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Using a Fork as a Hairbrush: Investigating Dual Routes to Release from Functional Fixedness

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Abstract

Functional fixedness involves difficulty with conceptualizing creative object uses. When it obstructs problem solving, individuals must reframe their approach. We examined how different training techniques – chunk decomposition (i.e., considering an object's basic parts and physical properties) and constraint relaxation (i.e., considering an object's different functions) – might rely upon different routes to creative reframing. Additionally, we investigated how different forms of cognitive load interact with these dual routes. Participants learned one of three techniques. Chunk decomposition participants created object breakdown diagrams; constraint relaxation participants created object functions lists; and, free association (control) participants wrote a word that they associated with each of several concrete nouns. After training, participants attempted to solve five functional fixedness problems. E1 investigated how increasing germane cognitive load via either direct or indirect prompting affected training transfer. Experiment 2 investigated how reducing extraneous cognitive load by providing no transfer instructions and using an eye-closure strategy. Across both experiments, results supported differences in accuracy and response latency by training. However, chunk decomposition and constraint relaxation did not follow the same pattern, suggesting different mechanisms of the effect. We discuss possible applications to increase innovation in real-world domains such as education, business, and engineering.

Keywords: functional fixedness, dual process, creativity, cognitive load, problem solving

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Functional fixedness occurs when a person focuses on an object's common use at the expense of more atypical action possibilities (e.g., Duncker, 1945). It decreases demands on mental resources to produce quicker identification of and interaction with objects for their typical uses (e.g., Rosch, Mervis, Gray, Johnson, & Boyes-Braem, 1976; Tucker, Ellis, Michaels, Tucker, & Circus, 1998). Although this mental roadblock proves useful in most situations, failing to consider atypical functions also hinders creativity (Chrysikou & Weisberg, 2005). For example, a post-it note is most typically used as a surface on which to write. However, the adhesive strip on the back could also be used to remove debris from small crevices (e.g., clean between the keys on a keyboard). The action possibility of writing tool typically blocks access to the action possibility of cleaning tool, making this atypical use less obvious.

Anecdotally, many people experience the "why didn't I think of that?" phenomenon, wherein a possible, yet atypical, use of an object seems obvious only after the solution has been revealed by others. During release from functional fixedness, studies show that access to the atypical action possibility was blocked (e.g., Dreisbach & Haider, 2009) through possible inhibitory functions designed to reduce interference (Beaty, Benedek, Silvia, & Schacter, 2016). Nevertheless, creativity researchers (e.g., Barr, Pennycook, Stolz, & Fugelsang, 2015; Gilhooly, Ball, & Macchi, 2015) have posited two separate routes or systems (one explicit and one implicit) by which problem solvers release from this fixed mental set.

The Dual Routes to Creative Problem Solving

Activating the explicit route through chunk decomposition. Although details differ slightly, mechanisms of this route might be similarly described as explicit (Dietrich & Haider, 2017), Type 2 (Barr et al., 2015), deliberate (Dietrich, 2004), and “business as usual” (Bowden, Jung-Beeman, Fleck, & Kounios, 2005). When in a state of functional fixedness, creative action possibilities are blocked because multiple experiences encourage chunking parts of an object into a single unit. This chunking process, therefore, reduces access to atypical uses of an object by focusing attention away from the object’s physical properties that might reveal different affordances (i.e., action possibilities enabled by the object’s material composition, shape, and size; Gibson, 1986). However, chunk decomposition (see also, functional decomposition; Gray, Yilmaz, Daly, Seifert, & Gonzalez, 2015; Umeda, Ishii, Yoshioka, Shimomura, & Tomiyama, 2010) reduces affordance blindness by revealing the variety of action possibilities of the object’s constituent parts.

Referring again to the post-it note, fixating on the writing tool action possibility can be overcome through chunk decomposition. The physical properties of the post-it note can be broken down into two parts: a small piece of paper with an adhesive strip on half of one side. The term “paper” still implies a use, so it can be further broken down to a thin, square-shaped piece of compressed wood. Similarly, the term “adhesive strip” still implies a use; so, it can be further broken down into a strip of sticky substance that covers only a portion of one side of the compressed wood. By decomposing the object into its constituent parts, other action possibilities (e.g., keyboard cleaning tool) are more easily accessible because the problem solver can hold the thin paper square on one end without the sticky substance and use the side with the sticky substance to stick to small debris in a tight space without damaging the keyboard.

Given the theoretical and applied value of creativity training, many researchers have investigated how and what types of interventions may most effectively potentiate release from functional fixedness (for a review, see Scott, Leritz, & Mumford, 2004). If such training involves deliberate steps to explicitly navigate through the problem-solving space, chunk decomposition is a strong candidate for practical applications. To test how fixating on the physical properties of the object affected problem solving, McCaffrey (2012) developed the generic parts technique. Participants diagrammed the breakdown of three everyday objects on the basis of their constituent parts and associated physical properties. Each participant was shown a line drawing of the object (e.g., a ladder) and was instructed to ask themselves two questions as they produced their diagrams: “Does this part imply a function?” and “Can I break this part down further?” Results from the generic parts technique group were compared with a control group who performed a free association task with each of 150 words. After the training phase, participants attempted to solve eight insight problems and were explicitly encouraged to use the strategy previously learned during the training phase. During the testing phase, participants were given eight minutes to solve each problem, during which time they were to write a solution, give it to the experimenter to check for accuracy, and continue with this process until they either produced a correct solution or ran out of time. Participants in the generic parts technique condition solved more functional fixedness problems than the control group.

Although this study (McCaffrey, 2012) provides some initial evidence to support training effectiveness, it fails to consider or compare both routes to problem solving. Further, this approach to chunk decomposition required a substantial involvement of the research assistant to not only provide guidance during the training phase (as would be typical when problem solvers are learning new strategies) but also to provide corrective feedback through a trial-and-error process during the testing phase (as would be atypical if training produces the ability to more independently solve problems). Would participants have performed as well under circumstances that require more spontaneous, learner-initiated transfer and use of the training to the testing phase? Could other problem-solving strategies provide similar creative advantages? To investigate these lingering questions, we designed two studies that (a) modified testing conditions that may influence the use of newly-trained problem solving approaches, and (b) contrasted training aimed at activating either the explicit route (i.e., chunk decomposition) or the implicit route (i.e., constraint relaxation).

