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Instructing via relations: Function transformations of response and consequence functions of upcoming contingencies

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A B S T R A C T

One part of the relational frame theory account of rule-governed behavior is relational responses between elements of a rule and the behavioral and consequential components of the upcoming contingency. This study reports two experiments that used a novel task designed to exert contextual control over relational responses involving components of upcoming reinforcement contingencies. The task presents participants with a series of choices between bubble-clicking tasks. Each trial begins by illustrating the number of bubbles to be clicked and points that may be earned for completing a source task, and presents Crel and Cfunc stimuli to indicate how the task options differ from this task in terms of the number of bubbles to be clicked and the amount of points that may be earned. Experiment 1 exposed participants to a version of the task employing natural language Crels and Cfuncs, and task performances were in line with experimenter expectations. Experiment 2 employed the task to establish Crel and Cfunc functions for novel stimuli, and investigated the impact of post-choice feedback on the development of these functions. Results indicated that the task can establish Crel and Cfunc functions for novel stimuli effectively and provides a means for investigating transformations of functions involving components of contingencies.

Human behavior is frequently a function of its prior consequences (Skinner, 1953). However, often behavior seems to be a function of imagined future consequences. Such is the situation when humans act according to a plan, which typically involves behaving in a particular way because of the consequences we imagine we will obtain when we do so (Moors et al., 2017). An example of such planning is using a cookbook to cook a nice meal so as to impress a date. Following the recipe provided in the cookbook does not require that all the behaviors have been engaged in previously. Nor does it require that the imagined consequence for following the recipe have been experienced in the past. To give another example, taking a job because you will get paid more than you have ever been paid cannot be explained by previously experienced salary payments alone. Explanations for such behavior cannot therefore appeal to a history of reinforcement for that behavior.

Behavior analysis has several concepts for analyzing responses that have no direct history of reinforcement. These include novel behaviors that emerge due to random variation (Neuringer, 2002) and behavioral generalization (Skinner, 1953). Behavior analysis approaches some responses with no history of direct reinforcement as instances of rule-governed behavior and relational responding (see below). Skinner (1966, 1969) defined rules as contingency-specifying stimuli. The contingencies specified by rules stood in place of a history of interaction with these contingencies. One example Skinner provides is the rule "Cigarette smoking causes lung cancer" which specifies a contingency between a behavior and a consequence (Skinner, 1969, pp. 149–150). Such a rule may influence the probability of smoking in spite of the fact that the individual following this rule has never experienced the contingency between smoking and cancer. Parrot (1987) took issue with Skinner's definition due to its failure to define in behavioral terms what it meant to specify, before later building on Sidman's work on stimulus equivalence (Sidman, 1994) when contributing a rigorous behavioral definition of contingency specification (Hayes & Hayes, 1989) that relies on the concept of the arbitrarily applicable relational responding (AARR; Hayes et al., 2001).

The concept of AARR has four essential components; that there are relational responses, that relational responses are operants, that they occur under contextual control, and that they influence the functional properties of stimuli. A relational response is a response to one stimulus based on its established relationship with another stimulus. As an example, consider a native English speaker who is learning French and at some point in time starts responding to the French word "chaude" in terms of the English word "hot" by turning the tap labelled "chaude" when taking a bath. Relational responses are operants, and as with any operant the probability of the relational response is a function of the history of consequences for their emission (Hayes et al., 1996). For instance, although responding to the word "chaude" by tuning the tap was never before reinforced in the history of the native English speaker, the behavior of relating a French word to an English word was. This

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previously reinforced behavior of relating French and English words is now applied to a new pair of words (i.e., "chaude" and "hot") which includes the transfer of functions from the word "hot" to the word "chaude". The concept of AARR thus allows behavior analysists to conceptualize the behavior of turning the tap labelled "chaude" as a previously established relational response rather than as a novel non-relational response, thereby explaining this behavior in terms of past reinforcement.

The context in which a relational response occurs plays a crucial role in determining the nature and behavioral impact of a relational response. There are a variety of patterns of relational responses (e.g., same as, more than, opposite to), and relational responses can be applied to virtually any pair of stimuli without regard to their non-arbitrary, or physical, properties. It is therefore important that environmental cues dictate the kind of relational response (e.g., same as, more than, etc.), and the stimulus properties that are altered as a result of the relational response. Stimuli that specify the kind of relation between stimuli are termed Crels, and stimuli that specify the stimulus properties that are transformed by the relational responses are termed Cfuncs.

