The Attraction of Anticipation: How Causal Interactions Draw People's Attention in Visual Tasks

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Abstract

We observe causal relationships naturally and quickly in events that we experience in our life. The current research investigates if causal events like collisions attract our attention to other changes in objects involved in the causal event. Participants reported colour changes in two objects, one involved in a causal event (collision) and the other independent. Aligning with our expectation, we observed that participants are more likely to report the colour change involved in the causal event when it happened at the same time as the collision. Against our prediction however, we observed a similar effect when colour changes happened before the collision, while the difference was less strong when the colour changes happened after the collision. One possible explanation is that the effect stems from participants anticipating causal events, leading them to pay extra attention to objects potentially involved in collisions. This focused attention makes participants more likely to notice colour changes during the anticipation period, which means people are actively devoting more cognitive resources anticipating and confirming causal interactions. This finding suggests that people prioritise causal observations in visual search tasks.

Keywords: Causal perception; anticipation; attention

Introduction

Causal cognition is an essential part of human thinking, profoundly shaping our understanding of the world, influencing decision-making and daily navigation. This critical ability that allows us to connect events, predict outcomes, learn from experiences, and assign responsibility, has been extensively studied in philosophy and psychology (for review see e.g., Waldmann, 2017).

Within the field of experimental psychology, research has shown that impressions of causality reliably emerge from specific arrangements of moving objects. A famous example is Michotte's (1946/2017) launching event. In a typical launching event, an object (the launcher), moving horizontally along a trajectory that leads to contact with the target. Upon contact, the target ceases its movement, and the launchee begins moving in the same direction, either at the same speed or slightly slower. In many experiments using this paradigm, observers consistently describe an impression wherein the launcher has caused the target's movement by colliding with it (e.g., Choi & Scholl, 2004, 2006; Scholl & Nakayama, 2002, 2004). To unravel the cognitive process, later studies following Michotte examined the factors influencing causal perception. Specifically, many studies investigated which elements in the visual stimuli lead participants to perceive causality in events resembling launches (e.g., Scholl & Tremoulet, 2000).

In contrast, very little work has investigated the downstream effects of visual impressions of causality. But if causality is a property of the environment that is processed quickly, automatically and effortlessly (Michotte,1946; Rips, 2011; Scholl & Tremoulet, 2000), then one would expect it to affect other aspects of cognition. In this paper we investigate the possibility that causality attracts attention. We predict that if our cognitive system automatically prioritizes observing cause-and-effect relationships, this quick and automatic process would use up more mental resources. As a result, other cognitive processes may have to sacrifice some attention, leading to causal interactions visually standing out during a visual search task (Treisman, 1985; Wolfe, 1994).

To find out if there is any attention-attracting effect of causal interactions, the current research employs a simple task, asking participants to report colour changes of round objects in motion (see Figure 1). During their movement, a collision will be introduced as the causal event. The collision is similar to Michotte's classic launching event, where no overlapping or passing through will occur with any of the objects. The only difference between the collision and the launching representation is that both colliding objects are moving before and after the collision, i.e., one cannot tell which one is the launcher and which one is the launchee, so that the collision seems less intentional and evident in the same way that people's attention can follow a one-direction path in a classic launching test. For each clip, the colour change will happen to two objects, one object involved in the causal event (causal object = CO) and one object independent of the causal event (independent object = IO) and both colour changes happen at the same time. Additionally, two balls will collide (i.e., the CO and another ball that does not change its colour). Participants were instructed to report only one of the colour changes and instructions do not mention the collision at all. The most important independent variable in our study was the involvement with the causal event. Hence, we are looking at the frequencies that participants report CO and IO in their responses.