Activating the implicit route through constraint relaxation. In contrast to the explicit system, a qualitatively distinct route might be similarly described as implicit (Dietrich & Haider, 2017), Type 1 (Barr et al., 2015), spontaneous (Dietrich, 2004), or special/intuitive in some way (Bowden et al., 2005; Chrysikou, 2006; Knoblich, Ohlsson, & Raney, 2001; Metcalfe, 1986; Ohlsson, 1992). When in a state of functional fixedness, creative action possibilities are blocked because current schemas built through past problem-solving experiences trigger constraints on the basis of the strongest association between the object and its typical use. The more experiences that a person has with a given item or the more assumptions that a person makes about the rules for solving the problem, the more fixed the constraints within the schema and heuristics become (e.g., Knoblich, Ohlsson, Haider, & Rhenius, 1999). For example, when attempting to produce a solution to the 9 dot problem (Maier, 1930), a person may assume that lines may only be drawn within the square implied by the array of dots. However, removing the assumption of those imposed constraints should make the solution more obvious.

In order to relax constraints and activate the implicit route, creative thinkers must adopt a more exploratory mindset by not only considering the actions that an object *typically* performs, but also the actions it could *possibly* perform. Consequently, this attentional refocusing spreads attention to atypical uses and, necessarily, reduces attention away from the most typical use (see also, redistribution theory; Ohlsson, 1992, 2011). Atypical action possibilities are then more likely to reach the threshold of conscious awareness, at which point they become available to the problem solver (Dietrich & Haider, 2017). Constraint relaxation can also be used to overcome functional fixedness in the post-it note example. The actions that a post-it note typically serves involve using it as a writing surface. The actions that a post-it note could serve include using in its original form as a keyboard cleaning tool, bookmark, flexible organizational tool, coaster, visual cover, and so forth. If the problem solver opts to change the shape by folding, it can also be used to hold small objects or form new shapes (e.g., origami). If the problem solver wants to adhere multiple pieces together using the sticky strips, even more action possibilities abound. By adopting a more exploratory mindset, atypical uses become more easily accessible.

Given that this route is implicit, training to encourage its use is not necessarily linear insomuch as an explicit process. Instead, previous training regimens involve approaches such as the Alternative Categories Test (ACT; Chrysikou, 2006), Unusual Uses Test (UUT; e.g., Wilson, Guilford, Christensen, & Lewis, 1954), and similarly-themed paradigms. Broadly speaking, these approaches all encourage an exploratory mindset that seeks to redistribute attention away from only one action possibility or schema to a wide range of plausible candidate possibilities. Across two studies, Chrysikou (2006) investigated transfer of constraint relaxation training to insight problem solving by randomly assigning participants to either an ACT or free association (control) group. ACT training encouraged participants to identify atypical categories into which 12 common items could be placed. For instance, a fork is typically categorized as an eating utensil. However, as a relatively-famous naive cartoon mermaid can attest, a fork could also be categorized as a hair styling tool. Participants were trained to recategorize common objects that either were or were not subsequently listed in additional insight problems (i.e., recategorizing a candle that would later be part of the Candle Problem; Duncker, 1945). Free association (control) training was similar to the approach adopted by McCaffrey (2012). The constraint relaxation group solved more problems than the free association group. Additionally, ACT participants performed just as well when they were encouraged to use the trained strategy (E1) as when they were not (E2). In other words, participants were able to spontaneously recognize the value of the constraint relaxation training without having to (a) be explicitly told and (b) use objects from the previous training phase.

This finding is noteworthy, as learners should be able to readily and spontaneously transfer knowledge from one situation to the next (e.g., Gick & Holyoak, 1983) when surface details are not identical, in order to establish the training's true effect. Prompting to use a strategy is a form of germane cognitive load that currently remains under explored for *both* the explicit (chunk decomposition) and implicit (constraint relaxation) routes. Therefore, the current studies seek to fill this gap in the literature by more fully manipulating how training and testing conditions affect the use and success of creativity training.

The Effect of Cognitive Load on the Dual Routes to Creative Problem Solving

One of the primary distinctions between the explicit and implicit routes involves the role of cognitive load. Working memory, a metric of cognitive load, affects creativity across a range of different types of problems (e.g., Price, Catrambone, & Engle, 2007). However, not all cognitive load influences problem-solving success in the same way. Cognitive load is typically characterized in three ways: 1) intrinsic, which exemplifies a type of load that is essential to completing the task, 2) germane, which is facilitatory cognitive load that enhances the efficacy of performance; and 3) extraneous, which usurps mental resources in such a way that does not benefit performance (Kalyuga, 2011). We should expect no real differences between performance on intrinsic load by training via the explicit or implicit creativity routes, provided that problem solvers are bringing necessary mental resources to bear in finding a solution. However, experimental manipulations to the testing environment might affect the types of germane and extraneous cognitive load to interact with the dual routes in different ways. Therefore, we integrated testing conditions to specifically examine these relationships.

Enhancing creativity by increasing germane cognitive load. Unlike intrinsic cognitive load, which represents the minimal amount of mental resources necessary to solve any problem, germane cognitive load recruits additional mental resources. These additional resources, therefore, increase the likelihood of successfully completing a goal. Concerning the training strategies, both would have some influence on germane load. However, explicit strategies should be more demanding (Kalyuga, 2011) to support the problem solver's conscious awareness. For example, chunk decomposition requires a diagramming sequence that is neither well-practiced nor automatic (McCaffrey, 2012). Refocusing attention to parts likely involves a great deal of executive functioning (e.g., working memory, planning, set-shifting, response suppression; Barr et al., 2015) to increase demands on germane cognitive load. In contrast, although constraint relaxation training might increase the likelihood of release from functional fixedness, this release may feel as if it crosses the threshold to conscious awareness by a special process or intuition (e.g., Knoblich et al., 2001).

To the extent that McCaffrey (2012) and Chrysikou (2006) made the use of their training approaches obvious, they enhanced germane cognitive load by encouraging participants to transfer knowledge from one domain to another. Similarly, requiring that participants keep working on a solution until they either provide a correct response or run out of time should also increase germane cognitive load. However, this latter intervention does not allow for the problem solver to use (or fail to see the value in using) a training approach without such an intervention.

Therefore, McCaffrey (2012) may have overrepresented the influence of the chunk decomposition training.

Subsequently, we modified the paradigm from McCaffrey (2012) in our first experiment to more closely examine the effect of a realistic degree of germane cognitive load (by way of either direct or indirect transfer prompting) and establish the relationship between the explicit route and chunk decomposition and the implicit route and constraint relaxation. To make our experimental trainings as similar as possible, with the exception of the functional approach, we also created a constraint relaxation training built upon the principles of the ACT (Chrysikou, 2006). Participants in the constraint relaxation training were directed to think of several unique action possibilities for the same common objects that were diagrammed in the chunk decomposition group.

