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EXAMINING CREATIVITY: THE ROLE OF EXAMPLES AND EXECUTIVE FUNCTION IN IDEA GENERATION

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Abstract

Examining creativity: The role of examples and executive function in idea generation

Mercedes T. Oliva

This Dissertation investigated the interplay between executive function, creative thinking, and examples. Over 200 participants completed this experiment consisting of a battery of five creative thinking tasks and a battery of seven executive function tasks. All participants completed two different versions of each of the creative thinking tasks, one version with the help of examples to get them started on idea generation and one version without the help of examples. Data were analyzed both as latent and observed variables.

Key results indicated that: (1) participants generated ideas that were rated as more creative when they had the help of examples than when they did not have examples; (2) executive function (particularly inhibition) was positively related to creativity in both conditions; (3) the role of executive function was not observed to depend on whether examples were involved in the idea generation process; and (4) conformity to examples was not observed to mediate the relation between executive function and creativity.

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Creativity in the Face of Examples, as Explained by Executive Function

Creativity is an increasingly important aspect of modern society, valued in personal and professional contexts. Our ability to do things like generate unique ideas, solve problems in new ways, and develop novel questions is what allows society to advance (and it also makes life more interesting!). However, much about the cognitive mechanisms facilitating creativity is still unknown.

What is "creativity"? While many people generally and colloquially understand what makes something "creative," creativity researchers disagree on the more fine-grained nuances. Some researchers (e.g., Barron, 1955) support the idea of two factors, novelty and usefulness; others (e.g., Campbell, 1960) hold to a three-criterion definition of originality, utility, and surprise; still others (e.g., Boden, 2004) prefer the idea of novelty, value, and surprise. Whatever the minutiae, the overall essence of creativity remains consistent between these definitions (and we, in this proposal, will generally abide by the novelty and usefulness perspective to maintain consistency with the broader literature).

Theories of Creativity

Historically Significant Theories

The theoretical explanations for creativity are varied. Mednick's (1962) theory of associative hierarchy describes the notion that creative ideas come from associative processes in semantic memory. Here, some people are better or worse at making distant (and creative) semantic associations, depending on the individual’s semantic network structure. Campbell's (1960) theory of blind variation and selective retention describes how people repeatedly combine random features and select the product that most satisfies their goal. Guilford's (1968) structure-of-intellect model describes up to 180 types of cognition, including convergent and divergent thinking. Convergent thinking describes the type of creativity that involves putting pieces of information together to solve a problem or result in one single solution. Its frequent companion in the literature, divergent thinking, describes beginning from a single starting point and generating many ideas or solutions. Although some statistical questions have been raised around the structure-of-intellect model more broadly, the ideas of convergent and divergent thinking still enjoy empirical support today.

Creative Cognition

Increasingly, we are seeing interest specifically in the cognitive underpinnings of creativity. As an example of an approach from this perspective, *creative cognition* describes creativity not as a mystical, magical, unknowable force that happens *to* us but rather explains creativity as the result of the same cognitive processes studied in cognitive psychology more broadly (Smith et al., 1995). Taking this perspective is advantageous because it allows us to research creativity empirically at a more nuanced level than when taking some other perspectives, since it draws inspiration from tried-and-true strategies employed in other areas of cognitive psychology.

Creative cognition proposes the Geneplore Model (Finke et al., 1992). This model works from the understanding that creativity is not a single construct but the result of many generative and exploratory processes that contribute to creative thinking. Generative processes are aptly named in that they are the processes that facilitate the generation of ideas. These include memory retrieval, association, mental synthesis, mental transformation, analogical transfer, and categorical reduction, among others. Conversely, exploratory processes are related to evaluating and modifying the ideas that came from the generative process. These include attribute finding, conceptual interpretation, functional inference, contextual shifting, hypothesis testing, and searching for limitations. In the Geneplore Model, the generative and exploratory processes are iterative in that people often cycle through the two types more than once during the creative process. That is to say, an idea may be generated, evaluated, and found to be wanting somehow. A person may move forward to another round of the generative process, having considered the feedback from the evaluative process. This process may occur multiple times before generating an idea that meets all the task's requirements.

Take, for example, a common task from the divergent thinking literature, the Alternative Uses Task (AUT; Guilford, 1957). In this task, individuals are asked to list uses for a common object (e.g., brick) that are *different* from the regular use of the item. The responses are then measured on factors like how many uses the person generated (fluency) and whether the uses were very different from each other (flexibility). It seems clear, however, that various cognitive processes must have been involved in this task. Benedek and Fink (2019) describe the importance of functions like memory, attention, and cognitive control in creative cognition, and Ward (2007) specifies particular processes like episodic retrieval, mental imagery, analysis of features, and abstraction as being implicated in even tasks as seemingly straightforward as the AUT. As a dramatic simplification, when I generate ideas for alternative uses for a brick, I first picture a brick in my mind. This might immediately trigger the retrieval from long-term memory of the many times I have seen a brick in the past. Then, I may attend to the brick's role in each instance – Is it part of a building? A wall? A sidewalk? A patio? I may analyze the features, noticing similarities and differences between these uses, deciding which features may be useful to hold onto and which are better ignored for the current purpose. Then, I may decide to move forward by iterating on one or more of those instances, probably employing other searches through long-term memory, and maybe even cycling through the whole process multiple times and using these myriad cognitive processes differently each time. All of this is necessary to help develop a new idea, and it all occurs through standard cognitive processes!

Associative Theory

The associative theory of creativity is included in concepts like the serial order effect (ideas increase in creativity sequentially; Beaty & Silvia, 2012; Kudrowitz & Dippo, 2013), some theories of insight (when an idea occurs seemingly out of nowhere; Cai et al., 2009; Luchini et al., 2023), and some theories of incubation (a person can be more successful at solving a problem after taking a break; Sio & Rudowicz, 2007). These theories all describe creativity or problem-solving as happening through spreading activation in the semantic network. They also seem to take place with s effort.

Controlled Attention

The Controlled Attention theory of creativity (see Beaty et al., 2014) accounts for the fact that much creative thinking does not occur automatically and effortlessly but is more the result of conscious and directed work. This theory describes creativity as being top-down and reliant on abilities like attention and working memory.

A study by Beaty and Silvia (2013) showed evidence for the Controlled Attention Theory. Participants were asked to generate creative metaphors (e.g., describing what it was like to sit through the most boring class they have ever been in). The metaphors were scored on creativity on a scale of 1 – 5 by three independent raters who were asked to consider remoteness, novelty, and cleverness when scoring. Results indicated that the creativity of the metaphors was associated with increased fluid intelligence and broad retrieval ability (both of which are associated with executive processes). Another study (Gilhooly et al., 2007) examined the processes involved in the AUT. They used an interesting approach, where, after generating their creative alternative uses, participants identified which of the uses were "new" to them. This procedure lets experimenters consider that an idea may be new and novel to a rater but not new to the participant who generated the idea (and vice versa). Results indicated that participants who performed better on a letter fluency task (to indicate greater executive capacity) also produced more "new" responses in the AUT.

There is, of course, reason to think that creativity is a function of both associative and executive processes. For example, in their study demonstrating the serial order effect (where ideas increase in frequency sequentially as you generate a series of ideas), Beaty and Silvia (2012) also reported that the effect was moderated by intelligence and retrieval ability (strongly linked with executive processes; Benedek et al., 2014; Buczyłowska et al., 2020; Unsworth et al., 2009) such that as intelligence increased the serial order effect decreased. Specifically, they showed that individuals with higher fluid intelligence started off at a more creative level than those with lower fluid intelligence, so the individuals with higher intelligence did not have as much space to improve. They suggest that this is evidence that executive processes may help people inhibit irrelevant and/or unoriginal ideas.

Dual Process Model

The Dual Process Model of creativity integrates aspects of the Associative and Controlled Attention theories. This approach corresponds to a related model, the dual process model of cognition. As it is applied to cognition more generally, the Dual Process Model describes two types of thinking, Type 1 and Type 2 (Evans, 2009). Type 1 cognitions are those that are automatic and fast; Type 2 cognitions are those that are effortful and controlled, often relying on working memory. These can easily be applied to creative cognitions. Research generally supports the idea that creativity involves both Type 1 and Type 2 processes to support the generation of ideas (Type 1) and the evaluation or modification of ideas to fit a goal (Type 2) (e.g., Barr, 2017; Beaty et al., 2015; Wiley & Jarosz, 2012).

Leaky Attention or Flexible Attention

Some work supports the idea that we can often benefit from integrating environmental cues into our ideas. Maier's (1931) two-string problem (trying to tie together two strings that were suspended from the ceiling far enough away from each other that a person could not reach both at the same time) is a classic example where participants were more likely to be able to find a solution (use an object in the room as a weight at the end of one string to allow it to swing toward the second string) after an experimenter "accidentally" knocked into a string and set it swinging. An individual's ability to take that supposedly irrelevant-to-the-task-at-hand cue and integrate it into a solution could be an example of leaky attention.

Other work supports the idea that it is not so much leaky attention that facilitates creativity but rather flexible attention, or the ability to overcome invalid or inappropriate cues quickly (Zabelina et al., 2016; Zabelina & Robinson, 2010). Interestingly, leaky attention and flexible attention make rather different predictions about the role of top-down processes in creative thinking. Leaky attention seems to suggest that top-down processes may be less helpful because incorporating seemingly irrelevant information is good for creativity; flexible attention seems to suggest that top-down processes may be more helpful because they allow a person to ignore irrelevant information flexibly.

Mental Fixation

Examples → Conformity Effect

One cognitive mechanism important to the study of creativity is mental fixation (Smith et al., 1995). Mental fixation describes the situation in which prior experience impedes the creative thinking process. For example, when an individual tries to create a new work of art and observes that they are thinking about a painting they saw and loved last week, the memory of the other painting may make it difficult to create a brand new, very creative painting. Similarly, in the lab, we may observe that participants struggle to generate a new and creative idea when they were previously exposed to related-but-unhelpful information.

In two experiments, Agogué, Kazakçi, et al. (2014) considered the role that the type of example could play in mental fixation. Experiment 1 asked participants to generate ideas to prevent an egg from breaking when dropped from a 10-meter height. They found three categories of responses were generated particularly frequently: damping the shock, protecting the egg, and slowing the fall. The authors described ideas that fell into those categories as being “within the fixation effect” or “restrictive”; other ideas were described as being “outside the fixation effect” or “expansive”.

In Experiment 2 of the same study, participants were split into three conditions: some received no examples, some received a restrictive example (e.g., slow the fall with a parachute, within the fixation effect), and some received an expansive example (e.g., freeze the egg before dropping it, outside the fixation effect). The authors determined that exposure to a restrictive example resulted in decreased originality relative to the condition that did not receive any example; conversely, they also reported that exposure to an expansive example resulted in increased originality relative to the condition that did not receive an example. They also showed that participants exposed to an expansive example generated more ideas outside of the fixation effect than either of the other two conditions. This is to say that exposing participants to less-common examples increased the likelihood of participants generating less-common ideas.

Mental fixation can appear in many forms, but one type commonly addressed in the empirical literature is conformity to examples, or the conformity effect. The quintessential conformity effect paper was by Smith and colleagues (1993). In this set of experiments, participants were asked to draw, label, and describe ideas for a new toy and an alien creature (similar to Ward, 1994). Half of the participants were first shown three examples, and half were not shown examples. These examples all shared three common (critical) features: all toy examples involved a ball, an electronic component, and exercise, while the alien creatures all involved four legs, antennae, and a tail. Conformity was operationalized as the rate of inclusion of these critical features. Results indicated that participants exposed to examples before completing the task were more likely to include those critical features than those who were not. This pattern (the conformity effect) was demonstrated even when participants were instructed to diverge from the examples.

A substantial literature has stemmed from the Smith et al. (1993) findings to demonstrate mental fixation and the conformity effect (e.g., Chrysikou et al., 2016; Dahl & Moreau, 2002; Fink et al., 2012; Sio et al., 2015). For example, Marsh et al. (1996) showed two ways to increase the conformity effect: increasing the number of examples and introducing a delay between when participants were exposed to examples and when they generated their own ideas. Chrysikou and Weisberg (2005) demonstrated that, even when participants were shown examples that were specifically described as problematic, the conformity effect was still shown (although diminished).

Conformity Effect → Less Creativity?

Since originality is a key piece of many definitions of creativity, it might seem intuitive that anything that shares commonalities with something else must be less creative than something that is entirely unlike something else. However, that is rarely possible in day-to-day life. Welling (2007) included this understanding by featuring "combinations" – the combination or rearrangement of existing features in a new way – in his description of the four key mental operations in creative cognition. The other three operations were application, analogy, and abstraction. Combination being a key mental operation in creative cognition suggests that creativity might be less about generating ideas where every individual feature is entirely novel, and more about creating an idea that is novel when taken as a whole. Although conformity and creativity seem semantically antithetical, this presupposition may not bear out in daily life or the lab.

Combinations may be one reason why conformity seems to affect creativity positively. Sio et al. (2015) conducted a meta-analysis of studies that looked at examples and fixation and found that, although introducing examples to the idea generation process makes people more likely to show the conformity effect, the ideas were more novel. They went on to say that presenting a single uncommon example (rather than many uncommon examples, a single common example, or many common examples) results in the most high-quality and novel ideas.

George et al. (2019) also followed up on the toy design condition from Smith et al. (1993) to examine whether the conformity effect was necessarily bad for novelty. Sixty-eight participants were assigned to either be exposed or not exposed to examples before generating their own toy ideas. As in Smith et al. (1993), they were asked to draw, label, and describe ideas for as many new and different toys of their own design as possible. Conformity was scored as a count of whether a critical feature was included in the participant's idea (0 - 3). Novelty was operationalized on a scale of 1 (not at all novel) to 5 (highly novel), where non-toys and toys that already exist were given ratings of 1 by default, and the average rating from two independent raters was used. Results replicated the conformity effect (as expected) but added that the level of conformity was actually positively correlated with the novelty of the ideas that were generated (as would have been predicted based on the 2015 meta-analysis from Sio et al.).

George and colleagues (2019) state that, although examples can help support the novelty of ideas, their experiments' results cannot definitively conclude that this is the case for all conditions. The current set of dissertation experiments intends to consider executive function as a factor that may moderate the relation between conformity and creativity.

Executive Function

Broadly, "executive function" (EF) describes higher-order thinking, which allows people to do things like regulate thoughts and behavior, make plans, attend to specific information, and ignore other information. Research generally supports three "core" executive functions (Friedman & Miyake, 2017; Miyake & Friedman, 2012): updating, inhibition, and shifting.

Updating refers to the process of monitoring and coding incoming information and altering (updating) memory as appropriate based on the new information. Although intimately related to memory more broadly, the updating skill, sometimes called working memory (WM), distinguishes itself from memory in that its focus is not the storage of information but rather its active manipulation.

Of the three core executive functions, inhibition can feel like the broadest term. In the literature, it can refer to selective attention (e.g., Neill et al., 1995), cognitive inhibition (e.g., Aron, 2007), or behavioral inhibition (e.g., Barkley, 1997). Selective attention describes the ability to resist proactive interference or interference from distractors. Cognitive inhibition refers to the ability to prevent prepotent responses or overlearned behavior. Relatedly, behavioral inhibition is essentially self-control.

Shifting, or cognitive flexibility, refers to the ability to switch between tasks or mental sets (Monsell, 1996). It may look like the ability to apply particular rules under certain conditions, imagine viewing an object from a different spatial perspective, or even take someone else's perspective in an argument. To accomplish any of these tasks, a person needs to be able to deactivate or inhibit the mental set or perspective that is currently active and initiate the mental set or perspective that is most applicable for the moment. In this way, the shifting ability builds on the other two components of executive function, updating and inhibition. Shifting can be difficult due to attentional inertia, or a tendency to attend to what was previously relevant.

Although the three core EFs are frequently differentiated at an abstract level, it is difficult to differentiate between them in practice. Some have proposed that this is a function of the task impurity problem – any task we would use to measure an EF necessarily relies on other skills unrelated to the factor of interest. For example, the Stroop task is commonly cited as a measure of inhibition. In this task, participants are shown a color-name (e.g., RED). That color-name is sometimes shown in a corresponding color ink (red), and sometimes shown in a different color ink (blue). Participants are tasked with saying the color of the ink (blue) (not the color-name, RED). Thus, they need to inhibit the prepotent response (which, here, is reading the word that is written).

Aside from the inhibition that is theoretically being tapped by the Stroop task, other things go along with successfully completing the Stroop task. Reading, color vision, and motor response time are all obvious candidates for other factors involved in this process, none of which are what we are interested in when we administer this task. The Stroop task might also rely on other executive functions, like updating to keep track of the goal of the task and switching to flexibly respond as appropriate.

Researchers have developed ways to attempt to get around this task impurity problem, for example by including a separate task that asks participants to read color-names written in black ink. The time it takes participants to do that simpler version of the task can then be used as a statistical control for the more complicated task. This is, however, a less-than-perfect solution, and problems like this are common in the executive function literature.

Another reason for the struggle to differentiate between EFs is that the EFs seem to rely on and work with each other. Miyake and Friedman have put forth an influential model for EF, referred to as the Unity/Diversity Framework (summarized nicely in Miyake & Friedman, 2012). The framework proposes that EFs are correlated but separable (showing unity and diversity). This results in a factor that explains whatever abilities are involved across all EFs (Common EF), as well as EF-specific factors (Updating-specific, Shifting-specific). However, Miyake and Friedman note that they failed to find evidence of an Inhibition-specific factor, and suggest that inhibition is entirely subsumed by the Common EF factor.

Executive Function and Creativity

As a prime example of higher-order thinking, it is reasonable to predict that executive functions are involved in creativity. A substantial literature tries to explain the relation between the various EFs (generally focusing on the core EFs) and creativity. As a whole, the pattern is inconclusive.

Some literature points to higher inhibition being linked to higher creativity (Benedek et al., 2014). Camarda et al. (2018) experimentally manipulated inhibition with the help of a dual task (Stroop task) that participants completed while they generated ideas to help stop an egg from breaking when dropped. Results indicated that, relative to participants in the easy, low-inhibition-draining condition, participants in the more difficult, high-inhibition-draining condition performed worse on the creative thinking task in terms of fluency and ability to generate ideas other than the common ideas (they generated more restrictive ideas than expansive ideas, to use the parlance of Agogué, Kazakçi, et al., 2014). Thus, a positive relation between inhibition and creativity was observed, in that participants who were allocating a substantial portion of their inhibitory capacity to the dual task performed worse than participants who had access to their full inhibition. A review paper from Cassotti, Agogué, et al. (2016) concluded that inhibition is positively related to creativity in that it facilitates the ability to resist fixation effects.

However, other literature has found that lower inhibition may be faciliatory of creative thinking (e.g., Veraksa et al., 2022). For example, Radel et al. (2015) experimentally manipulated inhibition by exhausting EF with a prolonged experience with the Simon and/ or Flanker tasks. Participants then completed the AUT. The participants in the high-inhibition-involved condition performed better on the fluency and flexibility aspects of the AUT than those in the low-inhibition-involved condition. Importantly, they also reported improved originality of ideas from participants in the high-inhibition-involved condition relative to the low-inhibition-involved condition.

One study examined the role of Shifting in divergent-thinking tasks and found it to be associated with higher creativity (Veraksa et al., 2022), while Pan & Yu (2018) reported that Shifting was not predictive of originality.

Executive Function & Creativity/ Fixation/ Examples

There is reason to think that the relation between executive function and creativity may depend on particular features of the task, like whether some element of fixation is involved. Empirically, fixation is often operationalized by giving participants examples of ideas to induce mental fixation, and then asking participants to generate their own ideas.

Abraham et al. (2006) gave participants a series of creativity tasks like the alien creature task (Ward, 1994), the toy design task (Smith et al., 1993), a creative imagery task (Finke, 1990), and the alternative uses task (Guilford, 1968; Wallach & Kogan, 1965). One of these tasks, the recently activated knowledge task from Smith et al. (1993), used examples. This was also the only task on which participants with ADHD (n = 11) outperformed non-ADHD comparison participants (n = 21). This pattern might suggest that a lower level of executive function (executive dysfunction is theorized to be a core deficit in ADHD; Barkley, 1997) may be conducive to performance on tasks where examples are employed or where a specific element of mental fixation needs to be overcome. Another study reported that 40% of their sample of creative children (measured to be at least in the 90^{th} percentile on the Torrance Test of Creative Thinking; Torrance, 1998) showed elevated but subclinical levels of symptoms associated with ADHD, a rate that is substantially higher than that of the general population (Healey & Rucklidge, 2006).

The Current Dissertation

In this experiment, participants completed a series of creative thinking tasks and a battery of executive function tasks. Each creative thinking task had two versions for a participant to complete: one to be completed after being exposed to examples of ideas and one to be completed without examples. We then compared the role of executive function in creative thinking when examples were and were not involved.

The current study drew inspiration from the results demonstrated by Abraham et al. (2006). Executive dysfunction is theorized to be a core deficit associated with ADHD (Barkley, 1997), making ADHD a compelling context in which to consider the role of executive function. Abraham et al. compared performance on various creative thinking tasks between participants with ADHD and participants without ADHD. One task, the toy design task, included an aspect of recently activated knowledge in the form of examples. The other tasks did not include examples in any form. The toy design task was also the only task for which participants with ADHD outperformed participants without ADHD. It is reasonable to conclude that executive dysfunction may contribute to creativity when examples are involved and there is fixation to be overcome, but not necessarily when examples are not involved. For example, it is possible that lowered inhibition or switching helps participants take advantage of the examples to use Combination as a strategy. Thus, this dissertation proposes that the relation between executive function and creativity is moderated by the presence of recently activated knowledge in the form of examples. This dissertation will examine whether the nature of the relation between executive function and creativity differs depending on whether examples are involved.

We considered creativity at the latent variable level, administering five creative thinking tasks in each condition, to construct a latent variable for creativity with examples and a separate latent variable for creativity without examples. Treating creativity at a latent variable level allowed us to capture a more generalizable underlying essence of creativity in the two conditions in a way that is separate from creativity at a task-specific level. We wanted to make conclusions about creativity with and without examples, not about, for example, creativity in the AUT. For examples of other studies that have considered creativity at the latent variable level, see Benedek et al. (2012), Dygert & Jarosz (2020), Jauk et al. (2014), Lee & Therriault (2013). That being said, we did also analyze our data as observed variables by simply averaging performance across tasks within a condition. This approach, of analyzing data in two ways, provided the most flexibility to capture whatever differences were available to be observed.

Results from this study stand to provide more generalizable information about the relation between EF and creativity when examples are not involved, thanks to the latent variable approach that includes a variety of EF tasks and creativity tasks. Results also stand to indicate if this relation is different when examples are involved, which is particularly important since that is often the context in which we think creatively in our daily lives. Creativity is a higher-order type of cognition, and to suggest that its relationship with EF is the same regardless of conditions like mental fixation seems unlikely. Involving examples in the creative thinking process should alter the role that EFs play. For example, people with high EF may be skilled at inhibiting the unhelpful features of the example, maintaining in memory the goal of generating a creative idea, switching flexibly from feature to feature or combination to combination, adjusting their mental picture of the idea with each new addition or modification, etc. People with low EF may be more likely to fixate on less helpful features of the example, lose track of the goal, be unable to hold and manipulate many features or combinations in mind at a time, etc. On the other hand, if strategies like Combination facilitate creativity, then perhaps it would be beneficial for EFs to be *lowered*, so as to not inhibit features of examples that might be useful for Combinations or switch too far from the example prematurely. For this reason, EF may moderate the relation between conformity and creativity, and the direction of the effect helps to extrapolate strategies that support creativity in the face of examples and individual differences in using those strategies.

Even if the role of EF in creativity is shown to be the same between conditions, this is still informative from an applied and theoretical standpoint. For example, if this were the case, then it might suggest that the results demonstrated by Abraham et al. (2006) had some other factor associated with ADHD (other than executive dysfunction) as the source of the difference in performance between the Toy Design task (including examples) and the other tasks (without examples). EF may predict creativity in the same direction and to the same extent regardless of whether examples are included. If increased EF predicts increased creativity in both conditions, then this might suggest that EF facilitates the ability to adjust flexibly to changing task requirements and allocate cognitive resources accordingly. The idea of variable or flexible attention in creativity has a fair amount of support in the literature (Vartanian, 2009; Zabelina et al., 2016; Zabelina & Robinson, 2010), and failing to find evidence of a significant difference in this experiment may be considered evidence consistent with this theory.

Method

Participants

Published work on individual differences in executive function and creativity (Benedek et al., 2012; Dygert & Jarosz, 2020; Jauk et al., 2014; Lee & Therriault, 2013) ranges in sample size from approximately 100 participants to 300 participants. Using the main analysis (EF predicting Creativity differently depending on Condition) as a guide, a power analysis indicated 193 participants would be sufficient to detect a small effect (0.20) with 80% power and a 5% chance of a Type I error.

Anticipating that we would lose participants for one reason or another, we elected to overshoot the number of participants recommended by the power analysis, choosing to collect data through the end of the quarter in which data collection was taking place. Thus, a total of 241 undergraduate students at the University of California, Santa Cruz took part in the study for partial course credit. After removing participants identified as outliers on one or more of the executive function tasks (N = 8) and participants who did not complete the study (N = 14), the final sample consisted of 219 participants.

Design

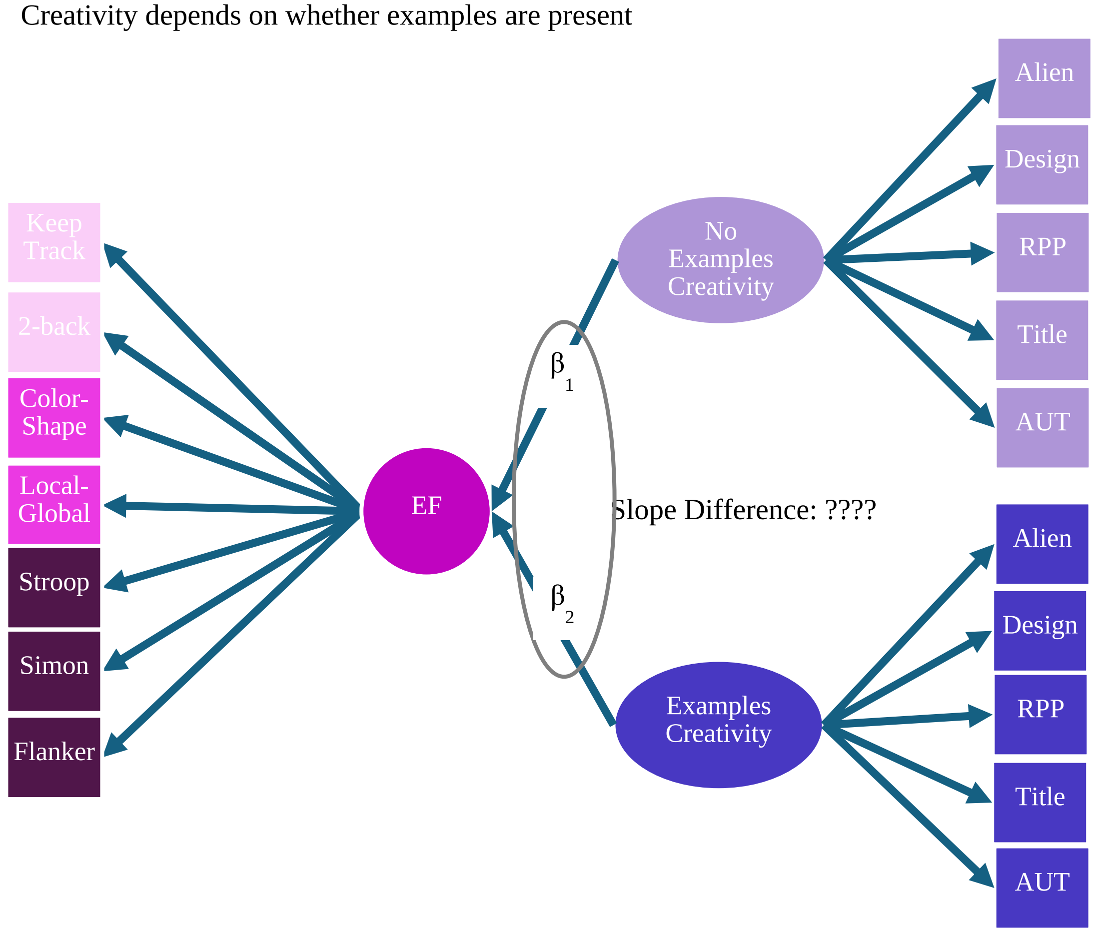
Primary Analyses

The proposed model is shown in Figure 1. The latent variable model was constructed with the *lavaan* package of R (*lavaan* code included in Appendix C;

SPSS script included in Appendix D). Condition was manipulated within-subjects. Participants completed: (a) a battery of creative thinking tasks with examples of ideas (Examples condition), (b) a battery of creative thinking tasks without examples (No Examples condition), and (c) a battery of executive function tasks. The key question is whether executive function (EF) predicts creativity differently depending on whether examples are presented. The two creativity variables and the EF variable were treated both as latent variables and observed variables.

Figure 1

The key model being estimated, considering whether the relation between EF and Creativity depends on whether examples are present



Manipulated/ Moderating Variable. Each of the five creativity tasks had two versions, one that included examples and one that did not include examples. For example, a given participant may have completed the AUT for the object *brick* with examples and for the object *paperclip* without examples. Another participant may have done the reverse, completing *brick* without examples and *paperclip* with examples. All participants completed all five tasks in both conditions.

Dependent Variables. A team of six undergraduate students rated creativity for all tasks. Each independent rater would rate the ~723 ideas (3 ideas from 241 participants) for a particular task (e.g., the AUT). First, a rater would look at the first idea (e.g., build a house) and use that as a starting point. Then, they would consider whether the next idea (e.g., grind it up and use the dust as pigment) was more or less creative than the other idea. They would put that idea in its proper place and then consider whether the next idea (e.g., painting it and using it as décor) was more or less creative than each of the other two ideas. After placing the ideas in ranked order of increasing creativity, ratings on a scale of 1 (low) to 7 (high) were assigned to all ideas by each rater. This method allows Creativity to be rated in comparison to our own sample rather than in comparison to some amorphous, magical "perfect" level of creativity.

In this way, all six independent raters ranked and rated all of the upwards of 700 ideas that were generated by the sample for a given task. This process was completed for all tasks. For a sense of scale (alongside the deepest appreciation to the undergraduate raters), each of the six raters ultimately ranked and rated ~7,230 ideas

(3 ideas per task for 5 tasks, of which there were 2 versions, for 241 participants).

To construct the latent variables, we calculated an idea score by averaging across the ratings from the 6 raters for a given idea. Then, we constructed a task score by averaging across the 3 idea scores. This task score was then used as the indicator for the Creativity latent variable. This was done for each of the two conditions, giving us a No Examples Creativity latent variable with five indicators and an Examples Creativity latent variable with five indicators.

We also constructed two observed variables (Examples Creativity and No Examples Creativity) by averaging across the task scores (described above) within a condition.

Latent and observed variables were then *z*-scored. The *z*-scored versions of the variables were used for most analyses, as appropriate.

Predictor Variable. Executive Function was treated as a single latent variable defined by performance (*z*-scored) on two tasks associated with Updating, the 2-back task and the Keep Track task, performance on two tasks associated with Switching, the Local-Global task and the Color-Shape task, and performance on three tasks associated with Inhibition, the Flanker task, the Simon Task, and the Stroop Task. 2-back, Local-Global, and Color-Shape were accessed from PsyToolkit (Stoet, 2010, 2017); Keep Track was accessed from Experiment Factory (Sochat, 2018); Flanker, Simon, and Stroop were accessed from the Engle Lab at the Georgia Institute of Technology (Burgoyne et al., 2022).

We also analyzed the individual components of EF, Inhibition, Switching, and

Updating as their own separate latent variables (each with 2 – 3 indicators). We also constructed observed variables for Executive Function (broadly) and Inhibition, Switching, and Updating (separately) by averaging the *z*-scores from the tasks.

Secondary Analyses

The set of Secondary Analyses concerns the possibility of a mediating factor explaining the relation between EF and Creativity. If EF is predictive of Creativity, it may not be the EF itself that drives the effect on Creativity; rather, it may be done through a third variable. We propose that Conformity to examples may fill this role. Suppose we observe a positive correlation between EF and Creativity in our set of Primary Analyses. This effect may be less because *people with higher EF generate ideas that are rated as more Creative than people with lower EF* and more because *people with higher EF are better at using strategies, like Conforming to examples, to support their creativity*.

As in the Primary Analyses, we constructed latent and observed versions of our Conformity-related variables. Ultimately, we had two related measures of Conformity: Critical Features (CFs) and Holistic Conformity (HC).

Our team of 6 undergraduate raters assessed each example that we showed participants to determine features that were “critical” to the identity of the example. These were features that, without which, the example would have lost its identity. After reaching a consensus on the critical features of the examples, the raters then calculated the proportion of CFs that were included for each idea. The six raters’ proportions were then averaged for a given idea, and then that average was averaged for all three ideas within a task and condition. Then, those were averaged across all tasks within a condition, resulting in two observed variables, No Examples CFs and Examples CFs. For the latent variables, the six raters' proportions were averaged across an idea. Then, the averages for the three ideas within a task and condition were averaged to give a single CFs score per task in a given condition. Then, those five averages served as indicators for the two latent variables, No Examples CFs and Examples CFs.

We fully acknowledge that there are many ways in which a participant's generated idea might be similar to our examples, even outside of the CFs. To respond to this, we also included a Holistic Conformity (HC) variable. In this, our six independent raters rated every idea generated by participants on a scale of 1 (low) – 7 (high). Raters were instructed to consider the idea as a whole, in direct comparison to the three examples that the participants were shown. An idea would be rated as a 1 if it did not, to the rater's mind, share anything at all in common with any of the three examples; an idea would be rated as a 7 if it was, to the rater's mind, essentially the same as one of the three examples. These scores were then averaged across raters, and ideas, and tasks (following the same process described for Creativity and CFs) to construct two latent variables, No Examples HC and Examples HC, and two observed variables, No Examples HC and Examples HC.