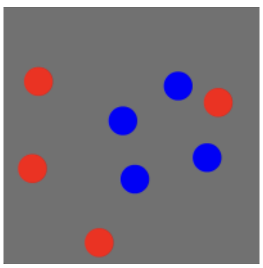

Figure 1: Screenshot from the experimental stimuli

Two online experiments were conducted and there were three conditions in total. The first experiment where the colour change happens at the same time as the collision (*Same*) aims to look at whether the attention-attracting effect of causal interactions exists. The prediction is that if the effect exists, CO will be reported more frequently. Our second experiment has two conditions, colour change happening after collision (*After*) and colour change happening before collision *Before*), looks at when the attention-attracting effect starts influencing participants. We predict that if the causal event attracts attention as it happens, we will observe similar effects in *After* and *Same* conditions, while expecting no difference in reporting frequency between CO and IO in the *Before* condition.

Experiment 1

Participants

We recruited 100 participants from Prolific with a payment of £9 per hour. The mean age of participants was 38.56, with a minimum of 18 years and maximum of 73 years. Participants were adults living within the UK that spoke English as their first language. The experiment was conducted via Qualtrics, with an estimated completion time of 10 minutes. Both experiments received full ethical approval from the UCL Department of Experimental Psychology Ethics committee.

Design and Measures

Participants were asked to complete 32 randomly distributed trials. Within each trial, participants were asked to first watch a three second video clip (visual display of 400 × 400 pixels[1], with a frame rate of 30 frames per second), followed by answering a multiple-choice question to report

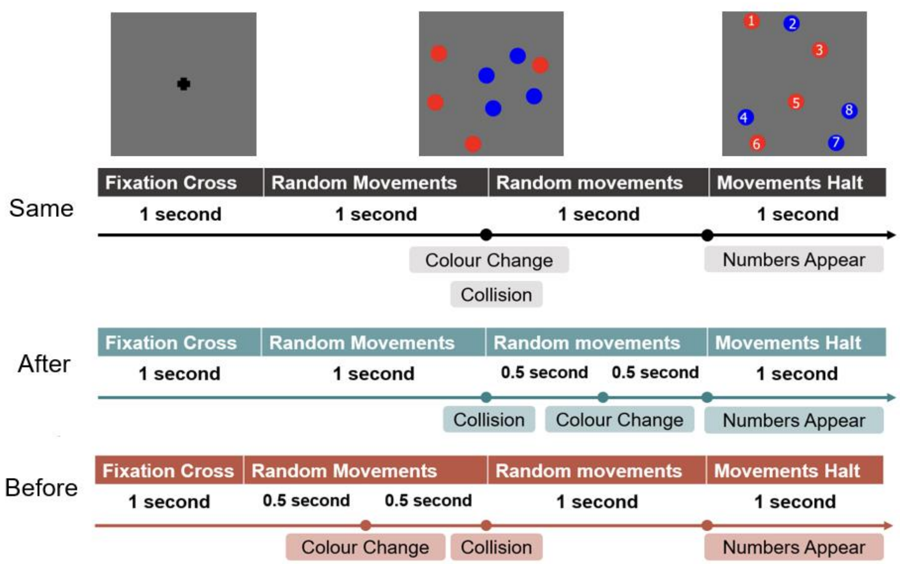

Figure 2 (a) top left, (b) top middle, (c) top right: Screenshots from the experimental stimuli. Bottom: timeline of the event sequence

[1]The actual size of video depends on participant's device. For 31.5 Inch, 16:9 Full HD 1920 x 1080 monitor the video is 14cm x 14cm on screen.

which ball has changed colour. Participants were informed that in each clip two balls will change their colour and in the multiple-choice questions they will be asked to report only one of the balls that showed a colour change.

The first one second of the video shows a black fixation cross against a grey background (Figure 2a), which is followed by eight equal sized round shapes (mimicking the movement of balls in a 2-dimension display), four in red and four in blue, moving around in straight lines towards different directions for one second. Then two out of the eight balls collide with each other, during which one ball changes its colour (either from blue to red or from red to blue). At the same time, another ball that was not involved in the collision also changes its colour. The two colour-changes are counterbalanced, i.e., one is from blue to red and the other is from red to blue, to maintain a total of four red and four blue balls throughout the clip (Figure 2b). Following the collision and colour changes, the balls continue moving for another second and are assigned numbers ranging from 1 to 8 (Figure 2c).