We compared these two groups on the basis of solution rates (by way of overall and step-by-step accuracy) and response latencies using a less intrusive approach than the trial-and-error method. We predicted that both chunk decomposition and constraint relaxation would have higher solution rates than free association in terms of overall, but perhaps not step-by-step, accuracy. Further, we predicted that chunk decomposition should produce higher response latencies and step-by-step accuracy compared to constraint relaxation and free association. We additionally predicted that response latencies may interact with prompting, such that they should be higher under direct prompting than indirect prompting, but only for our experimental training conditions. It remains unclear about the role of direct and indirect prompting on solution rates. If our results follow the pattern of Chrysikou (2006), then we can predict no differences for the constraint relaxation group. However, since McCaffrey (2012) did not test this influence; direct and indirect prompting may differently influence solution rates for the chunk decomposition group.

Experiment 1

Method

Participants

A convenience sample of 132 undergraduate participants (94 female; aged 18 to 50 years; $M = 24.64$, $SD = 7.70$) completed the experiment in exchange for partial course credit. All experimental procedures were approved by the Institutional Review Board for ethical compliance.

Power analysis

In order to determine the appropriate sample size for our design, we referred to the documented effect sizes in McCaffrey (2012) and Chrysikou (2006). In a comparison between the Generic Parts Technique (GPT) and Word Association (WA), McCaffrey reported a Cohen's *d* of 1.59 (with subsequent interpretation of values above 0.80 being large, 0.50 being medium, and 0.25 being small) which converts to $f = 0.795$ (with 0.40 considered large, 0.25 considered medium, and 0.10 considered small; Cohen, 1988). Although Chrysikou did not directly report effect sizes, we used reported means, standard deviations, and sample sizes for the Alternative Categories Test (ACT) and WA groups to calculate Cohen's *d* between 0.85 and 1.15 (*f* between 0.425 and 0.575) for the two experimental variations. Therefore, we conducted an *a priori* power analysis in G*Power (Faul et al., 2007) using the statistical test for "ANOVA: Fixed effects, special, main effects and interactions" using the most conservative effect size of $f = 0.425$ with a desired power (1-β probability) of 0.95 for six groups (3 types of training by two types of testing, all between participants). G*Power indicated a required sample size of $n = 116$. Thus, even with the most conservative values, our sample size of n =132 (n = 120 after exclusions described in the Response Coding section below) exceeded the sample size necessary to achieve sufficient power.

Design

The experiment was broken up into two phases: training and testing. Participants were randomly assigned to one of three training conditions (chunk decomposition, constraint relaxation, or free association) and two testing conditions (direct prompt or indirect prompt) in a between-subjects design.

Procedure

After providing informed consent, participants began the training phase by reading instructions about their randomly assigned training condition.

Training phase. The chunk decomposition training (adapted from McCaffrey's, 2012 GPT) instructed participants to view three line drawings (i.e., a bell, kettle, and ladder) and draw a diagram that deconstructed each object into its constituent parts (see Figure 1a). Participants were given five minutes to build each diagram by asking themselves "Can I decompose this further into parts?" and "Does my description imply a use?" After each trial, a research assistant provided feedback and examined the accuracy of each diagram. If incorrect, the research assistant would assist the participant to make the needed corrections. Then, the computer screen displayed the correct diagram. Participants were encouraged to ask questions to ensure understanding before moving on to the testing phase.

The constraint relaxation training instructed participants to view the same three line drawings, one at a time, and create a list of possible functions (see Figure 1b). Participants were given five minutes to create each list by asking themselves "What is the purpose of this object?"

and “What can this object do?” After each trial, a research assistant provided feedback and examined the accuracy of each list. If incorrect, the research assistant would provide guidance on paper to make the corrections needed. Then, the computer screen displayed a non-exhaustive list of 10 possible functions. Participants were encouraged to ask questions to ensure understanding before moving on to the testing phase.

Free-association training instructed participants to view 150 words, one at a time, on a computer screen and write the first word that came to mind (e.g., flower, dark, music) using pencil on paper (see Figure 1c). Participants completed all 150 words before moving on to the testing phase.

Testing phase. After completing the training phase, participants were told that they should attempt to solve five problems [the candle problem (Duncker, 1945); prisoner and rope problem (Isaak & Just, 1995); and the desk lamp, wristwatch, and hot coals problems (McCaffrey, 2012)] displayed in random order. Problems were displayed one at a time for five minutes each and participants used the blank space underneath each problem to type their solution. Additionally, participants were instructed to only use the objects mentioned in the problem (i.e., no items from their pockets).

To avoid a potential shift to an explicit route in the implicit condition, participants in the current study did not receive feedback during the testing phase. Instead, the research assistant only remained in the room in the event that a participant asked a question. During the testing phase, participants were randomly assigned to one of the two testing prompt conditions: indirect or direct. Participants in the indirect prompt condition read, “Consider the activity you just completed when attempting to come up with a solution” before seeing the five problems. Participants in the direct prompt condition read the same instructions as the indirect condition prior to seeing the five problems. Additionally, they were reminded to continue to use the training method by reading, “Remember to use to the [Training] approach to solve the problems” before reading each problem.

Results

Prior to data analysis, all open-ended responses were coded by trained research assistants for accuracy and exclusionary criteria as described below.

Response coding. At least two assistants with an inter-rater agreement of .90 coded each response. All disagreements were resolved by a third assistant. Accuracy was coded in two ways: overall and step-by-step. Overall accuracy represented participants’ general understanding of the concept and production of a workable solution. For example, an answer such as “you would use the box of tacks to hold the candle upright and the book of matches to light the candle” would be as correct overall to the candle problem. An overall accuracy score of 5 indicated perfect performance for all five problems. Step-by-step accuracy represented the number of specific steps [in line with reported correct step-based solutions provided in McCaffry (2012)] produced when attempting to provide a workable solution. For example, an answer such as “I would take the book of matches and empty out all the matches in it. I would use the tacks to place the match book on the wall to secure it. Then I would place the candle on top and light it. The candle wax will drip on the match box, but not onto the table” would have 4 correct steps out of 4 possible correct steps for the candle problem. Each problem varied in the number of steps, with a step-by-step accuracy score of 16 indicating perfect performance by producing all the correct steps for all five problems. A solution could be scored as meeting the conditions of overall accuracy, without providing all of the necessary steps. Alternatively, a solution could include some, but not all, of the necessary steps to arrive at a workable solution. Participants were excluded for failing to comply with instructions on three or more problems (e.g., blank solutions, meaningless answers, using objects not stated in the problems). These criteria resulted in excluding n=12 participants. Exclusion due to response coding was not related to training group membership (n = 6, n = 3, and n = 3 for the chunk decomposition, constraint relaxation, and free association groups, respectively).