Finally, we constructed a composite Combined Conformity measure by multiplying the CFs and HC scores to capture both aspects of conformity.

Materials and Procedure

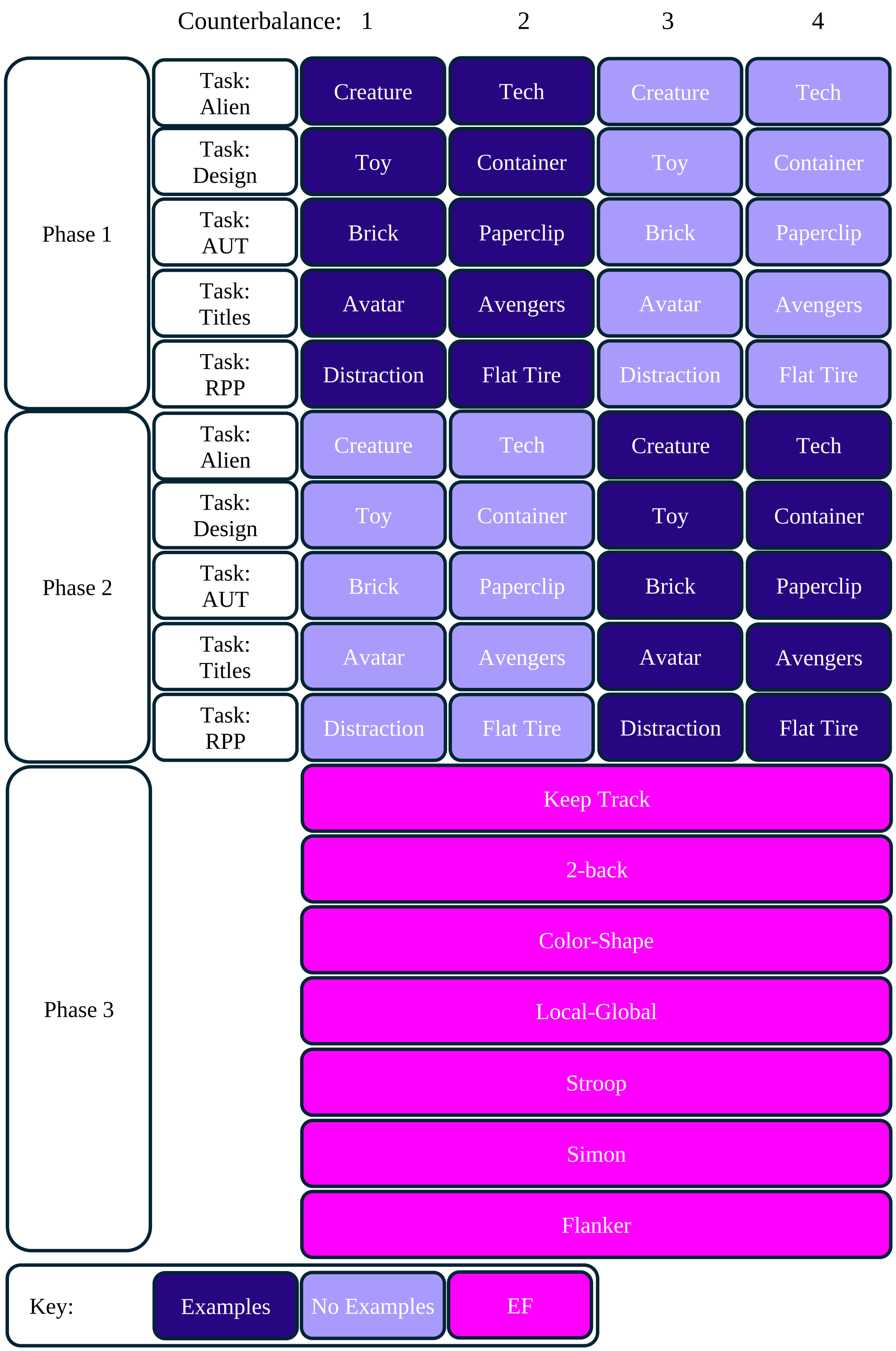
The experiment was completed in 3 Phases (Figure 2).

In Phase 1, participants completed a battery of five creative thinking tasks.

In Phase 2, participants completed a battery of complementary (alternate versions) of the same five creative thinking tasks. The versions of the tasks were designed to ask participants to work toward the same goal but with different details, so that completing one version would not affect performance in the other version. For example, participants generated ideas for a brick (Version 1) and a paperclip (Version 2) in the AUT. Condition (Examples, No Examples) was counterbalanced between Phases, such that half of the participants received Examples in Phase 1 and No Examples in Phase 2, while the other half of the participants received No Examples in Phase 1 and Examples in Phase 2. Additionally, the task's particular version (Version 1, Version 2) was counterbalanced such that the versions were equally likely to be in each Phase and equally likely to be in each Condition.

In Phase 3, participants completed a battery of EF tasks.

Figure 2
Procedure



Executive Function Battery

Two tasks were selected as indicators of Updating, the 2-back task and the Keep Track task. In the 2-back task, participants were shown a series of letters on a computer screen, one after the other, and instructed to hit the “m” key if the current letter matched the letter that was 2 letters ago. In the Keep Track task, participants learn a series of target categories. They were then shown a series of words that included some words from the target categories and some words from other, non-target categories. At the end of each trial, participants wrote down the last exemplar from each of the target categories. In both tasks, performance was operationalized as the proportion of correct responses.

Two tasks were selected as indicators of Switching, the Local-Global task and the Color-Shape task. In the Local-Global task, participants were shown on the computer screen a series of letters that, taken together as a whole percept made up another letter (e.g., a large “L” (global) made up of smaller “S”s (local)). Participants clicked the “b” key if they saw an “H” or an “O” at either the local or global level, and clicked the “n” key if they did not see either an “H” or an “O” at either the local or global level. In the Color-Shape task, participants were told that some trials would be the Color task and some trials would be the Shape task, and that there was a different set of rules for each task. In the Color task, they clicked the “b” key if the stimulus was blue and the “n” key if the stimulus was yellow; In the Shape task, they clicked the “b” key if the stimulus was a circle and the “n” key if the stimulus was a rectangle. In both tasks, performance was operationalized as the difference in response time (for correct answers) between consecutive trials that switched tasks and trials that were the same task.

Three tasks were selected as indicators of Inhibition, the Flanker task, the Simon Task, and the Stroop task. In the Flanker task, participants were shown a series of five arrows, where some combination of those arrows were either pointing left or right. Below that set, there were two smaller sets of five arrows each. Participants were supposed to select whichever small set matched the direction of the small set's outside arrows to the large set's center arrow. In the Simon task, an arrow appeared on the screen, pointing either left or right and either on the left side of the screen or the right side of the screen. Below, were the words "left" and "right", which sometimes switched in terms of which word was on which side. Participants were supposed to select the word the indicated which direction the arrow was pointing. In the Stroop task, participants were shown a color-name in a certain colored ink, which might either correspond to the color-name or not. Below were two other color-name/ word-meaning combinations. Participants were supposed to match the color of the stimulus word with the meaning of the word below. Participants received a point for a correct response and lost a point for an incorrect response. Performance was operationalized as the number of points received in the allotted amount of time.

Creative Thinking Battery

Five creative thinking tasks were included in this battery. These tasks (or variations of these tasks) are commonly used in the literature to study idea generation and divergent thinking. Each participant completed two versions of each task, one with examples and one without examples. Tasks were batched such that all Examples tasks were completed consecutively, and all No Examples tasks were completed consecutively. The order of tasks was held constant within each batch and between participants: Alien, Design, Alternative Uses, Titles, Realistic Presented Problem (Friedman et al., 2008; Zaitchik et al., 2014). Condition and Task Version were counterbalanced between participants such that No Examples and Examples were equally likely to be in Phase 1 or Phase 2, and such that Version 1 and Version 2 were equally likely to be in Phase 1 or Phase 2.

The Alien and Design tasks were on paper and pen to accommodate drawing; all other tasks used a Qualtrics survey.

The two conditions were strongly differentiated to determine if the role of EF depends on whether there is some mental fixation in the form of examples to overcome. To that end, the Examples condition included several examples (Marsh et al., 1996) which were pictorial where appropriate (see Appendix A; Chrysikou et al., 2016). Before beginning data collection, undergraduate and graduate student lab-members were asked to complete the creative thinking tasks. From their ideas, we selected three representative creative examples for both Versions of each Task. This was done to ensure that the examples we showed participants in the study reflected the actual quality of work that the participants themselves may be expected to demonstrate.

For each task, all participants were instructed to be as creative and unusual as possible and to try not to duplicate existing ideas (creatures/ technologies, toys/

beverage containers, uses, titles, or solutions to real-life problems).

If they were in the Examples condition, the writing period was preceded by 30 seconds to examine the examples. The instructions were identical to those in the No Examples condition, except they were also instructed to integrate features from the provided examples into their own ideas.

The instructions for both Versions of all Tasks in both Conditions can be found in Appendix B.

Alien Task. This task was modeled after Ward's (1994) study of structured imagination. The two versions of the task were Alien Creature (Version 1) and Alien Technology (Version 2). Participants were given 6 minutes to imagine, draw, and describe three alien creatures/ technologies that could exist on a planet that is very different from Earth, using a separate page for each.

Design Task. This task was modeled after Smith et al.'s (1993) study of mental fixation. The two versions of the task were Toy (Version 1) and Beverage Container (Version 2). Participants were given 6 minutes to imagine, draw, and describe three new toys/ beverage containers, using a separate page for each.

Alternative Uses Task. This task is a version of the Alternative Uses Task (Guilford, 1957). The two versions of the task were Brick (Version 1) and Paperclip (Version 2). Participants were given 3 minutes to list three alternative uses for a brick/ paperclip.

Titles Task. A version of this task was used by Runco et al. (2016), who adapted in from Guilford (1968). The two versions of the task were Avatar (Version

1) and The Avengers (Version 2). Participants were given 3 minutes to list three alternative titles for Avatar/ The Avengers.

Realistic Presented Problem Task. The Realistic Presented Problem task was used by Runco et al. (2016) and Hao et al. (2017), who adapted it from Runco and Okuda (1988). The two versions of the task were Distraction (Version 1) and Flat Tire (Version 2). Participants were given 3 minutes to list three ideas for ways to solve real-world problems, like if you have a distracting friend preventing you from paying attention in lecture or if you are supposed to meet a friend somewhere but you have a flat tire.

Results

Results are organized by research question, with five primary questions concerning the link between EF and creativity in our two conditions, followed by six secondary questions that introduce the notion of conformity to examples (Conformity Effect; Smith et al., 1993) to the mix. Within each research question, we include analyses of the observed variables followed by the latent variable analyses. Further, within each set of analyses, we include analyses of EF generally, followed by a breakdown of Inhibition, Updating, and Switching, as appropriate. *Lavaan* code can be found in Appendix C; R script can be found in Appendix D. A summary of the results can be found in Table 1, with a more detailed summary (including standardized betas and confidence intervals) can be found in Appendix E.

Table 1

A Review of the Research Questions and a Summary of the Results

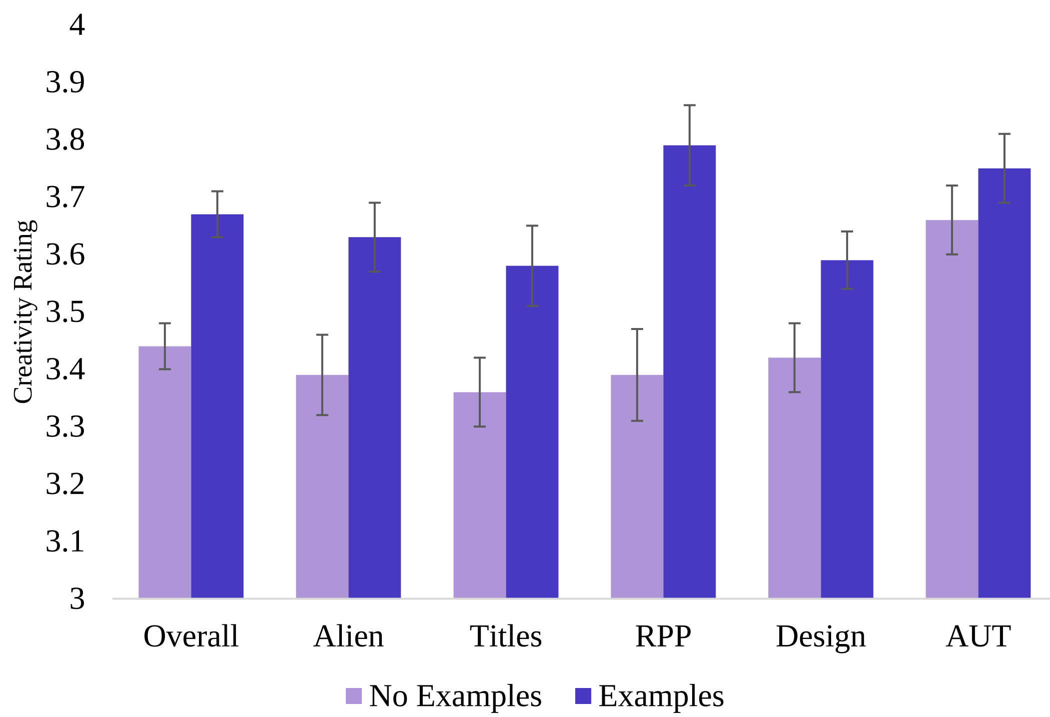
	Research Question	Summary
Primary	Did participants generate ideas that were more creative in the Examples condition than in the No Examples condition?	Yes
	Does EF predict Creativity in the No Examples condition?	Yes, more so for latent variable models than observed variable analyses, and most strongly for Inhibition specifically
	Does EF predict Creativity in the Examples condition?	Inconclusive, but leaning towards "yes"
	Does EF predict Creativity differently in the Examples condition than it does in the No Examples condition?	No evidence to support this
	Does EF predict the improvement in Creativity between the No Examples condition to the Examples condition?	No evidence to support this
Secondary	Was the Conformity Effect demonstrated?	Yes
	Does EF predict Conformity in the No Examples condition (baseline level of Conformity)	Yes
	Does EF predict Conformity in the Examples condition?	No evidence to support this
	Does Conformity predict Creativity in the No Examples condition?	Yes
	Does Conformity predict Creativity in the Examples condition?	No evidence to support this
	Does Conformity mediate the relation between EF and Creativity?	No evidence to support this

Primary Analyses -- Creativity

Did participants generate ideas that were more creative in the Examples condition than in the No Examples condition?

First and foremost, we considered whether participants generated ideas that were rated as more creative when they had access to examples than when they did not have access to examples. A paired samples *t*-test revealed that participants generated ideas that were rated as more creative in the Examples condition (M = 3.67, SE = .04) than in the No Examples condition (M = 3.44, SE = .04), $t(220) = 5.78$, $p < .001$, d = .39 [0.25, 0.53]. As shown in Figure 3, this pattern was consistent for all five creativity tasks, with Cohen's *d*'s ranging from 0.11 [-0.03, 0.25] to 0.36 [0.21, 0.50] (full results in Table 2).

Figure 3
Creativity Ratings Between Conditions, by Task



Note. Error bars represent 2 SE.

Table 2

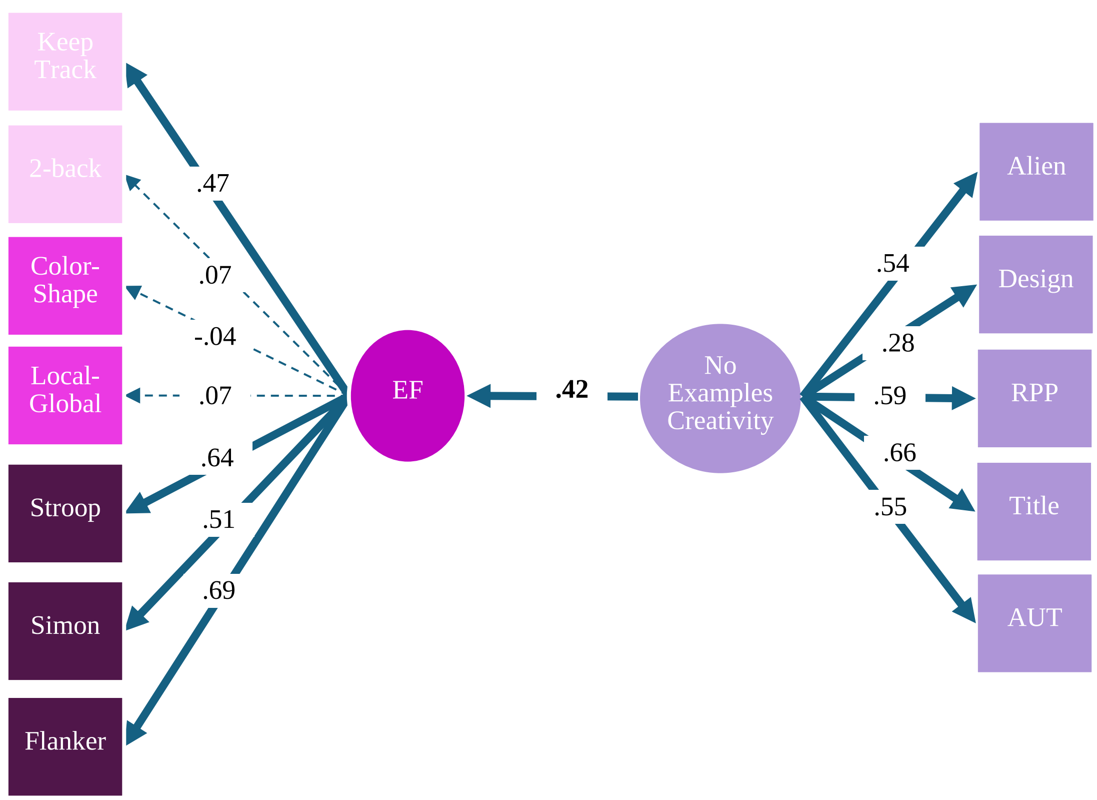
Paired Samples T-test Results Comparing Creativity Ratings between Conditions, by Task

	No Examples	Examples				
Task	***M(SE)***	***M(SE)***	***t***	***df***	***p***	***d* [95%CI$_d$]**
Overall	3.44 (.04)	3.67 (.04)	5.78	220	< .001	0.39 [0.25, 0.53]
Alien	3.39 (.06)	3.63 (.06)	3.55	219	< .001	0.24 [0.11, 0.37]
Titles	3.36 (.06)	3.58 (.07)	3.03	182	.003	0.22 [0.08, 0.37]
RPP	3.39 (.08)	3.79 (.07)	5.01	197	< .001	0.36 [0.21, 0.50]
Design	3.42 (.06)	3.59 (.05)	2.39	216	.02	0.16 [0.03, 0.30]
AUT	3.66 (.06)	3.75 (.06)	1.50	195	.14	0.11 [-0.03, 0.25]

Does EF predict Creativity in the No Examples condition?

Latent Variables. First, we investigated how EF predicts Creativity in the No Examples condition. The model allowed all paths to be freely estimated, χ^2 (66) = 67.77, p = .08; CFI = .92, RMSEA = .04 (90% CI: .00, .07); SRMR = .07. The model revealed that the EF latent variable significantly predicted the latent variable Creativity, β = 0.42 [0.20, 0.63], p < .001. The base model is shown in Figure 4.

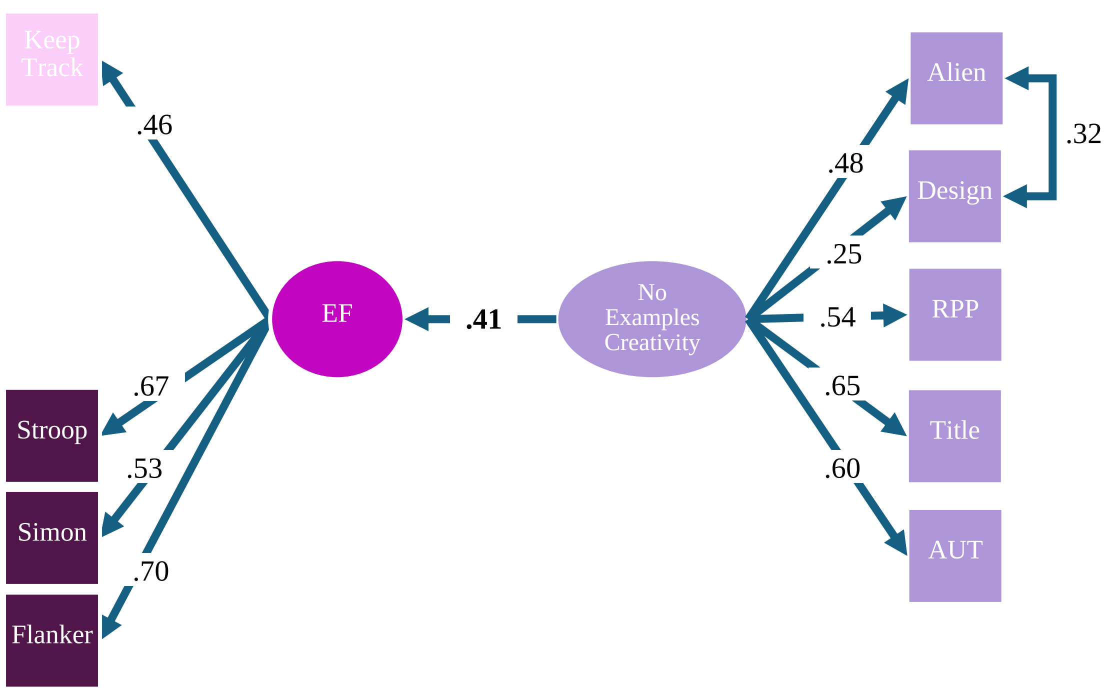
Figure 4
Creativity in the No Examples condition as predicted by EF (base model)



Note. Dashed lines indicate non-significant paths.

Modification indices indicated that the Alien and Design tasks were correlated enough that the overall fit of the model might be improved if we allowed those two tasks to correlate. We also observed that three of the seven EF indicators (2-back, Color-Shape, and Local-Global) were not shown to be significantly related to the overall EF latent variable. If we allowed Alien and Design to correlate, and removed the problematic EF indicators, we expected that the fit of the model might improve. So, we tried this (Figure 5), and the model fit the data well, χ^2 (52) = 58.05, p = .26; CFI = .97, RMSEA = .03 (90% CI: .00, .06); SRMR = .06. The strength of the relation between EF and Creativity was relatively unaffected (although the confidence interval did narrow), β = 0.41 [0.22, 0.60], p < .001.

Figure 5
Creativity in the No Examples condition as predicted by EF (improved model)

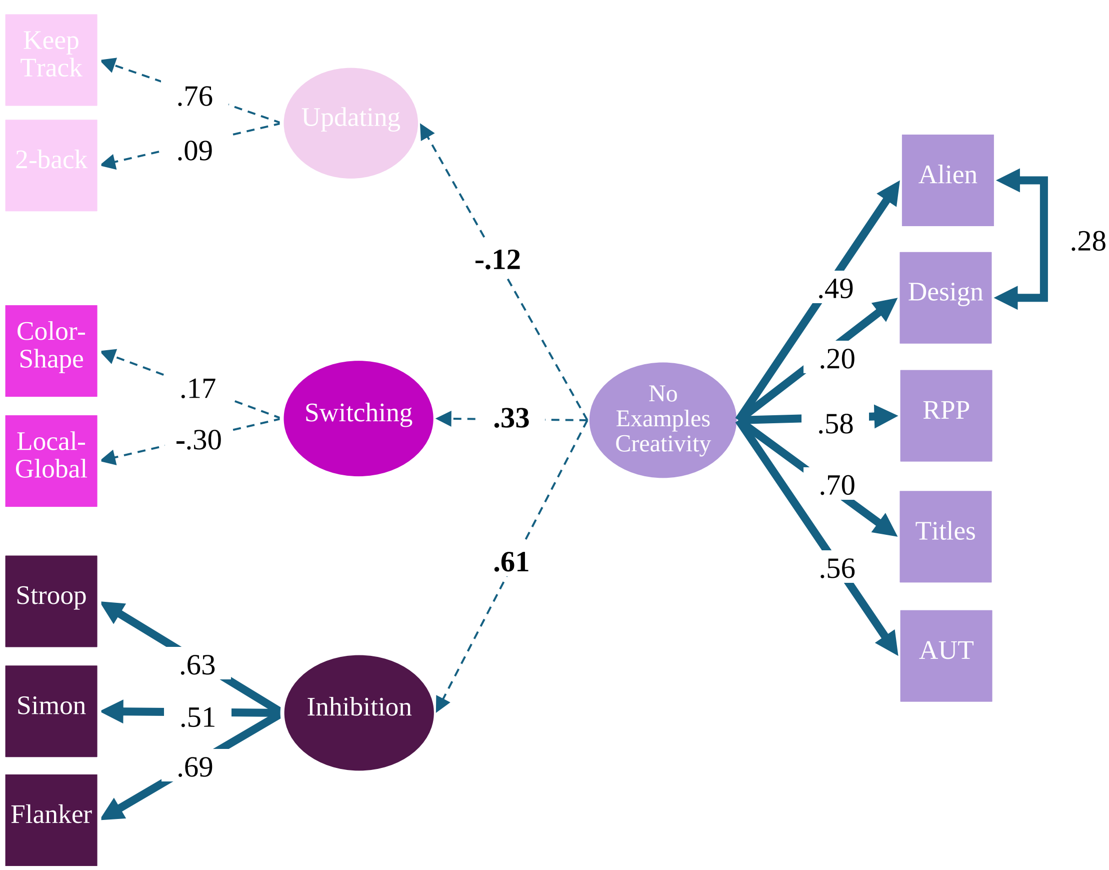


Note. Dashed lines indicate non-significant paths.

We then considered whether Inhibition, Switching, and Updating predicted Creativity, allowing Alien and Design to correlate. The overall model fit well, χ^2 (47) = 56.30, *p* = .17; CFI = .95, RMSEA = .04 (90% CI: .00, .07), SRMR = .06. However, neither Inhibition (β = 0.61 [-0.37, 1.59], nor Switching (β = 0.33 [-0.67, 1.33]), nor Updating (β = -0.12 [-0.93, 0.69]) were shown to significantly predict Creativity (Figure 6).

Figure 6

Creativity in the No Examples condition predicted by Updating, Switching, and Inhibition

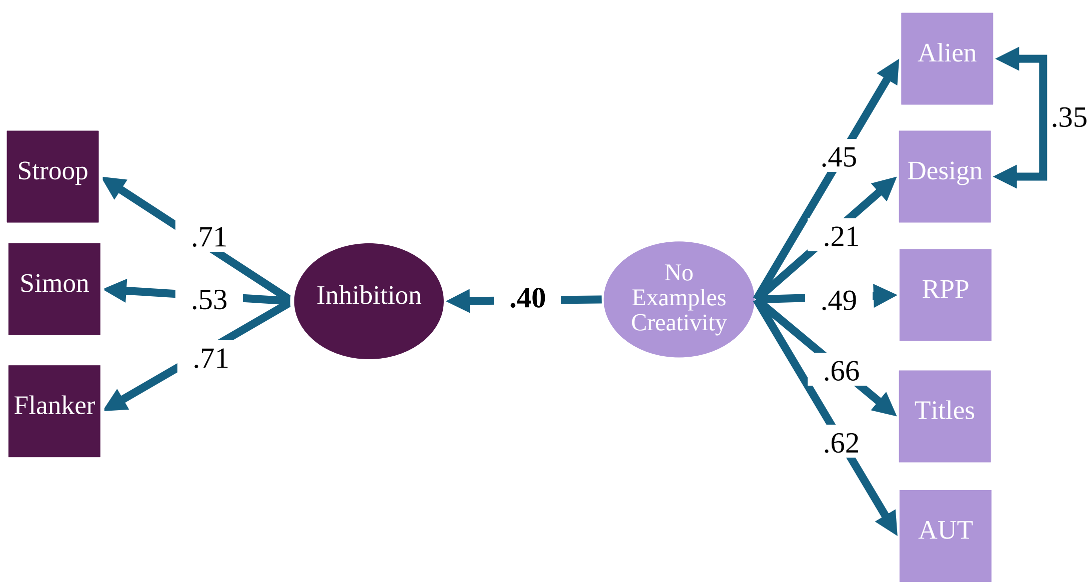


Note. Dashed lines indicate non-significant paths.

However, the indicators for Updating and Switching were not shown to be correlated with their respective latent variables. It was possible that the inclusion of Updating and Switching in the model detracted from the effect of Inhibition. As such, we also ran the regression model with Inhibition entered on its own as a predictor of Creativity, once again allowing Alien and Design to correlate. The model fit well, χ^2 (18) = 22.51, p = .21; CFI = .98, RMSEA = .04 (90% CI: .00, .08); SRMR = .05, and the role of Inhibition in Creativity was shown to be significant, β = 0.40 [0.20, 0.59], p < .001. Figure 7 shows the standardized factor loading and path coefficients of the model.

Figure 7

Creativity in the No Examples condition predicted by Inhibition



Note. Dashed lines indicate non-significant paths.

Observed Variables. A linear regression did not indicate that EF significantly predicted Creativity in the No Examples condition, $R^2 = .01$, $F(1, 163) = 2.00$, $p = .16$, $\beta = -0.11$ [-0.26, 0.04].

To consider whether individual components of EF had differential effects on Creativity, we ran another linear regression, with Inhibition, Switching, and Updating entered into the model at the same time. Results indicated that the model as a whole predicted Creativity, $R^2 = .07$, $F(3, 158) = 4.09$, $p < .01$. This effect was driven only by the contribution from Inhibition, however, with Switching and Updating playing a relatively smaller role. Specifically, Inhibition positively predicted Creativity, $\beta = 0.26$ [0.11, 0.41], $p < .001$; Switching ($\beta = 0.01$ [-0.16, 0.18], $p = .88$) and Updating ($\beta = 0.05$ [-0.10, 0.21], $p = .49$) were not shown to significantly predict Creativity.

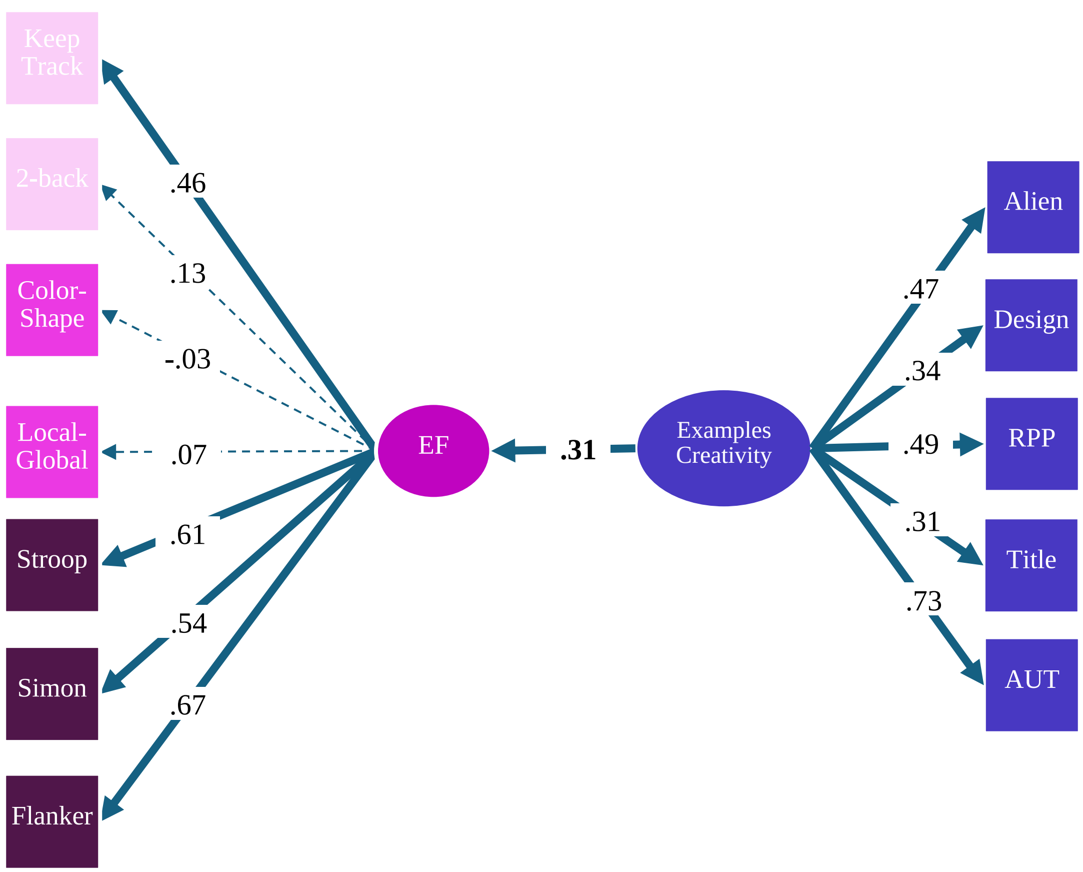
Inhibition was also shown to predict Creativity when it was entered into the model on its own, $R^2 = .04$, $F(1, 212) = 8.03$, $p < .01$, $\beta = 0.19$ [0.06, 0.32].

Does EF predict Creativity in the Examples condition?

Latent Variables. We investigated how EF predicted Creativity in the Examples condition. The model allowed all paths to be freely estimated, and fit the data well: χ^2 (53) = 49.61, *p* = .61; CFI = 1.00, RMSEA = .00 (90% CI: .00, .05); SRMR = .06. The model indicated that EF positively predicted Creativity, β = 0.31 [0.08, 0.54], *p* = .01 (Figure 8).

