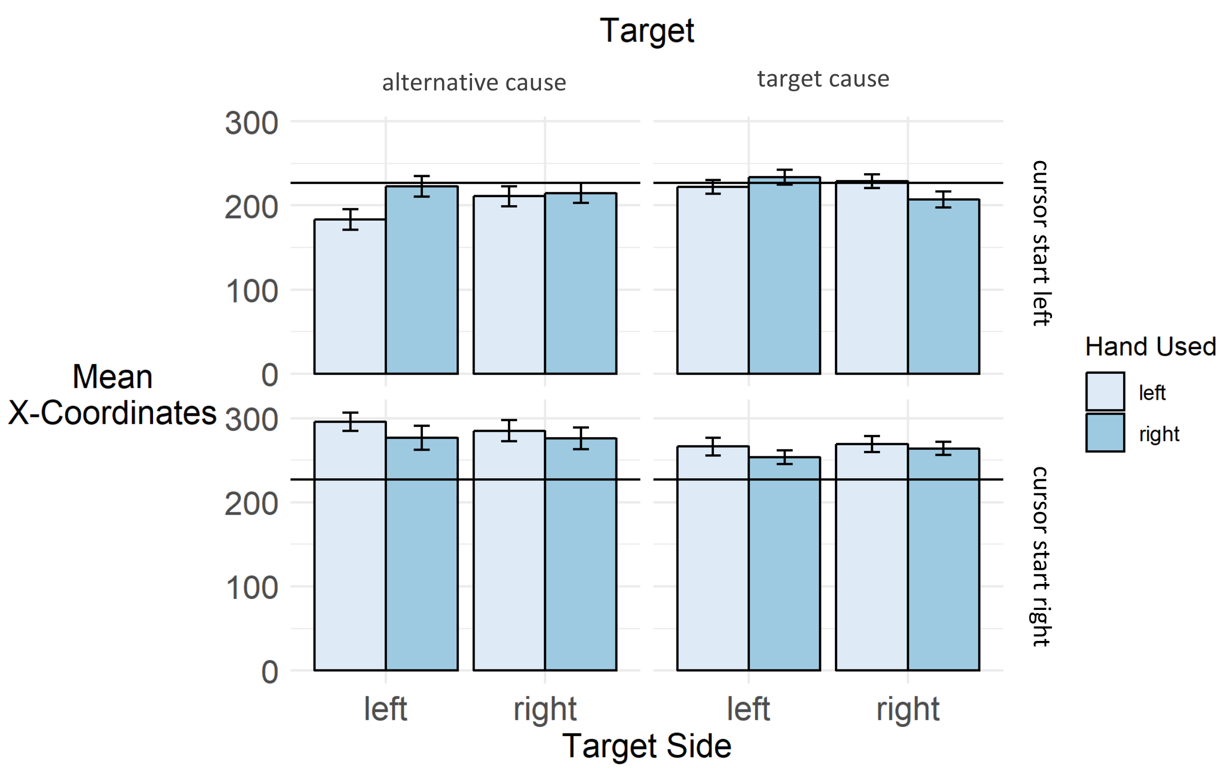

Figure 7. Mean x-coordinates across spatial conditions. This graph presents participants' mean x-coordinate selections by the variables of hand used, target, target side, and starting cursor location. Horizontal lines indicate the center of the color selector (x-Coordinate = 227). Error bars are 1 *SE*.

In order to determine whether or not a clicking bias was present, single-sample Bayesian t-tests were run against the midpoint coordinate of the color selector, 227. When the cursor began on the left side of the screen, selected x-coordinates were tested to see if the mean chosen coordinate was less than 227, implying that these selections favored the left half of the color selector. The average chosen x-coordinate (*M* = 215.6, *SD* = 89.52; *d* = -.13, BF_{10} = 10.65) exhibits moderate evidence in favor of the alternative hypothesis, that when the cursor began on the left side of the screen, participants' color selections were biased towards the left side of the screen.

When the cursor began on the right side of the screen, selected x-coordinates were tested to see if the mean chosen coordinate was greater than 227, implying that these selections favored the right half of the color selector. The average chosen x-coordinate (*M* = 273.9 *SD* = 91.06; *d* = .52, BF_{10} = 7.695e + 25) exhibits decisive evidence in favor of the alternative hypothesis, that when the cursor began on the right side of the screen, participants' color selections were biased towards the right side of the screen.