Data analysis. After exclusions, data from participants in the chunk decomposition (n = 38), constraint relaxation (n = 40), and free association (n = 42) groups were analyzed using a univariate analysis of variance (ANOVA) with an alpha level of .05 (used throughout unless otherwise noted). A 3 (training: chunk decomposition, constraint relaxation, or free association) X 2 (testing: direct prompt or indirect prompt) design was used to examine overall accuracy, step-by-step accuracy, and response latency (ms; see Figure 2).

Overall Accuracy. There was a significant main effect of training on overall accuracy, $F(2, 114) = 3.29$, $p < .041$, η^2_p =.055. Post hoc comparisons using the Bonferroni test indicated that both the chunk decomposition condition (M = 2.11, SD = 1.27) and the constraint relaxation condition (M = 2.00, SD = 1.01) solved more problems than the free association condition (M = 1.50, SD = 1.07); however, the chunk decomposition condition and constraint relaxation condition did not differ in the number of problems solved. There was no main effect of testing on overall accuracy, $F(1, 114)$ =.01, p = .932, η^2_p = .001. Additionally, there was no interaction effect of training and testing on overall accuracy, $F(2, 114)$ = .08, p = .926, η^2_p = .001.

Step-by-Step Accuracy. There was a significant main effect of training on step-by-step accuracy, $F(2, 114)$ = 6.81, p =.002, η^2_p = .107. Post hoc comparisons using the Bonferroni test indicated that the constraint relaxation condition (M = 6.13, SD = 2.72) solved more steps than the chunk decomposition condition (M = 4.68, SD = 2.66) and the free association condition (M

= 4.02, *SD* = 2.45); however, the chunk decomposition condition and free association condition did not differ in the number of steps solved. There was no main effect of testing on step-by-step accuracy, $F(1, 114) = .85$, $p = .358$, $\eta^2_p = .007$. Additionally, there was no interaction effect of training and testing on step-by-step accuracy, $F(2, 114) = .93$, $p = .398$, $\eta^2_p = .016$.

Response Latency. There was a significant main effect of training on response latency, $F(2, 114) = 29.78$, $p < .001$, $\eta^2_p = .343$. Post hoc comparisons using the Bonferroni test indicated that the chunk decomposition condition (*M* = 193877.10, *SD* = 47806.95) and the constraint relaxation condition (*M* = 192353.00, *SD* = 45794.05) had a longer response latency than the free association condition (*M* = 122968.30, *SD* = 51060.14); however, the chunk decomposition and constraint relaxation did not differ in response latency. There was no main effect of testing on response latency, $F(1, 114) = 1.68$, $p = .198$, $\eta^2_p = .014$. Additionally, there was no interaction between training and testing on response latency, $F(2, 114) = 1.92$, $p = .152$, $\eta^2_p = .033$.

To test whether response latency predicted either type of accuracy (overall or step-by-step), we computed bivariate correlations for each of the training groups. Results (see Figure 3) confirmed that increased response latencies were only positively correlated with step-by-step accuracy in the chunk decomposition group, $r = .385$, $p = .01$, adjusted $r^2 = .128$. All other correlations were not statistically significant.

Discussion

Experiment 1 had two major findings of theoretical interest. First, both types of experimental training (chunk decomposition and constraint relaxation) outperformed our control (free association) participants in terms of accuracy. Extending upon the work of McCaffrey (2012), we support the conclusion that chunk decomposition increases correct solution rates. In contrast to that work, however, we find a similar degree of creative facilitation in terms of overall accuracy of an alternative strategy designed to activate the implicit route. Second, step-by-step accuracy was significantly higher for constraint relaxation than chunk decomposition. These differences are noteworthy, primarily because no theory would make a direct prediction that constraint relaxation would outperform chunk decomposition, all other things being equal, on this second indicator of accuracy. If anything, considering the physical composition of objects by devoting explicit attentional resources might have led us to predict the opposite effect, wherein chunk decomposition would favor a step-by-step approach.

One possible explanation for this effect lies in demands upon cognitive load. As previously discussed, working memory capacity limits the extent to which mental resources can be applied to a task. If an explicit training process already produced a high demand upon such resources, then prompting may have been unnecessary and even distracting. Response latencies confirmed that participants who were directed to use a creativity-enhancing training (as opposed to a free association training) took longer before attempting to provide a solution. Importantly, though, this increased response latency compared to control was uniform across both direct and indirect prompting: a subtle suggestion to use the strategy learned in the training phase was sufficient to potentiate its benefit. However, for the chunk decomposition group, increased response latencies were predictive of increased step-by-step accuracy. This strengthens the theoretical position that chunk decomposition activated the explicit route (where more time on task should theoretically benefit creative performance) and that constraint relaxation activated the implicit route (where time on task was not predictive of such a relationship).

Therefore, in Experiment 2, we more closely examined the impact of other forms of cognitive load, primarily extraneous, on creative strategy use as measured by accuracy and response latency. First, we removed the prompting, to more truly measure the problem solvers' spontaneous transfer of training to testing without necessarily being told (e.g., Experiment 2 - Chrysikou, 2006; Gick & Holyoak, 1983). We predicted that an explicit task may not benefit to the same degree from any type of explicit prompt, as its transfer relies upon conscious awareness. Instead, the explicit task might have seen detriments from a cognitive overload under such conditions. Further, we predicted that an implicit task might have found a *goldilocks zone* (i.e., a performance-arousal peak; Yerkes & Dodson, 1908) from an increase in germane cognitive load brought about by prompting. Without such prompting, participants may not spontaneously realize the value of the training to the testing phase. We, therefore, predicted that removing the prompting might decrease solution rates for this group. Second, we sought to remove extraneous cognitive load that may have more strongly affected our explicit than our implicit group.