Figure 8

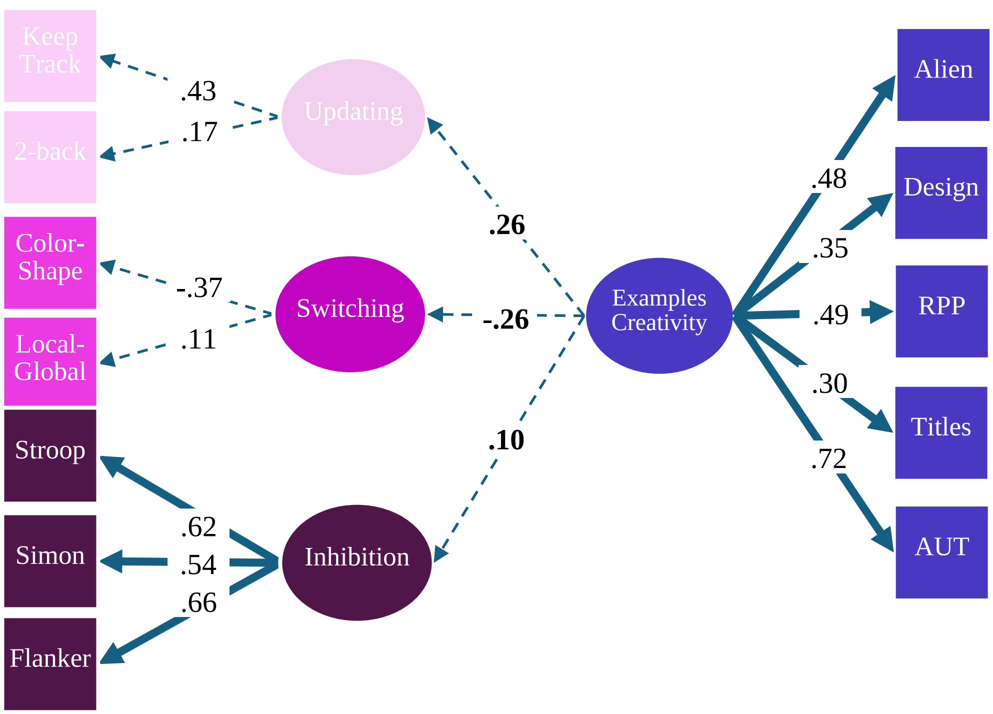
Creativity in the Examples condition predicted by EF (base model)



Note. Dashed lines indicate non-significant paths.

We also considered whether individual components of EF predict Creativity, χ^2 (48) = 45.69, p = .57; CFI = 1.00, RMSEA = .00 (90% CI: .00, .05); SRMR = .05. As shown in Figure 9, the model does not indicate that Inhibition (β = 0.10 [-2.50, 2.69], p= .94), Switching (β = -0.26 [-1.45, 0.94], p = .67), or Updating (β = 0.26 [-2.33, 2.85], p = .84) significantly predicted Creativity.

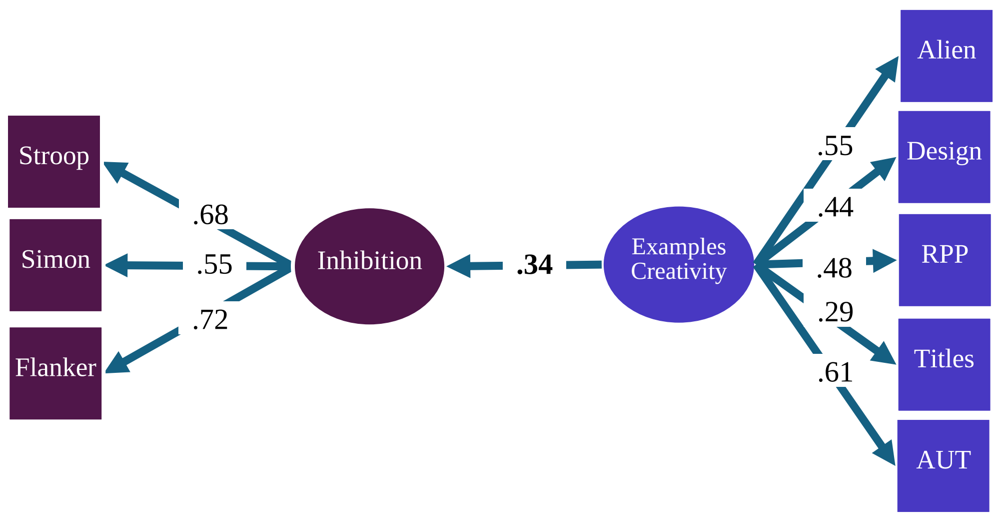
Figure 9
Creativity in the Examples condition predicted by Updating, Switching, and Inhibition



Note. Dashed lines indicate non-significant paths.

However, knowing that the latent variables of Switching and Updating were not particularly strong, based on their indicators, we also ran the model with Inhibition entered on its own as a predictor of Creativity. As shown in Figure 10, the model fit the data well, $\chi^2(19) = 25.67$, $p = .14$; CFI = 0.96, RMSEA = 0.04 (90% CI: 0.00, 0.08), SRMR = .05, and indicated that Inhibition positively predicted Creativity, $\beta = 0.34$ [0.13, 0.54], $p = .001$, when it was the only predictor in the model.

Figure 10
Creativity in the Examples condition predicted by Inhibition



Note. Dashed lines indicate non-significant paths.

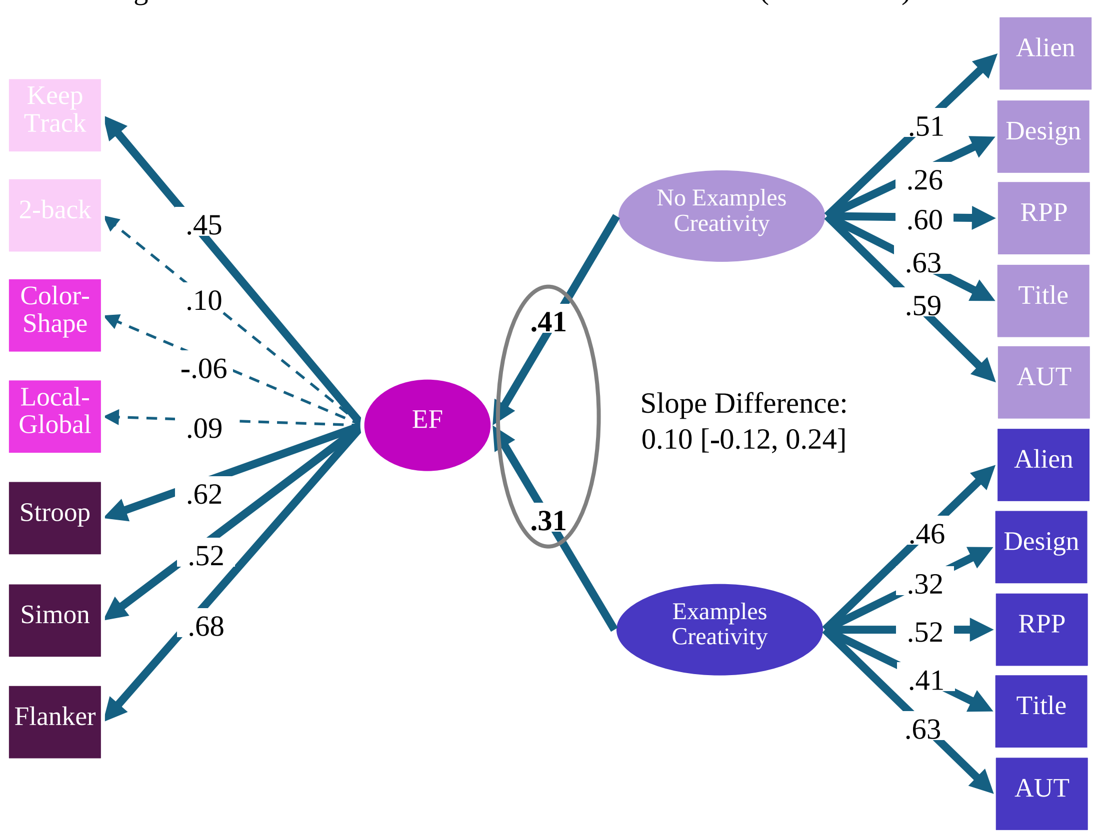
Observed Variables. A linear regression indicated that EF negatively predicted Creativity in the Examples condition, $R^2 = .03$, $F(1, 163) = 4.30$, $p = .04$, $\beta = -0.16$ [-0.31, -0.01]. To consider whether individual components of EF had differential effects on Creativity, we ran another linear regression, with Inhibition, Switching, and Updating entered into the model at the same time. Results did not indicate that the model significantly predicted Creativity, $R^2 = .02$, $F(3, 158) = 1.28$, $p = .28$. Additionally, neither Inhibition ($\beta = 0.08$ [-0.08, 0.23], $p = .35$), nor Switching ($\beta = -0.13$ [-0.31, 0.03], $p = .11$), nor Updating ($\beta = -0.04$ [-0.19, 0.12], $p = .66$) were shown to significantly predict Creativity individually.

Given that we also investigated the role of Inhibition on its own in the set of latent variable analyses, we did the same here. Inhibition was not shown to significantly predict Creativity when it was included in the model on its own, $R^2 = .01$, $F(1, 212) = 2.12$, $p = .15$, $\beta = -0.10$ [-0.04, 0.24].

Does EF predict Creativity differently in the Examples condition than it does in the No Examples condition?

Latent Variables. We investigated whether the role of EF in Creativity was different between conditions. The model allowed all paths to be freely estimated. The original model did not fit the data particularly well, $\chi^2(116) = 165.74$, $p = .002$; CFI = .84, RMSEA = .06 (90% CI: .04, .07); SRMR = .08, but overall did not indicate that the role of EF varied between the No Examples condition (β = 0.41 [0.19, 0.63]) and the Examples condition (β = 0.31 [0.07, 0.56], as the slope difference (shown in Figure 12) was nonsignificant (0.10 [-0.12, 0.32], $p = .37$) (Figure 11).

Figure 11
Estimating the difference in the role of EF between conditions (base model)

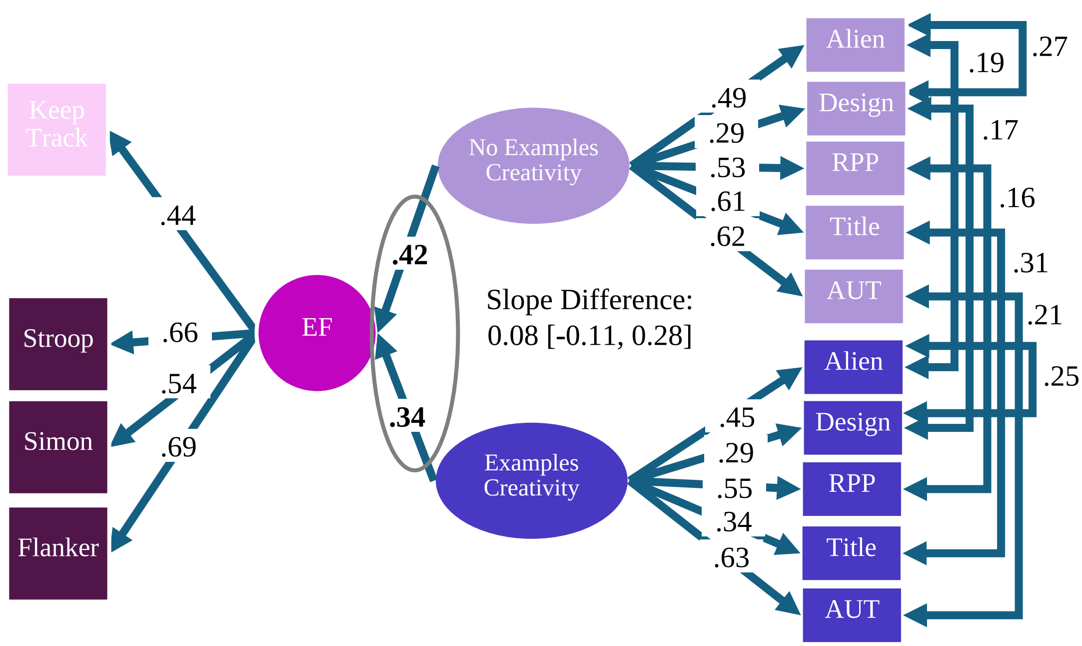


Note. Dashed lines indicate non-significant paths.

Although we suspected that we two slopes were not significantly different from one another, we tried to improve the fit of the model by (1) removing the troublesome EF indicators (2-back, Local-Global, and Color-Shape), (2) allowing performance in the Alien and Design tasks within a condition to correlate, and (3) allowing performance on the two versions of each Creativity task to correlate (e.g., allowing performance on the AUT in the No Examples condition to correlate with performance on the AUT in the Examples condition). This improved the fit, χ^2 (67) = 70.00, p = .38; CFI = .99, RMSEA = .02 (90% CI: .00, .05); SRMR = .05, and further demonstrated that although EF predicted Creativity in both the No Examples condition (β = 0.42 [0.22, 0.62] and the Examples condition (β = 0.34 [0.12, 0.56]), the two slopes were not observed to be significantly different (0.08 [-0.11, 0.28], p = .41) (Figure 12).

Figure 12

Estimating the difference in the role of EF between conditions (improved model)

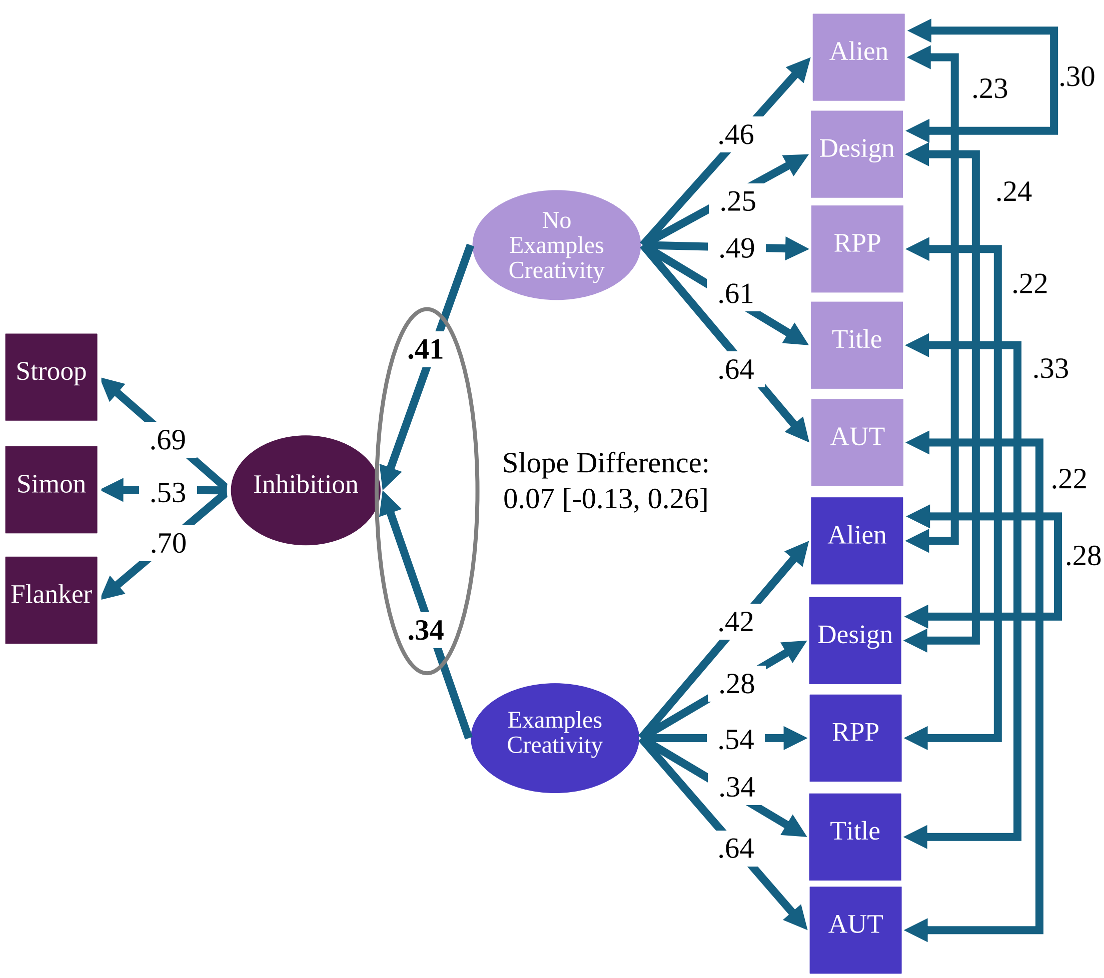


Note. Dashed lines indicate non-significant paths.

A separate model with Inhibition as the sole predictor, allowing tasks between Conditions to correlate, and allowing Alien and Design within a condition to correlate, fit the data well, χ^2 (55) = 61.42, *p* = .26; CFI = .98, RMSEA = 0.03 (90% CI: 0.00, .06); SRMR = .05. This model showed the Inhibition predicted No Examples Creativity (β = 0.41 [0.21, 0.61]) and Examples Creativity (β = 0.34 [0.13, 0.56]). The model did not, however, indicate that the difference between the two slopes was different, 0.07 [-0.13, 0.26], *p* = .51 (Figure 13).

Figure 13

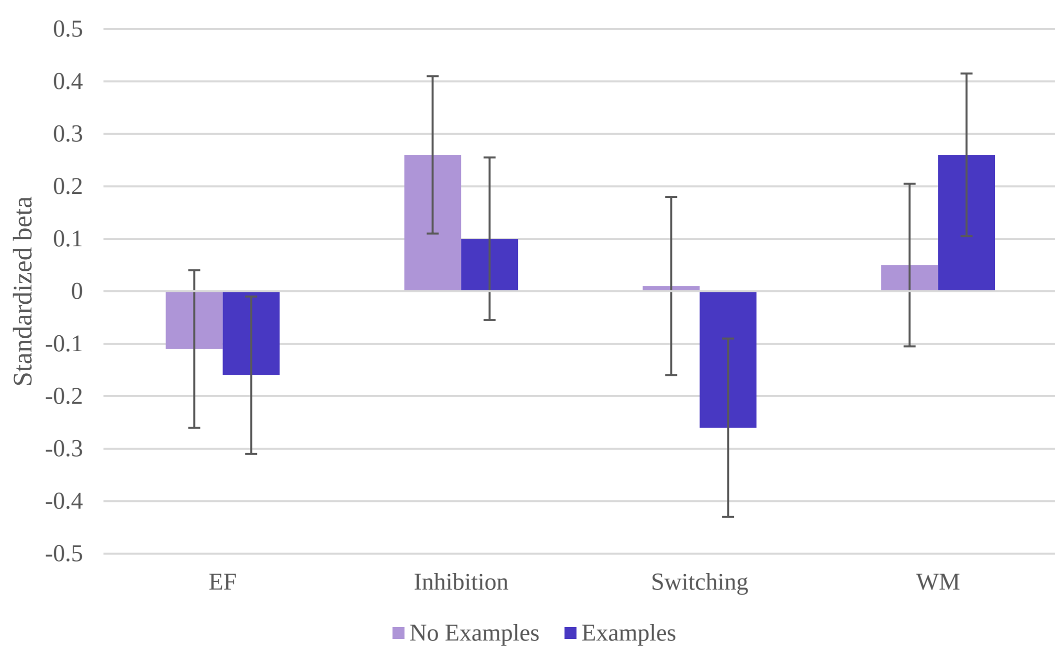
Estimating the difference in the role of Inhibition between conditions



Note. Dashed lines indicate non-significant paths.

Observed Variables. The two linear regressions examining the role of EF on Creativity in the No Examples condition and in the Examples condition indicated that EF significantly predicted Creativity in the Examples condition but failed to demonstrate this in the No Examples condition. The 95% confidence intervals for β were almost completely overlapping between the two conditions, $\beta_{\text{No Examples}}$ = -0.11 [-0.26, 0.04]. and β_{Examples} = -0.16 [-0.31, -0.01], respectively. The individual components of EF – Inhibition, Switching, and Updating – also failed to show clear differences in terms of their impacts on Creativity between conditions. This set of data failed to provide conclusive evidence that the predictive power of EF (or Inhibition, Switching, or Updating) depended on the presence or absence of examples (Figure 14).

Figure 14
Standardized betas for Creativity (observed variables) between EF component, by Condition



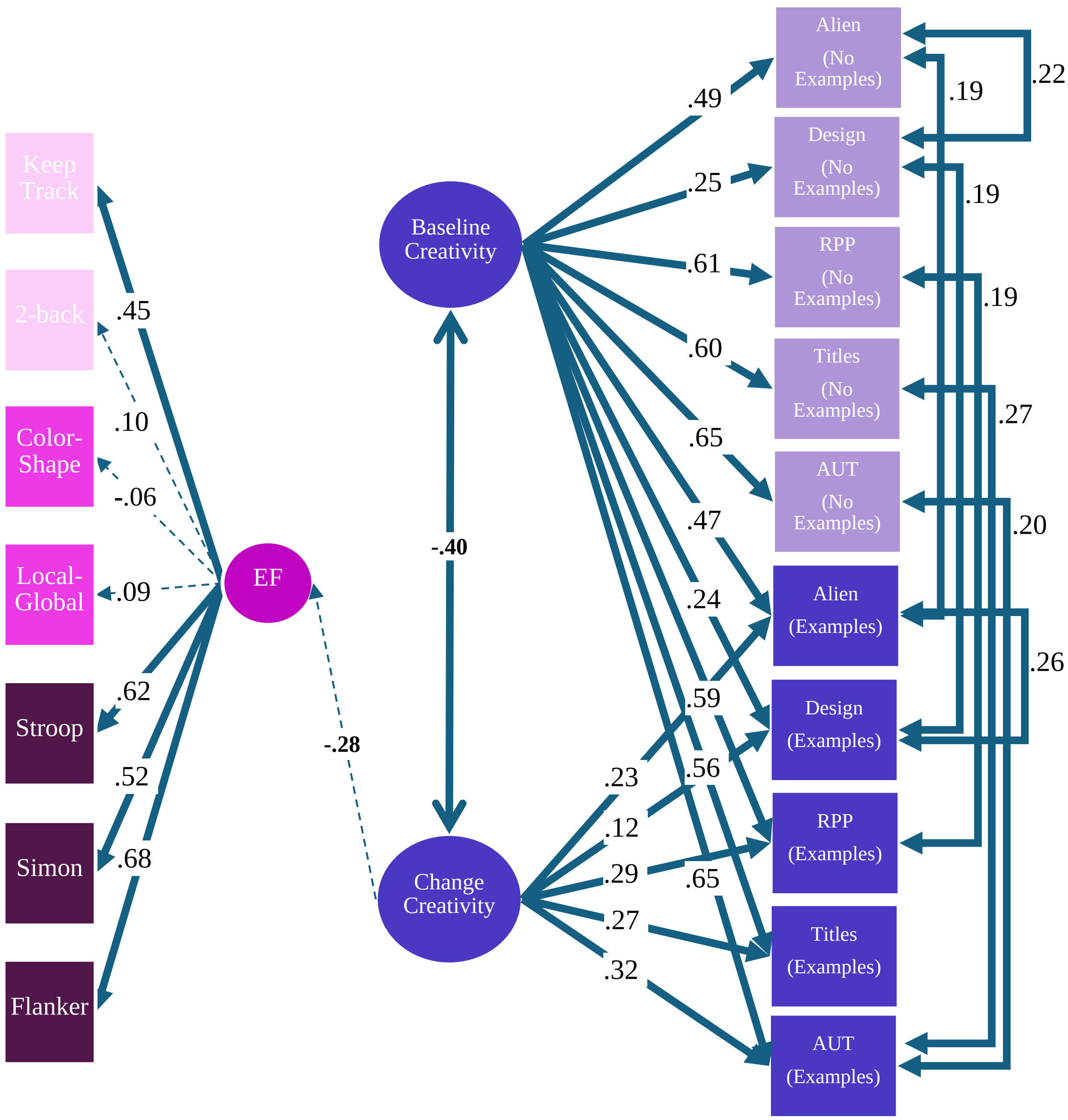
Note. Error bars represent 95% CIs.

Does EF predict the change in Creativity between the No Examples condition to the Examples condition?

Latent Variables. Most participants were more creative in the Examples condition than in the No Examples condition. To ascertain whether the size of the change was predicted by EF, we created a latent change model that included: all seven EF tasks in the latent variable EF, all five creativity tasks in *both* conditions in a Baseline Creativity latent variable, and the five creativity tasks in the Examples condition in a Change Creativity latent variable. The latent Creativity variables were allowed to correlate, as were the Creativity for both tasks between Conditions, as well as the Alien and Design tasks within a condition. We then set the slope for one EF task (Stroop), one No Examples Creativity task, and one Examples Creativity task (Alien task for both) to be equal to 1. The Creativity task slopes were also set to match between the Baseline and Change latent variables. The full change model, including standardized slope coefficients, can be seen in Figure 15. The model fit the data well, $\chi^2(113) = 118.54$, $p = .34$; CFI = .98, RMSEA = .02 (90% CI: .00, .05); SRMR = .07. Notably, although the key path – between EF latent variable and the Change Creativity latent variable – did not reach the level of significance, it was in the expected direction, $\beta = -0.28$ [-0.71, 0.15], p = .20. This directionality (and why we think this direction makes sense) will continue to be explored in the Observed Variables section, below.

Figure 15

Estimating the change in Creativity between Conditions as a function of EF

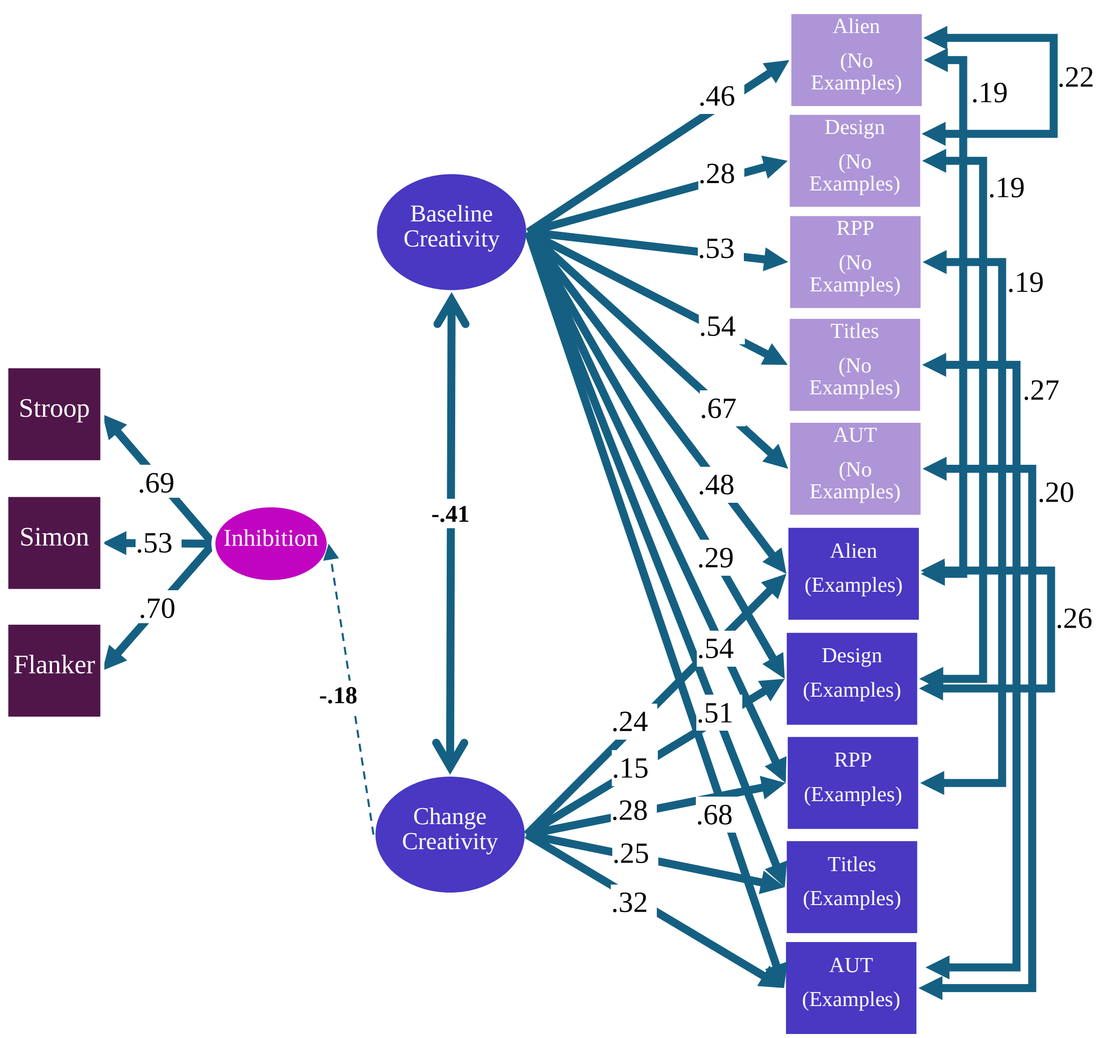


Note. Dashed lines indicate non-significant paths.

We adapted the prior model to investigate the role of Inhibition specifically. The model fit the data well, χ^2 (59) = 67.44, *p* = .21; CFI = .98, RMSEA = .03 (90% CI: .00, .06); SRMR = .06. Although the role of Inhibition was not shown to predict the change in Creativity between conditions, β = -0.18 [-0.57, 0.21], *p* = .36, it was still in the expected direction (Figure 16).

Figure 16

Estimating the change in Creativity between Conditions as a function of Inhibition



Note. Dashed lines indicate non-significant paths.

Observed Variables. To consider whether the size of the change from the No Examples condition to the Examples condition was a function of EF, we ran three linear regressions. The first did not indicate that EF did predicted the size of the change in Creativity from the No Examples condition to the Examples condition, $R^2 = .001$, $F(1, 163) = 0.11$, $p = .74$, β = -0.02 [-0.17, 0.12].

The second regression considered whether individual components of EF had differential effects on the size of the change in Creativity between conditions. In this regression, Inhibition, Switching, and Updating were entered into the model at the same time. Results indicated that the model significantly predicted the size of the change in Creativity between conditions, $R^2 = .07$, $F(3, 158) = 4.24$, $p < .01$. This effect was mostly driven by the role of Inhibition, which significantly negatively predicted the size of the change in Creativity from the No Examples condition to the Examples condition, β = -0.23 [-0.36, -0.07], $p < .01$. That is, higher levels of Inhibition were associated with smaller changes from the No Examples condition to the Examples condition. Switching (β = -0.14 [-0.30, 0.02], $p = .08$) and Updating (β = -0.09 [-0.23, 0.05], $p = .22$) were not shown to predict the change in Creativity from the No Examples condition to the Examples condition (although it may be worth nothing that the effects are all leaning in the negative direction, suggesting that, if anything, these components of EF may all be reflective of a similar underlying pattern, for all that they did not reach the level of significance).

The third regression considered whether Inhibition might be predictive of the change between conditions on its own. Interestingly, although Inhibition was predictive of the change in Creativity between conditions when Updating and Switching were included in the model (above), it did not meet the level of significance when it was the only factor in the model, although the direction was consistent, R^2 = .01, $F(1, 212) = 2.76$, p = .10, β = -0.11 [-0.24, 0.02].

Now let us explore the directionality of the effects hinted at between EF and the size of the difference in Creativity between conditions. Although results did not indicate that EF predicted the size of the change between the No Examples condition and the Examples condition to the level of statistical significance, all analyses trended toward the negative direction, indicating that participants with higher EF showed a smaller improvement. There are a handful of possible ways that the data could fit this pattern, which we will explore more in depth, since that is what really tells us a lot about how EF and examples interact.

One possibility is that participants with higher (High EF) rather than lower levels of EF had a higher starting point for Creativity (here, in the baseline, No Examples condition), so they did not have as much space for improvement as those participants with lower EF (Low EF). This would line up nicely with the findings on the serial order effect from Beaty and Silvia (2012), when they reported that intelligence (highly intertwined with EF) moderated the serial order effect such that participants with higher intelligence showed a smaller effect because they started off at a higher position thana those participants with lower intelligence.

An alternative explanation for the negative direction of the relation between EF and the change in Creativity is that all participants might start off at the same level of Creativity, but Low EF might really shine – even rising above High EF – when there are examples. If, for example, the leaky attention theory of creativity was the key player, then we might expect a pattern like this.

There are certainly other explanations, but let us first examine the data. We ran a repeated measures mixed ANOVA, with Creativity in the No Examples condition and Creativity in the Examples condition as within-subjects variables, and EF (Low, High; median split) as a between-subjects variable (Figure 17A). Results showed a main effect of Condition, where participants generated ideas that were rated as more Creative in the Examples condition (M = 3.68, SE = .04) than in the No Examples condition (M = 3.47, SE = .05), $F(1, 163) = 25.28$, $p < .001$, $\mu_p^2 = .13$. Neither Low EF (M = 3.56, SE = .06) nor High EF (M = 3.60, SE = .06) participants were shown to have generated ideas that were rated as more Creative, $F(1, 163) = 0.23$, $p = .63$, $\mu_p^2 = .001$. There was also no interaction, $F(1, 163) = 1.08$, $p = .30$, $\mu_p^2 = .01$. Numerically, the difference between conditions is smaller for the High EF participants (M = 0.17, SE = 0.06) than for the Low EF participants (M = 0.26, SE = 0.06), but this difference was small (thus, the lack of an interaction).