The concept of AARR helps resolve the issue of specification central to behavioral accounts of rule following. A rule can be said to specify a contingency when the stimuli participating in the rule are responded to in terms of actual events in the environment, and when responses to if-then components of a rule produce an appropriate sequence of behaviors and consequences. When making this point it is important to acknowledge that rules are not technical concepts within RFT, rather networks of AARRs are technical concepts within RFT (see Harte & Barnes-Holmes, 2021). For instance, in the rule "Cigarette smoking causes lung cancer" some stimuli (e.g., the words "cigarettes" and "lung cancer") refer to other stimuli (i.e., actual cigarettes, and to the illness). These words specify events in the world because they participate with them in AARRs of equivalence, and so the word "cigarettes" is responded to in terms of actual cigarettes. The remaining parts of the rule specify that behaving in a particular way with respect to cigarettes (i.e., smoking them) will lead to a consequence (i.e., lung cancer). The word "causes" serves as a cue for AARRing involving if-then relations that orders the smoking behavior and the lung cancer into a sequence, with the result that smoking behavior obtains a function with cancer. The forgoing offers just one example of how rules may specify behavioral contingencies. It is not the only way this may occur. That is, rules need not explicitly specify antecedents, behaviors, consequences, or if-then relations to function as rules (Reece, 1989). Indeed, there is no agreed upon technical definition of rules within RFT (Harte & Barnes-Holmes, 2021). That said, behavior-analytic descriptions of rules and accounts of them in terms of AARRing frequently describe relations between the stimuli composing a rule and other stimuli or behaviors and explicit or implicit invocation of if-then relations between these stimuli and behaviors. This indicates a general consensus that the stimuli in rules implicitly or explicitly specify behavioral contingencies or elements of behavioral contingencies.

Although central to modern accounts of rule following, it appears that there are no studies that set out to specify elements of behavioral contingencies via stimulus relations, and that where this was achieved it was incidental to the study aims. For instance, there are several studies in which stimulus relations specify the conditions for the performance of a particular response. For instance, Dymond and Barnes (1994, 1995) established discriminative function for a stimulus (i.e., one press on the spacebar produces the feedback "CORRECT"), and a relationship between this stimulus and another stimulus such that the other stimulus was "more than" the first, and thus specified the emission of more than one press on the spacebar. However, in these studies the consequence for performing specified responses is not specified by stimulus relations. That is, no elements of the procedure indicated any relationship between the consequences for pressing the spacebar more than once in the presence of the second stimulus and the consequence for pressing the spacebar once in the presence of the first stimulus. Therefore, these studies do not specify elements of contingencies as described by the RFT account of rule-following. Indeed, this is true of the literature as a whole. There are no studies in which the consequence of a particular response is specified via a stimulus relation. There exist studies in which the relative reinforcing value of stimuli is specified via stimulus relations, and these stimuli are subsequently used to differentially reinforce particular response patterns, for example, of forced choices (Hayes et al., 1991; Whelan, & Barnes-Holmes, 2004; 2006). While these studies and others like them establish reinforcing functions for a stimulus (e.g., X is 2 points, Y is more than X), they do not specify the consequence of a behavior via stimulus relations, as is, for instance, the case when people are instructed that they will earn $20 for doing Task A and that they will earn *more than* $20 for doing Task B. By indicating the relationship between consequences, the latter example specifies the consequence component of a contingency via stimulus relations. Given that such specification of contingency components is central to the RFT account of rule following, this represents a significant gap in a literature, particularly in a literature with historical roots in arguments that a crucial human capacity is the ability to respond to stimuli that specify behavioral contingencies (Barnes-Holmes, et al., 2018; Hayes, 1991; Hayes et al., 2001; Hayes & Hayes, 1989; Skinner, 1966, 1969). The current study addresses this gap by employing a procedure that permits the specification of both the behavioral and consequential components of behavioral contingencies. The purpose of these studies was to develop a procedure for producing Crel and Cfunc stimuli that specify function transformation of contingency components.

This study builds upon efforts at establishing Crel and Cfunc stimuli reported by Finn and De Houwer (2021). That study employed a computer-based task to establish Cfunc stimuli that specified the transformation of functions for the stimulus properties speed and direction according to relations of same or opposite. These stimulus properties were relevant to the task participants completed in each trial, which was to select the racecar that would win the subsequent race (i.e., the winning racecar would go quickly in the direction of the finish line). Participants were first shown the performance of a sample racecar (i.e., whether it moved quickly or slowly and whether it moved toward or away from the finish line). The relationships between the performance of the sample racecar and each of the racecars that would participate in the subsequent race were specified by Crels and Cfuncs presented within the task. On the basis of these two pieces of information (i.e., the performance of the sample racecar, and how this performance related to the performance of the alternative racecars) participants could select a winning racecar. Critically, doing so required relational responses under control of the Crels and Cfuncs presented within the task. Although the racecar task is not amenable to investigating specification of contingency components (because the stimuli in the task did not differ in terms of the responses that could be made with respect to them or in terms of the consequences that could be obtained), the current procedure is broadly similar to the one described by Finn and De Houwer. The procedures differ with respect to the stimulus properties that are subject to transformations of functions. These were speed and direction in the Finn and De Houwer study but are number of responses and number of points in the current study. However, several task features are generic to both procedures: demonstrating the features of a sample stimulus, specifying relationships between this stimulus and other stimuli with Crels and Cfuncs, and obtaining forced-choice responses to these stimuli that permit the inference that transformations of functions have occurred. The development of multiple methods for the study of Crel and Cfunc control is advantageous because it allows for two means of investigation which reduces the risk of method specificity of findings. More importantly for the current study, these generic task features allow for repeated instantiation of transformations of functions. In the current study these transformations of functions involve the number of responses (a behavior) and number of points (a consequence) involved in as yet to be completed tasks (see below). Thus, the procedure facilitates the specification of components of contingencies via arbitrarily applicable relational responses as per the RFT model of rule-governed behavior.