Taken together, these results suggest that clicking behavior was influenced by where on-screen the cursor began prior to making color selections. When comparing the effect sizes of chosen x-coordinates between left (*d* = -.13) and right (*d* = .52) on-screen cursor starting locations, there does appear to be a slight rightward bias in clicking behavior. As previously mentioned, however, one select group of respondents seemed to exhibit a stronger than average leftward bias in their clicking behavior. When participant's cursor began on the left side of the screen and they were using their left hand to respond to the alternative cause when it was presented on the left side of the screen, the average selected coordinate (*M* = 183.1 *SD* = 99.99; *d* = -.44, BF_{10} = 92.05) exhibits very strong evidence in favor of the alternative hypothesis; that this specific group exhibited a leftward bias in their clicking behavior. In contrast to the previous result, this leftward shift could be the product of an overwhelming amount of non-right information supplementing the non-causal nature of the alternative cause, thus overriding the aforementioned rightward preference. Because it is the weaker of the two causes, it is more strongly associated with the weaker of their two hands and its respective side of space – the left.

Discussion

In this experiment, I created an alternate assessment measure (color selector) of causal effectiveness judgments to explore how spatio-numeric biases influence causal judgments in trial-by-trial learning tasks. Decisive evidence was found that supports participants' use of the scale as an alternative to a traditional numeric measure (e.g., number line). More importantly, no main effects on causal judgments for the variables of hand used, target side, and cursor starting location were found, which suggests that the color selector measure mitigated spatio-numeric effects that would have otherwise arisen when using a number line (e.g., Goedert & Czarnowski, 2017). In fact, the only robust spatial influence found was in participants' clicking behavior, only suggesting their preferences for where on the color selector they made their selections while leaving their actual judgments unaffected. Thus, using color as a means of assessing causal strength serves as a viable alternative when attempting to make spatial biases less salient in trial-by-trial causal learning tasks.

Accuracy of Judgments

While participants were able to successfully use the color selector to discriminate between the alternative cause (causal power = 0) and the target cause (causal power = .49), they were not able to do so with great accuracy. This was to be expected, however, as participants were not using an exact number system (i.e., number line), nor were they instructed to think in terms of numbers, when making their responses. The color selector forced participants to transform their causal judgments into non-numerical approximations. Therefore, even though the alternative cause (Causal Power = 0) was never present during instances of plant blooming, participants still gave it a mean rating of 25.68 in terms of its effectiveness in making the plant bloom. Similarly, while the target cause (Causal Power = .49) only made the plant bloom in about half of its total applications, participants' mean judgment of the target was still 62.21.

Limitations

Handedness. One major limitation of the current experiment is that it used an entirely right-handed sample. Previous research has found that right-handed and left-handed individuals experience different physiological and behavioral biases. For example, Petersen et. al (1989) found that, on average, right-handed individuals experience a 10% greater grip strength when using their right hand when compared to their left. Left-handed individuals, however, experience no such difference. Right-handed individuals also overestimate their reaching ability when using their right arm when compared to their left (Linkenauger et al., 2009). Do left-handed individuals experience an analogous bias? Additionally, Bareham et al. (2014) found that right-handed individuals experience a rightward shift in their spatial attention when drowsy. Left-handed individuals, however, do not experience a comparable drowsiness-induced leftward shift in their spatial attention (Bareham, Bekinschtein, Scott, & Manly 2015). Considering the presence of these differences, it is possible that some unknown bias inherent to left-handed individuals would yield different results in such a trial-by-trial learning task.

Stimuli. While the color selector used in the study did not overtly evoke spatio-numeric concepts, it is possible that participants were able to superimpose a number system on the color selector and use that to inform their judgments. Examination of the color selector reveals twelve distinct color areas presented as a bullseye. Participants may have therefore defaulted to counting the colored bands and then using a spontaneous 1-12 scale to ground their judgment, simply picking the representative colored band. Were this to be the case, however, it would provide interesting insight in that, even when using a manufactured number system, participants' judgments were not influenced by the spatial factors upon which the number system was derived. Meaning, even after counting through and assigning values from 1-12 to each of the bands, spatial factors such as response hand, cursor starting location, and side of screen did not affect their proxy numerical judgment.

Implications and Future Directions

These findings suggest that individuals can use a color-based assessment to measure causal attitudes. The importance of this finding is twofold. First, it suggests that we do not necessarily rely on a number-based system in order to make tangible our understanding of causal strength. Instead, we may form a more abstract causal concept that is only transformed into a concrete output (e.g., number, color) when an assessment measure provokes a specific response.

Second, it suggests that a color-based measure is able to mitigate the spatio-numeric biases that are inherent to using number-based measures. This is important because SNARC effects can have a marked influence on participant responses (Dehaene, Bossini, & Giraux, 1993). As is the case with the current experiment, where concepts of left and right are very salient, using a number line as an assessment measure for causal judgments exacerbates the mapping of lower values to the left and higher values to the right, ultimately leading to artificially inflated or deflated causal judgments (Fias, 1996). Goedert and Czarnowski's (2017) results may have been subject to this, as the number lines used therein directly mapped numerical values to sides of space. In the current experiment, use of the color selector may have produced more accurate judgments because there was no overt mapping of numerical values to the measure's spatial characteristics.