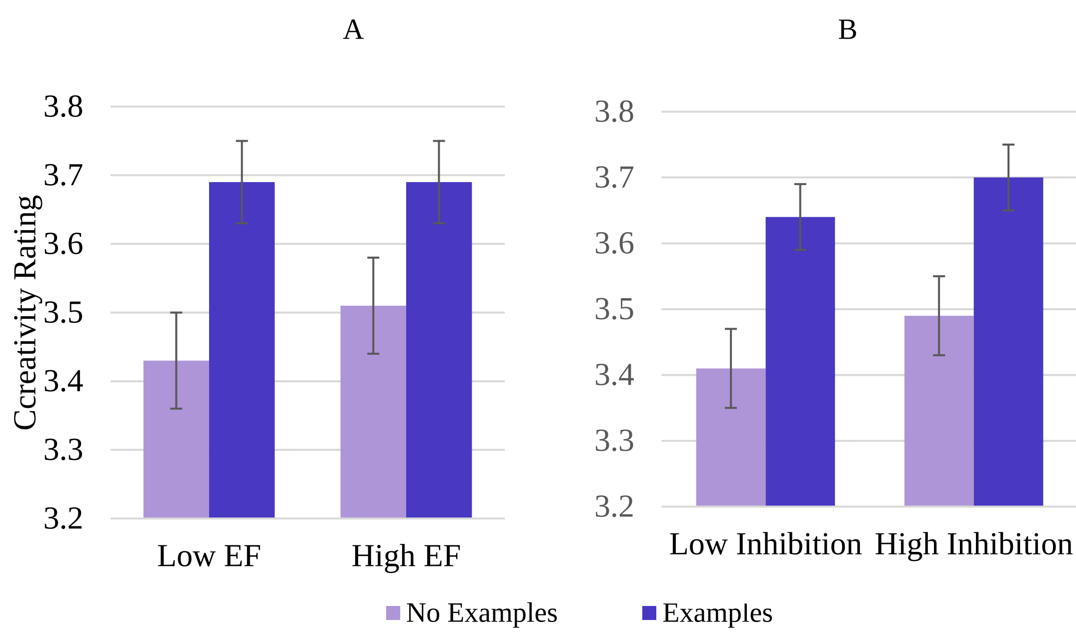
We observed that (1) in the No Examples condition, the High EF participants' ideas (M = 3.51, SE = 0.07) were numerically rated as more Creative than the Low EF participants' ideas (M = 3.43, SE = 0.07), $p = .40$, and (2) in the Examples condition, the High EF participants' ideas (M = 3.69, SE = 0.06) and the Low EF participants' ideas (M = 3.69, SE = 0.06) were rated extremely similarly, $p = .94$. Numerically, these results supported the explanation that participants with higher EF had a higher baseline/ No Examples level of creativity than participants with lower EF, but that the help of Examples helped bring participants with lower EF up to the level of participants with higher EF, almost serving to level the playing field.

We ran the same analysis focusing on Inhibition, since that was the component of EF that has consistently been the strongest in our analyses. Although the broader EF variable did not give an extremely clear explanation of how EF, Creativity, and Examples interact, Inhibition may be a more powerful factor to examine (Figure 17B). Running the analysis, however, we saw essentially the same pattern of results: (1) main effect where ideas generated in the Examples condition (M = 3.67, SE = 0.04) were rated as more Creative than ideas generated in the No Examples condition (M = 3.45, SE = 0.04), $F(1, 212) = 32.07$, $p < .001$, $\mu_p^2 = .13$; (2) no effect of Inhibition group, where ideas generated by participants in the Low Inhibition group (M = 3.52, SE = 0.05) were not shown to be more or less Creative than ideas generated by participants in the High Inhibition group (M = 3.60, SE = 0.05), $F(1, 212) = 1.13$, $p = .29$, $\mu_p^2 = .01$; (3) no interaction between Condition and Inhibition, $F(1, 212) = 0.07$, $p =.79$, $\mu_p^2 =.00$.

The Low Inhibition participants improved from the No Examples condition to the Examples condition, from 3.41 (SE = 0.06) to 3.64 (SE = 0.05); the High Inhibition group showed a relatively smaller improvement, from 3.49 (SE = 0.06) to 3.70 (SE = 0.05). More importantly, we see similarities and small differences from the EF analysis. Similarly, in the No Examples condition the Low Inhibition group generated ideas that were rated as less Creative than the High Inhibition group did.

But whereas in the EF analysis the Low Inhibition and High Inhibition groups were basically identical in the Examples condition, in this analysis on Inhibition, the Low EF group's ideas were rated as slightly less Creative than the High Inhibition group's ideas were.

Figure 17
Creativity between Conditions, by EF (Panel A) and Inhibition (Panel B) (observed)



Note. Error bars represent 2 SE. Panel A shows EF; Panel B shows Inhibition.

It is important to remember that, other than the clear main effect of Condition, any differences that we have noted are numerical only, and non-significant. It is possible that things are muddied by the participants who did not actually show an improvement from No Examples to Examples. Although most participants did show that pattern, not all of them did. Specifically, 69.9% of participants improved from the No Examples condition to the Examples condition. One important question is, "Who are those participants who got better with the help of examples?" A series of ANOVAs did not indicate that the participants who *improved* with examples were different from participants who got *less creative* with examples in terms of Updating ($F(1, 160) = 0.42$, $p = .52$), Switching ($F(1, 160) = 0.09$, $p = .76$), Inhibition ($F(1, 160) = 2.35$, $p = .13$), or overall EF ($F(1, 160) = 0.83$, $p = .36$).

There was one difference between participants who improved with the help of examples and those who did not improve with the help of examples: The participants who improved with the help of examples were more likely to have ideas that *shared similarities* with the examples. We will consider this conforming tendency as a series of secondary analyses in the next section.

Secondary Analyses – Conformity

Was the Conformity effect demonstrated?

First, we considered whether participants were more likely to generate ideas that were similar to the examples in the Examples condition than in the No Examples condition (i.e., replicating the conformity effect). We considered this question with two metrics and one composite measure. First, we calculated the proportion of Critical Features (CFs) that were included in a participant's ideas. Then, we took a more holistic approach to conformity, with a rating of Holistic Conformity (HC) from 1 (low) – 7 (high). Finally, we created a general Conformity variable that included both of these measures of conformity to examples by taking the product of the two scores.

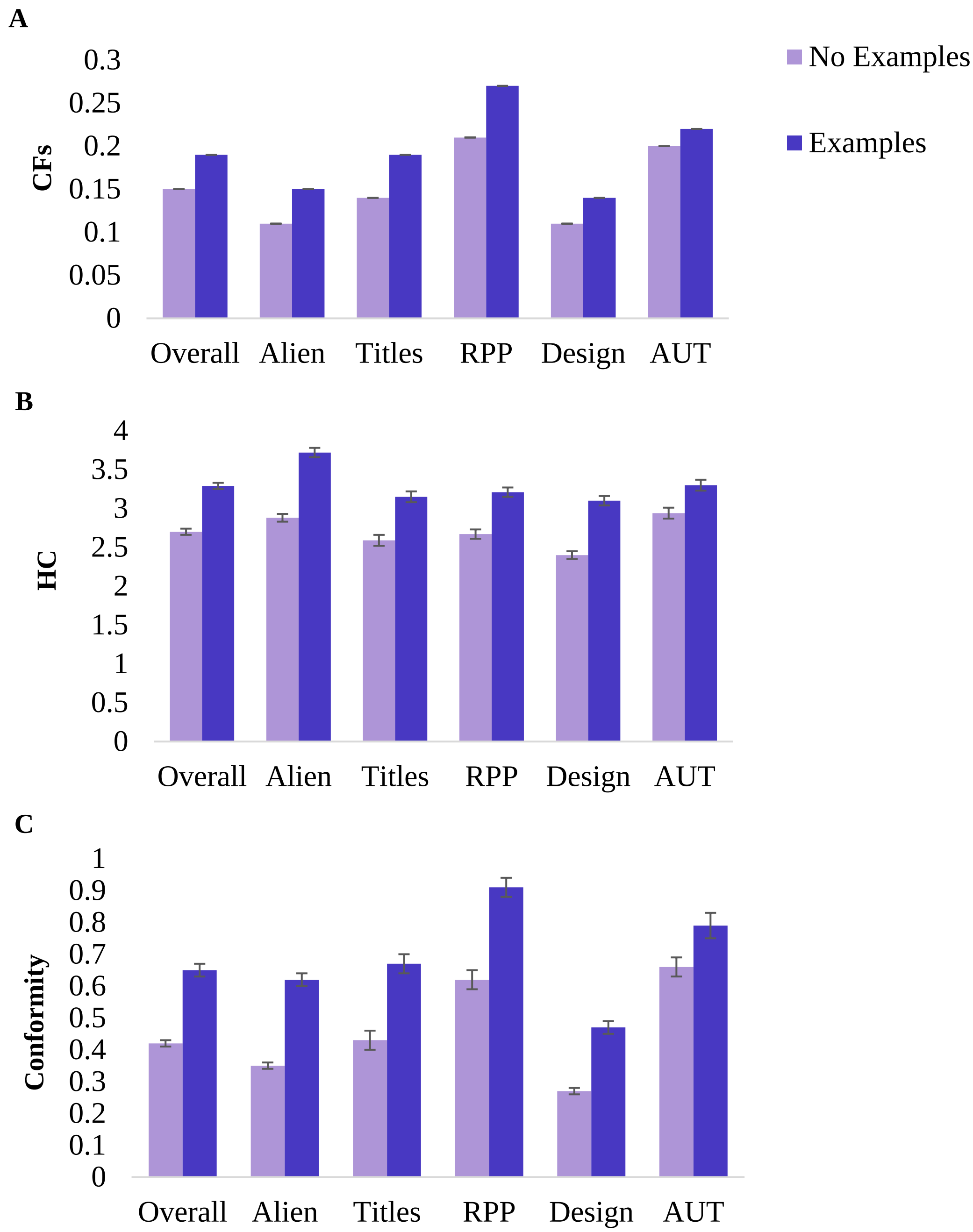
A paired samples *t*-test revealed that participants' ideas did include more CFs in the Examples condition (*M* = .19, *SE* = 0.00) than in the No Examples condition (*M* = .15, *SE* = 0.00), *t*(220) = 10.33, *p* < .001, *d* = 0.70 [0.55, 0.84]. As shown in Figure 18A, this pattern was consistent for all five creativity tasks, with Cohen's *d*'s ranging from 0.16 [0.02, 0.29] to 0.61 [0.47, 0.76].

Another paired samples *t*-test revealed that participants generated ideas that were rated higher on Holistic Conformity in the Examples condition (*M* = 3.29, *SE* = .04) than in the No Examples condition (*M* = 2.70, *SE* = .04), *t*(220) = 11.62, p < .001, *d* = .78 [0.63, 0.93]. This pattern was consistent for all five creativity tasks, with Cohen's *d*'s ranging from 0.25 [0.10, 0.39] to 0.74 [0.59, 0.89] (Figure 18B).

Just to confirm, the third paired samples *t*-test showed that participants generated ideas that were higher on Conformity in the Examples condition (*M* = 0.65, *SE* = .02) than in the No Examples condition (*M* = 0.42, *SE* = .01), *t*(220) = 11.21, *p* < .001, *d* = 0.75 [0.60, 0.90]. As shown in Figure 18C, this pattern was consistent for all five creativity tasks, with Cohen's *d*'s ranging from 0.18 [0.03, 0.32] to 0.68 [0.53, 0.82]. Thus, the conformity effect was supported by both metrics of conformity and the composite variable (shown in Table 3).

Figure 18

Conformity Metrics Between Conditions, by Task



Note. Error bars represent 2 SE. Panel A shows CFs; Panel B shows HC; Panel C shows Conformity.

Table 3

Paired Samples *T*-test Results Comparing CFs, HC, and Conformity Ratings between Conditions, by Task

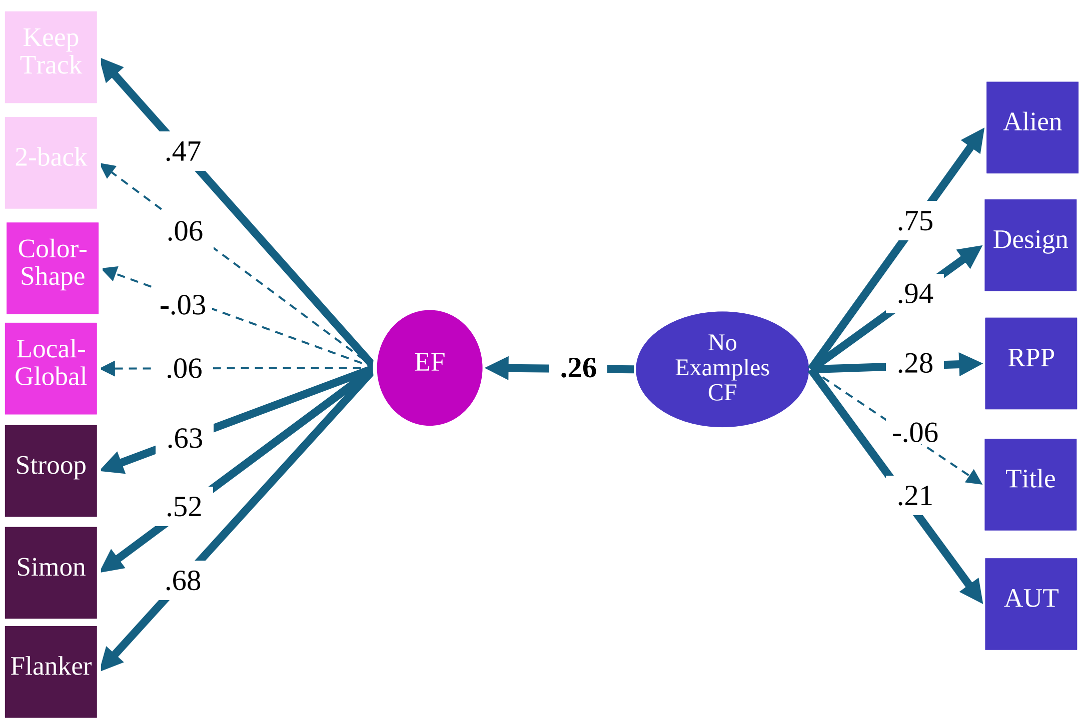
		No Examples	**Examples**				
	Task	***M(SE)***	***M(SE)***	***t***	***df***	***p***	***d* [95%CI$_d$]**
CFs	Overall	.15 (.00)	.19 (.00)	10.33	220	< .001	0.70 [0.55, 0.84]
	Alien	.11 (.00)	.15 (.00)	9.10	220	< .001	0.61 [0.47, 0.76]
	Titles	.14 (.01)	.19 (.01)	5.49	185	< .001	0.40 [0.25, 0.55]
	RPP	.21 (.01)	.27 (.01)	7.29	201	< .001	0.51 [0.36, 0.66]
	Design	.11 (.00)	.14 (.00)	7.49	220	< .001	0.50 [0.36, 0.64]
	AUT	.20 (.01)	.22 (.01)	2.21	199	.01	0.16 [0.02, 0.29]
HC	Overall	2.70 (.03)	3.29 (.04)	11.62	220	< .001	0.78 [0.63, 0.93]
	Alien	2.88 (.05)	3.72 (.06)	11.03	220	< .001	0.74 [0.59, 0.89]
	Titles	2.59 (.07)	3.15 (.07)	5.60	180	< .001	0.42 [0.26, 0.57]
	RPP	2.67 (.06)	3.21 (.06)	6.31	196	< .001	0.45 [0.30, 0.59]
	Design	2.40 (.05)	3.10 (.06)	8.49	217	< .001	0.58 [0.43, 0.72]
	AUT	2.94 (.07)	3.30 (.07)	3.43	194	< .001	0.25 [0.10, 0.39]
Conformity	Overall	0.42 (.01)	0.65 (.02)	11.21	220	< .001	0.75 [0.60, 0.90]
	Alien	0.35 (.01)	0.62 (.02)	10.06	220	< .001	0.68 [0.53, 0.82]
	Titles	0.43 (.03)	0.67 (.03)	5.54	180	< .001	0.41 [0.26, 0.56]
	RPP	0.62 (.03)	0.91 (.03)	6.75	196	< .001	0.48 [0.33, 0.63]
	Design	0.27 (.01)	0.47 (.02)	8.37	217	< .001	0.57 [0.42, 0.71]
	AUT	0.66 (.03)	0.79 (.04)	2.46	195	.01	0.18 [0.03, 0.32]

Does EF predict Conformity in the No Examples condition (baseline level of Conformity)?

CF.

Latent Variables. A model including all seven EF tasks in the EF latent variable and the number of CFs included in the five creativity tasks in the No Examples condition fit the data well, χ^2 (53) = 52.79, p = .48; CFI = 1.00, RMSEA = .00 (90% CI: .00, .05); SRMR = .07. Results indicated that EF positively predicted CFs, β = 0.26 [0.06, 0.46], p = .01 (Figure 19).

Figure 19
CFs in the No Examples condition predicted by EF (base model)

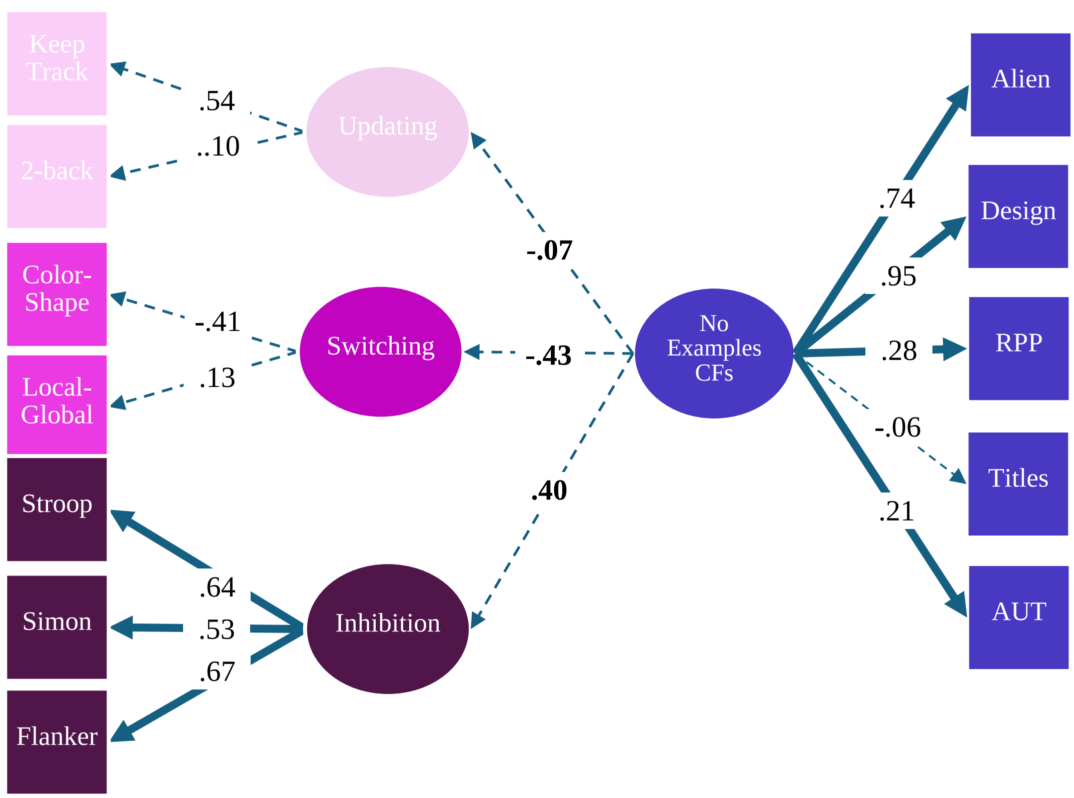


Note. Dashed lines indicate non-significant paths.

We constructed a model with Updating, Switching, and Inhibition as predictors of CFs in the No Examples condition. The model fit the data well, χ^2 (48) = 47.50, p = .49; CFI = 1.00, RMSEA = 0.00 (90% CI: 0.00, 0.05); SRMR = .06. Neither Updating (β = -0.07 [-4.89, 5.75], p = .98), nor Switching (β = -0.43 [-3.11, 2.25], p = .75), nor Inhibition (β = 0.40 [-4.40, 5.19], p = .87) were shown to predict CFs in the No Examples condition (Figure 20).

Figure 20

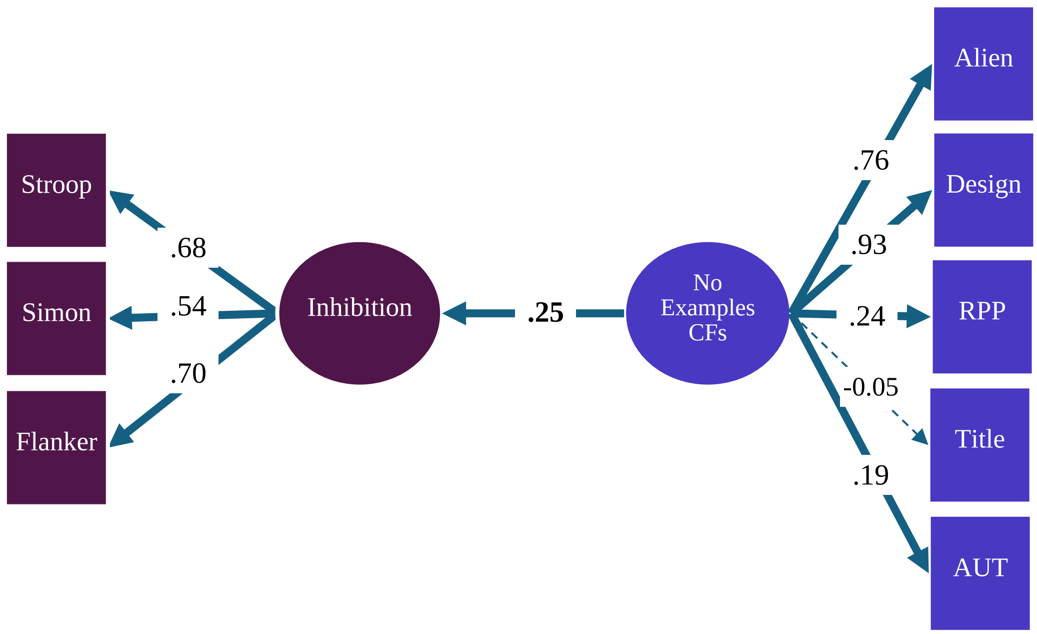
CFs in the No Examples condition predicted by Updating, Switching, and Inhibition



Note. Dashed lines indicate non-significant paths.

We considered the role of Inhibition specifically in CFs. The model fit the data well, χ^2 (19) = 15.48, p = .69; CFI = 1.00, RMSEA = 0.00 (90% CI: 0.00, 0.05); SRMR = .05, and indicated that Inhibition positively predicts CFs, β = 0.25 [0.07, 0.43], p = .01 (Figure 21).

Figure 21
CFs in the No Examples condition predicted by Inhibition



Note. Dashed lines indicate non-significant paths.

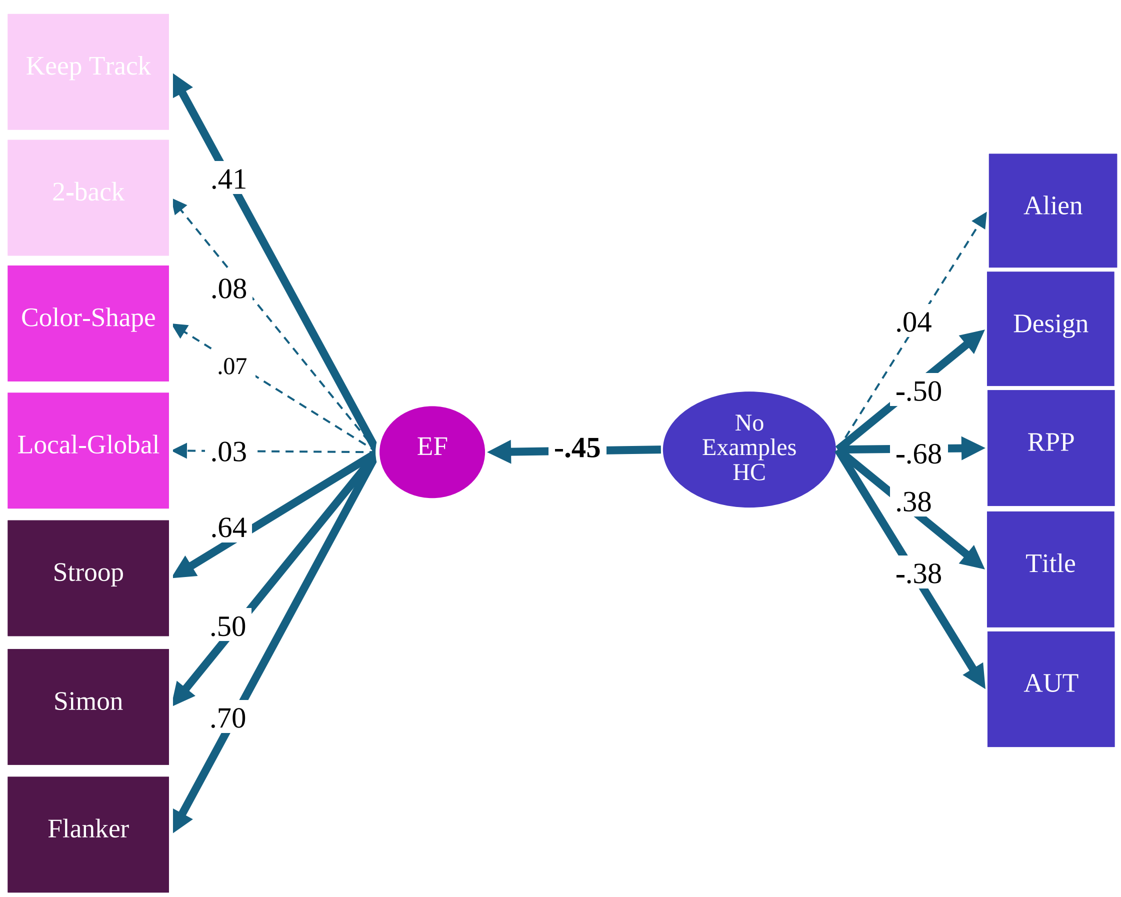
Observed Variables. A linear regression did not indicate that EF predicted CFs in the No Examples condition, R^2 = .00, F(1, 163) = 0.04, p = .84, β = 0.02 [-0.14, 0.17]. To consider whether individual components of EF may have differential effects on CFs, we ran another linear regression, where Inhibition, Switching, and Updating were entered into the model at the same time. Results did not indicate that the model as a whole predicted CFs, R^2 = .04, F(3, 158) = 1.95, p = .12. Inhibition was the only component that was shown to play a predictive role in CFs in the No Examples condition, β = 0.19 [0.03, 0.34], p = .02. Switching was not shown to be predictive of CFs, β = -0.03 [-0.20, 0.15], p = .75), nor was Updating, β = -0.004 [-0.16, 0.15], p = .96.

We also considered the role of Inhibition specifically in CFs by including this as the only predictor in the regression. Doing this, we saw that the relation almost reached the threshold for significance and was positive, R^2 = .02, F(1, 212) = 3.86, p = .051, β = 0.13 [0.00, 0.27].

Holistic Conformity.

Latent Variables. A model including all seven EF tasks in the EF latent variable and the HC ratings from the five creativity tasks in the No Examples condition in the HC latent variable fit the data well, χ^2 (43) = 24.98, p = .99; CFI = 1.00, RMSEA = .00 (90% CI: .00, .00); SRMR = .04. Results indicated that EF negatively predicted HC, β = -0.45 [-0.66, -0.23], p < .001 (Figure 22).

Figure 22
HC in the No Examples condition predicted by EF (base model)

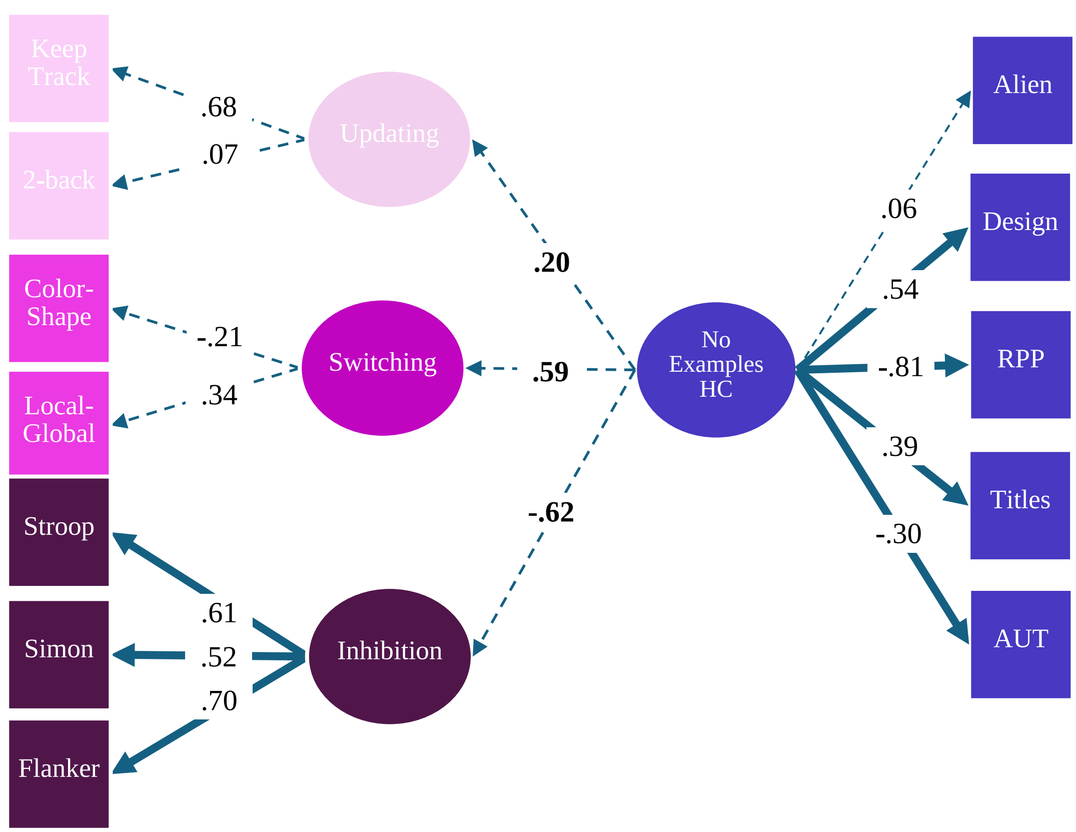


Note. Dashed lines indicate non-significant paths.

We constructed a model with Updating, Switching, and Inhibition as predictors of HC in the No Examples condition. The model fit the data well, χ^2 (48) = 25.69, p = .94; CFI = 1.00, RMSEA = 0.00 (90% CI: 0.00, 0.02); SRMR = .05. Neither Updating (β = 0.20 [-1.52, 1.92], p = .82), nor Switching (β = 0.59 [-0.57, 1.75], p = .32), nor Inhibition (β = -0.62 [-2.40, 1.15], p = .49) were shown to predict HC in the No Examples condition (Figure 23).

Figure 23

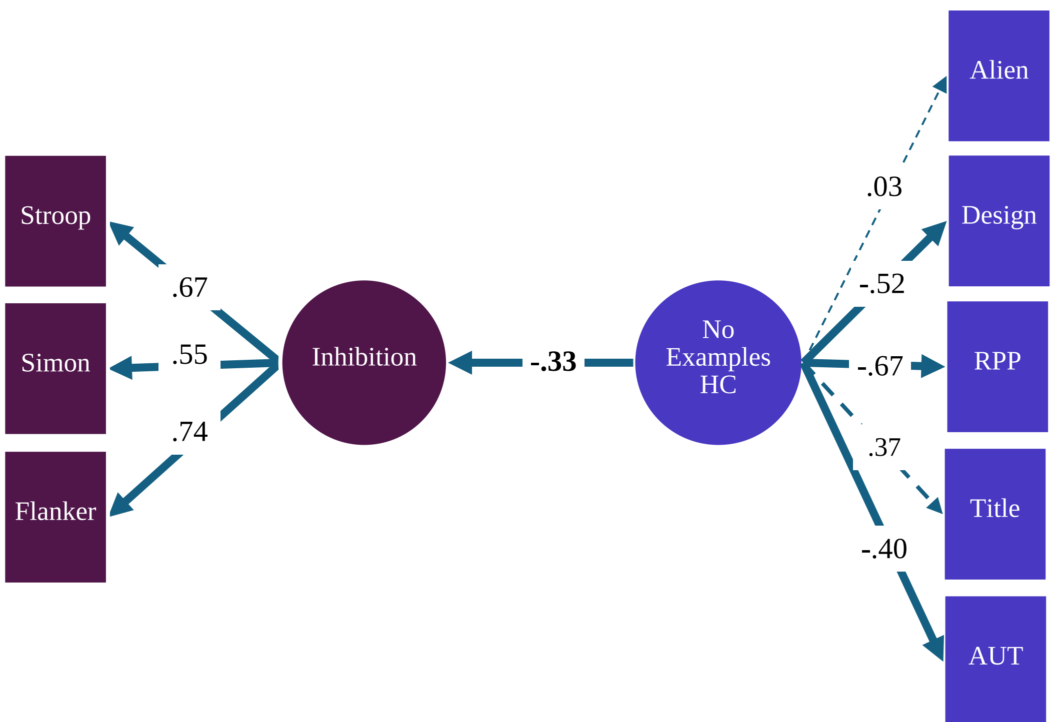
HC in the No Examples condition predicted by Updating, Switching, and Inhibition



Note. Dashed lines indicate non-significant paths.

We constructed a separate model investigating the role of Inhibition in HC ratings. The model fit the data well, χ^2 (19) = 7..57, p = .99; CFI = 1.00, RMSEA = 0.00 (90% CI: 0.00, 0.00); SRMR = .03, and indicated that Inhibition negatively predicted HC, β = -0.33 [-0.54, -0.12], p = .002 (Figure 24).

Figure 24
HC in the No Examples condition predicted by Inhibition



Note. Dashed lines indicate non-significant paths.

Observed Variables. A linear regression did not indicate that EF predicted Holistic Conformity in the No Examples condition, $R^2 = .00$, $F(1, 160) = 0.02$, $p = .89$, β = 0.003 [-0.04, 0.04]. To consider whether individual components of EF may have differential effects on CFs, we ran another linear regression, with Inhibition, Switching, and Updating entered into the model at the same time. Results did not indicate that the model as a whole predicted HC in the No Examples condition, $R^2 = .04$, $F(3, 158) = 1.89$, $p = .13$. As part of this larger model, Inhibition was very nearly shown to predict HC (β = 0.14 [-0.001, 0.29], $p = .05$). On the other hand, neither Switching (β = -0.05 [-0.21, 0.11], $p = .56$) nor Updating (β = -0.09 [-0.24, 0.05], $p = .21$) were shown to predict HC.