The procedure employed in the current study is called the bubble task. A brief description of the task is provided here (see Method for a full description). Participants are instructed that their goal is to earn as many points as possible. Points can be earned by successfully clicking all the moving bubbles in a bubble-clicking task in a fixed time window. Points are lost when participants fail to successfully complete a bubble-clicking task (i.e., click all bubbles within the fixed time window). Each trial of the bubble task begins by presenting an animation of a source task that shows a number of moving bubbles and indicates a number of points. Crels and Cfuncs presented at this point in each trial specify how a number of alternative task options differ from this source task option with respect to the number of bubbles to be clicked and points these tasks offer. These between task differences are indicated by symbols that act as Crels and Cfuncs that specify transformations of number and points properties via the relations of more than and less than. On this screen participants must choose between the alternative task options (i.e., more or less bubbles or points). Upon selection the chosen bubble-clicking task is initiated. The proportion of bubbles clicked, and points earned in that trial are provided as post-trial feedback as is the running points total. The effort to accumulate points entails responding appropriately to the experimenter programmed Crels and Cfuncs which facilitates the generation of Crels and Cfuncs.

The bubble task allows for the specification of components of contingencies. The bubble-clicking component that is central to the bubble task engenders a fixed ratio reinforcement contingency – participants must click all bubbles within the time window to earn points. Before beginning a bubble-clicking task participants can choose between alternative task options. These task options differ in the precise formulation of the fixed ratio reinforcement contingency. Some task options result in more bubbles having to be clicked, and some result in fewer bubbles. These are differences in the response component of the contingency. Further, some task options offer more points for successful completion, and some offer fewer points for successful completion. These are differences in the consequence component of the contingency. Across trials of the bubble task each of these differences in contingencies relative to the source task are specified by Crels and Cfuncs. The bubble task thus specifies transformations of functions where the functions undergoing transformation are components of contingencies. The functions that are transformed are the functions of the components of the target task, more specifically a response component (how many bubbles need to be pressed) and a consequence component (how many points can be earned). These functions are transformed by relating the upcoming task to a source task, more specifically, to the response and consequence components of the standard task. The way in which the source and target task are related is specified by Crels (that specify a relation of more or less) and Cfuncs (that specify whether this relation applies to the response component or the consequence component). It should be noted that the target task does not employ cues to specify the contingency itself (i.e., it does not specify if-then relationships between behaviors and consequences). Instead, the reinforcement contingency within the task is directly experienced.

Reported here are two experiments investigating some variables influencing the establishment of novel Crels and Cfuncs in the bubble task.[1] The overarching aim was to establish Crels and Cfuncs that specify transformations of functions of the response and consequence components of reinforcement contingencies. The first experiment reported here set a benchmark for performance in the bubbles task by employing natural language stimuli in place of novel Crel and Cfunc stimuli, and by providing additional post-choice feedback. The second experiment examined the influence of this post-choice feedback on the establishment of novel Crels and Cfuncs. Ethical approval for these experiments was granted by the Ethics committee of the Faculty of Psychology and Educational Sciences at Ghent University All experiments were preregistered and details of the preregistration as well as experimental scripts, data, and analysis scripts can be found on the osf (https://osf.io/py9cz/).

1. Experiment 1

Experiment 1 made three alterations relative to pilot experiments (see Footnote 1). The purpose of these alterations is to see whether participants will select the task-options deemed optimal under idealized conditions. First, the same point loss contingency was employed for all bubble-clicking tasks. Second, natural language words were used as Crels and Cfuncs in place of abstract symbols. Finally, to facilitate discriminations between task-options, a post-choice feedback screen was added (see below).

1.1. Method

Data were collected online via Prolific Academic where participants were paid £7.50 for completing the procedure. The preregistered stopping rule for recruitment was 20 participants completing all phases of the procedure and indicating that their data could be included in the study. All participants were prescreened by Prolific Academic and indicated that they spoke English as a first language and were aged between 18 and 65. No participant had previously participated in an experiment conducted by our research group.