Reducing extraneous cognitive load. Several strategies have been successfully adopted to reduce extraneous cognitive load including segmenting information to be encoded, reducing redundant information, and removing incidental processing (e.g., Mayer & Moreno, 2003). Given that the explicit training is highly visual (and participants may, or may not, opt to physically recreate their diagrams on the blank worksheets provided), interventions to reduce visual load may enhance the effect of training. Further, recent evidence suggests that an eye-closure strategy, which has been successfully used in memory studies to eliminate extraneous sensory information Perfect, Andrade, & Eagan, 2011, may enhance creative problem solving effectiveness (Ritter, Abbing, & van Schie, 2018). In their study, Ritter and colleagues directed participants to perform a series of creativity tasks (e.g., Alternative Uses Task, Remote Associates Test) with their eyes either closed or open. Results supported a benefit of the eye closure technique on creativity task performance.

Therefore, we explored the degree to which eye-closure affects accuracy and response latencies using the same three training conditions used as Experiment 1. As in Experiment 1, we predicted higher solution rates and response latencies for our chunk decomposition compared to control. However, those differences may not be as striking if the removal of the prompting reduces spontaneous transfer of chunk decomposition training to the testing phase. In terms of constraint relaxation, we predict higher solution rates, but perhaps not response latencies, compared to control. We also predicted that, in line with Ritter and colleagues (2018), participants who received one of the experimental training conditions may benefit from the eye-closure technique with increased solution rates compared to the control condition.

Experiment 2

Method

Participants

A convenience sample of 185 undergraduate participants (144 female; aged 18 to 39 years; M = 20.85, SD = 12.35) completed the experiment in exchange for partial course credit.

Power analysis

For Experiment 2, we considered both the effect sizes from Experiment 1 and previous literature in determining a sufficiently large sample size to detect an effect. Although previous literature using similar procedures (e.g., Chrysikou, 2006; McCaffrey, 2012) reported effect sizes that would all be considered large, our Experiment 1 findings put the effect sizes closer to the medium range. Therefore, we used the same approach to calculate *a priori* power analyses as before, with f = 0.335 (a medium to large effect size estimate that represents the arithmetic average between the two possibilities). G*Power (Faul et al., 2007) analysis revealed a required sample size of n = 141. Thus, even with the most conservative values, our sample size of n =185 (*n* = 167 after exclusions described in the Response Coding section below) exceeded the sample size necessary to achieve sufficient power based upon this estimate.

Design & Procedure

Although the training phase was identical to Experiment 1, we altered the instructions during the testing phase for Experiment 2. After reading the instructions, participants were randomly assigned to the eyes closed or eyes open condition. Participants in the eyes open condition received no additional instruction; however, participants in the eyes-closed condition were instructed to close their eyes while thinking of each solution in order to visualize the objects described in each problem. Afterwards, a research assistant remained in the room to ensure instructional compliance. Following the presentation of all problems, participants were debriefed, thanked, and dismissed.

Results

Coding procedures were identical to Experiment 1, resulting in *n* = 18 excluded participants (*n* = 0, *n* = 6, and *n* = 12 in the chunk decomposition, constraint relaxation, and free association groups, respectively)[1]. After exclusions, data from participants in the chunk decomposition (*n* = 45), constraint relaxation (*n* = 62), and free association (*n* = 60) groups were analyzed using a 3 (training condition: chunk decomposition, constraint relaxation, or free association) X 2 (testing condition: eyes open or eyes closed) design. As with E1, we compared overall accuracy, step-by-step accuracy, and response latency (ms; see Figure 2).

[1] Upon closer consideration of the exclusionary justifications, most of the participants were excluded on the basis of providing meaningless answers (e.g., “I don’t have a clue and I’m going to sit here until the next question pops up.”), which we might speculate was related to a creative impasse that was not alleviated by the training (constraint relaxation or free association) in the absence of prompting. To keep consistency with E1, we applied the same exclusions. However, data analysis of the entire E2 sample did not alter the overall pattern of the results.

Overall Accuracy. There was a significant main effect of training on overall accuracy, $F(2, 161) = 5.44$, $p = .005$, $\eta^2_p = .063$. Post hoc comparisons using the Bonferroni test indicated that the chunk decomposition condition ($M = 2.20$, $SD = 1.22$) solved more problems than the free association condition ($M = 1.47$, $SD = 1.08$). Constraint relaxation ($M = 1.71$, $SD = 1.12$) did not differ from either group. There was no main effect of testing on overall accuracy, $F(1, 161) =.00$, p = .981, $\eta^2_p = .001$. Additionally, there was no interaction effect of training and testing on overall accuracy, $F(2, 161) =.47$, $p = .629$, $\eta^2_p = .006$.

Step-by-Step Accuracy. There was a significant main effect of training on step-by-step accuracy, $F(2, 161) = 4.51$, $p = .012$, $\eta^2_p = .053$. Post hoc comparisons using the Bonferroni test indicated that the chunk decomposition condition ($M = 6.09$, $SD = 2.70$) solved more steps than the free association condition ($M = 4.57$, $SD = 2.55$). As with overall accuracy, the constraint relaxation condition ($M = 5.08$, $SD = 2.58$) did not differ from either group. There was no main effect of testing on step-by-step accuracy, $F(1, 161) = .01$, $p = .908$, $\eta^2_p = .000$. Additionally, there was no interaction effect of training and testing on step-by-step accuracy, $F(2, 161) = 1.07$, $p = .345$, $\eta^2_p = .013$.

Response Latency. There was a significant main effect of training on response latency, $F(2, 161) = 3.41$, $p = .036$, $\eta^2_p = .041$. Post hoc comparisons using the Bonferroni test indicated that the chunk decomposition condition ($M = 208229.00$, $SD = 36478.76$) had a longer response latency than the free association condition ($M = 186064.09$, $SD = 50479.14$). However, the constraint relaxation condition ($M = 191418.41$, $SD = 41888.33$) did not differ from either group. There was no main effect of testing on response latency, $F(1, 161) = .34$, $p = .559$, $\eta^2_p = .002$. Additionally, there was no interaction between training and testing on response latency, $F(2, 161) =.11$, $p = .897$, $\eta^2_p = .001$.

To test whether response latency predicted either type of accuracy (overall or step-by-step), we computed bivariate correlations for each of the training groups. Unlike Experiment 1, none of the correlations were statistically significant (see Figure 3).

Discussion

Building upon the foundation laid in Experiment 1, Experiment 2 replicated the benefit of chunk decomposition on release from functional fixedness. In contrast to Experiment 1, constraint relaxation no longer demonstrated a significant increase in solution rates compared to control. Instead, it is perhaps the case that germane cognitive load brought about by prompting was necessary for the creative benefit to be more fully realized. Without such a prompt, performance on both indices of accuracy declined.