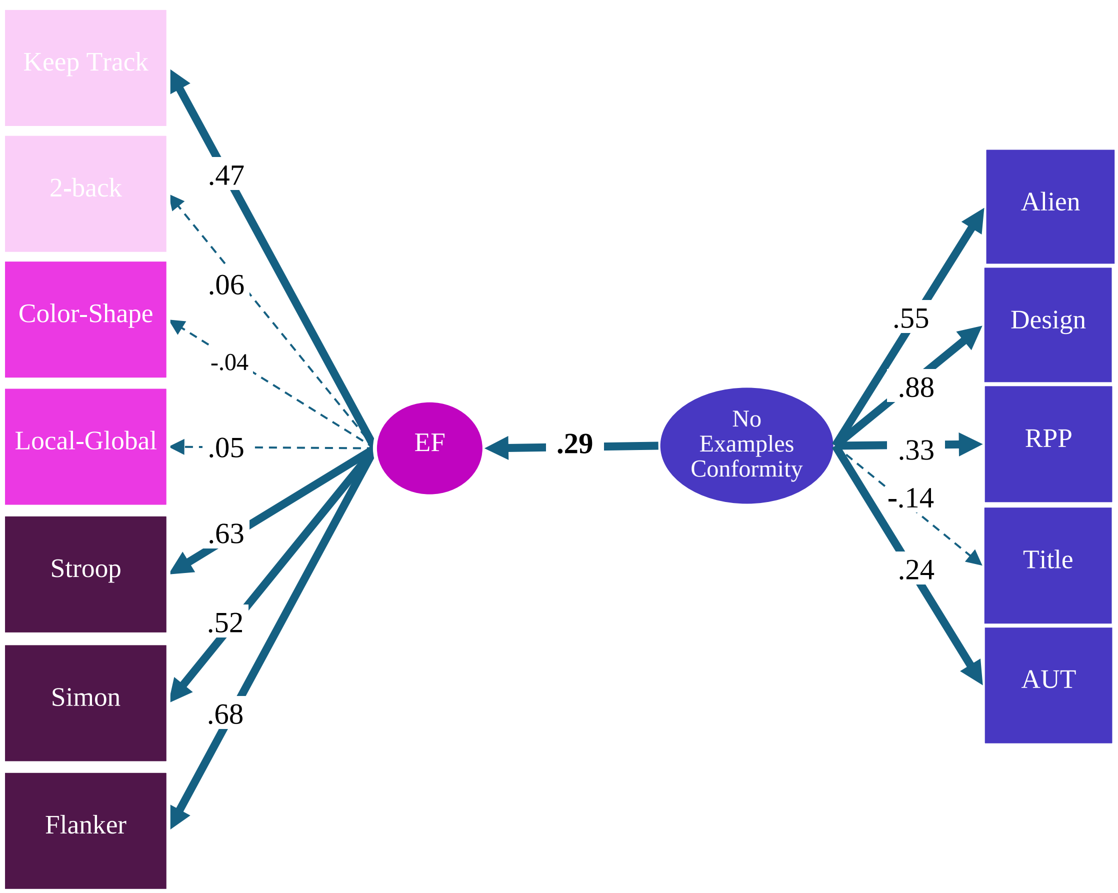
Another linear regression including only Inhibition in the model as a predictor did not show it to be predictive of Holistic Conformity, $R^2 = .01$, $F(1, 212) = 1.27$, $p = .22$, β = 0.08 [-0.05, 0.20].

Conformity.

Latent Variables. We constructed a model including our composite Conformity score (the product of CF and HC) as the predictor of No Examples Creativity. The model fit the data well, χ^2 (53) = 55.30, p = .39; CFI = 0.98, RMSEA = 0.02 (90% CI: 0.00, 0.06); SRMR = .07, and indicated that EF positively predicted Conformity, β = 0.29 [0.08, 0.51], p = .01 (Figure 25).

Figure 25

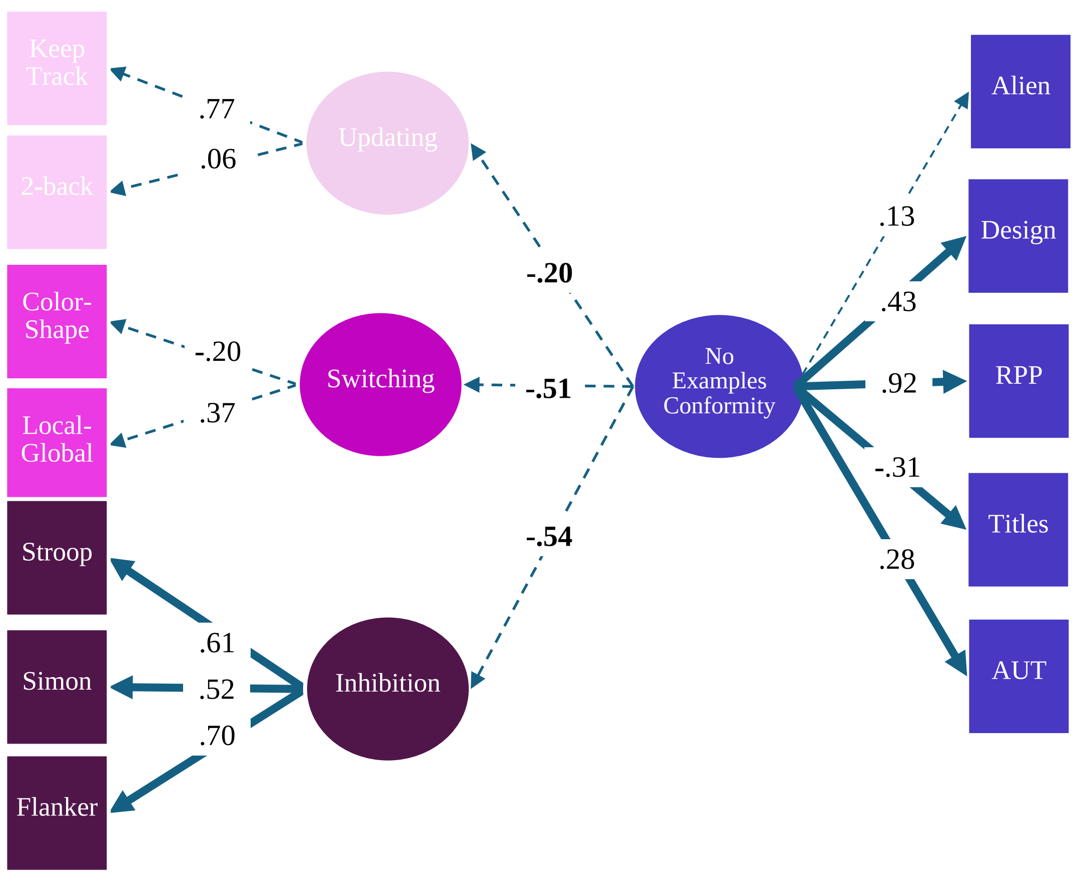
Conformity in the No Examples condition predicted by EF (base model)



Note. Dashed lines indicate non-significant paths.

We constructed a model with Updating, Switching, and Inhibition as predictors of Conformity in the No Examples condition. The model fit the data well, χ^2 (48) = 24.49, *p* = .96; CFI = 1.00, RMSEA = 0.00 (90% CI: 0.00, 0.00); SRMR = .05. Neither Updating (β = -0.20 [-1.56, 1.16], *p* = .77), nor Switching (β = -0.51 [-1.47, 0.45], *p* = .30), nor Inhibition (β = 0.54 [-0.82, 1.91], *p* = .44) were shown to predict Conformity in the No Examples condition (Figure 26).

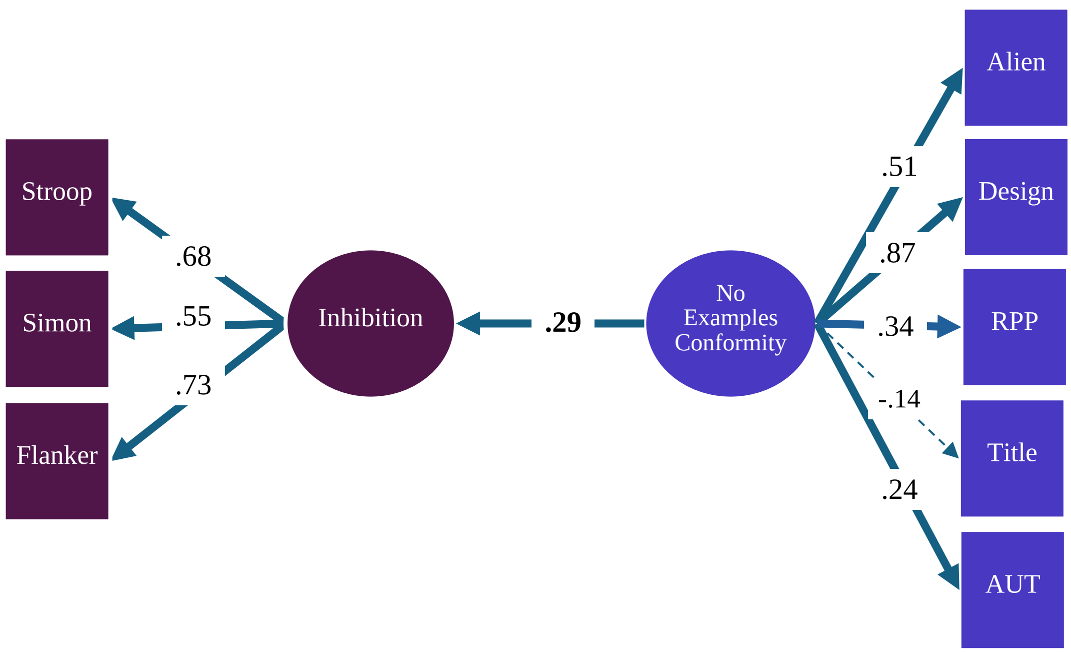
Figure 26
Conformity in the No Examples condition predicted by Updating, Switching, and Inhibition



Note. Dashed lines indicate non-significant paths.

A separate model with Inhibition as the predictor also fit the data well, χ^2 (19) = 23.15, p = .23; CFI = 0.97, RMSEA = 0.04 (90% CI: 0.00, 0.07); SRMR = .06, and indicated that Inhibition positively predicted Conformity, β = 0.29 [0.10, 0.48], p = .003 (Figure 27).

Figure 27
Conformity in the No Examples condition predicted by Inhibition



Note. Dashed lines indicate non-significant paths.

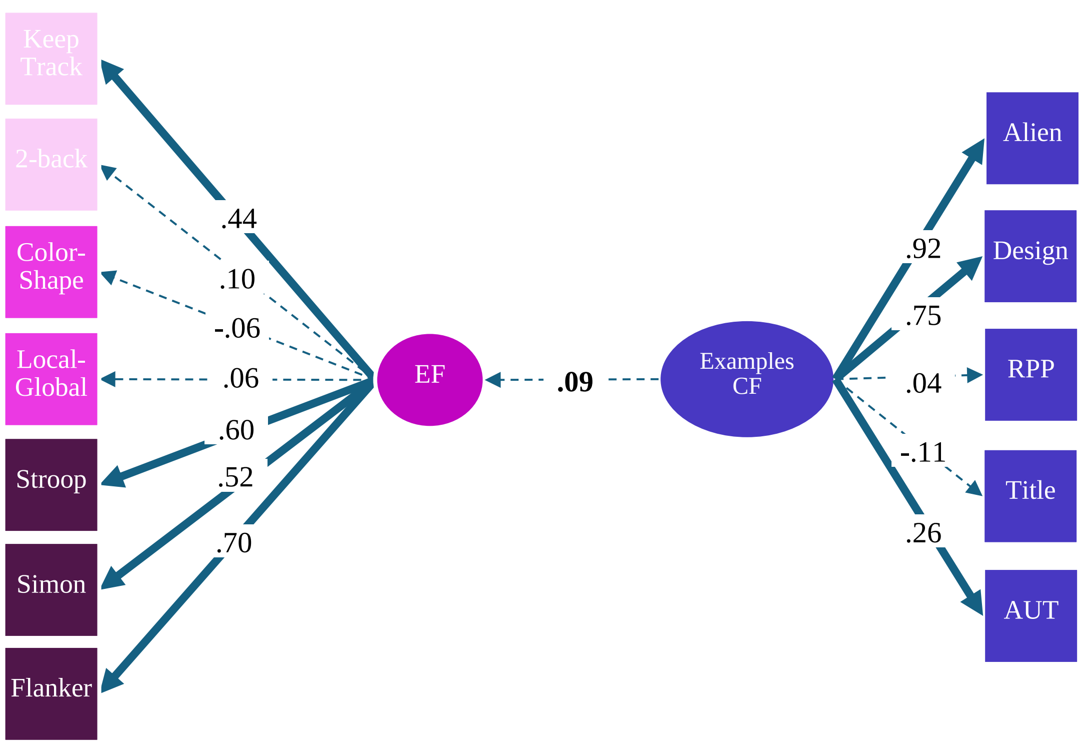
Observed Variables. A linear regression did not indicate that EF predicted Conformity in the No Examples condition, R^2 = .00, F(1, 163) = .004, p = .95, β = 0.01 [-0.15, 0.15]. To consider whether individual components of EF had differential effects on CFs, we ran another linear regression, with Inhibition, Switching, and Updating entered into the model at the same time. Results did not indicate that the model as a whole predicted Conformity in the No Examples condition (although it was close), R^2 = .04, F(3, 158) = 2.43, p = .07. As part of this larger model, Inhibition was shown to predict Conformity (β = 0.20 [0.05, 0.35], p = .01), but Switching was not shown to predict Conformity (β = -0.03 [-0.20, 0.14], p = .75), nor was Updating (β = -0.04 [-0.19, 0.12], p = .65). Another linear regression including only Inhibition in the model as a predictor also did not show it to be predictive of Conformity (although it was *marginally* significant, and in the positive direction), R^2 = .02, F(1, 212) = 3.82, p = .05, β = 0.13 [-0.001, 0.26].

Does EF predict Conformity in the Examples condition?

CF.

Latent Variables. A model including all seven EF tasks in the EF latent variable and the proportion of CFs included in the five creativity tasks in the Examples condition fit the data well, χ^2 (53) = 56.38, *p* = .35; CFI = .98, RMSEA = .02 (90% CI: .00, .06); SRMR = .07. Results did not indicate that EF predicted CFs, β = 0.09 [-0.12, 0.30], *p* = .41 (Figure 28).

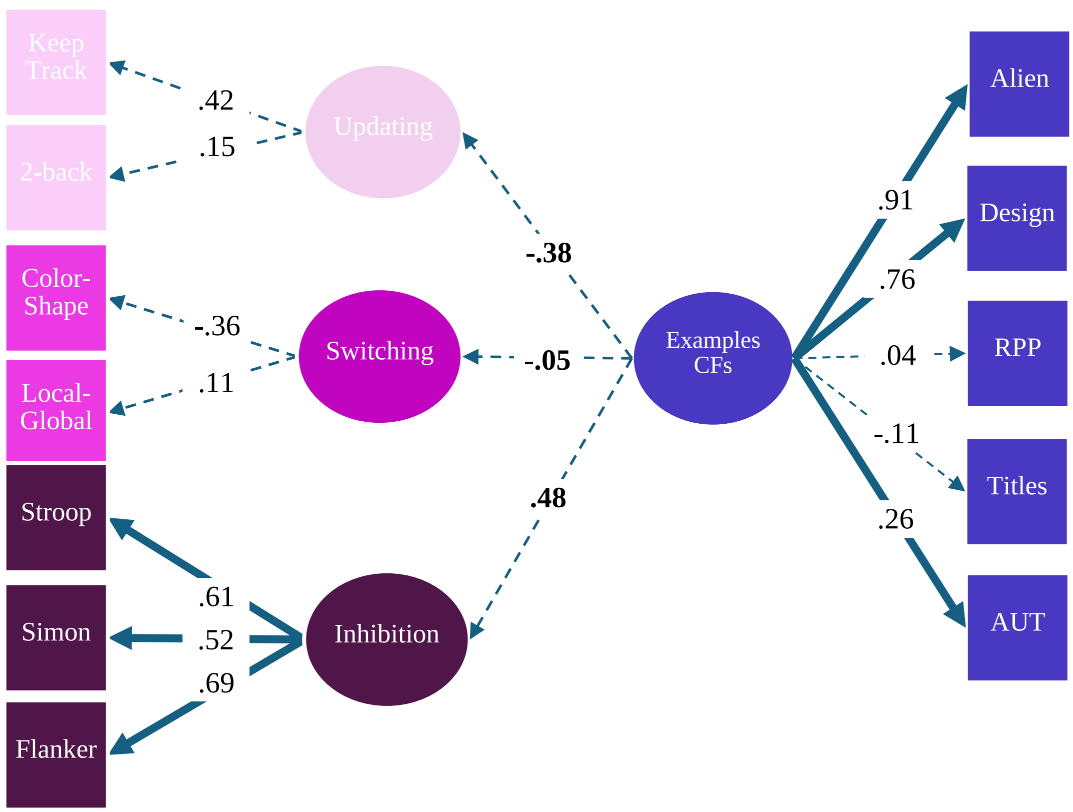
Figure 28
CFs in the Examples condition predicted by EF



Note. Dashed lines indicate non-significant paths.

We constructed a model with Updating, Switching, and Inhibition as predictors of CFs in the Examples condition. The model fit the data well, χ^2 (48) = 53.91, p = .26; CFI = 0.97, RMSEA = 0.03 (90% CI: 0.00, 0.06); SRMR = .07. Neither Updating (β = -0.38 [-2.81, 2.06], p = .76), nor Switching (β = -0.05 [-1.40, 1.30], p = .94), nor Inhibition (β = 0.48 [-1.91, 2.88], p = .69) were shown to predict CFs in the Examples condition (Figure 29).

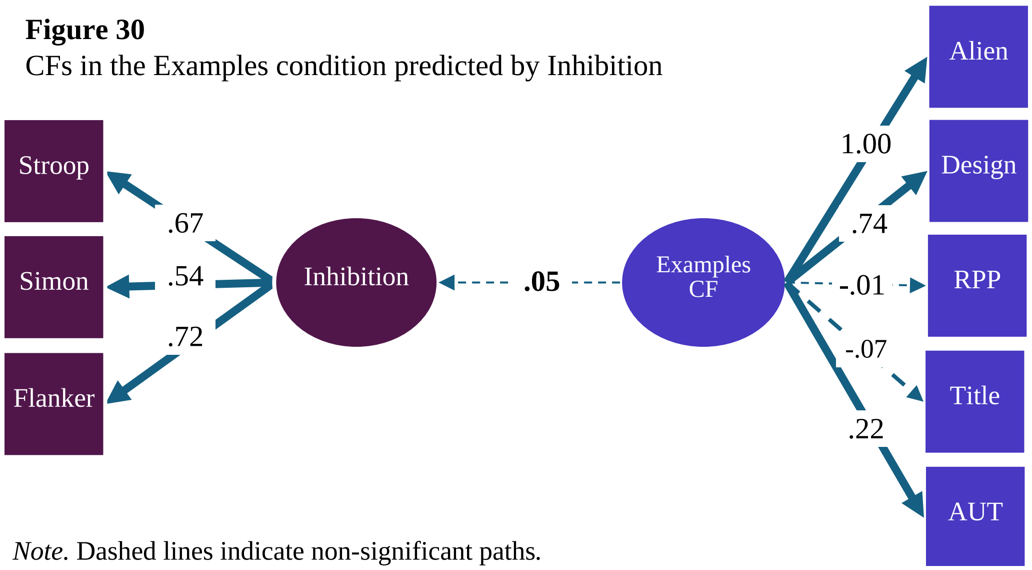
Figure 29
CFs in the Examples condition predicted by Updating, Switching, and Inhibition



Note. Dashed lines indicate non-significant paths.

Investigating Inhibition, the model fit the data well, χ^2 (19) = 17.93, *p* = .53; CFI = 1.00, RMSEA = 0.00 (90% CI: 0.00, 0.06); SRMR = .06, but it did not indicate that Inhibition was predictive of CF, β = 0.05 [-0.12, 0.22], *p* = .54 (Figure 30).

Figure 30
CFs in the Examples condition predicted by Inhibition



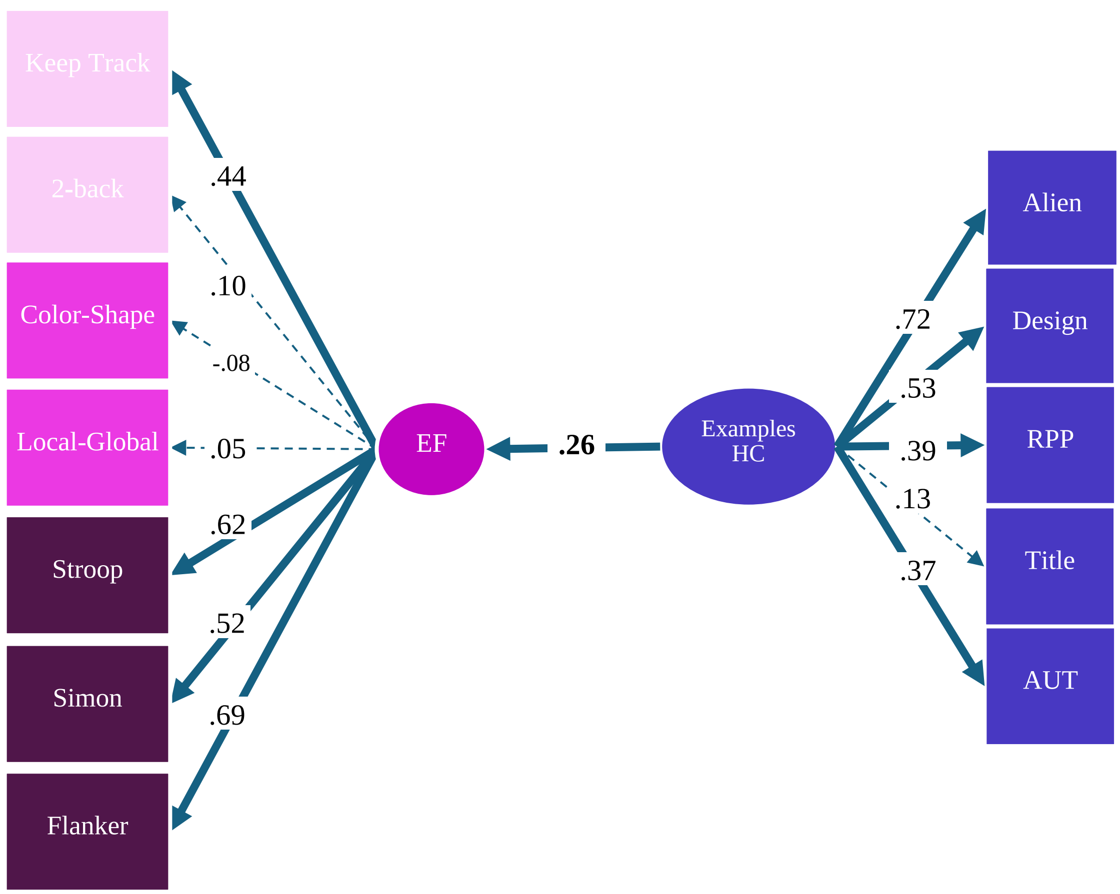
Note. Dashed lines indicate non-significant paths.

Observed Variables. A linear regression did not indicate that EF predicted CFs in the Examples condition, R^2 = .00, *F*(1, 163) = 0.30, *p* = .58, β = 0.00 [-0.01, 0.01]. To consider whether individual components of EF had differential effects on CFs, we ran another linear regression, with, Inhibition, Switching, and Updating entered into the model at the same time. Results did not indicate that the model as a whole predicted CFs in the Examples condition, R^2 = .02, *F*(3, 158) = 0.88, *p* = .46. As part of this larger model, Inhibition was not shown to predict CFs in the Examples condition (β = 0.09 [-0.07, 0.24], *p* = .28), nor was Switching (β = -0.07 [-0.24, 0.11], *p* = .44), nor was Updating (β = -0.08 [-0.23, 0.08], *p* = .35). When Inhibition was entered as the only predictor it also did not significantly predict CFs, R^2 = .01, *F*(1, 212) = 2.08, *p* = .15, β = 0.10 [-0.04, 0.23].

Holistic Conformity.

Latent Variables. A model including all seven EF tasks in the EF latent variable and the Holistic Conformity ratings in the five creativity tasks in the Examples condition fit the data well, χ^2 (53) = 59.31, p = .26; CFI = .95, RMSEA = .03 (90% CI: .00, .06); SRMR = .07. Results indicated that EF positively predicted HC, β = 0.26 [0.02, 0.50], p = .03 (Figure 31).

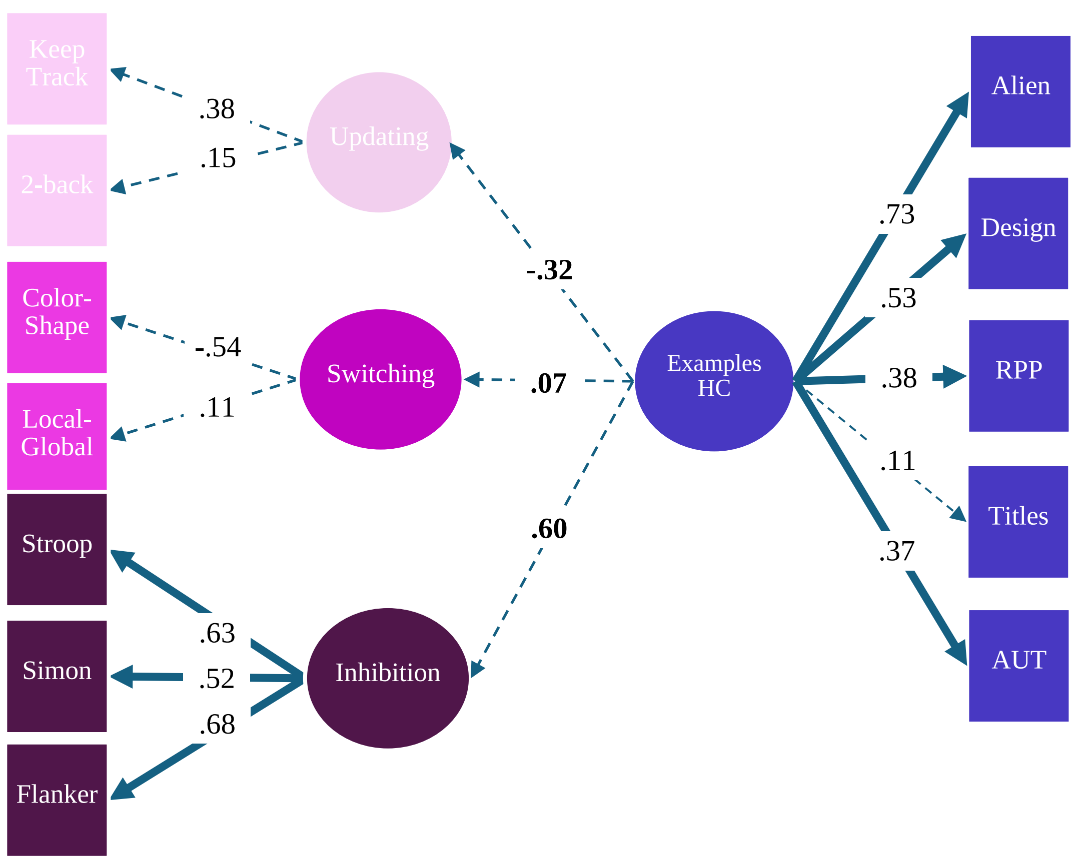
Figure 31
HC in the Examples condition predicted by EF (base model)



Note. Dashed lines indicate non-significant paths.

We constructed a model with Updating, Switching, and Inhibition as predictors of HC in the Examples condition. The model fit the data reasonably well, χ^2 (48) = 56.21, p = .19; CFI = 0.93, RMSEA = 0.04 (90% CI: 0.00, 0.07); SRMR = .07. Neither Updating (β = -0.32 [-2.91, 2.28], p = .81), nor Switching (β = 0.07 [-1.06, 1.19], p = .91), nor Inhibition (β = 0.60 [-2.02, 3.21], p = .66) were shown to predict HC in the Examples condition (Figure 32).

Figure 32
HC in the Examples condition predicted by Updating, Switching, and Inhibition

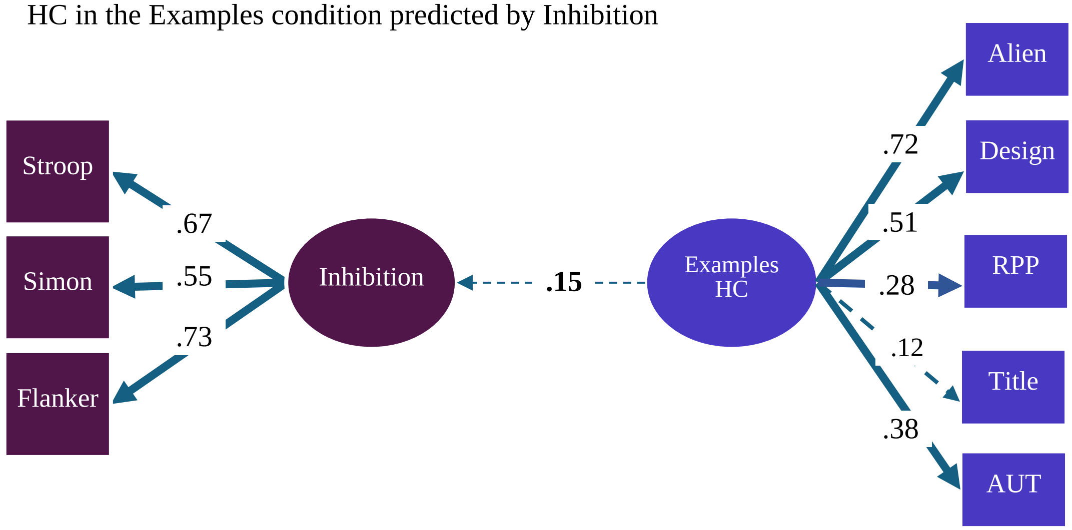


Note. Dashed lines indicate non-significant paths.

We also investigated the role of Inhibition specifically. The model fit the data well, χ^2 (19) = 21.76, *p* = .30; CFI = .98, RMSEA = .03 (90% CI: .00, .07); SRMR = .05. It did not, however, provide substantial evidence that EF predicted HC, β = 0.15 [-0.07, .37], *p* = .18 (Figure 33).

Figure 33

HC in the Examples condition predicted by Inhibition



Note. Dashed lines indicate non-significant paths.

Observed Variables. A linear regression did not indicate that EF predicted Holistic Conformity in the Examples condition, R^2 = .00, *F*(1, 160) = .00, *p* = .99, β = 0.00 [-0.05, 0.05]. To consider whether individual components of EF had differential effects on Holistic Conformity, we ran another linear regression. Inhibition, Switching, and Updating entered into the model. The model was not shown to predict Holistic Conformity, R^2 = .01, *F*(3, 158) = 0.64, *p* = .59. Inhibition was not shown to be predictive of Holistic Conformity in the Examples condition, β = 0.06 [-0.09, 0.22], *p* = .42, nor was Switching, β = 0.04 [-0.14, 0.21], *p* = .70), nor was Updating, β = -0.09 [-0.24, 0.07], *p* = .28. When Inhibition was entered as the only predictor it also was not shown to significantly predict CFs, R^2 = .00, *F*(1, 212) = 0.85, *p* = .36, β

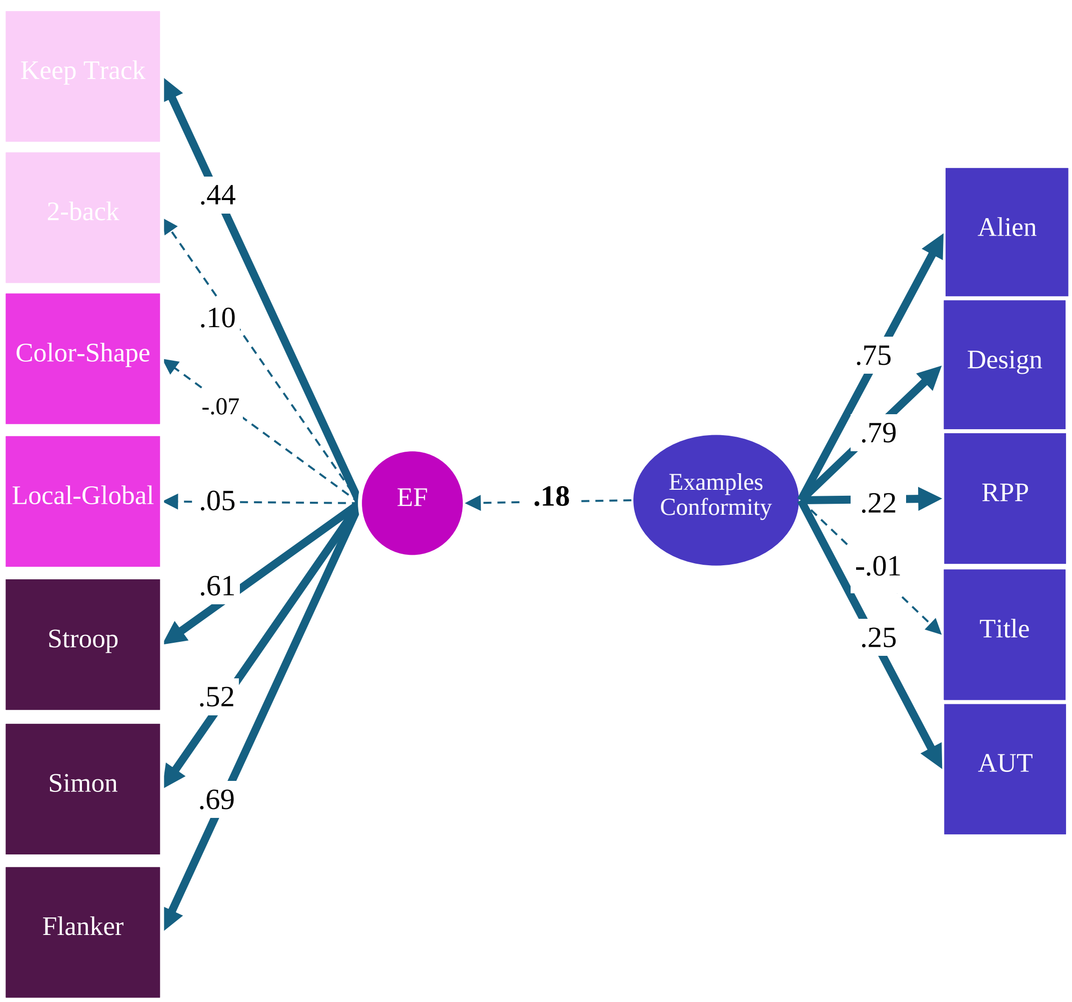
= 0.06 [-0.07, 0.20].