1.2. Participants

20 participants (13 female, mean age = 38, *SD* = 15) completed Experiment 1.

1.3. Procedure

The procedure began by presenting study guidelines, obtaining informed consent, then collecting demographic data of age and gender. The bubbles task was then initiated. The bubbles task consists of three phases; Phase 1) walkthrough and calibration of bubble-clicking tasks to the participant; Phase 2) establishing Crels and Cfuncs; Phase 3) testing the established Crels and Cfuncs.

1.3.1. Phase 1: walkthrough and calibration of bubble-clicking tasks

The bubbles task began with a walkthrough that described the task to participants. Participants were informed they would complete a series of trials involving choices between tasks, and completion of the chosen tasks. They were shown an example selection screen the various elements of which are illustrated; the source, the miniature source task, the task options and positions they may occupy relative to the source, the presence of symbols indicating how the task options compare to the source task. The symbols for which Crel and Cfunc functions were to be established were not presented in the walkthrough. The calibration phase began immediately after the walkthrough. The purpose of calibration was to ensure that changes in the number of bubbles within the task bore upon the likelihood of earning points. During calibration participants completed a series of seven trials in which the source task was the only available option. The first trial presented seven bubbles to be clicked within the 5 s time window. Participants were provided up to 10 opportunities to complete the first trial. Each subsequent trial increased the number of bubbles to be clicked within this time window by two. The sequence terminated when the participant failed to complete a trial. The number of bubbles clicked in the final successful trial was the calibrated set point for that participant. This calibrated set point could be 7, 9, 11, 13, 15, 17, or 19.

[1] Two pilot studies that constitute the initial attempts to establish Crels and Cfuncs using the bubble task are described in a separate report available on the osf (https://osf.io/py9cz/). All materials and data associated with these experiments are publicly available.

1.3.2. Phase 2: establishing Crels and Cfuncs

In this part of the task participants were provided with choices between two tasks that differed along task relevant dimensions (i.e., number of bubbles, number of points; Fig. 1a). On each trial participants first viewed the miniature source task that displayed a number of moving bubbles that varied across trials around the calibrated set point for that participant (i.e., the calibrated set point $\pm$ 1; Fig. 1b) and a message indicating the number of points on offer (i.e., 50 points $\pm$ 5 points) that appeared immediately above the miniature source task (see Fig. 1b). The source task could not be selected, but the two other task options displayed on each selection screen could. The task options were presented at an equal distance from the source task, and can appear at 30°, 90°, 150°, 210°, 270°, and 330° angles relative to the source task. The precise location of each option, and its angle relative to the source task was counterbalanced across trials. The manner in which the properties of each task differed from the source task was specified by Crels and Cfuncs appearing on the arrows between the source stimulus and the stimuli representing the alternative task options (see Fig. 1c). In this experiment the Crel and Cfunc stimuli were drawn from natural language (i.e., "more points", "fewer points", "more bubbles", and "fewer bubbles"). On each trial there was an optimal choice. To ensure this is the case on every trial participants were offered choices between the options making up the following pairs: more points or less points, more points or more bubbles, less bubbles or less points, and less bubbles or more bubbles. Note that the first option in each pair was deemed the optimal choice. Upon selecting a task option participants were exposed to a post-choice feedback screen (see Fig. 1d). This screen was presented for between 3 and 10 s and could be terminated by clicking a continue button after 3 s. The screen displayed a miniature version of each of the alternative task options including the number of bubbles and the message indicating the number of points on offer. The task the participant selected on the previous screen appeared within a green border. The purpose of this component was to facilitate discriminating the difference between the task options. Following the post-choice feedback screen participants were exposed to a bubbles task with the specified properties (e.g., Fig. 1e). Specifically, relative to the source, less bubbles meant a 50% decrease in bubbles, more bubbles meant a 50% increase in the number of bubbles, more points increased the number of points by 50, and less points decreased the number of points by 40. Responses in each trial were deemed correct and counted toward the calculation of training criterion when participants selected the optimal choice and successfully completed the selected bubble task. A trial was deemed incorrect if a participant failed to fulfill either of these criteria. This phase comprised five 30 trial blocks, and terminated either upon completion of these five blocks, or upon reaching the training criterion of 17 or more correct trials across the previous 20 trials within a block.