The 32 clips were generated manually using Adobe animate and Adobe premiere. Eight original clips were created as:

1. Two variations where the colliding ball changed from being the same colour to different colours during the collision, and the other colour change happens on the same half of the screen.
2. Two variations where the colliding ball changed from being in different colours to being the same colour during the collision, and the other colour change happens on the same half of the screen.
3. Two variations where the colliding ball changed from being the same colour to different colours during the collision, and the other colour change happens diagonal in the opposite corner.
4. Two variations where the colliding ball changed from being in different colours to being the same colour during the collision, and the other colour change happens diagonal in the opposite corner.

These eight original clips were then mirrored horizontally and vertically, resulting in 32 clips in total.

After each clip, participants had to choose one of the eight balls that they believed changed its colour. After their choice they decided when to continue to the next trial.

Results

Descriptive statistics of participants. Table 1 shows the average frequencies with which participants choose each of the three possible response categories out of the 32 trials in Experiment 1, either the ball involved in the collision that changes colour (CO), the ball not involved in the collision that changes colour (IO), or a ball that does not change colour Error). In line with our hypothesis that causal interactions attract attention, participants were much more likely to report the CO ball than the IO ball.

Table 1: Participants' average response frequencies (out of 32) and corresponding SDs in Experiment 1

	Mean	SD
CO	21.69	4.27
IO	7.21	3.91
Error	3.81	2.62

Analytic Approach. To analyse the pattern shown in Table 1 statistically, we analysed the individual-level response frequencies for the three response categories in Table 1 using a hierarchical-Bayesian Multinomial Processing Tree (MPT) model. The analysis was performed using `TreeBUGS` (Heck et al., 2018).

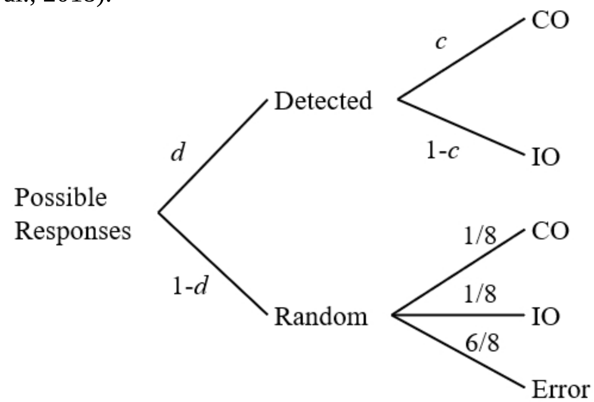

Figure 3: The Multinomial Processing Tree used in the current experiment.

An MPT is a cognitive measurement model for categorical data that assumes each observed response results from a sequence of discrete cognitive states. The MPT model developed for the present task is shown in Figure 2. The model assumes two distinct cognitive states, a detection state in which a correct response is given and a guessing state in which a random response is given. This model structure allows us to focus on the critical contrast between CO and IO responses while simultaneously accounting for guessing.

In the model, with probability d the detection state is reached in which at least one colour change is detected. In this case, with probability c the CO ball involved in the collision is reported and with probability $1 - c$ the IO ball not involved in the collision is reported. The value of the c parameter is the critical measure of our study. If c is significantly above .5 this means that participants are more likely to detect and report the CO compared to the IO ball. Conversely, if c is significantly below .5 this would indicate that participants were more likely to detect and report the IO compared to the CO ball.

In case participants fail to detect a colour change, with probability $1 - d$, the guessing state is reached. In this case, with probability 1/8 they randomly report a ball which leads to the corresponding response probabilities given in the lower-right branch of Figure 3.

The model fit the data adequately, $p_{T1} = .505$ and $p_{T2} = .500$ (Klauer, 2010). Because we analyse the individual-level data using a hierarchical Bayesian MPT, we focus in our analysis on the group-level parameters which represent the overall means.

Group-level MPT Parameters. In line with the descriptive results reported in Table 1, the model results indicated a very high level of performance with *d*, the probability to detecting at least one change, equal to 0.86, 95% CI [0.83, 0.88]. More importantly, the *c* parameter indicated a clear bias towards CO, with a value of 0.78, 95% CI [0.75, 0.81].