We can speculate that the role of prompting may have been more important for constraint relaxation than chunk decomposition. However, such an interpretation does not align with Chrysikou (2006), who used implicit training tasks and found that participants still performed well in the absence of a prompt. One possibility is that the Alternative Categories Test (ACT) adopts a similar approach to our modified constraint relaxation task, but does not tap into the same balance of the dual routes to creative problem solving. In an attempt to make the constraint relaxation training task similar to the chunk decomposition training task, with the exception of the functional approach, we only asked participants to list the common functions of the same three items that were diagrammed by the chunk decomposition group. It remains possible that our relatively shorter training, which used 3 objects instead of 12, as in ACT, might not have solidified the training mindset to the same degree that allowed for more spontaneous transfer.

Another alternative might be explained by considering the time course of problem-solving strategies within the training and testing periods. For our chunk decomposition group, the desirable strategy and instructions were structured and clear: create a parts diagram of a presented object. Given the explicit nature of the instructions, we expected participants to gain speed in their diagramming approach across the practice trials (i.e., shorter amount of time to generate an accurate, complete diagram in the third practice trial compared to the first). This order effect served as the primary motivation for including the practice trials during training, thus increasing the likelihood of a greater degree of independence when transferring the strategies to the testing phase. On the other hand, the constraint relaxation group was trained to generate a list of possible functions for common items without a structured approach as to how to accomplish the goal. Participants likely adopted a variety of strategies that vacillated between recalling uses from memory and generating novel uses as a function of the training itself.

As a point of comparison, Gilhooly and colleagues (2007) investigated both the strategy use and time course of generated ideas for the Alternative Uses Task (AUT). In the first study, participants were prompted to perform the AUT on a common item and describe their strategies for each response (i.e., think-aloud approach). The majority of participants reported using disassembly (i.e., chunk decomposition) and property use (i.e., physical characteristics that give rise to action possibilities) for a small number of responses. This finding reinforces the idea that strategies applied by our constraint relaxation participants may have borne some resemblance to the chunk decomposition training. Further, a second study revealed that early responses to the AUT were more strongly related to memory retrieval strategies whereas later responses were more strongly related to executive processes, again similar to the chunk decomposition training.

Tasks designed to activate the exploratory mindset and reduce mental constraints have undergone far more updating and revisions (e.g., Wilson et al., 1954) than more relatively recent approaches in chunk decomposition (e.g., McCaffrey, 2012). Given the procedural similarities, however, it seems likely that our constraint relaxation training would show a similar pattern of findings to Gilhooly et al. (2007). However, were cannot directly test this possibility given the nature of our experimental procedures. Therefore, future studies should continue to investigate the optimal balance between training time, strategy use, and learner-initiated transfer in both laboratory and applied domains.

Turning to the extraneous cognitive load manipulation, eye closure did not confer a reliable benefit on accuracy or response latencies. A slight uptrend is noticeable, but not significant, for the chunk decomposition group when their eyes were closed. However, our data do not replicate Ritter (2018), who found a benefit of eye closure for both divergent (e.g., functional fixedness) and convergent (e.g., remote associations) tasks. In our study, participants needed to strategically apply the eye-closure strategy in order for it to be useful. Ritter encouraged participants to keep their eyes closed during the duration of the creativity tasks, while a research assistant read the problems and participants responded verbally. It remains possible that adopting such an approach, involving more interaction with the research assistant during the testing phase, may have produced a benefit in our paradigm as well. However, future studies would need to test that possibility.

General Discussion

Across two studies, we tested the interaction of cognitive load and creative strategy training on functional fixedness. Both studies supported an overall benefit of a chunk decomposition strategy, which encouraged participants to mentally uncouple common objects into their constituent parts (e.g., physical properties, size, shape) as opposed to their typical functions. This type of training was useful in increasing solution rates and response latencies, regardless of whether or not participants were directly instructed to apply it. In contrast, an alternative creative strategy that was designed to activate the implicit route through constraint relaxation did not follow the same pattern of results. When participants who were trained on constraint relaxation received a prompt to transfer that training to a problem solving phase, they demonstrated increased response latencies and solution rates over the control group. In the absence of such prompting, however, we found no significant differences compared to control.

It is noteworthy that our cognitive load manipulations did not have the same effect on the chunk decomposition and constraint relaxation groups. Neither group benefited from the direct prompt approach compared to a subtler suggestion. This finding suggests that the very hands-on trial-and-error approach (McCaffrey, 2012) might have both increased germane cognitive load and sharpened the effects of training by also integrating feedback. Admittedly, our participants did exhibit higher release from functional fixedness than control (E1), but scored nowhere close to ceiling. Future studies should investigate the room for improvement using different types and durations of training that capitalize on the principles of cognitive load in learning and transfer (Kalyuga, 2011).

Many of the most impactful/important innovations strongly rely on overcoming functional fixedness to use objects more creatively. Therefore, more empirical research needs to uncover the reliable mechanisms under which such creative inspiration occurs. Overall, we provide another study in the growing body of dual-process evidence (e.g., Gilhooly et al., 2015) that is quite ubiquitous across many cognitive domains (e.g., Thompson, Prowse Turner, & Pennycook, 2011). Research suggests that these two routes are *qualitatively* different. Chunk decomposition (paired with implementation of the trained diagramming) is explicit, cognitively demanding, and encourages a linear path through the problem space to attain a goal. In contrast, constraint relaxation is implicit and may lend itself to something closer to a special/intuitive process encouraged by a more exploratory mindset. Nevertheless, our research supports that creativity can be potentiated across both paths, without necessarily making use of the strategy obvious to participants (e.g., spontaneous transfer was supported).

After as little as 20 minutes, participants in the experimental training conditions were able to learn and transfer a creative strategy to solve functional fixedness problems. As life hacks become increasingly popular, societies' desire to seek out simple solutions to persistent problems represents an interesting and important real-world research area. Likewise, schools of engineering, business, and entrepreneurship could use evidence-based practices around which to structure their training. Some functional decomposition research (e.g., Gray et al., 2015; McCaffrey & Krishnamurty, 2015; Umeda et al., 2010) has already advocated and applied integrating these cognitive principles to improve innovation in engineering. Work in other applied domains holds the potential to catalyze advancements across many different fields.