1.3.3. Phase 3: testing the established Crels and Cfuncs

In this part of the task participants completed trials involving task options multiple steps from the source. The format of the selection screen in Phase 3 trials is illustrated in Fig. 1c and thus differs from the selection screen in Phase 2 as illustrated in Fig. 1a. The source was always presented in the center of the screen. The task options one step removed from the source appeared at opposite sides of the source at 90° and 270°, 30° and 210°, and 150° and 330° angles relative to the source respectively. This ensured that all task options appeared equidistant from the source. The exact locations, and natural language stimuli appearing between the task options were counterbalanced across trials. As in Phase 2, there was an optimal choice on each trial. The optimal choice was always two-steps removed from the source and involved either 25% fewer bubbles, 100 more points, or 50 more points and 50% fewer bubbles. Responses were deemed correct when the optimal choice had been selected and the related task was successfully completed. Unlike Phase 2 the post-choice feedback screen (Fig. 1d) was not presented in Phase 3. Phase 3 involved two 30 trial blocks and terminated upon completion of these trials. The experiment concluded with debriefing and payment.

2. Results and discussion

Table 1 presents the nine outcome metrics for Experiment 1. Accuracy was not defined in the preregistration document and two alternative accuracy metrics are presented. The first of these is the accuracy as recorded by the program (i.e., selecting the optimal task and clicking all bubbles in the subsequent task). Crel and Cfunc control is indexed by task selection and so this metric of Crel and Cfunc control is contaminated by bubble-clicking task performance. An alternative metric – optimal path choices – defines accuracy as selections of task-options along paths from the source that include only cues for "more points" and "less bubbles" (i.e., "more points", "less bubbles", "twice increased points", "twice decreased bubbles", "increased points and decreased bubbles").[2] This metric is a better index of Crel and Cfunc control because it assesses task selection, is not influenced by success in subsequent bubble-clicking tasks, and allows for participants selecting task-options one step removed from the source as in training (compare panels **a** and **d** of Fig. 1). Statistical analysis of scores calculated by the optimal path metric is presented here because these analyses have higher face validity. The training criterion (i.e., accuracy $\geq$17/20 across the previous 20 trials) was met by all participants in Experiment 1. The optimal path test accuracy score indicated accuracy was significantly above 50% ($M = 91$, $SD = 9.6$, $t(19) = 19.24$, $p < 0.001$, 90% CI = [88.5, 100], BF > 9.1×10^{10}, not preregistered),[3] and indicated that 17 of the 20 participants achieved accuracy $\geq$50/60 (see Fig. 2).

On trials where the optimal choice was not selected, comparisons were made between the option that was selected and the available task options. This was done to assess whether task options deemed by the experimenter to be appetitive and aversive were actually so. When doing this the selected sub-optimal task could have involved more bubbles or offered fewer points than the alternatives.[4] In Experiment 1 an average of 8% of chosen tasks offered fewer points than alternatives, and 13% of chosen tasks involved more bubbles than alternatives. A Welch two sample t-test ($t(26.33) = 1.28$, $p = 0.21$, 90% CI = [−11.8, 1.6], BF = 1, not preregistered) indicated these alternatives were not differentially aversive. On this basis it can be inferred that holding the point loss contingency constant across task options is an effective approach. Overall, the results of Experiment 1 indicate that participant behavior in the bubble task under idealized conditions is in line with experimenter expectations when an appropriate accuracy metric is employed.

3. Experiment 2

Experiment 2 assessed whether the procedure employed in Experiment 1 is effective in establishing Crel and Cfunc functions for novel stimuli. Experiment 2 also assessed the impact of post-choice feedback on the emergence of Crel and Cfunc functions. The first condition replicated Experiment 1 but with novel stimuli, the second condition was the same as the first condition except that post-choice feedback was

[2] By this metric selections of two of the six possible response options are deemed correct, and the probability a test accuracy score of more than 83% is p < 1 x 10–15.

[3] A Bayes factor (BF) is the ratio of the probability of the null effect given the data versus the probability of the alternative effect given the data. Bayes factors are interpretable as an odds ratio (Rouder et al., 2009). Larger Bayes factors indicate that the alternative effect is relatively more likely.

[4] In making such comparisons the relative difference between choices offering more bubbles and choices fewer points is interpretable, because on average across trials the optimal task (i.e., one of the alternatives) was equally likely to involve fewer bubbles or more points. Absolute scores are not interpretable because some trials presented options that were optimal in one respect but suboptimal in another (e.g., more points and more bubbles, or less bubbles and less points) and not choosing these may have been appropriate.