Discussion

The results support our prediction that participants are more likely to report CO than IO, suggesting that causal interactions have a downstream effect on human perception in visual tasks. The estimated likelihood of participants successfully detecting the colour change showed that the participants understood their task in this experiment and are capable of successfully completing the task. In the next experiment, we test if this difference is due to the attention-attracting effect given by the causal interaction as it happens.

Experiment 2

To break down the biasing effect we observed in Experiment 1, in Experiment 2 we created a short time-gap between the target event (colour change) and the causal event (collision). Our prediction is that if the biasing effect is due to causal events drawing participants' attention, making them more likely to detect the colour change for the object involved in the collision (CO), this attention drawing effect will still be observable when the colour change happens after the collision. In contrast, when the colour change happens before the collision, we predict that participants are equally likely to report CO and IO, as their attention should be equally distributed across all eight balls.

Participants and Procedure

Two different groups of participants were recruited through Prolific. The demographic information is included in Table 2.

Table 2: Demographic information of participants in *After* and *Before* conditions

Condition	N	Mean age	Minimum age	Maximum age
After	100	39.43	19	77
Before	100	41.32	19	76

Design and Measures

Both conditions were replications of Experiment 1, with the only change being that both of the colour changes appeared either 0.5 seconds (15 frames in a 30 frames per second video) before the collision, in the *Before* condition, or 0.5 seconds after the collision, in the After condition. To this end, we manipulated the original 32 clips such that the change happened either 0.5 earlier or later resulting in 32 new clips for each condition. We did this so that the movement of each ball in each clip of Experiment 2 was identical to their counterpart in Experiment 1, leaving the only difference being the timing of the colour change.

Results

Descriptive statistics of participants Table 3 shows a participants' average response frequencies for the three response categories separately for each condition. As in Experiment 1 errors were much less likely than correct responses. And while CO responses were still more likely than IP responses, the difference was much smaller than in Experiment 1.

Table 3: Participants' responses in *After* and *Before* condition

Condition		Mean	SD
After	CO	15.75	3.42
	IO	13.86	3.52
	Error	2.39	1.80
Before	CO	18.41	3.90
	IO	11.41	3.68
	Error	2.18	2.38

Group-level MPT Parameters. We estimated the MPT model shown in Figure 2 separately for each condition using `TreeBUGS`. Same as Experiment1, the model fit the data adequately (*After*: $p_{T1} = .510$, $p_{T2} = .464$, *Before*: $p_{T1} = .491$, $p_{T2} = .476$). In both conditions, the probability to detect at least one change, captured in parameter *d*, was again very high, 0.90, 95% CI [0.89, 0.92], in the After condition and 0.93, 95% CI [0.91, 0.95], in the *Before* condition. So overall performance levels were similar, or even slightly better, compared to Experiment 1.

However, when looking at participants' bias for CO versus IO as captured in parameter *c*, the pattern differed markedly from Experiment 1. While in both conditions there still was a bias towards CO, this bias was considerably less pronounced. In the After condition, the *c* parameter was estimated to be 0.53, 95% CI [0.51, 0.56] so only just above .5. In the *Before* condition, the bias was more noticeable, with *c* equal to 0.62, 95% CI [0.60, 0.65].

Discussion

Contrary to our prediction, the *After* condition did not replicate the biasing effect we had observed in Experiment 1 to the same extent. Delaying the colour changes to 0.5 seconds after the collision in fact reduced the difference between the frequencies of reporting CO and IO and almost removed any bias towards CO. This result suggests that although the causal event might have attracted participants' attention towards the objects involved in the collision, this attention-attracting effect might disappear quickly.

The results from the *Before* condition showed a salient effect of causal event on biasing participants' likelihood of reporting CO. Because the bias for CO was stronger in the *Before* than in the *After* condition, the results of Experiment 2 undermined the explanation that the biasing effect we observed in Experiment 1 was simply due to causal events drawing participants' attention towards objects involved in it when the causal event happens.