While there were no effects for these spatio-numeric biases, that does not mean that spatial concepts were not activated. The spatial concepts of left and right were perhaps made salient through cursor movement. Because participants used a cursor to make selections on the color selector, they were free to move the cursor around the space until they found a color that accurately captured their causal judgment. Due to the nature of the measure, this means they could select both low and high judgments using the left and right halves of the color selector. With the left and right sides of the color selector being functionally identical, some form of rightward bias must have been driving participants' clicking behavior. Because right-handed individuals associate the right side of space with their dominant hand, and thus better act within it (e.g., Linkenauger et al., 2005), perhaps the right half of the color selector was more conducive to "selecting" their causal judgment, as selecting a color required a physical action (navigating cursor and button press).

The only time this pattern did not hold was when participants were evaluating the alternative cause presented on the left side of the plant, using their left hand, when their cursor started on the left side of the screen. Considering how wholly "non-right" this specific scenario is, participants may have recognized that their conceptualization of "right" (i.e., being causal; Linkenauger et al., 2005; Petersen et al., 1989) was not made salient by the information in this scenario, and thus they could not meaningfully use the right side of the color selector to make their judgments. Figure 7 shows that under almost identical conditions, save for response hand (right instead of left), clicking behavior for judgments of the alternative was practically at the mid-point of the color selector. Considering this disparity, response hand must have played an important role in how salient the concepts of left and right were to the participants. This would be expected, given the relationship between force and our understanding of causality (e.g., Wolff, Ritter, & Holmes, 2014; Rakison & Krogh, 2012).

The current study provides evidence that a non-numeric assessment for causal judgments serves as a viable alternative to number-based assessments. However, this experiment was conducted in the context of a task that only explored generative causes (those that produce effects). What if some of the stimuli in the task had a preventative effect on making plants bloom (e.g., growth inhibitors; Goedert & Czarnowski, 2017)? In cases such as this, SNARC effects may serve different roles. For example, a growth inhibitor presented on the left side of space may be reported to have exacerbated preventative strength. If there is a cognitive congruency between the preventative stimulus and the semantic idea of left being “less” or “reduced”, participants may report that it has more potential to cause less growth (i.e., artificially inflated preventative power). Therefore, future work should attempt to adapt the use of a color selector so that it can capture both preventative and generative causal judgments in order to further tease apart these spatial influences.

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Appendix A

Imagine the following. In this part of the experiment you are going to learn about the effects of different liquids on Calendula flower blooming. Calendula flowers are medicinal and can be used as a topical treatment for cuts and burns. Imagine that while looking though the garage of the house you have just rented, you find some very interesting-looking containers of liquid. Your landlady tells you that some of them are very expensive plant-treatment liquids and some of them are just colored water. Of the plant treatment liquids, she remembers that some of them are flower-growth stimulators (fertilizers) and that the liquids came in various strengths -- but she does not remember which liquid is which. She also thinks some liquids might just be colored water. She does want you to find out, however, and is willing to reduce your rent if you can figure it out. You decide to test whether these different liquids will affect the blooming of Calendula flowers. To figure it out, you are going to investigate the effects of two different sets of liquids as they are poured in various combinations onto different Calendula plants (Goedert & Czarnowski, 2017).

Appendix B

Bayesian Statistics

In order to predict the absence of an effect, I had to test a null hypothesis; that participants will not be sensitive to effects that arise as a result of spatial variables (hand used, target side, and cursor location). Frequentist statistical methods are not comparative in nature, and thus cannot test for evidence against versus evidence in favor of a null hypothesis (Jarosz & Wiley, 2014). In order to test my hypothesis, I employed Bayesian statistical methods, which examine how well the data fits both the null and alternative hypotheses. Bayesian statistics centers around the construction of models that best explain data, and then testing those models against competing hypotheses (Wagenmakers et al., 2018). The test statistic, the Bayes Factor, represents the ratio of how much more likely the data is to occur under the null versus the alternative hypothesis (Jarosz & Wiley, 2014). The calculation of the Bayes Factor, therefore, considers these likelihoods:

$$BF_{10} = \frac{\text{Likelihood of data under } H_1}{\text{Likelihood of data under } H_0}$$

Considering this equation, a Bayes Factor of 1 would mean that the data is equally likely to occur given either the null or alternative hypothesis (Kass & Raftery, 1995). A Bayes Factor of less than 1 would indicate that the data is more likely to occur under the null hypothesis than it is under the alternative hypothesis. A Bayes Factor of greater than 1 indicates that the data is more likely to occur under the alternative hypothesis than it is under the null hypothesis.