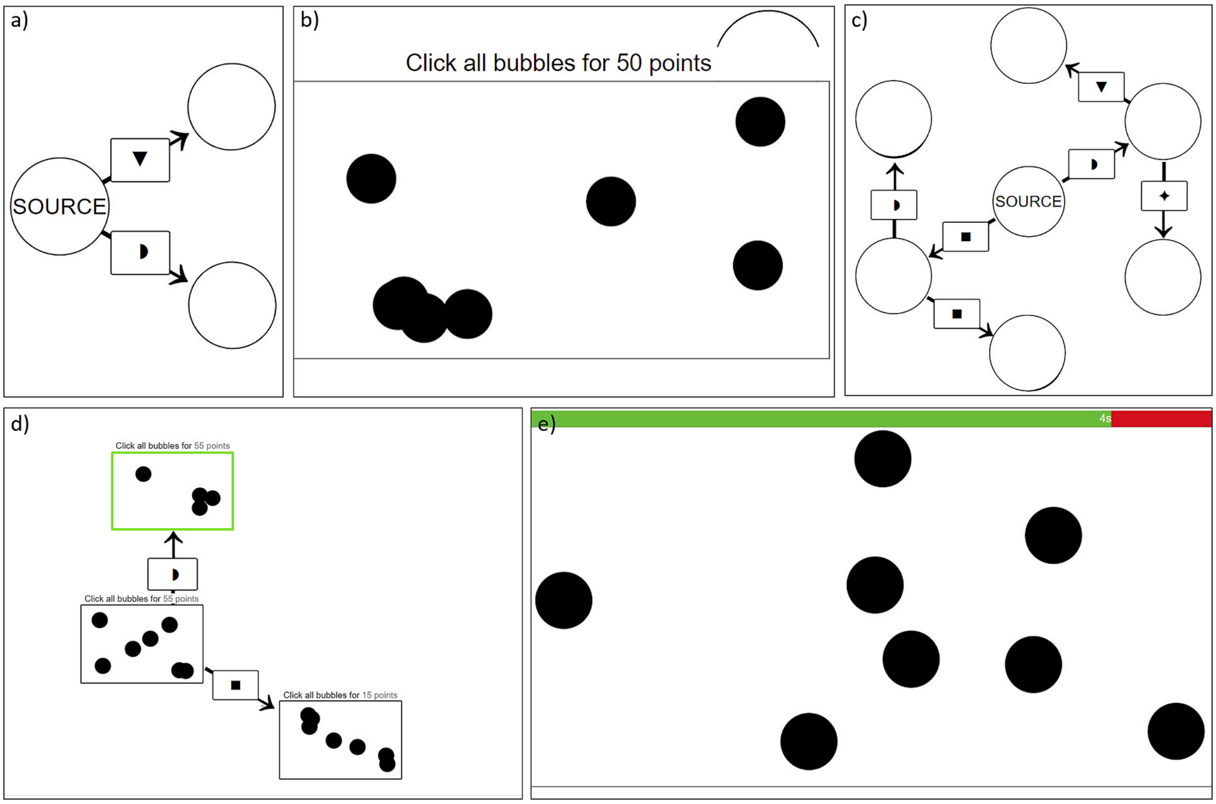

Fig. 1. *Note.* **a)** an example of the selection screen in Phase 1. **b)** an example of a miniature source task. **c)** an example of a selection screen in Phase 3 of Experiment 2. **d)** an example of a post-choice feedback screen. **e)** example bubble-clicking task. All panels show the symbols presented in Experiment 2 instead of the natural language stimuli presented in Experiment 1. In Experiment 1 the natural language Crels and Cfuncs were "more points", "fewer points", "more bubbles", and "fewer bubbles". In Experiment 2 the novel Crels and Cfuncs were ◗, ■, ✦, and ▾.

Table 1
Group-level descriptive statistics for the outcome metrics for the two experiments

	Training				Test				
	Acc.	Clicking task success	*N* trials	*N* of 20 meeting criterion	Acc.	Clicking task success	*N* of 20 acc. ≥50/60	Opt. path choices	*N* of 20 Opt. path choices ≥50/60
Exp 1	79%	87%	37	20	81%	94%	11	91%	17
Exp 2 f.	75%	86%	40	19	72%	96%	10	86%	14
Exp 2 nf.	68%	85%	81	15	57%	93%	5	78%	12

Note. Acc. is accuracy calculated across all trials within a phase and requires successful completion of the subsequent bubble-clicking task. *N of 20 acc. ≥ 50/60* is the number of participants achieving an accuracy score of greater than 50/60 by the Acc. metric. *Opt. path choices* is the number of selections of task-options along paths from the source that include only cues for "more points" and "less bubbles". Exp 2 f. refers to the feedback condition in Experiment 2. Exp 2 nf. refers to the no feedback condition in Experiment 2.

not provided.

3.1. Method

Details of data collection were the same as the previous experiment. The stopping rule was applied separately for both conditions so that data were collected from 20 participants per condition.

3.2. Participants

40 participants (23 female, mean age = 38, *SD* = 14) completed Experiment 2.