Figure 4 shows a comparison of the biasing effect across all three conditions. Combining all three results, here we are going to suggest a new explanation, which is that the biasing effect of causal event is not given by the causal interaction itself, rather, it is the anticipation of a causal interaction that draws participants' attention to the objects that will be engaging in a causal event according to the participants' prediction. Here, we define the anticipation as a period of time from the beginning of the clips till the moment that the collision happens. In other words, participants start anticipating a collision from the beginning of the clip, even though they were not informed about any collisions. As a result, they are focusing more on objects that could collide with one another as compared to the other objects. Once their anticipation of a collision is confirmed when the collision actually occurs, the attention devoted to anticipation is released and their attention becomes evenly distributed across all objects.

Figure 5 illustrates the position of the colour changes and the anticipation period on a parallel timeline across three conditions; we can see in both *Same* and *Before* conditions that the colour changes are included in the anticipation period. We argue that what happens during the anticipation period is that participants focus on observing the movements of two soon-to-be colliding balls, instead of all eight balls. Hence in both *Same* and *Before* condition, when the colour changes happen participants will be reporting one colliding, colour-changing ball (CO) out of two colliding balls, instead of two colour-changing balls (CO and IO) out of all eight balls. This selecting effect due to the anticipation leads to a biasing effect toward CO when participants report the colour changes after the end of the clip.

Making a comparison across all three conditions, we also notice a slightly weaker biasing effect in *Before* compared to *Same*. This can also be explained by the anticipation period, as in the *Before* condition participants will have a shorter time period (0.5 second) to observe and decide which two balls will be the colliding balls, hence when the colour changes happen, they might not have enough evidence to decide

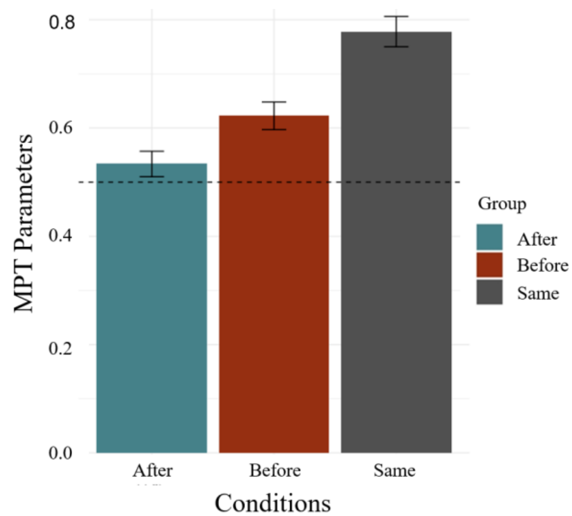

Figure 4: A comparison of likelihood of reporting CO across all three conditions (i.e., the c parameters of the model shown in Figure 2 for each condition).

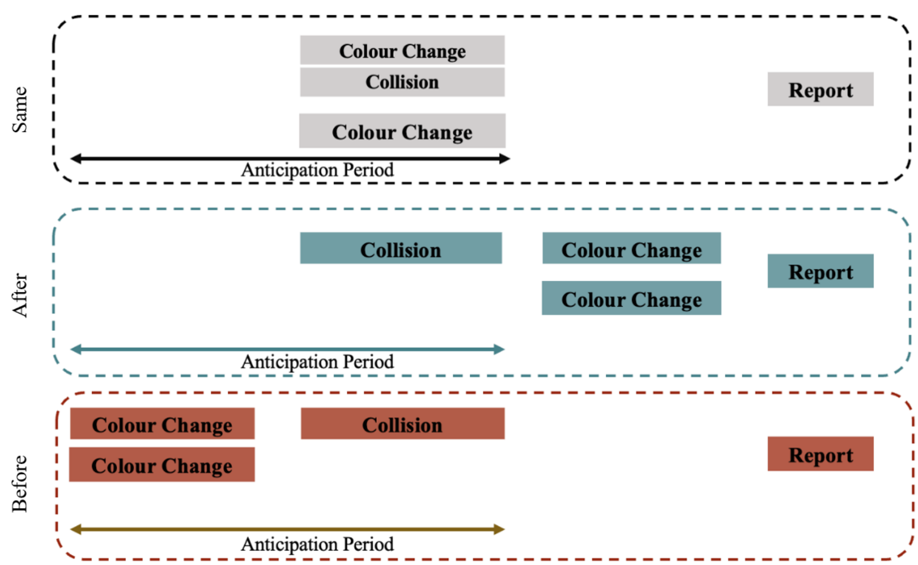

Figure 5: Position of colour changes, collision and anticipation period across all three conditions