Conformity.

Latent Variables. We constructed a model including our composite Conformity score (the product of CF and HC) as the predictor of Examples Creativity. The model fit the data well, χ^2 (53) = 57.81, *p* = .30; CFI = 0.97, RMSEA = 0.03 (90% CI: 0.00, 0.06); SRMR = .07, but did not indicate that EF predicted Conformity, β = 0.18 [-0.04, 0.40], *p* = .11 (Figure 34).

Figure 34

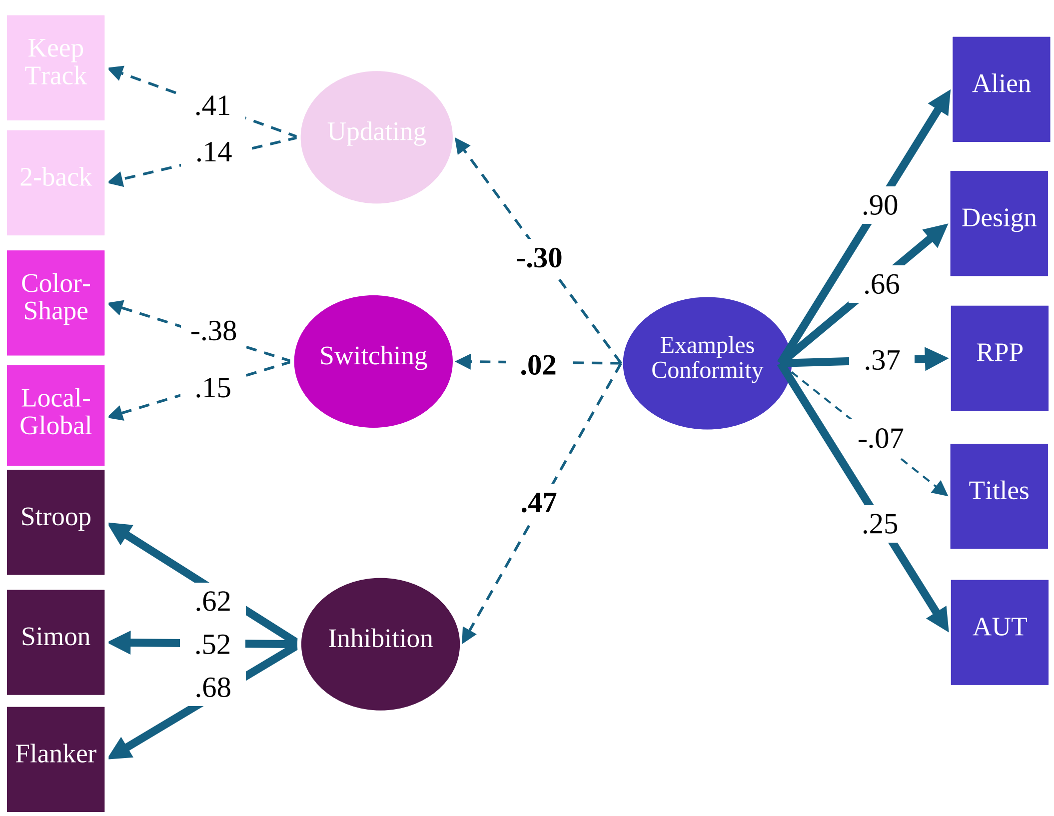
Conformity in the Examples condition predicted by EF (base model)



Note. Dashed lines indicate non-significant paths.

We constructed a model with Updating, Switching, and Inhibition as predictors of Conformity in the Examples condition. The model fit the data well, χ^2 (48) = 39.81, p = .39; CFI = 0.99, RMSEA = 0.02 (90% CI: 0.00, 0.06); SRMR = .06. Neither Updating (β = -0.30 [-2.70, 2.10], p = .81), nor Switching (β = 0.02 [-1.21, 1.26], p = .97), nor Inhibition (β = 0.47 [-1.96, 2.91], p = .70) were shown to predict Conformity in the Examples condition (Figure 35).

Figure 35
Conformity in the Examples condition predicted by Updating, Switching, and Inhibition

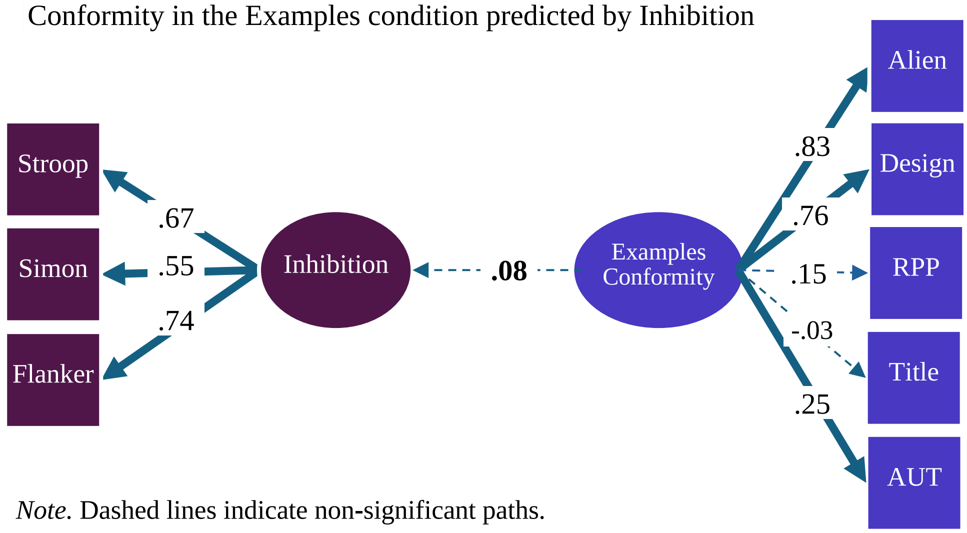


Note. Dashed lines indicate non-significant paths.

A separate model with Inhibition as the predictor also fit the data well, χ^2 (19) = 21.88, *p* = .29; CFI = 0.99, RMSEA = 0.03 (90% CI: 0.00, 0.07); SRMR = .05. The model did not, however, indicate that Inhibition predicted Conformity, β = 0.08 [-0.12, 0.27], *p* = .44 (Figure 36).

Figure 36

Conformity in the Examples condition predicted by Inhibition



Note. Dashed lines indicate non-significant paths.

Observed Variables. A linear regression did not indicate that EF predicted Conformity in the Examples condition, R^2 = .01, $F(1, 163)$ = 0.84, *p* = .36, β = 0.07 [-0.08, 0.23]. To consider whether individual components of EF had differential effects on Holistic Conformity, we ran another linear regression, with Inhibition, Switching, and Updating entered into the model at the same time. The model as a whole was not shown to predict Holistic Conformity, R^2 = .01, $F(3, 158)$ = 0.69, *p* = .56. Inhibition was not shown to be predictive of Conformity in the Examples condition, β = .08 [-0.08, 0.24], *p* = .34, nor was Switching, β = -0.03 [-0.21, 0.16], *p* = .78), nor was Updating, β = -0.09 [-0.25, 0.07], *p* = .28. Another linear regression including only Inhibition in the model as a predictor did not show it to be predictive of Conformity,

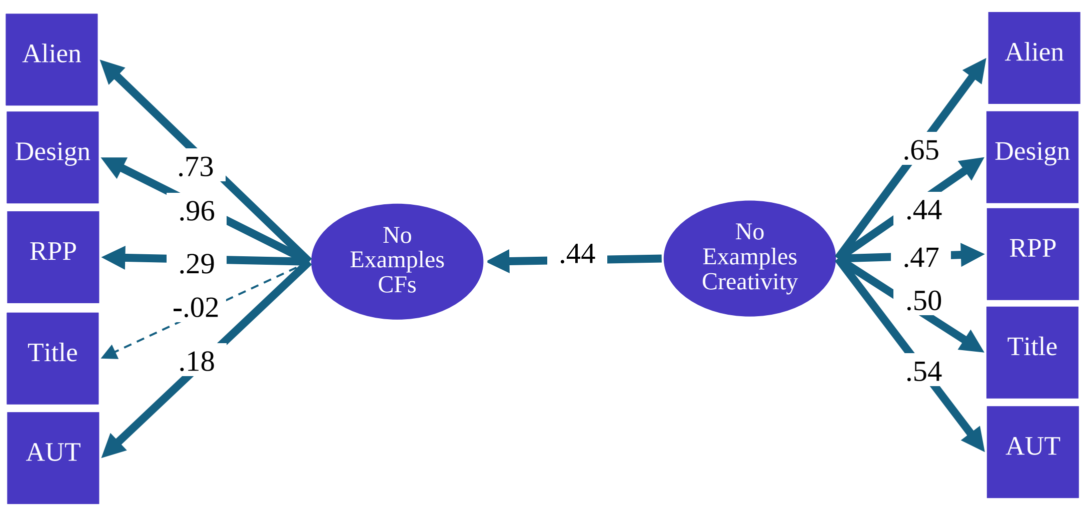
R^2 = .01, F(1, 212) = 1.46, p = .23, β = 0.08 [-.05, 0.22].

Does Conformity predict Creativity in the No Examples condition?

CF.

Latent Variables. We constructed a model with the CF latent variable (from all 5 Creativity tasks) predicting the Creativity latent variable (from all 5 Creativity tasks). The model did not fit the data particularly well, χ^2 (34) = 92.55, p < .001; CFI = .82, RMSEA = .10 (90% CI: .07, .12); SRMR = .08. The model did show that Creativity was positively predicted by CFs, β = 0.44 [0.28, 0.61], p < .001 (Figure 37).

Figure 37
Creativity predicted by CFs in the No Examples condition



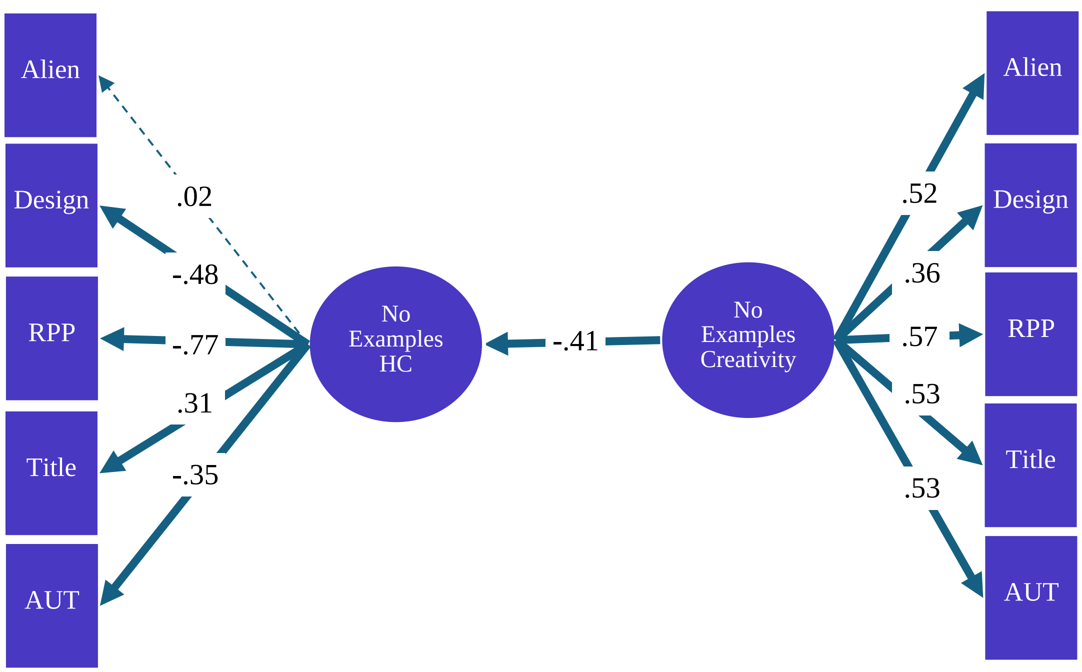
Note. Dashed lines indicate non-significant paths.

Observed Variables. A linear regression indicated that CFs positively predicted Creativity in the No Examples condition, R^2 = .09, F(1, 219) = 22.13, p < .001, β = .30 [0.18, 0.43].

Holistic Conformity.

Latent Variables. We constructed a model with the HC latent variable (from all 5 Creativity tasks) predicting the Creativity latent variable (from all 5 Creativity tasks). The model did not fit the data particularly well, χ^2 (34) = 84.52, $p < .001$; CFI = .76, RMSEA = 0.09 (90% CI: 0.07, 0.11); SRMR = .08. The model did show that Creativity was negatively predicted by HC, β = -0.41 [-0.61, -0.20], $p < .001$ (Figure 38).

Figure 38
Creativity predicted by HC in the No Examples condition



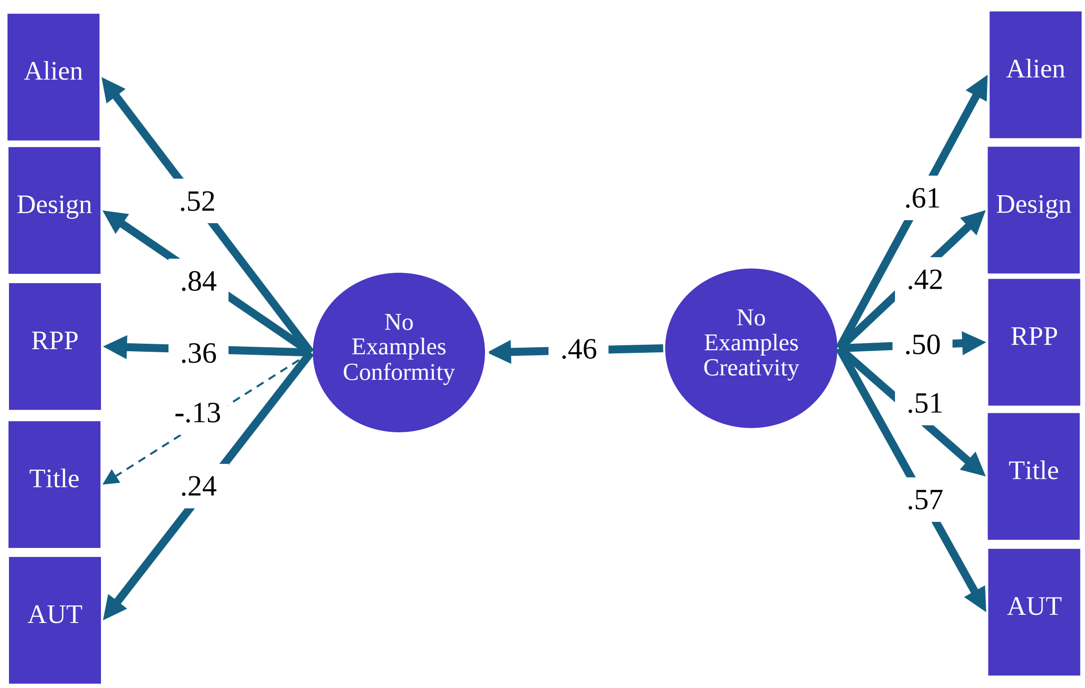
Note. Dashed lines indicate non-significant paths.

Observed Variables. A linear regression indicated that Holistic Conformity predicted Creativity, $R^2 = .06$, $F(1, 219) = 14.43$, $p < .001$, β = 0.25 [0.12, 0.38].

Conformity.

Latent Variables. We constructed a model with the Conformity latent variable (from all 5 Creativity tasks) predicting the Creativity latent variable (from all 5 Creativity tasks). The model did not fit the data particularly well, χ^2 (34) = 103.32, $p < .001$; CFI = .72, RMSEA = 0.11 (90% CI: 0.08, 0.13); SRMR = .08. The model did show that Creativity was positively predicted by Conformity, β = 0.46 [0.27, 0.64], $p < .001$ (Figure 39).

Figure 39
Creativity predicted by Conformity in the No Examples condition



Note. Dashed lines indicate non-significant paths.

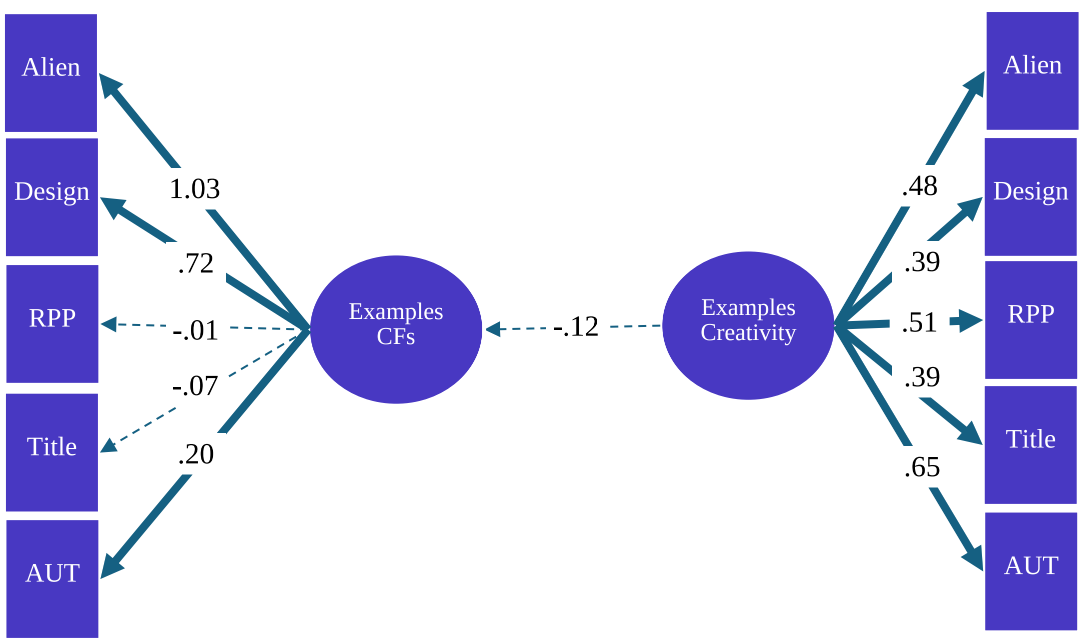
Observed Variables. A linear regression indicated that Conformity predicted Creativity, $R^2 = .08$, $F(1, 219) = 19.48$, $p < .001$, β = 0.29 [0.16, 0.41].

Does Conformity predict Creativity in the Examples condition?

CF.

Latent Variables. We constructed a model with the CF latent variable (from all 5 Creativity tasks) predicting the Creativity latent variable (from all 5 Creativity tasks). The model did not fit the data particularly well, χ^2 (34) = 98.71, p < .001; CFI = .78, RMSEA = .10 (90% CI: .08, .13); SRMR = .10. The model did not show that Creativity was predicted by CFs, β = -0.12 [-0.30, 0.06], p = .19 (Figure 40).

Figure 40
Creativity predicted by CFs in the Examples condition



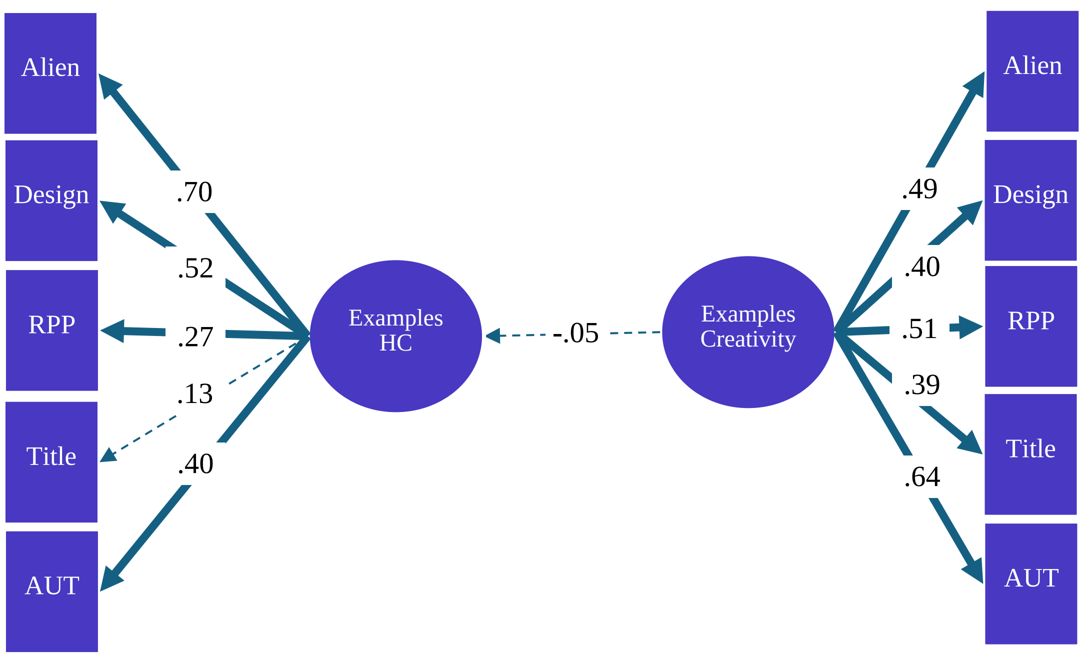
Note. Dashed lines indicate non-significant paths.

Observed Variables. A linear regression provided evidence that CFs predicted Creativity in the Examples condition, R^2 = .02, F(1, 219) = 5.17, p = .02, β = 0.15 [0.20, 0.29].

Holistic Conformity.

Latent Variables. We constructed a model with the HC latent variable (from all 5 Creativity tasks) predicting the Creativity latent variable (from all 5 Creativity tasks). The model did not fit the data particularly well, χ^2 (34) = 89.93, $p < .001$; CFI = .69, RMSEA = .09 (90% CI: .07, .12); SRMR = .09. The model did not show that Creativity was predicted by CFs, β = -0.05 [-0.28, 0.18], $p = .66$ (Figure 41).

Figure 41
Creativity predicted by HC in the Examples condition



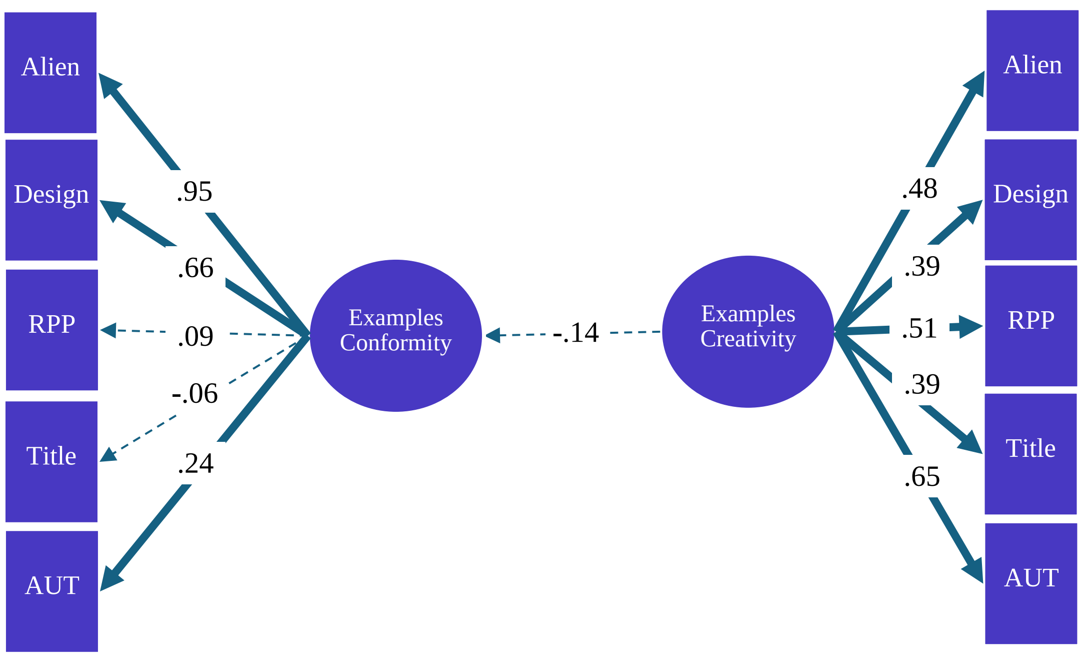
Note. Dashed lines indicate non-significant paths.

Observed Variables. A linear regression did not provide evidence that HC predicted Creativity in the Examples condition, $R^2 = .01$, $F(1, 219) = 1.88$, $p = .17$, β = 0.09 [-0.04, 0.22].

Conformity.

Latent Variables. We constructed a model with the Conformity latent variable (from all 5 Creativity tasks) predicting the Creativity latent variable (from all 5 Creativity tasks). The model did not fit the data particularly well, χ^2 (34) = 97.99, p < .001; CFI = .73, RMSEA = .10 (90% CI: 0.08, 0.13); SRMR = .10. The model did not indicate that Creativity was predicted by Conformity, β = -0.14 [-0.33 0.05], p = .14 (Figure 42).

Figure 42
Creativity predicted by Conformity in the Examples condition



Note. Dashed lines indicate non-significant paths.

Observed Variables. A linear regression provided evidence that Conformity predicted Creativity in the Examples condition, R^2 = .02, F(1, 219) = 3.91, p = .049, β = 0.13 [0.00, 0.27].

Does Conformity mediate the relation between EF and Creativity?

CF.

Latent Variables. We conducted a mediation analysis to examine the associations among three latent variables, Creativity (outcome) and CFs (mediator) in the Examples condition and EF (predictor). The standardized estimates revealed a significant positive direct effect between EF and Creativity, β = 0.18 [0.003, 0.35], p = .046. However, the indirect effect was small and non-significant, β = -0.01 [-0.003, 0.02], p = .54. The total effect was marginally significant, β = 0.17 [-0.003, 0.35], p = .06. Overall, while the direct effect of EF on Creativity was significant, the mediation analysis did not support a significant indirect effect through CFs (Figure 43A).

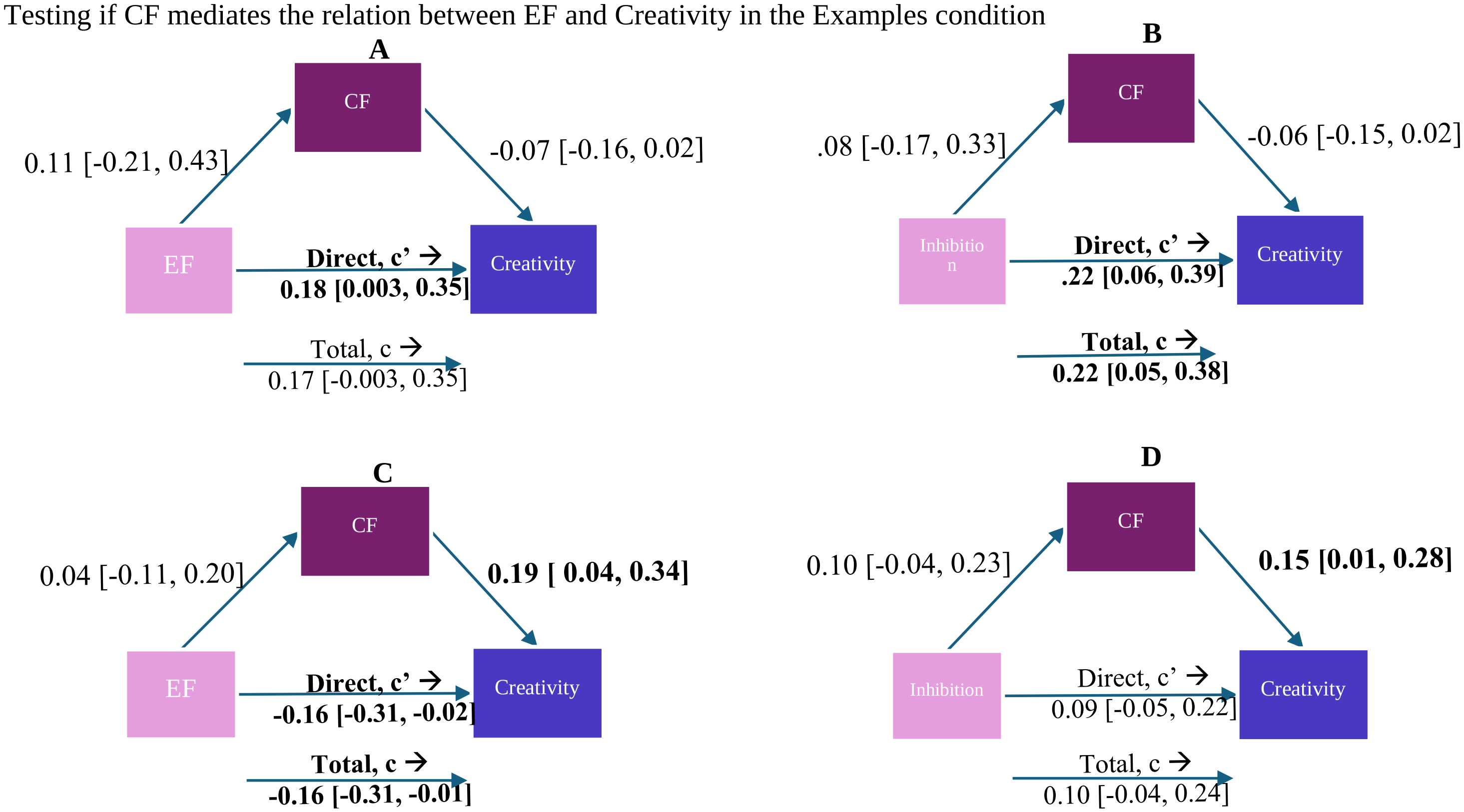
We ran a second mediation analysis, switching out the EF latent variable for the Inhibition latent variable. The standardized estimates revealed a significant positive direct effect between Inhibition and Creativity, β = 0.22 [0.06, 0.39], p = .01. However, the indirect effect was small and non-significant, β = -0.01 [-0.02, 0.01], p = .59. The total effect was significant, β = 0.22 [0.05, 0.38], p = .01. Overall, while the direct effect of Inhibition on Creativity was significant, the mediation analysis did not support a significant indirect effect through CFs (Figure 43B).

Observed Variables. A mediation analysis was conducted to examine the relations among three observed variables, Creativity (outcome) and CFs (mediator) in the Examples condition and EF (predictor). The standardized estimates revealed a significant negative direct effect between EF and Creativity, β = -0.16 [-0.31, -0.02], p = .03. However, the indirect effect was small and non-significant, β = 0.01 [-0.02, 0.04]. The total effect was significant, β = 0.16 [-0.31, -0.01], $p = .04$. Overall, while the direct and total effects of EF on Creativity were significant, the mediation analysis did not support a significant indirect effect through CFs (Figure 43C).

We conducted a second mediation analysis, switching out Inhibition for EF. Results did not indicate a significant direct effect (β = 0.09 [-0.05, 0.22], $p = .21$), indirect effect (β = 0.01 [-0.003, 0.04], or total effect (β = 0.10 [-0.04, 0.24], $p = .15$). Overall, no evidence was found to support the idea of Inhibition predicting Creativity through CFs (Figure 43D).

Figure 43

Testing if CF mediates the relation between EF and Creativity in the Examples condition



Note. Panel A shows the latent variable mediation analysis testing if CFs mediate the relation between EF and Creativity in the Examples condition. Panel B shows the latent variable mediation analysis testing if CFs mediate the relation between Inhibition and Creativity in the Examples condition. Panel C shows the observed variable mediation analysis testing if CFs mediate the relation between EF and Creativity in the Examples condition. Panel D shows the observed variable mediation analysis testing if CFs mediate the relation between Inhibition and Creativity in the Examples condition.

Holistic Conformity.

Latent Variables. We conducted a mediation analysis to examine the associations among three latent variables, Creativity (outcome) and HC (mediator) in the Examples condition and EF (predictor). The standardized estimates revealed a significant positive direct effect between EF and Creativity, β = 0.21 [0.02, 0.40], p = .03. However, the indirect effect was small and non-significant, β = -0.04 [-0.09, 0.02], p = .22. The total effect was marginally significant, β = 0.17 [-0.003, 0.34], p = .054. Overall, while the direct effect of EF on Creativity was significant, the mediation analysis did not support a significant indirect effect through HC (Figure 44A).