3.3. Procedure

The procedure matched that of Experiment 1 except that novel stimuli for which both Crel and Cfunc functions were to be established were presented in place of natural language Crels and Cfuncs (i.e., ◗, ■, ✦, and ▾). The functional roles of these novel stimuli differed across the two counterbalancing conditions in Experiment 2. In counterbalancing condition 1 these functional roles were: ◗ = more points, ■ = more bubbles, ✦ = less bubbles, and ▾ = less points. In counterbalancing condition 2 these functional roles were: ◗ = less bubbles, ■ = less points, ✦ = more points, and ▾ = more bubbles. In another difference from Experiment 1 for one condition the training phase involved presenting post-choice feedback for between 3 and 10 s after each selection screen. This feedback was not presented during testing. After completing training and testing on the bubble task participants were asked to indicate what they thought each of the Crel and Cfunc symbols presented in Experiment 2 meant.

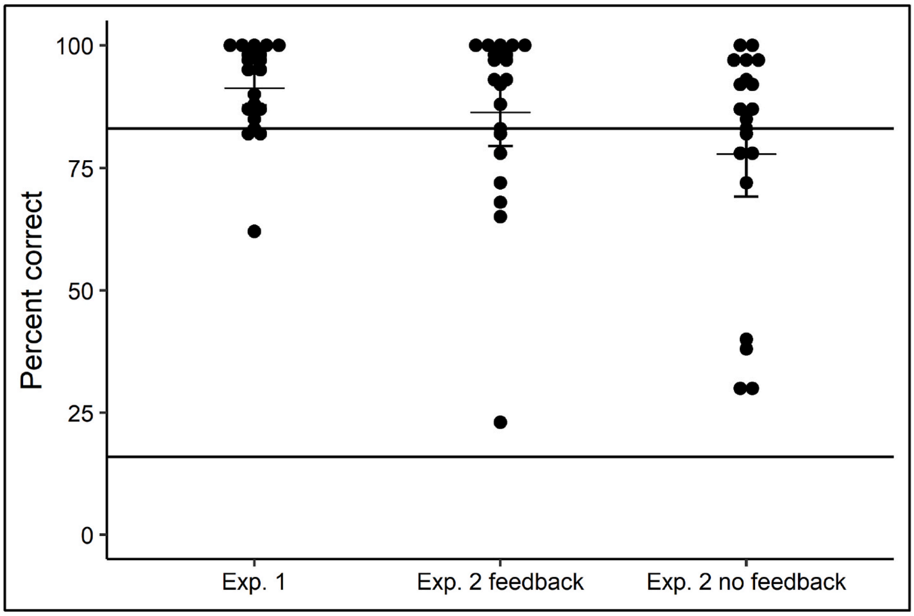

Fig. 2. *Note.* Individual participant percentages for selections of task-options along paths from the source that include only cues for "more points" and "less bubbles". Group means for each condition and associated 90% confidence intervals are presented also.

4. Results and discussion

Table 1 presents the nine outcome metrics for Experiment 2. The number of participants achieving the training criterion was 19 in the feedback condition compared to 15 in the no feedback condition. The number of training trials completed was smaller when post-choice feedback was provided ($M = 40.3$, $SD = 31.2$) than when it was not ($M = 81.4$, $SD = 51.1$, ($t(38) = 3.06$, $p < 0.01$, 90% CI of difference in means = [18.4, 100], BF > 10, preregistered). Statistical analysis of the optimal path accuracy metric found that test accuracy was greater than 50% in both the post-choice feedback condition ($M = 86.4$, $SD = 18.7$, $t(19) = 8.68$, $p < 0.001$, 90% CI = [80.8, 100], BF = 2.8×10^5, not preregistered) and the condition without post-choice feedback ($M = 77.9$, $SD = 23.6$, $t(19) = 5.28$, p < 0.001, 90% CI = [70.8, 100], BF = 596, not preregistered). The number of participants achieving test accuracies ≥50/60 was 14 in the post-choice feedback condition and 12 in the condition without post-choice feedback. Test accuracies in the post-choice feedback condition ($M = 86.4$, $SD = 18.7$) and the no feedback condition ($M = 77.9$, $SD = 23.6$) did not differ statistically ($t(36.1) = 1.25$, $p = 0.11$, 90% CI of difference in means = [−2.9, 100], BF = 0.57, preregistered). Verbal reports of the meaning of the four symbols are presented in Appendix A. Three participants, all of whom were in the feedback condition, provided a verbal response to each of the Crel and Cfunc stimuli that can be interpreted as corresponding to their function. The discrepancy between this number and number of individuals achieving the test criterion (i.e., 3 vs 26) attests to the difference between the Crel and Cfunc functions of stimuli and the control they may exert over tacts. Overall the results from Experiment 2 indicate that the bubbles task can generate Crel and Cfunc functions for novel stimuli when post-choice feedback is provided and when post-choice feedback is not provided but less effectively.