Interpretations of Bayes Factors are as follows:

Table 1B

Interpretation of Bayes Factors

Bayes Factor (*BF_{10}*)	Evidential Strength
>100	Decisive evidence for alternative
32-100	Very Strong evidence for alternative
10-32	Strong evidence for alternative
3.2-10	Some evidence for alternative
0.312 – 3.2	Inconclusive evidence for alternative or null
0.100 – 0.313	Some evidence for null
0.031 – 0.100	Strong evidence for null
0.010 – 0.031	Very Strong Evidence for null
< 0.010	Decisive evidence for null

Note. Derived from Kass & Raftery (1995) and Leppink, O'sullivan, and Winston (2017)

Using the Bayes Factor, comparisons can be drawn that contrast the likelihood of an effect's presence versus its absence in a given data set.

The primary analysis employed here was a 2 (Hand used) X 2 (Target Side) X 2 (Causal Power) X 2 (Cursor Start) Bayesian repeated measures ANOVA was run, which produced an excess of 150 models. In order to analyze only relevant models, specific predictors, or effects, need to be examined in isolation. This is accomplished by evaluating the Bayes Factor of inclusion ($BF_{inclusion}$). This statistic represents the support for each model that contains the predictor/effect of interest compared to models that exclude the predictor/effect of interest. Conceptually, this statistic explains the extent to which the data (across all models) are supported by the presence of the predictor/effect. On the other hand, the inverse of the $BF_{inclusion}$ (1/ $BF_{inclusion}$), represents the support for the null hypothesis based on the influence of the factor of interest. A low $BF_{inclusion}$ for a particular factor would thus mean that the data are relatively unchanged when you consider the specific influence of that factor (Kass & Raftery, 1995). A high $BF_{inclusion}$, on the other hand, suggests that the data strongly support the influence of that factor when it is present.

Appendix C

Frequentist Statistics

Table 1C

Repeated Measures ANOVA on Derived Causal Judgments

	SS	*DF*	*MS*	*F*	*P*
Block	356.637	2	178.318	0.638	0.53
Block ✻ Hand Used	116.692	2	58.346	0.209	0.812
Target	372661.95	1	372661.95	127.054	< .001
Target ✻ Hand Used	0.005	1	0.005	1.559e -6	0.999
Side of Screen	150.784	1	150.784	0.299	0.586
Side of Screen ✻ Hand Used	160.602	1	160.602	0.319	0.574
Block ✻ Target	1261.271	2	630.635	0.842	0.432
Block ✻ Target ✻ Hand Used	290.504	2	145.252	0.194	0.824
Block ✻ Side of Screen	845.517	2	422.758	1.378	0.255
Block ✻ Side of Screen ✻ Hand Used	452.37	2	226.185	0.737	0.48
Target ✻ Side of Screen	642.097	1	642.097	0.59	0.445
Target ✻ Side of Screen ✻ Hand Used	2162.039	1	2162.039	1.985	0.162
Block ✻ Target ✻ Side of Screen	1201.83	2	600.915	0.771	0.464
Block ✻ Target ✻ Side of Screen ✻ Hand Used	729.152	2	364.576	0.468	0.627

Note. Type III Sum of Squares

Table 2C

Repeated Measures ANOVA on Derived Causal Judgments for Target Only

	SS	*DF*	*MS*	*F*	*P*
Block	1325.38	2	662.69	1.082	0.341
Block ✻ Hand Used	383.1	2	191.55	0.313	0.732
Target Side	85.28	1	85.285	0.108	0.743
Target Side ✻ Hand Used	1750.58	1	1750.581	2.211	0.14
Block ✻ Target Side	16.35	2	8.173	0.013	0.987
Block ✻ Target Side ✻ Hand Used	1156.99	2	578.495	0.927	0.398

Note. Type III Sum of Squares

Table 3C

Repeated Measures ANOVA on Causal Judgments for Alternate Only

	SS	*DF*	*MS*	*F*	*P*
Block	292.53	2	146.26	0.352	0.704
Block ∗ Hand Used	24.1	2	12.05	0.029	0.971
Target Side	707.6	1	707.6	0.883	0.35
Target Side ∗ Hand Used	572.06	1	572.06	0.714	0.4
Block ∗ Target Side	2031	2	1015.5	2.199	0.114
Block ∗ Target Side ∗ Hand Used	24.53	2	12.27	0.027	0.974

Note. Type III Sum of Squares