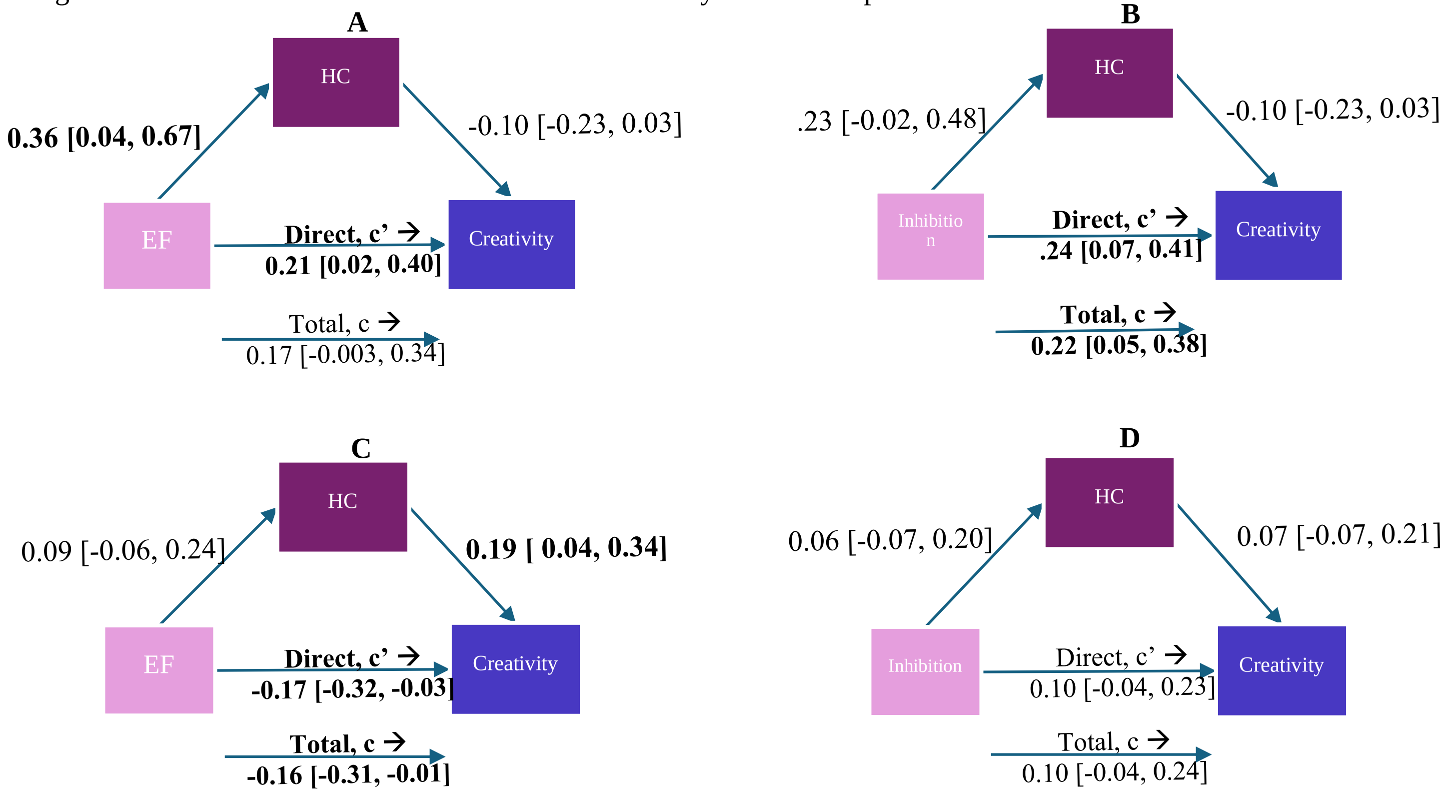
We ran a second mediation analysis, switching out the EF latent variable for the Inhibition latent variable. The standardized estimates revealed a significant positive direct effect between Inhibition and Creativity, β = 0.24 [0.07, 0.41], p = .01. However, the indirect effect was small and non-significant, β = -0.02 [-0.06, 0.02], p = .26. The total effect was significant, β = 0.22 [0.05, 0.38], p = .01. Overall, while the direct effect of Inhibition on Creativity was significant, the mediation analysis did not support a significant indirect effect through HC (Figure 44B).

Observed Variables. We conducted a mediation analysis to examine the associations among three observed variables, Creativity (outcome) and HC (mediator) in the Examples condition and EF (predictor). The standardized estimates revealed a significant negative direct effect between EF and Creativity, β = -0.17 [-0.32, -0.03], p = .02. However, the indirect effect was small and non-significant, β = 0.02 [-0.01, 0.05]. The total effect was significant, β = -0.16 [-0.31, -0.01], $p = .04$. Overall, while the direct and total effects of EF on Creativity were significant, the mediation analysis did not support a significant indirect effect through HC (Figure 44C).

We conducted a second mediation analysis, switching out Inhibition for EF. Results did not indicate a significant direct effect (β = 0.10 [-0.04, 0.23], $p = .17$), indirect effect (β = 0.004 [-0.01, 0.03], or total effect (β = 0.10 [-0.04, 0.24], $p = .15$). Overall, no evidence was found to support the idea of Inhibition predicting Creativity through HC (Figure 44D).

Figure 44

Testing if HC mediates the relation between EF and Creativity in the Examples condition



Note. Panel A shows the latent variable mediation analysis testing if HC mediates the relation between EF and Creativity in the Examples condition. Panel B shows the latent variable mediation analysis testing if HC mediates the relation between Inhibition and Creativity in the Examples condition. Panel C shows the observed variable mediation analysis testing if HC mediates the relation between EF and Creativity in the Examples condition. Panel D shows the observed variable mediation analysis testing if HC mediates the relation between Inhibition and Creativity in the Examples condition.

Conformity.

Latent Variables. We conducted a mediation analysis to examine the associations among three latent variables, Creativity (outcome) and Conformity (mediator) in the Examples condition and EF (predictor). The standardized estimates revealed a significant positive direct effect between EF and Creativity, β = 0.19 [0.01, 0.37], p = .04. However, the indirect effect was small and non-significant, β = -0.02 [-0.06, 0.02], p = .30. The total effect was marginally significant, β = 0.17 [-0.003, 0.34], p = .06. Overall, while the direct effect of EF on Creativity was significant, the mediation analysis did not support a significant indirect effect through Conformity (Figure 45A).

We ran a second mediation analysis, switching out the EF latent variable for the Inhibition latent variable. The standardized estimates revealed a significant positive direct effect between Inhibition and Creativity, β = 0.23 [0.06, 0.40], p = .01. However, the indirect effect was small and non-significant, β = -0.01 [-0.04, 0.01], p = .38. The total effect was significant, β = 0.22 [0.05, 0.38], p = .01. Overall, while the direct effect of Inhibition on Creativity was significant, the mediation analysis did not support a significant indirect effect through Conformity (Figure 45B).

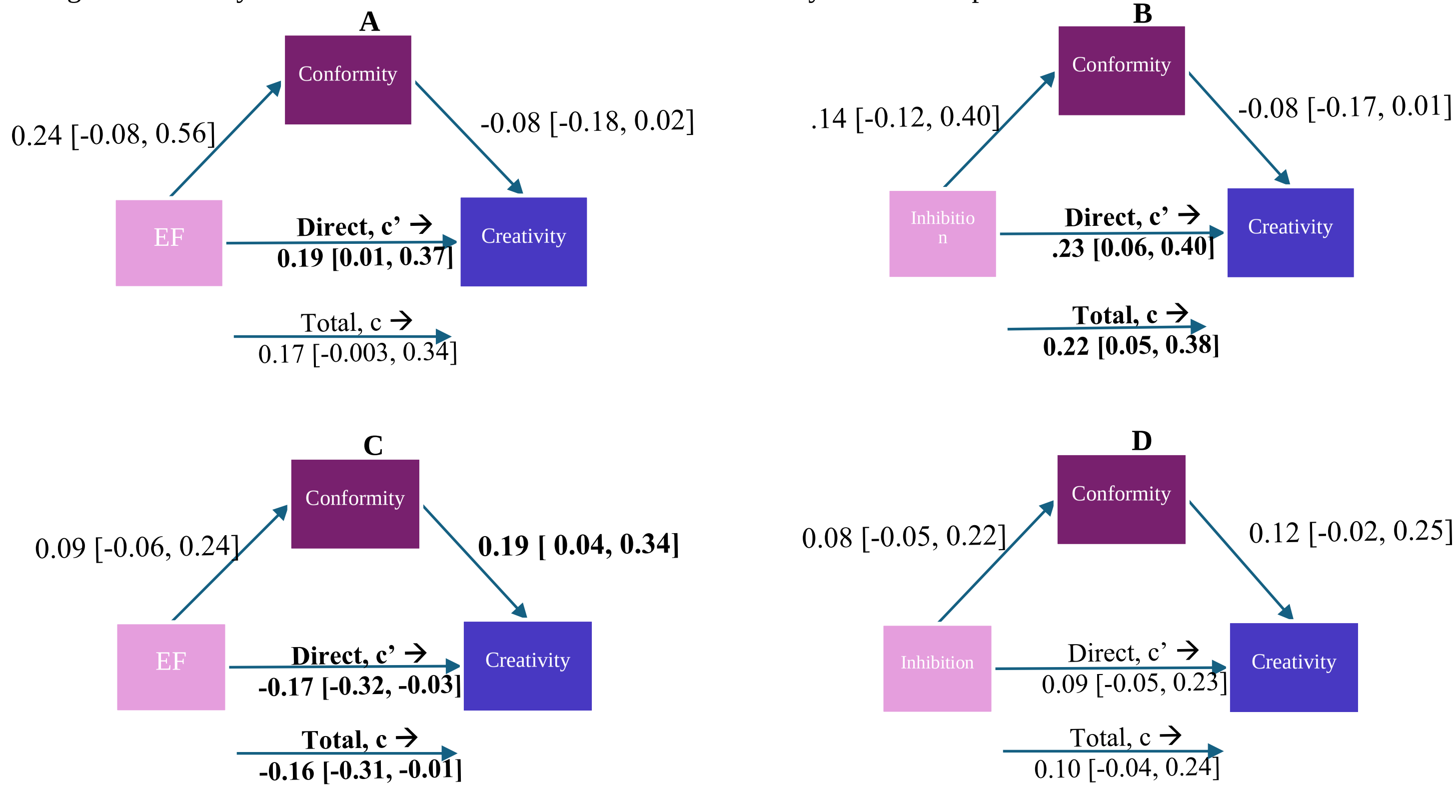
Observed Variables. We conducted a mediation analysis to examine the relations among three observed variables, Creativity (outcome) and Conformity (mediator) in the Examples condition and EF (predictor). The standardized estimates revealed a significant negative direct effect between EF and Creativity, β = -0.17 [-0.32, -0.03], p = .02. However, the indirect effect was small and non-significant, β =

0.01 [-0.02, 0.05]. The total effect was significant, β = -0.16 [-0.31, -0.01], p = .04. Overall, while the direct and total effects of EF on Creativity were significant, the mediation analysis did not support a significant indirect effect through Conformity (Figure 45C).

We conducted a second mediation analysis, switching out Inhibition for EF. Results did not indicate a significant direct effect (β = 0.09 [-0.05, 0.23], p = .19), indirect effect (β = 0.01 [-0.004, 0.03], or total effect (β = 0.10 [-0.04, 0.24], p = .15). Overall, we found no evidence to support the idea of Inhibition predicting Creativity through Conformity (Figure 45D).

Figure 45

Testing if Conformity mediates the relation between EF and Creativity in the Examples condition



Note. Panel A shows the latent variable mediation analysis testing if Conformity mediates the relation between EF and Creativity in the Examples condition. Panel B shows the latent variable mediation analysis testing if Conformity mediates the relation between Inhibition and Creativity in the Examples condition. Panel C shows the observed variable mediation analysis testing if Conformity mediates the relation between EF and Creativity in the Examples condition. Panel D shows the observed variable mediation analysis testing if Conformity mediates the relation between Inhibition and Creativity in the Examples condition.

Discussion

A Review of the Research Questions

Primary

1. Did participants generate ideas that were more creative in the Examples condition than in the No Examples condition?
2. Does EF predict Creativity in the No Examples condition?
3. Does EF predict Creativity in the Examples condition?
4. Does EF predict Creativity differently in the Examples condition than it does in the No Examples condition?
5. Does EF predict the improvement in Creativity between the No Examples condition to the Examples condition?

Secondary

6. Was the Conformity Effect demonstrated?
7. Does EF predict Conformity in the No Examples condition (baseline level of Conformity)
8. Does EF predict Conformity in the Examples condition?
9. Does Conformity predict Creativity in the No Examples condition?
10. Does Conformity predict Creativity in the Examples condition?
11. Does Conformity mediate the relation between EF and Creativity?

Did participants generate ideas that were more creative in the Examples condition than in the No Examples condition?

In every single Creativity task, participants generated ideas that were more creative in the Examples condition than they did in the No Examples condition. This evidence supports our initial premise – based on (a) the empirical finding from George and colleagues (2019) that participants generated ideas that were rated as more novel in an examples condition than a control condition, and (b) the theoretical concept of combination as a key mental operation in creativity from Welling (2007) – that examples in the idea generation process may support creative thinking.

Does EF predict Creativity in the No Examples condition?

The latent variable models showed EF to be positively predictive of Creativity in the No Examples condition, replicating the broader literature. Interestingly, our results broadly support an observation made by Benedek and colleagues (2014), that studies of the relation between intelligence and creativity often yield stronger results from latent variable modeling (Jauk et al., 2014; Silvia, 2008) than from analyses of observed variables (e.g., Kim, 2005). Knowing that EF and intelligence are highly interrelated, we also expected to see stronger associations between EF and creativity in our latent variable analyses than in our observed variable analyses, which was generally shown to be true, for this research question and for others. For this particular research question, for example, the standardized beta describing the relation between EF and Creativity in the No Examples condition was 0.42 [0.20, 0.63] in our latent variable analysis, compared to a non-significant -0.11 [-0.26, 0.04] from the observed variables. Similarly, Inhibition was shown to predict Creativity with a standardized beta of 0.40 [0.20, 0.59] from the latent variables and 0.19 [0.06, 0.32] from the observed variables.

In the latent variable analyses, although we observed EF to be predictive of creativity, that effect was mostly driven by the effect of Inhibition. This does replicate other literature (Benedek et al., 2012, 2014; Edl et al., 2014; Groborz & Necka, 2003), but we still hesitate to make conclusive statements about the role of Switching and Updating in creativity. Our latent variable models repeatedly showed that our indicators (Color-Shape, Local-Global, and 2-back) were not correlated with their respective latent variable. Models generally got stronger when we removed those tasks from the model. To be clear, in either type of model (the base model that included all tasks or the improved model that removed troublesome tasks) the role of Inhibition in creativity was clear. It is only that we are hesitant to conclude that Updating and Switching do *not* play a role in Creativity.

Does EF predict Creativity in the Examples condition?

The latent variable analyses and the observed variable analyses tell different stories here, where the latent variables indicate a positive correlation between EF (specifically, Inhibition) and Creativity in the Examples condition and the observed variables indicate a negative correlation. The latent variable approach also showed a *stronger* association between the two variables than the observed variable approach, in terms of having standardized betas and confidence intervals that were farther from zero. In fact, the confidence interval for the observed variable analysis looking at the relation between EF and Creativity very nearly included zero, running from -0.31 to -0.01. Additionally, when we focused the analysis only on Inhibition, that effect diminished. Thus, we feel more comfortable making the conclusion of a positive association (or possibly a non-significant association) between EF and Creativity in the Examples condition than a negative association.

To our knowledge, this is the first empirical work examining the link between EF and creativity specifically within the context of examples.

Does EF predict Creativity differently in the Examples condition than it does in the No Examples condition?

We did not find any evidence to support our prediction that EF is differentially involved depending on if examples were included in the idea generation process. Although the latent variable models (Base, Improved, and Inhibition) consistently showed higher standardized betas for the No Examples condition than the Examples condition, the difference never met the level of significance, so we cannot conclude that EF plays a larger role in Creativity in the No Examples condition than it does in the Examples condition.

Some work has suggested that intelligence may be an important moderating factor of the link between intelligence and creativity, where the association is stronger for participants below a certain threshold of intelligence (the threshold effect; Cho et al., 2010; Jauk et al., 2013; Karwowski & Gralewski, 2013). The presence of this effect is generally supported by the literature, although the thresholds are generally somewhat arbitrary and vary between studies as to their operationalization. We debated including an implementation of this effect in our data analysis but ultimately decided against it for several reasons: (1) although there are many ways in which EF and intelligence overlap, they are not perfect correlates; (2) it is likely that our sample of UC undergraduate students falls, for the most part, above whatever the threshold would be; (3) even if we were to split our sample into, say, quartiles based on EF and compare the bottom quartile to the top quartile, the statistical power of these small subgroups would not be sufficient to make conclusions. Regardless, this effect may be one reason why we failed to observe a difference in the role of EF on Creativity between Conditions with our particular sample. When looking for a difference between conditions, it is generally a good idea, methodologically-speaking, to set yourself up for success by making your conditions and manipulations as strong as possible, and it may be that we simply were not sampling from the population who was most likely to demonstrate these effects or any possible interactions.

It is also possible that participants were simply just ready to be done with the experiment by the time they got to the EF battery. The experiment session as a whole ranged from an hour and a half to two hours in duration, and participants may have been tired by the end, leading them to not be as careful and attentive as otherwise possible during the EF tasks. Our research assistants were well aware of this possibility, though, and were trained to offer breaks as necessary and also to emphasize to participants that *every individual participant's data was very important, so please try your best on these tasks*.

Does EF predict the difference between Creativity in the No Examples condition

and the Examples condition?

Observing that most participants generated ideas that were rated as more creative in the Examples condition than they did in the No Examples condition, we examined whether EF might predict how much a person improved between the two conditions. Stated another way, we wondered if there were certain people who might benefit more than others from the help of examples as a starting point for generating creative ideas. For example, it seemed possible that participants with lower EF might benefit dramatically from the help of examples (perhaps from a narrowing of the search space, or from a lessening of the cognitive load of having to generate all components of their own ideas), to a greater extent than participants with higher EF, who potentially had a higher starting level of creativity and so might not have as much space to improve. On the other hand, it was also possible that participants with higher EF might benefit more from the help of examples because they might be more well-equipped to make use of the examples to generate new and creative ideas, while participants with lower EF might get unduly fixated on the examples to the detriment of their own creative thinking.

Although our latent variable models (Base, Inhibition) did not conclusively support either direction, the standardized betas both trended in the negative direction. Had the results been more definitive/ significant, this direction would have indicated that participants with lower EF showed a larger improvement from their No Examples Creativity to their Examples Creativity than participants with higher EF showed. Following up on this finding with our observed variables, we investigated the precise nature of these improvements.

We had some sense of what we might see when investigating this pattern from the previous analyses, which indicated that increased EF was generally related to increased Creativity in both conditions. From this we deduced that we probably would not see evidence that participants with lower EF made their large improvements in a way that resulted in them having higher creativity than the higher EF participants.

Bearing in mind that neither the latent variable analysis nor the repeated measures ANOVAs with the observed variables met the level of significance, it did appear that the Low EF participants generated ideas that were rated as less Creative than high EF participants did in the No Examples condition, suggesting a lower baseline level of Creativity for lower EF participants. But things got interesting in the Examples condition, where Low EF participants leapt up to the same rated level of Creativity as the High EF participants.

Taken within the context of the broader results of this study, this suggests that examples support creative thinking, and that low EF participants in particular may benefit from the help of examples, in a way that helps to close the gap between Low EF and High EF participants. Said another way, this might suggest that anyone (or, rather, with any level of EF) can come up with creative ideas given the right form of support.

Was the Conformity Effect demonstrated?

Across all five creativity tasks, participants' ideas were more similar to examples in the Examples condition than they were in the No Examples condition, thus replicating the conformity effect. However, it is important to remember that our instructions in the Examples condition specifically tasked participant with including features from the examples in their own ideas, so the “conformity effect” here is almost more a measure of whether participants were able to follow that instruction than it is a measure of mental fixation.

It is also important to note that participants scores (CFs, HC, and Conformity) indicate that they were not simply copying the examples (which was also part of the instructions they were provided) – the maximum average score for HCs was 0.29 (out of 1.00) and for HC was 5.31 (out of 7).

Does EF predict Conformity in the No Examples condition (baseline level of Conformity)?

Latent and observed variable models indicated that increased EF, specifically Inhibition, was predictive of generating ideas that were more similar to the examples that we provided participants *without ever seeing those examples*. If anything, this result probably says more about our undergraduate and graduate student lab members who generated the examples (i.e., that they probably would have fallen into the High EF group) than it says about our participants.

Does EF predict Conformity in the Examples condition?

Generally speaking, we did not see any evidence to support the idea that EF predicts Conformity in the Examples condition. This may indicate that the conformity effect is more of a broad, generalizable effect than something that individual differences (at least, in terms of EF) determine. It is possible that other factors, like those related to personality might affect conformity, though.

This pattern (or lack thereof) goes along nicely with our Creativity analyses, which did not indicate that either Low EF or High EF participants were more or less Creative in the Examples condition. It also foreshadows our analysis of whether Conformity predicts Creativity.

Does Conformity predict Creativity in the No Examples condition?

Latent and observed variable analyses indicated that Conformity and Creativity were positively correlated in the No Examples condition. This result suggests less about our participants and suggests more about our examples. Specifically, it indicates that our examples tended to be relatively creative (given that ideas that were more like the examples were also rated as more creative). Here, it is important to remember some important things about the raters: (1) the 6 Creativity raters were different from the 6 Conformity raters, so these ratings are independent of each other, and (2) the Creativity raters never saw the examples that we showed participants, so the Creativity ratings were independent of the raters' knowledge of the examples.

Does Conformity predict Creativity in the Examples condition?

This is another instance where the findings from the latent variable model do not quite agree with the results from the observed variable analyses. The latent variable models did not find any association between Conformity and Creativity in the Examples condition. If anything, the standardized betas skewed toward the negative direction, which would indicate that increased Conformity was associated with decreased Creativity. However, we are dubious about concluding anything about that directionality, given that Conformity and Creativity were positively correlated in the No Examples condition, a patten which, if anything, should have been continued here. That pattern was, in fact, continued in the Observed variable analyses. We conclude that a positive correlation (or no relation) is more likely to be the true relation between Conformity and Creativity than a negative correlation (although no relation is certainly also possible).

Does Conformity mediate the relation between EF and Creativity in the Examples condition?

At the outset of this study, we had supposed that EF would be predictive of Creativity, and that this would be because certain people (high EF people, possibly) would be more adept at integrating features of examples into their own ideas, ultimately resulting in more creative ideas.

We found no evidence to support the idea that Conformity mediates the relation between EF and Creativity. Although the direct and total effects of EF on Creativity were generally significant, the effects of EF on Conformity and Conformity on Creativity were almost never significant.

Significance and Future Directions:

There were admittedly many research questions evaluated in this experiment, each with their own implications. However, there are some findings from this experiment that are particularly noteworthy.

First, from the primary analyses, this Dissertation provided further support for the positive link between EF (particularly inhibition) and creative thinking, at both a latent variable level and an observed variable level. Relatively few studies of this connection have used such a wide variety of tasks. Our EF battery and our Creativity battery both included more tasks covering a wider span of cognition than more studies have included. This is important, in that we feel confident that our assessment of an overall positive correlation between EF and creativity is generalizable to a broad spectrum of creative thinking and idea generation tasks.

This Dissertation also concludes that the generally positive correlation between EF and creativity extends to even cases in which individuals are given examples from which to begin generating their own ideas. We are not aware of any other study making the connection between EF and creativity when examples are provided in the idea generation process. This is an important development given that it feels much more true to life – when we attempt to generate a new idea in the real world we often do so in the face of examples.

This Dissertation also provided a within-subjects comparison of the role of EF in creativity in two conditions, one that included the help of examples in the idea generation process and one that did not. Generally speaking, we observed that participants generated ideas that were rated as more creative when they had the help of examples than when they were not provided examples, supporting the idea that examples can be a helpful tool to implement toward facilitating creative thinking, rather than a hinderance to avoid. Although we had presumed that we might observe a difference between the two conditions in terms of the predictive power and influence of EF (where, for example, EF was more important in the Examples condition than in the No Examples condition, or vice versa), we did not observe any such differences.

That said, however, there is a *hint* that providing examples may help level the playing field between individuals with lower EF and those with higher EF, where individuals with lower EF may benefit more from the help of examples than those with higher EF, bringing both EF-levels to a comparable level of creativity. Although this pattern failed to meet the level of significance in either our latent variable or observed variable analyses, there are theoretical reasons that would support this possibility. For example, narrowing the search space in creative thinking has been shown to be an effective tool for enhancing creativity, and it is possible that participants with lower EF may be particularly overwhelmed by a wide search space, leaving substantial space for improvement with a narrowing of the search space provided by examples.

Another possibility is that there is certainly a substantial cognitive load associated with needing to generate from nothing all features of a creative idea. Having a starting point, with features that you are encouraged to include in your own idea, may simply help to offset some of that cognitive burden, and individuals with lower EF may show that improvement to a greater extent than individuals with higher EF might show it.

Another major takeaway from this experiment, drawn from the secondary analyses, is the lack of evidence supporting our proposal that Conformity to examples mediates the relation between EF and Creativity. Although the direct and total effects were often significant (and addressed by the Primary Analyses discussing the relation between EF and Creativity), the indirect effects of EF predicting Conformity and of Conformity predicting Creativity were not generally shown to be significant. Said another way, although EF positively predicts Creativity, our study failed to provide evidence of Conformity as a potential mechanism to explain the association.

There are many lingering questions that may be worthwhile lines of research, some of which have been hinted at already. One such line of questioning might involve the threshold effect. It is possible that our results may have been different (stronger effect sizes of the links between EF and Creativity, and possibly a difference in the role of EF in Creativity between Conditions) had we either focused on a group of lower-EF participants or simply attempted to ensure a wider spread.

Another question worth pursuing would involve the quality of the examples that were provided to participants. Our study did not reveal much of note in terms of Conformity either in relation to EF or Creativity. There are many possible explanations for this. First, it may be that our examples were inconsistent in terms of quality, such that participants would benefit from using some of them as a starting point but not be helped by using others as a starting point. It is also possible that there are individual differences in which examples are “good” or “bad” starting points, perhaps based on something like prior life experience.

We specifically selected our examples from a pool of ideas generated by members of our lab in order to give participants examples of the type of quality of work that they might be expected to generate. Unfortunately, that did remove some of our experimental control over what the examples actually *were*. Further research might re-claim that experimental control by designing examples that share more common features, to increase the strength of the conformity effect.

Ultimately, this Dissertation adds to our understanding of the interplay between creative thinking, executive function, and examples in a way that is more comprehensive than can be found in the published literature.

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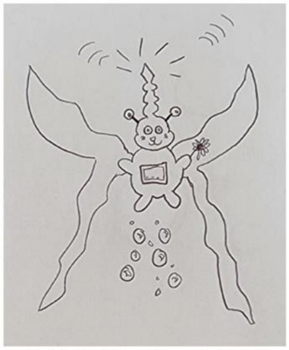
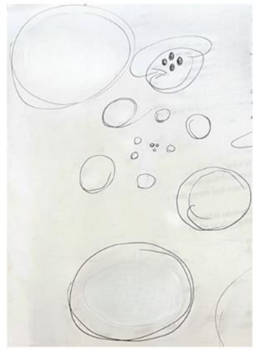
Appendix A: Examples

Alien, Creature



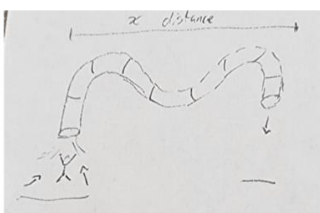
Bobink Alien from Bobink Planet. When they flew around, bubbles come out. They have healing powers in their wands. They have TV's on their bellies & the TV show reflects their mood. The antenna on their head is how they communicate.



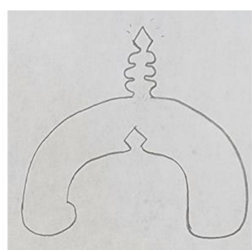
Amorphous blorbs that have inverse gravity (smaller and less dense blorbs exert stronger gravitational force). Googley eyes have multiple pupils and can slide all around the body for optimal vision. This planet is farther away from the Sun than ours, so they have lots of pupils to take in more light! It's all one creature.

Can disguise itself as many different plants. Petals to disguise with plants. Tentacles for swimming through water (its habitat).

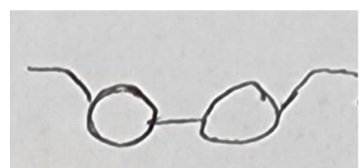
Alien, Technology



Tubes that move people like a subway system but there's no wait for trains or cars.



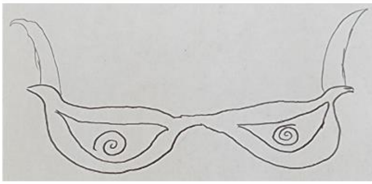
Alien helmet used to help aliens have gravity on planets that don't have gravity. Diamond space for technology sold separately called "the core" which allows aliens to communicate with aliens from different planets.



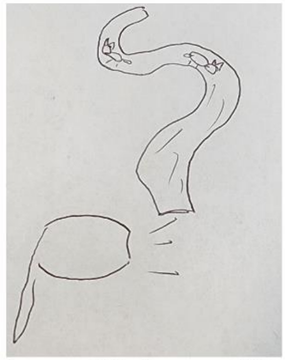
These are sensors that can be placed on any part of a body that translate any living creature's biometric data into a universal language.

Appendix A (continued)

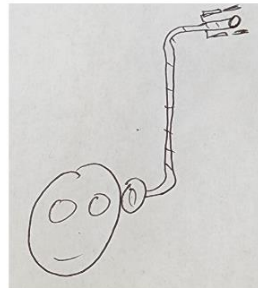
Design, Toy



Transporter goggles! The wearer puts the goggles on & envisions a place and is immediately transported there. There's a 30 minute limit before being transported back for safety reasons.

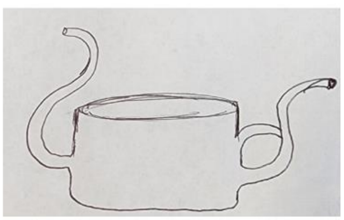


A waterslide for cats with a blow-dryer at the bottom.



Flexible optical tube that allows you to look around corners. Light on the end makes it especially useful for looking down gopher holes or in other underground mysterious places.

Design, Beverage Container



Cup that couples of friends can use to share drinks.

Pop-top dog water bowl. Soda can lid for your dog's favorite beverages on the go.

This container is an edible gelatin layer that can surround any liquid and can be consumed. No plastic, no allergens!

Appendix A (continued)

AUT, Brick

Bury next to an anthropological site to confuse anthropologists

Crack nuts

Grind it up and mix it with water to use as eyeshadow

AUT, Paperclip

Earrings

As a hair barrette

Getting a SIM card out of a cell phone

Titles, Avatar

Space CGI

Blue People

Space Capitalism

Titles, The Avengers

Tight Suits

The Resultful Adult-Children with Superpowers

Heroes Destroy Cities

RPP, Distraction

Offer your friend to take notes for them so they can leave.

Bring a fake finger with fake blood and a fake knife beforehand. As soon as your friend starts talking to you, pretend to slice your finger off and have the fake blood spray all over your friend. The idea is this will traumatize your friend into silence.

Tell your friend you have an ear infection so you need everything to be as quiet as possible so that you can actually hear in class.

RPP, Flat Tire

Stuff tire with grass or newspaper

Pretend to be hurt and call an ambulance, then jump out at the right time when you pass your meeting place

Use a metal cutter and fashion the bike into a unicycle

Appendix B: Creativity Task Instructions

This appendix includes the instructions provided to participants for all the tasks in the battery of creativity tasks. The first few sentences are in (parentheses) to indicate that these were the instructions provided in the No Examples condition. The entire paragraph, including what is in parentheses, was provided to participants in the Examples condition.

Alien, Creature

(You will have 6 minutes to imagine, draw, and describe three (3) alien creatures that could exist on a planet that is very different from Earth. Be as creative and unusual as possible, and try not to duplicate existing creatures. Please use the papers we have given you for this task. Use a new page for each of the three (3) alien creatures.) Before your 6 minutes begin, you will have 30 seconds to examine some examples of alien creatures. Take inspiration from the examples we show you, which other participants generated. You should include features from these examples in your own ideas, but it is very important that you do not just copy those features. One way to think creatively can be to take elements from examples and combine those elements in new ways with other ideas that you may have. Modify, combine, or otherwise build off the features, and then integrate them into your own idea. Click to the next page to see the examples. When the 30 seconds are up, the page will automatically advance to a screen showing the timer for your 6 minutes. You can begin drawing at that time (do not start early).

Alien, Technology

(You will have 6 minutes to imagine, draw, and describe three (3) alien technologies that could exist on a planet that is very different from Earth. Be as creative and unusual as possible, and try not to duplicate existing technologies. Please use the papers we have given you for this task. Use a new page for each of the three (3) alien technologies.) Before your 6 minutes begin, you will have 30 seconds to examine some examples of alien technologies. Take inspiration from the examples we are showing you, which other participants generated. You should include features from these examples in your own ideas, but it is very important that you do not just copy those features. One way to think creatively can be to take elements from examples and combine those elements in new ways with other ideas that you may have. Modify, combine, or otherwise build off the features, and then integrate them into your own idea. Click to the next page to see the examples. When the 30 seconds are up, the page will automatically advance to a screen showing the timer for your 6 minutes. You can begin drawing at that time (do not start early).

Design, Toy

(You will have 6 minutes to imagine, draw, and describe three (3) new ideas for toys. Be as creative and unusual as possible, and try not to duplicate existing toys. Please use the papers we have given you for this task. Use a new page for each of the three (3) toys.) Before your 6 minutes begin, you will have 30 seconds to examine some examples of toys. Take inspiration from the examples we are showing you, which other participants generated. You should include features from these examples in your own ideas, but it is very important that you do not just copy those features.

One way to think creatively can be to take elements from examples and combine those elements in new ways with other ideas that you may have. Modify, combine, or otherwise build off the features, and then integrate them into your own idea. Click to the next page to see the examples. When the 30 seconds are up, the page will automatically advance to a screen showing the timer for your 6 minutes. You can begin drawing at that time (do not start early).

Design, Beverage Container

(You will have 6 minutes to imagine, draw, and describe three (3) new ideas for beverage containers. Be as creative and unusual as possible, and try not to duplicate existing beverage containers. Please use the papers we have given you for this task. Use a new page for each of the three (3) beverage containers.) Before your 6 minutes begin, you will have 30 seconds to examine some examples of beverage containers. Take inspiration from the examples we are showing you, which other participants generated. You should include features from these examples in your own ideas, but it is very important that you do not just copy those features. One way to think creatively can be to take elements from examples and combine those elements in new ways with other ideas that you may have. Modify, combine, or otherwise build off the features, and then integrate them into your own idea. Click to the next page to see the examples. When the 30 seconds are up, the page will automatically advance to a screen showing the timer for your 6 minutes. You can begin drawing at that time (do not start early).

AUT, Brick

(You will have 3 minutes to list three (3) creative alternative uses for a brick. Be as creative and unusual as possible, and try not to duplicate existing uses for a brick.) Before your 3 minutes begin, you will have 30 seconds to examine some examples of alternative uses for a brick. Take inspiration from the examples we are showing you, which other participants generated. You should include features from these examples in your own ideas, but it is very important that you do not just copy those features. One way to think creatively can be to take elements from examples and combine those elements in new ways with other ideas that you may have. Modify, combine, or otherwise build off the features, and then integrate them into your own idea. Click to the next page to see the examples. When the 30 seconds are up, the page will automatically advance to a screen showing the timer for your 3 minutes. You can begin listing your ideas at that time (do not start early).