5. General discussion

The aim of the current studies was to establish Crels and Cfuncs that specify transformations of functions of the response and consequence components of reinforcement contingencies. The results from Experiment 1 indicated that under idealized conditions performances in the bubble task were in line with experimenter expectations and provided a useful benchmark for performance in the task. Further, the results from Experiment 2 indicate that the effort to establish Crels and Cfuncs that specify transformations of functions of components of reinforcement contingencies was a success, and that the bubble task is an effective means for establishing Crel and Cfunc functions. Experiment 2 also found that post-choice feedback (i.e., illustrating the differences between stimuli being related and associating programmed Crels and Cfuncs with these inter-stimulus differences) significantly reduced the number of training trials completed. Although not a statistically significant difference, test performance in the feedback condition exceeded that of the no-feedback condition. In the feedback condition mean accuracies by two different metrics were statistically greater than the 50% null and depending on the metric between 10 and 14 of the 20 participants had test accuracies greater than 83%. Inspection of Table 1 shows that this level of performance was comparable to that in Experiment 1 which employed natural language Crel and Cfunc stimuli. Thus, while the data from Experiment 2 indicate further room for improvement in mean accuracy scores and the reliability with which individual participants achieve high levels of test accuracy, any such expectations should be tempered by knowledge of performance levels when natural language stimuli are used and by acknowledging that participants were exposed to the procedure's contingencies once only. Likewise, overly optimistic interpretations of these results should be tempered also. The procedure employed here established Crel and Cfunc functions for novel stimuli only. New stimulus control topographies were established but given that all participants were adults the idea that the behavioral repertoire involved was established within the bubble task itself can be ruled out (i.e., the repertoire for transformations of functions according to relations of "more than" and "less than" was intact before completing this experiment). Nonetheless, in developing the bubble task, progress has been made in the establishment of novel Crels and Cfuncs.

The findings of the current study are consistent with prior research in this area. A similar rate of success in generating Crels and Cfuncs was reported by Finn and De Houwer (2021). The current study and the study by Finn and De Houwer are similar in that the stimulus from which functions were derived possessed multiple functions and the function undergoing transformation was specified by programmed Crels and Cfuncs. A further similarity between the studies, and indeed the majority of studies establishing Crels (e.g., Dymond & Barnes, 1994, 1995), is that they leveraged a history of differential reinforcement to produce Crels and Cfuncs (see also Perez et al., 2023; Delabie et al., 2022 for an alternative approach). Bearing this in mind the results reported here are perhaps unsurprising. On the other hand, they likely generalize to efforts at establishing Crels and Cfuncs in different contexts and employing topographically (but not functionally) dissimilar procedures. An important difference with previous work is the kind of stimulus functions that were subject to transformations of functions. As noted in the introduction we are aware of no previous study that sought to subject multiple components of reinforcement contingencies to independent transformations of function. The current study advances the experimental analysis of contingency specification by developing a procedure that specifies components of contingencies. In this regard the study contributes to RFT-based behavior-analytic study of rule-governed behavior which as argued in the introduction involves the implicit or explicit specification of contingencies. Specifying components of contingencies as done in the experiments reported here is one element of contingency specification, the specification of the contingency itself is another. A further advance would involve adapting the bubble task to integrate Crels and Cfuncs specifying the if-then relations comprising the contingencies themselves. An important contribution of the current work is the bubbles task itself. The bubble-clicking tasks can potentially vary along the dimensions of bubble size, speed, number, duration of the bubble-clicking task, and number of points awarded for successful completion. In theory, this allows for the generation of Crels and Cfuncs specifying transformations of functions along five functional dimensions. In addition, variation along each of these five dimensions bears upon the likelihood of task success and by extension on probability of reinforcement. The bubble task thus provides a rich context for examining the establishment of contextual cues for a variety of transformations of functions, and for studying the relationship between these behaviors and their consequences. The task may also facilitate efforts to predict-and-influence the impact of AARRing on choices between reinforcement contingencies. Of course, these remain possibilities at present.

There remain a host of questions that remain to be asked about using a methodology such as the bubble task. For instance, in the current study the yield of participants achieving accuracies of 83% did not exceed 17/20 even when using natural language stimuli. It remains unclear why this was the case (i.e., which task features were controlling responding). Another question concerns how to most efficiently establish novel Crels and Cfuncs when the task involves variations along more than two dimensions (e.g., number, points, *and* time). Answering this question may be of particular importance by informing efforts at establishing a wide range of Crels and Cfuncs in multi-faceted applied contexts. Yet another set of questions relate to the repertoires required by the task—repertoires for transformations of functions. Success in the task requires a repertoire for transformations of functions and may hold promise for indexing this repertoire and for training it, or simply for assessing the relationship between this repertoire and other aspects of arbitrarily applicable relational responding. Only time will tell whether the task is indeed useful in endeavors like those just described, but, at the very least, we are now equipped to find out.

Declaration of competing interest

None.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jcbs.2023.11.005.

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