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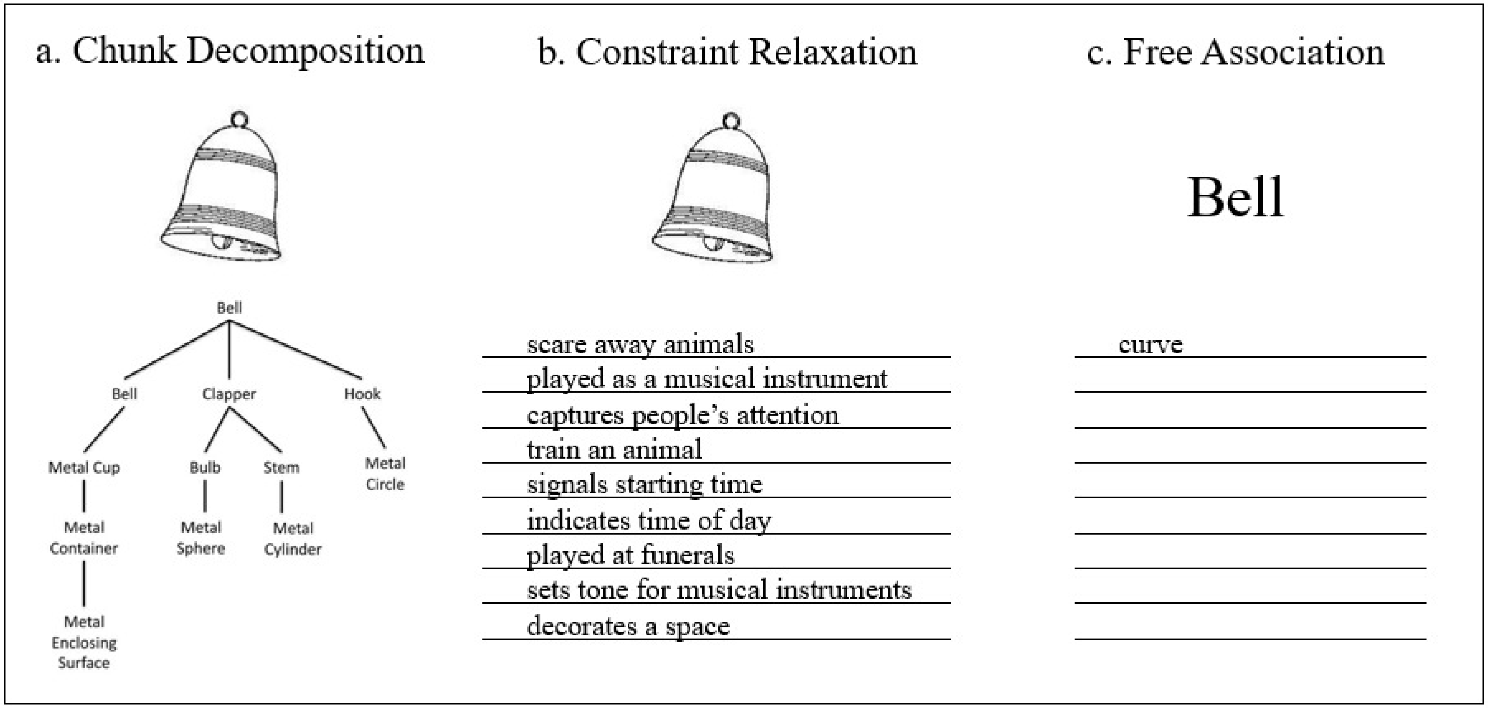
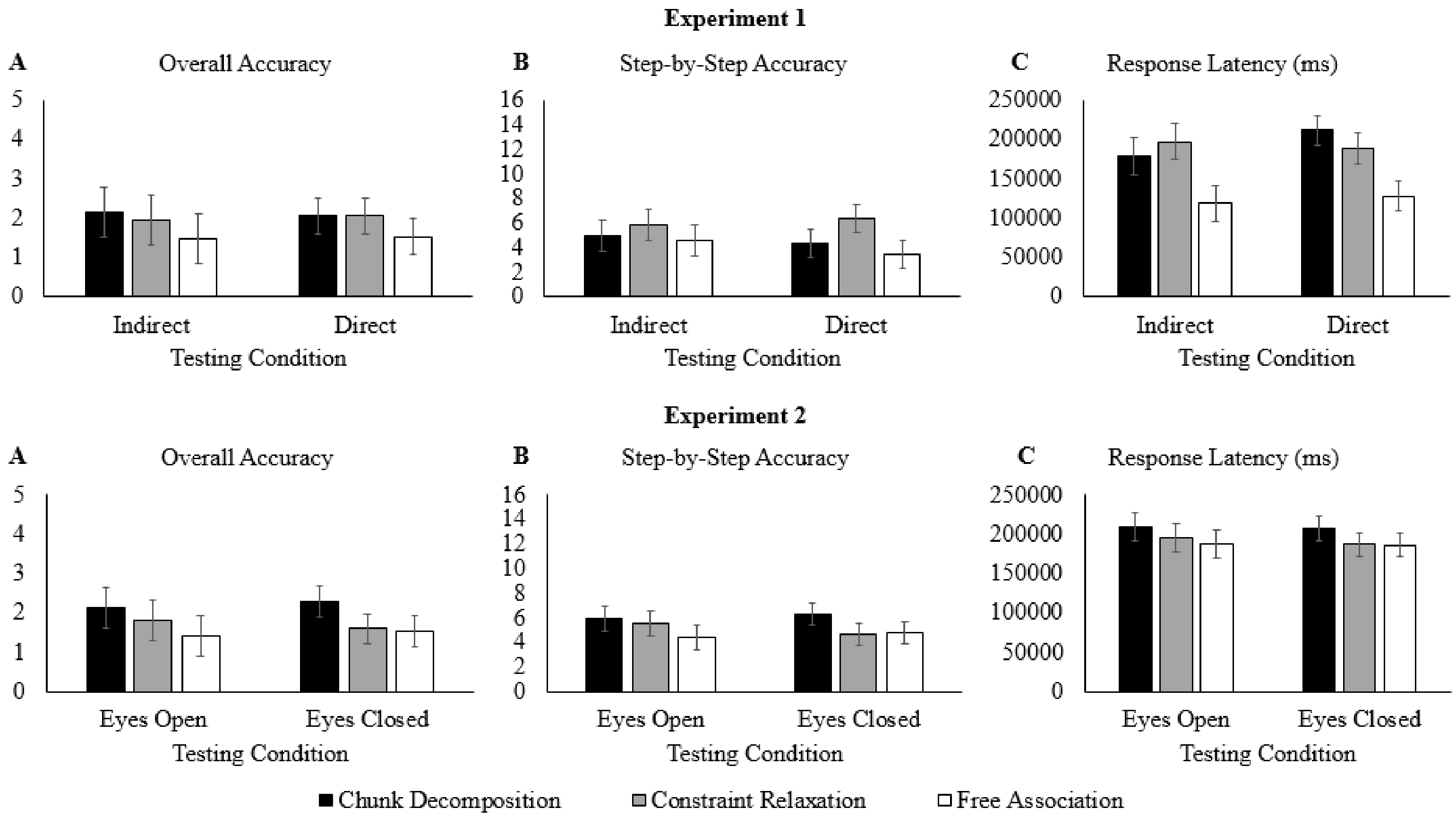