which two balls will collide; while in the *Same* condition the colour changes happen exactly at the same time as the collision, participants had more time to track the potential colliding balls and receive confirmation when the colour change happened. As a result, the biasing effect in the *Same* condition is stronger as the prediction/confirmation effect is stronger than in the *Before* condition, where participants might have not been able to make a firm prediction when the colour changes happened.

General Discussion

The current study looked at the effects of causal interactions on people's performance of a visual task, in which they were asked to report colour changes of moving objects in animated video clips. Experiment 1 showed that when a collision between two objects happened at the same time as the colour change, participants were more likely to report the colour change of the objects that were involved in the collision (CO), compared to colour changes that were independent of the collision (IO). This result suggests that causal events such as collisions might have a biasing effect, which means causal perception has an influence on people's cognitive process in addition to perceiving causality.

To find out how this biasing effect affects the cognitive process, Experiment 2 tested whether the effect persists when the causal event happened after or before the target event (i.e., the colour change). Our original hypothesis was that causal events attract people's attention towards objects involved in the event when they happen, which predicted that the effect would persist when colour changes happened after collision, as participants have their attention around the area where CO would change its colour. Contrary to this prediction, we observed a much weaker biasing effect when the colour change happened after the collision (*After*). Instead, a different salient bias was observed in conditions where colour changes happened before the collision (*Before*).

The results suggest that it might not be the causal interaction itself that attracts participants' attention; rather, it is the anticipation of causal interaction that makes participants pay more attention to the CO and, hence, more likely to detect and report colour changes of CO. This anticipation effect disappears very quickly as soon as the causal interaction has been confirmed. As a result, we have observed a biasing effect towards reporting the colour changes of CO only when the colour changes happened during or at the end of the anticipation period (i.e., in *Same* and *Before* condition).

A limitation of the current experiment is that we are not sure whether the biasing effect was due to the fact that participants are more likely to notice the colour change happening on the colliding balls or they are simply more likely to report them. In our next series of experiments, we plan to have participants reporting both of the colour changes if they can. If there is still a significant difference between the likelihood of reporting CO and IO, it suggests that the biasing effect was more likely due to the attention grabbing effect than just a reporting bias.

Further applying the paradigm, we will look at the after effect of the anticipation period and see if the biasing effect is still observable if the causal event happens less than 0.5 seconds before the target event. If the anticipation period has a very fast-fading effect to draw participants' attention towards objects that will involve in causal interactions, we will expect to see a similar pattern of Experiment 2 when the time gap between collision and colour change has been reduced. In this working proposal, we will set the new time gaps as 100 ms, 150 ms and 300 ms. As research on how causality could reverse people's perception of sequence of events suggested (Bechlivanidis et al., 2022), people had reported event B happened earlier than event C, despite B happening 150 ms later than C in the actual visual stimuli, when a presence of event A hints to the fact that the sequence of A-B-C fits the rule of causality. This result suggests that a 150 ms gap is less significant for participants to consider two events as separated. Hence by testing the current paradigm with time interval shorter than/equal to/longer than the 150 ms gap, we aim to find out if the attention drawing effect is significant only within a small time gap between causal event and the colour change.

Placing this finding in the literature on causal cognition, the current research gives supportive evidence to the suggestion that observing causal interactions has an additional effect that influences other parts of human perception. Before a causal event happens in a visual task, participants devote attention to anticipating causal interactions. Once their anticipation has been confirmed as they have observed a causal interaction, the attentional resource will be re-distributed, and the attracting effect will disappear. As a result, if changes happen during the anticipation period, people are more likely to notice changes to the objects involved in causal events compared to changes happening somewhere else.

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