a. Chunk Decomposition
b. Constraint Relaxation
c. Free Association
Bell
Bell
Bell
Clapper
Hook
Metal Cup
Bulb
Stem
Metal Circle
Metal Container
Metal Sphere
Metal Cylinder
Metal Enclosing Surface
scare away animals
played as a musical instrument
captures people's attention
train an animal
signals starting time
indicates time of day
played at funerals
sets tone for musical instruments
decorates a space
curve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Overall Accuracy
5
4
3
2
1
0
Indirect
Direct
Testing Condition
B
Step-by-Step Accuracy
16
14
12
10
8
6
4
2
0
Indirect
Direct
Testing Condition
C
Response Latency (ms)
250000
200000
150000
100000
50000
0
Indirect
Direct
Testing Condition
Experiment 2
A
Overall Accuracy
5
4
3
2
1
0
Eyes Open
Eyes Closed
Testing Condition
B
Step-by-Step Accuracy
16
14
12
10
8
6
4
2
0
Eyes Open
Eyes Closed
Testing Condition
C
Response Latency (ms)
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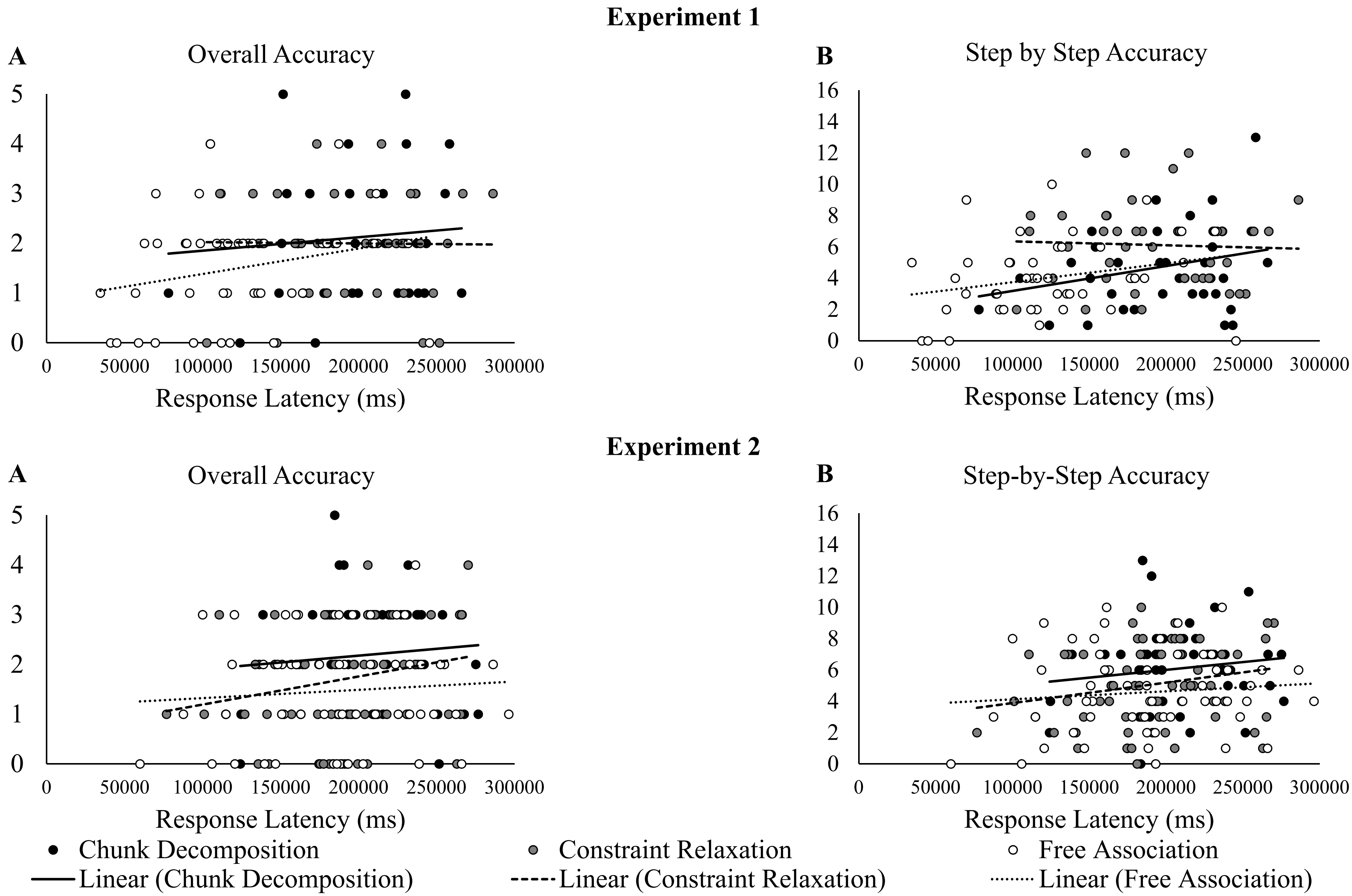
Testing Condition
Chunk Decomposition
Constraint Relaxation
Free Association


Experiment 1
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Overall Accuracy
0 1 2 3 4 5
0 50000 100000 150000 200000 250000 300000
Response Latency (ms)
B
Step by Step Accuracy
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0 50000 100000 150000 200000 250000 300000
Response Latency (ms)
Experiment 2
A
Overall Accuracy
0 1 2 3 4 5
0 50000 100000 150000 200000 250000 300000
Response Latency (ms)
B
Step-by-Step Accuracy
0 2 4 6 8 10 12 14 16
0 50000 100000 150000 200000 250000 300000
Response Latency (ms)
Chunk Decomposition
Constraint Relaxation
Free Association
Linear (Chunk Decomposition)
Linear (Constraint Relaxation)
Linear (Free Association)