AUT, Paperclip

(You will have 3 minutes to list three (3) creative alternative uses for a paperclip. Be as creative and unusual as possible, and try not to duplicate existing uses for a paperclip.) Before your 3 minutes begin, you will have 30 seconds to examine some examples of alternative uses for a paperclip. Take inspiration from the examples we are showing you, which other participants generated. You should include features from these examples in your own ideas, but it is very important that you do not just copy those features. One way to think creatively can be to take elements from examples and combine those elements in new ways with other ideas that you may have. Modify, combine, or otherwise build off the features, and then integrate them into your own idea. Click to the next page to see the examples. When the 30 seconds are up, the page will automatically advance to a screen showing the timer for your 3 minutes. You can begin listing your ideas at that time (do not start early).

Titles, Avatar

(You will have 3 minutes to list three (3) alternative titles for the film "Avatar". Be as creative and unusual as possible, and try not to duplicate existing titles.) Before your 3 minutes begin, you will have 30 seconds to examine some examples. Take inspiration from the examples we are showing you, which other participants generated. You should include features from these examples in your own ideas, but it is very important that you do not just copy those features. One way to think creatively can be to take elements from examples and combine those elements in new ways with other ideas that you may have. Modify, combine, or otherwise build off the features, and then integrate them into your own idea. Click to the next page to see the examples. When the 30 seconds are up, the page will automatically advance to a screen showing the timer for your 3 minutes. You can begin listing your ideas at that time (do not start early).

Titles, The Avengers

(You will have 3 minutes to list three (3) alternative titles for the film, "The Avengers". Be as creative and unusual as possible, and try not to duplicate existing titles.) Before your 3 minutes begin, you will have 30 seconds to examine some examples. Take inspiration from the examples we are showing you, which other participants generated. You should include features from these examples in your own ideas, but it is very important that you do not just copy those features. One way to think creatively can be to take elements from examples and combine those elements in new ways with other ideas that you may have. Modify, combine, or otherwise build off the features, and then integrate them into your own idea. Click to the next page to see the examples. When the 30 seconds are up, the page will automatically advance to a screen showing the timer for your 3 minutes. You can begin listing your ideas at that time (do not start early).

RPP, Distraction

(Imagine that you sit next to your friend in class, and your friend is very distracting. You want to be sure that you can pay attention to class. You will have 3 minutes to list three (3) ways to solve this problem. Be as creative and unusual as possible.) Before your 3 minutes begin, you will have 30 seconds to examine some examples of ideas. Take inspiration from the examples we are showing you, which other participants generated. You should include features from these examples in your own ideas, but it is very important that you do not just copy those features. One way to think creatively can be to take elements from examples and combine those elements in new ways with other ideas that you may have. Modify, combine, or otherwise build off the features, and then integrate them into your own idea. Click to the next page to see the examples. When the 30 seconds are up, the page will automatically advance to a screen showing the timer for your 3 minutes. You can begin listing your ideas at that time (do not start early).

RPP, Flat Tire

(Imagine that you are supposed to meet your friend, but you have a flat tire on your bike. You want to be sure that you are able to meet with your friend. You will have 3 minutes to list three (3) ways to solve this problem. Be as creative and unusual as possible and try not to duplicate existing ideas.) Before your 3 minutes begin, you will have 30 seconds to examine some examples of ideas. Take inspiration from the examples we are showing you, which other participants generated. You should include features from these examples in your own ideas, but it is very important that you do not just copy those features. One way to think creatively can be to take elements from examples and combine those elements in new ways with other ideas that you may have. Modify, combine, or otherwise build off the features, and then integrate them into your own idea. Click to the next page to see the examples. When the 30 seconds are up, the page will automatically advance to a screen showing the timer for your 3 minutes. You can begin listing your ideas at that time (do not start early).

Appendix C: *Lavaan* Code

	RQ	Model	Code
Primary	#1: Did participants generate ideas that were more creative in the Examples condition than in the No Examples condition?		
	#2: Does EF predict Creativity in the No Examples condition?	Base	2A
		Improved	2B
		3 Factor	2C
		Inhibition	2D
	#3: Does EF predict Creativity in the Examples condition?	Base	3A
		3 Factor	3B
		Inhibition	3C
	#4: Does EF predict Creativity differently in the Examples condition than it does in the No Examples condition?	Base	4A
		Improved	4B
		Inhibition	4C
	#5: Does EF predict the difference between Creativity in the No Examples condition and the Examples condition?	Base	5A
		Inhibition	5B
Secondary	#6: Was the Conformity Effect shown?		
	#7: Does EF predict Conformity in the No Examples condition (baseline level of Conformity)	Base	CF: 7A HC: 7B Combined: 7C
		3 Factor	CF: 7D HC: 7E Combined: 7F
		Inhibition	CF: 7G HC: 7H Combined: 7I
	#8: Does EF predict Conformity in the Examples condition?	Base	CF: 8A HC: 8B Combined: 8C
		3 Factor	CF: 8D HC: 8E Combined: 8F
		Inhibition	CF: 8G HC: 8H Combined: 8I
	#9: Does Conformity predict Creativity in the No Examples condition?	Base	CF: 9A HC: 9B Combined: 9C
	#10: Does Conformity predict Creativity in the Examples condition?	Base	CF: 10A HC: 10B Combined: 10C

	#11: Does Conformity mediate the relation between EF and Creativity?	Base	CF: 11A HC: 11C Combined: 11E
		Inhibition	CF: 11B HC: 11D Combined: 11F

```
library(lavaan)
library(foreign)
setwd("C:/Users/mtoli/OneDrive/Documents/Projects/Dissertation/Data")
mydata <- read.spss("dissertation_4.15.24.sav", to.data.frame = T)

#2A
	model <- '
	ZefLV =~
	  Zstroop +
	  Zflanker +
	  Zsimon +
	  Zkeeptrack_average +
	  Znback_average +
	  Zlocalglobal_switch_minus_sameRT +
	  Zcolorshape_switch_minus_sameRT
	creativity_noExamplesLV =~
	  Zcreativity_alien_cond0 +
	  Zcreativity_aut_cond0 +
	  Zcreativity_design_cond0 +
	  Zcreativity_rpp_cond0 +
	  Zcreativity_titles_cond0
	creativity_noExamplesLV ~ b1*ZefLV
	'
	fit<- sem(model, data = mydata, fixed.x = F)
	summary(fit, fit.measures = T, rsq = T)
	parameterEstimates (fit, ci = T, level = .95)
	standardizedSolution(fit)

#2B
	model <- '
	ZefLV =~
	  Zstroop +
	  Zflanker +
	  Zsimon +
	  Zkeeptrack_average
	creativity_noExamplesLV =~
```

```
  Zcreativity_alien_cond0 +
  Zcreativity_aut_cond0 +
  Zcreativity_design_cond0 +
  Zcreativity_rpp_cond0 +
  Zcreativity_titles_cond0
Zcreativity_alien_cond0 ~~ Zcreativity_design_cond0
creativity_noExamplesLV ~ b1*ZefLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

```
#2C
model <- '
ZupdatingLV =~
  Zkeeptrack_average +
  Znback_average
ZswitchingLV =~
  Zcolorshape_switch_minus_sameRT +
  Zlocalglobal_switch_minus_sameRT
ZinhibitionLV  =~
  Zstroop +
  Zsimon +
  Zflanker
creativity_noExamplesLV =~
  Zcreativity_alien_cond0 +
  Zcreativity_design_cond0 +
  Zcreativity_rpp_cond0 +
  Zcreativity_titles_cond0 +
  Zcreativity_aut_cond0
Zcreativity_alien_cond0 ~~ Zcreativity_design_cond0
creativity_noExamplesLV ~ b3*ZupdatingLV + b4*ZswitchingLV +
b5*ZinhibitionLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

```
#2D
model <- '
ZinhibitionLV  =~
  Zstroop +
```

```
  Zflanker +
  Zsimon
creativity_noExamplesLV =~
  Zcreativity_alien_cond0 +
  Zcreativity_aut_cond0 +
  Zcreativity_design_cond0 +
  Zcreativity_rpp_cond0 +
  Zcreativity_titles_cond0
  Zcreativity_alien_cond0 ~~ Zcreativity_design_cond0
creativity_noExamplesLV ~ b3*ZinhibitionLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)

#3A
model <- '
ZefLV =~
  Zstroop +
  Zflanker +
  Zsimon +
  Zkeeptrack_average +
  Znback_average +
  Zlocalglobal_switch_minus_sameRT +
  Zcolorshape_switch_minus_sameRT
creativity_examplesLV =~
  Zcreativity_alien_cond1 +
  Zcreativity_aut_cond1 +
  Zcreativity_design_cond1 +
  Zcreativity_rpp_cond1 +
  Zcreativity_titles_cond1
creativity_examplesLV ~ b1*ZefLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)


#3B.
model <- '
ZinhibitionLV  =~
  Zstroop +
```

```
  Zflanker +
  Zsimon
ZswitchingLV =~
 Zlocalglobal_switch_minus_sameRT +
 Zcolorshape_switch_minus_sameRT
ZupdatingLV =~
  Zkeeptrack_average +
  Znback_average
creativity_examplesLV =~
  Zcreativity_alien_cond1 +
  Zcreativity_aut_cond1 +
  Zcreativity_design_cond1 +
  Zcreativity_rpp_cond1 +
  Zcreativity_titles_cond1
creativity_examplesLV ~ b3*ZinhibitionLV + b4*ZswitchingLV +
b5*ZupdatingLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#3C.

```
model <- '
ZinhibitionLV  =~
  Zstroop +
  Zflanker +
  Zsimon
creativity_examplesLV =~
  Zcreativity_alien_cond1 +
  Zcreativity_aut_cond1 +
  Zcreativity_design_cond1 +
  Zcreativity_rpp_cond1 +
  Zcreativity_titles_cond1
creativity_examplesLV ~ b3*ZinhibitionLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#4A.

```
model <- '
ZefLV =~
```

```
  Zstroop +
  Zflanker +
  Zsimon +
  Zkeeptrack_average +
  Znback_average +
  Zlocalglobal_switch_minus_sameRT +
  Zcolorshape_switch_minus_sameRT
creativity_noExamplesLV =~
  Zcreativity_alien_cond0 +
  Zcreativity_aut_cond0 +
  Zcreativity_design_cond0 +
  Zcreativity_rpp_cond0 +
  Zcreativity_titles_cond0
creativity_examplesLV =~
  Zcreativity_alien_cond1 +
  Zcreativity_aut_cond1 +
  Zcreativity_design_cond1 +
  Zcreativity_rpp_cond1 +
  Zcreativity_titles_cond1
creativity_noExamplesLV ~ b1*ZefLV
creativity_examplesLV ~ b2*ZefLV
slopediff:= b1-b2
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#4B.

```
model <- '
ZefLV =~
  Zstroop +
  Zflanker +
  Zsimon +
  Zkeeptrack_average
creativity_noExamplesLV =~
  Zcreativity_alien_cond0 +
  Zcreativity_aut_cond0 +
  Zcreativity_design_cond0 +
  Zcreativity_rpp_cond0 +
  Zcreativity_titles_cond0
creativity_examplesLV =~
  Zcreativity_alien_cond1 +
  Zcreativity_aut_cond1 +
```

```
  Zcreativity_design_cond1 +
  Zcreativity_rpp_cond1 +
  Zcreativity_titles_cond1
Zcreativity_alien_cond0 ~~ Zcreativity_alien_cond1
Zcreativity_aut_cond0 ~~ Zcreativity_aut_cond1
Zcreativity_design_cond0 ~~ Zcreativity_design_cond1
Zcreativity_rpp_cond0 ~~ Zcreativity_rpp_cond1
Zcreativity_titles_cond0 ~~ Zcreativity_titles_cond1
Zcreativity_alien_cond0 ~~ Zcreativity_design_cond0
Zcreativity_alien_cond1 ~~ Zcreativity_design_cond1
creativity_noExamplesLV ~ b1*ZefLV
creativity_examplesLV ~ b2*ZefLV
slopediff:= b1-b2
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#4C

```
model <- '
ZinhibitionLV  =~
 Zstroop +
 Zflanker +
 Zsimon
creativity_noExamplesLV =~
  Zcreativity_alien_cond0 +
  Zcreativity_aut_cond0 +
  Zcreativity_design_cond0 +
  Zcreativity_rpp_cond0 +
  Zcreativity_titles_cond0
creativity_examplesLV =~
  Zcreativity_alien_cond1 +
  Zcreativity_aut_cond1 +
  Zcreativity_design_cond1 +
  Zcreativity_rpp_cond1 +
  Zcreativity_titles_cond1
Zcreativity_alien_cond0 ~~ Zcreativity_alien_cond1
Zcreativity_aut_cond0 ~~ Zcreativity_aut_cond1
Zcreativity_design_cond0 ~~ Zcreativity_design_cond1
Zcreativity_rpp_cond0 ~~ Zcreativity_rpp_cond1
Zcreativity_titles_cond0 ~~ Zcreativity_titles_cond1
Zcreativity_alien_cond0 ~~ Zcreativity_design_cond0
Zcreativity_alien_cond1 ~~ Zcreativity_design_cond1
```

```
creativity_examplesLV ~ b1*ZinhibitionLV
creativity_noExamplesLV ~ b2*ZinhibitionLV
slopediff:= b1-b2
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#5A

```
model <- '
ZefLV =~
  1*Zstroop +
  Zflanker +
  Zsimon +
  Zkeeptrack_average +
  Znback_average +
  Zlocalglobal_switch_minus_sameRT +
  Zcolorshape_switch_minus_sameRT
creativity_diffBaselineLV =~
  1*Zcreativity_alien_cond0 +
  b1*Zcreativity_aut_cond0 +
  b2*Zcreativity_design_cond0 +
  b3*Zcreativity_rpp_cond0 +
  b4*Zcreativity_titles_cond0 +
  1*Zcreativity_alien_cond1 +
  b1*Zcreativity_aut_cond1 +
  b2*Zcreativity_design_cond1 +
  b3*Zcreativity_rpp_cond1 +
  b4*Zcreativity_titles_cond1
creativity_diff1 =~
  1*Zcreativity_alien_cond1 +
  b1*Zcreativity_aut_cond1 +
  b2*Zcreativity_design_cond1 +
  b3*Zcreativity_rpp_cond1 +
  b4*Zcreativity_titles_cond1
creativity_diffBaselineLV ~~ creativity_diff1
Zcreativity_alien_cond0 ~~ Zcreativity_alien_cond1
Zcreativity_aut_cond0 ~~ Zcreativity_aut_cond1
Zcreativity_design_cond0 ~~ Zcreativity_design_cond1
Zcreativity_rpp_cond0 ~~ Zcreativity_rpp_cond1
Zcreativity_titles_cond0 ~~ Zcreativity_titles_cond1
Zcreativity_alien_cond0 ~~ Zcreativity_design_cond0
Zcreativity_alien_cond1 ~~ Zcreativity_design_cond1
```

```
creativity_diff1 ~ b5*ZefLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#5B

```
model <- '
ZinhibitionLV =~
 1*Zstroop +
 Zflanker +
 Zsimon
creativity_diffBaselineLV =~
 1*Zcreativity_alien_cond0 +
 b1*Zcreativity_aut_cond0 +
 b2*Zcreativity_design_cond0 +
 b3*Zcreativity_rpp_cond0 +
 b4*Zcreativity_titles_cond0 +
 1*Zcreativity_alien_cond1 +
 b1*Zcreativity_aut_cond1 +
 b2*Zcreativity_design_cond1 +
 b3*Zcreativity_rpp_cond1 +
 b4*Zcreativity_titles_cond1
creativity_diff1 =~
 1*Zcreativity_alien_cond1 +
 b1*Zcreativity_aut_cond1 +
 b2*Zcreativity_design_cond1 +
 b3*Zcreativity_rpp_cond1 +
 b4*Zcreativity_titles_cond1
creativity_diffBaselineLV ~~ creativity_diff1
Zcreativity_alien_cond0 ~~ Zcreativity_alien_cond1
Zcreativity_aut_cond0 ~~ Zcreativity_aut_cond1
Zcreativity_design_cond0 ~~ Zcreativity_design_cond1
Zcreativity_rpp_cond0 ~~ Zcreativity_rpp_cond1
Zcreativity_titles_cond0 ~~ Zcreativity_titles_cond1
Zcreativity_alien_cond0 ~~ Zcreativity_design_cond0
Zcreativity_alien_cond1 ~~ Zcreativity_design_cond1
creativity_diff1 ~ b5*ZinhibitionLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#7A

```
model <- '
ZefLV =~
  Zstroop +
  Zflanker +
  Zsimon +
  Zkeeptrack_average +
  Znback_average +
  Zlocalglobal_switch_minus_sameRT +
  Zcolorshape_switch_minus_sameRT
cf_noExamplesLV =~
  Zcf_alien_cond0 +
  Zcf_aut_cond0 +
  Zcf_design_cond0 +
  Zcf_rpp_cond0 +
  Zcf_titles_cond0
cf_noExamplesLV ~ b1*ZefLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#7B

```
model <- '
ZefLV =~
  Zstroop +
  Zflanker +
  Zsimon +
  Zkeeptrack_average +
  Znback_average +
  Zlocalglobal_switch_minus_sameRT +
  Zcolorshape_switch_minus_sameRT
hc_noExamplesLV =~
  Zholistic_conformity_alien_cond0 +
  Zholistic_conformity_aut_cond0 +
  Zholistic_conformity_design_cond0 +
  Zholistic_conformity_rpp_cond0 +
  Zholistic_conformity_titles_cond0
hc_noExamplesLV ~ b1*ZefLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
```

```
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#7C.

```
model <- '
ZefLV =~
  Zstroop +
  Zflanker +
  Zsimon +
  Zkeeptrack_average +
  Znback_average +
  Zlocalglobal_switch_minus_sameRT +
  Zcolorshape_switch_minus_sameRT
conformity_noExamplesLV =~
  Zconformity_alien_cond0 +
  Zconformity_aut_cond0 +
  Zconformity_design_cond0 +
  Zconformity_rpp_cond0 +
  Zconformity_titles_cond0
conformity_noExamplesLV ~ b1*ZefLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#7D.

```
model <- '
ZinhibitionLV  =~
  Zstroop +
  Zflanker +
  Zsimon
ZswitchingLV =~
  Zlocalglobal_switch_minus_sameRT +
  Zcolorshape_switch_minus_sameRT
ZupdatingLV =~
  Zkeeptrack_average +
  Znback_average
cf_noExamplesLV =~
  Zcf_alien_cond0 +
  Zcf_aut_cond0 +
  Zcf_design_cond0 +
  Zcf_rpp_cond0 +
  Zcf_titles_cond0
```

```
cf_noExamplesLV ~ b1*ZinhibitionLV + b2*ZswitchingLV +
b3*ZupdatingLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#7E.

```
model <- '
ZinhibitionLV  =~
 Zstroop +
 Zflanker +
 Zsimon
ZswitchingLV =~
  Zlocalglobal_switch_minus_sameRT +
  Zcolorshape_switch_minus_sameRT
ZupdatingLV =~
   Zkeeptrack_average +
   Znback_average
hc_noExamplesLV =~
  Zholistic_conformity_alien_cond0 +
  Zholistic_conformity_aut_cond0 +
  #Zholistic_conformity_design_cond0 +
  Zholistic_conformity_rpp_cond0 +
  Zholistic_conformity_titles_cond0
hc_noExamplesLV ~ b1*ZinhibitionLV + b2*ZswitchingLV +
b3*ZupdatingLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#7F.

```
model <- '
ZinhibitionLV  =~
  Zstroop +
  Zflanker +
  Zsimon
ZswitchingLV =~
  Zlocalglobal_switch_minus_sameRT +
  Zcolorshape_switch_minus_sameRT
ZupdatingLV =~
```

```
  Zkeeptrack_average +
  Znback_average
conformity_noExamplesLV =~
  Zconformity_alien_cond0 +
  Zconformity_aut_cond0 +
  Zconformity_design_cond0 +
  Zconformity_rpp_cond0 +
  Zconformity_titles_cond0
conformity_noExamplesLV ~ b1*ZinhibitionLV + b2*ZswitchingLV +
b3*ZupdatingLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#7G

```
model <- '
ZinhibitionLV =~
  Zstroop +
  Zflanker +
  Zsimon
cf_noExamplesLV =~
  Zcf_alien_cond0 +
  Zcf_aut_cond0 +
  Zcf_design_cond0 +
  Zcf_rpp_cond0 +
  Zcf_titles_cond0
#Zcf_alien_cond0 ~~ Zcf_design_cond0
cf_noExamplesLV ~ b1*ZinhibitionLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#7H

```
model <- '
ZinhibitionLV =~
  Zstroop +
  Zflanker +
  Zsimon
hc_noExamplesLV =~
  Zholistic_conformity_alien_cond0 +
```

```
  Zholistic_conformity_aut_cond0 +
  Zholistic_conformity_design_cond0 +
  Zholistic_conformity_rpp_cond0 +
  Zholistic_conformity_titles_cond0
hc_noExamplesLV ~ b1*ZinhibitionLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#7I.

```
model <- '
ZinhibitionLV =~
  Zstroop +
  Zflanker +
  Zsimon
conformity_noExamplesLV =~
  Zconformity_alien_cond0 +
  Zconformity_aut_cond0 +
  Zconformity_design_cond0 +
  Zconformity_rpp_cond0 +
  Zconformity_titles_cond0
conformity_noExamplesLV ~ b1*ZinhibitionLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#8A.

```
model <- '
ZefLV =~
  Zstroop +
  Zflanker +
  Zsimon +
  Zkeeptrack_average +
  Znback_average +
  Zlocalglobal_switch_minus_sameRT +
  Zcolorshape_switch_minus_sameRT
cf_examplesLV =~
  Zcf_alien_cond1 +
```

```
  Zcf_aut_cond1 +
  Zcf_design_cond1 +
  Zcf_rpp_cond1 +
  Zcf_titles_cond1
cf_examplesLV ~ b1*ZefLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

```
#8B.
model <- '
ZefLV =~
  Zstroop +
  Zflanker +
  Zsimon +
  Zkeeptrack_average +
  Znback_average +
  Zlocalglobal_switch_minus_sameRT +
  Zcolorshape_switch_minus_sameRT
hc_examplesLV =~
  Zholistic_conformity_alien_cond1 +
  Zholistic_conformity_aut_cond1 +
  Zholistic_conformity_design_cond1 +
  Zholistic_conformity_rpp_cond1 +
  Zholistic_conformity_titles_cond1
hc_examplesLV ~ b1*ZefLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

```
#8C.
model <- '
ZefLV =~
  Zstroop +
  Zflanker +
  Zsimon +
  Zkeeptrack_average +
  Znback_average +
  Zlocalglobal_switch_minus_sameRT +
  Zcolorshape_switch_minus_sameRT
```

```
conformity_examplesLV =~
  Zconformity_alien_cond1 +
  Zconformity_aut_cond1 +
  Zconformity_design_cond1 +
  Zconformity_rpp_cond1 +
  Zconformity_titles_cond1
conformity_examplesLV ~ b1*ZefLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

```
#8D.
model <- '
ZinhibitionLV  =~
  Zstroop +
  Zflanker +
  Zsimon
ZswitchingLV =~
  Zlocalglobal_switch_minus_sameRT +
  Zcolorshape_switch_minus_sameRT
ZupdatingLV =~
  Zkeeptrack_average +
  Znback_average
cf_examplesLV =~
  Zcf_alien_cond1 +
  Zcf_aut_cond1 +
  Zcf_design_cond1 +
  Zcf_rpp_cond1 +
  Zcf_titles_cond1
cf_examplesLV ~ b1*ZinhibitionLV + b2*ZswitchingLV + b3*ZupdatingLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

```
#8E.
model <- '
ZinhibitionLV  =~
  Zstroop +
  Zflanker +
  Zsimon
```

```
ZswitchingLV =~
  Zlocalglobal_switch_minus_sameRT +
  Zcolorshape_switch_minus_sameRT
ZupdatingLV =~
  Zkeeptrack_average +
  Znback_average
hc_examplesLV =~
  Zholistic_conformity_alien_cond1 +
  Zholistic_conformity_aut_cond1 +
  Zholistic_conformity_design_cond1 +
  Zholistic_conformity_rpp_cond1 +
  Zholistic_conformity_titles_cond1
hc_examplesLV ~ b1*ZinhibitionLV + b2*ZswitchingLV + b3*ZupdatingLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#8F.

```
model <- '
ZinhibitionLV  =~
  Zstroop +
  Zflanker +
  Zsimon
ZswitchingLV =~
  Zlocalglobal_switch_minus_sameRT +
  Zcolorshape_switch_minus_sameRT
ZupdatingLV =~
  Zkeeptrack_average +
  Znback_average
conformity_examplesLV =~
  Zconformity_alien_cond1 +
  Zconformity_aut_cond1 +
  Zconformity_design_cond1 +
  Zconformity_rpp_cond1 +
  Zconformity_titles_cond1
conformity_examplesLV ~ b1*ZinhibitionLV + b2*ZswitchingLV +
b3*ZupdatingLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#8G.

```
model <- '
ZinhibitionLV =~
  Zstroop +
  Zflanker +
  Zsimon
cf_examplesLV =~
  Zcf_alien_cond1 +
  Zcf_aut_cond1 +
  Zcf_design_cond1 +
  Zcf_rpp_cond1 +
  Zcf_titles_cond1
cf_examplesLV ~ b1*ZinhibitionLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#8H.

```
model <- '
ZinhibitionLV =~
  Zstroop +
  Zflanker +
  Zsimon
hc_examplesLV =~
  Zholistic_conformity_alien_cond1 +
  Zholistic_conformity_aut_cond1 +
  Zholistic_conformity_design_cond1 +
  Zholistic_conformity_rpp_cond1 +
  Zholistic_conformity_titles_cond1
hc_examplesLV ~ b1*ZinhibitionLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#8I.

```
model <- '
ZinhibitionLV =~
```

```
  Zstroop +
  Zflanker +
  Zsimon
conformity_examplesLV =~
  Zconformity_alien_cond1 +
  Zconformity_aut_cond1 +
  Zconformity_design_cond1 +
  Zconformity_rpp_cond1 +
  Zconformity_titles_cond1
conformity_examplesLV ~ b1*ZinhibitionLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#9A.

```
model <- '
cf_noExamplesLV =~
  Zcf_alien_cond0 +
  Zcf_aut_cond0 +
  Zcf_design_cond0 +
  Zcf_rpp_cond0 +
  Zcf_titles_cond0
creativity_noExamplesLV =~
  Zcreativity_alien_cond0 +
  Zcreativity_aut_cond0 +
  Zcreativity_design_cond0 +
  Zcreativity_rpp_cond0 +
  Zcreativity_titles_cond0
creativity_noExamplesLV ~ b1*cf_noExamplesLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#9B.

```
model <- '
hc_noExamplesLV =~
  Zholistic_conformity_alien_cond0 +
  Zholistic_conformity_aut_cond0 +
  Zholistic_conformity_design_cond0 +
  Zholistic_conformity_rpp_cond0 +
```

```
  Zholistic_conformity_titles_cond0
creativity_noExamplesLV =~
  Zcreativity_alien_cond0 +
  Zcreativity_aut_cond0 +
  Zcreativity_design_cond0 +
  Zcreativity_rpp_cond0 +
  Zcreativity_titles_cond0
creativity_noExamplesLV ~ b1*hc_noExamplesLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#9C.

```
model <- '
conformity_noExamplesLV =~
  Zconformity_alien_cond0 +
  Zconformity_aut_cond0 +
  Zconformity_design_cond0 +
  Zconformity_rpp_cond0 +
  Zconformity_titles_cond0
creativity_noExamplesLV =~
  Zcreativity_alien_cond0 +
  Zcreativity_aut_cond0 +
  Zcreativity_design_cond0 +
  Zcreativity_rpp_cond0 +
  Zcreativity_titles_cond0
creativity_noExamplesLV ~ b1*conformity_noExamplesLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#10A.

```
model <- '
cf_examplesLV =~
  Zcf_alien_cond1 +
  Zcf_aut_cond1 +
  Zcf_design_cond1 +
  Zcf_rpp_cond1 +
  Zcf_titles_cond1
creativity_examplesLV =~
```

```
  Zcreativity_alien_cond1 +
  Zcreativity_aut_cond1 +
  Zcreativity_design_cond1 +
  Zcreativity_rpp_cond1 +
  Zcreativity_titles_cond1
creativity_examplesLV ~ b1*cf_examplesLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#10B.

```
model <- '
hc_examplesLV =~
  Zholistic_conformity_alien_cond1 +
  Zholistic_conformity_aut_cond1 +
  Zholistic_conformity_design_cond1 +
  Zholistic_conformity_rpp_cond1 +
  Zholistic_conformity_titles_cond1
creativity_examplesLV =~
  Zcreativity_alien_cond1 +
  Zcreativity_aut_cond1 +
  Zcreativity_design_cond1 +
  Zcreativity_rpp_cond1 +
  Zcreativity_titles_cond1
creativity_examplesLV ~ b1*hc_examplesLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#10C.

```
model <- '
conformity_examplesLV =~
  Zconformity_alien_cond1 +
  Zconformity_aut_cond1 +
  Zconformity_design_cond1 +
  Zconformity_rpp_cond1 +
  Zconformity_titles_cond1
creativity_examplesLV =~
  Zcreativity_alien_cond1 +
  Zcreativity_aut_cond1 +
```

```
  Zcreativity_design_cond1 +
  Zcreativity_rpp_cond1 +
  Zcreativity_titles_cond1
creativity_examplesLV ~ b1*conformity_examplesLV
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit, fit.measures = T, rsq = T)
parameterEstimates (fit, ci = T, level = .95)
standardizedSolution(fit)
```

#11A.

```
model <- '
#M
cf_examplesLV =~
  Zcf_alien_cond1 +
  Zcf_aut_cond1 +
  Zcf_design_cond1 +
  Zcf_rpp_cond1 +
  Zcf_titles_cond1
#Y
creativity_examplesLV =~
  Zcreativity_alien_cond1 +
  Zcreativity_aut_cond1 +
  Zcreativity_design_cond1 +
  Zcreativity_rpp_cond1 +
  Zcreativity_titles_cond1
#X
ZefLV =~
  Zstroop +
  Zflanker +
  Zsimon +
  Zkeeptrack_average +
  Znback_average +
  Zlocalglobal_switch_minus_sameRT +
  Zcolorshape_switch_minus_sameRT
#direct effect, c'
  creativity_examplesLV ~ c*ZefLV
#mediator
  cf_examplesLV ~ a*ZefLV
  creativity_examplesLV ~ b*cf_examplesLV
#path a
  pathA := a
#path b
  pathB := b
```

```
#indirect effect
  indirect := a*b
#direct effect
  direct := c
#total effect
  total := c + (a*b)
  pathC_total := direct + indirect
#prop mediated
propmediated := indirect/total
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit)
parameterEstimates (fit, ci = T, level = .95)
```

#11B.

```
model <- '
#M
cf_examplesLV =~
  Zcf_alien_cond1 +
  Zcf_aut_cond1 +
  Zcf_design_cond1 +
  Zcf_rpp_cond1 +
  Zcf_titles_cond1
#Y
creativity_examplesLV =~
  Zcreativity_alien_cond1 +
  Zcreativity_aut_cond1 +
  Zcreativity_design_cond1 +
  Zcreativity_rpp_cond1 +
  Zcreativity_titles_cond1
#X
ZinhibitionLV =~
  Zstroop +
  Zflanker +
  Zsimon
#direct effect, c'
creativity_examplesLV ~ c*ZinhibitionLV
#mediator
cf_examplesLV ~ a*ZinhibitionLV
creativity_examplesLV ~ b*cf_examplesLV
#path a
pathA := a
#path b
pathB := b
```

```
	#indirect effect
	indirect := a*b
	#direct effect
	direct := c
	#total effect
	total := c + (a*b)
	pathC_total := direct + indirect
	#prop mediated
	propmediated := indirect/total
	'
	fit<- sem(model, data = mydata, fixed.x = F)
	summary(fit)
	parameterEstimates (fit, ci = T, level = .95)

#11C.
	model <- '
	#M
	hc_examplesLV =~
	  Zholistic_conformity_alien_cond1 +
	  Zholistic_conformity_aut_cond1 +
	  Zholistic_conformity_design_cond1 +
	  Zholistic_conformity_rpp_cond1 +
	  Zholistic_conformity_titles_cond1
	#Y
	creativity_examplesLV =~
	  Zcreativity_alien_cond1 +
	  Zcreativity_aut_cond1 +
	  Zcreativity_design_cond1 +
	  Zcreativity_rpp_cond1 +
	  Zcreativity_titles_cond1
	#X
	ZefLV =~
	  Zstroop +
	  Zflanker +
	  Zsimon +
	  Zkeeptrack_average +
	  Znback_average +
	  Zlocalglobal_switch_minus_sameRT +
	  Zcolorshape_switch_minus_sameRT
	#direct effect, c'
	creativity_examplesLV ~ c*ZefLV
	#mediator
	holistic_conformity_examplesLV ~ a*ZefLV
	creativity_examplesLV ~ b*holistic_conformity_examplesLV
```

```
#path a
pathA := a
#path b
pathB := b
#indirect effect
indirect := a*b
#direct effect
direct := c
#total effect
total := c + (a*b)
pathC_total := direct + indirect
#prop mediated
propmediated := indirect/total
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit)
parameterEstimates (fit, ci = T, level = .95)
```

#11D.

```
model <- '
#M
hc_examplesLV =~
  Zholistic_conformity_alien_cond1 +
  Zholistic_conformity_aut_cond1 +
  Zholistic_conformity_design_cond1 +
  Zholistic_conformity_rpp_cond1 +
  Zholistic_conformity_titles_cond1
#Y
creativity_examplesLV =~
  Zcreativity_alien_cond1 +
  Zcreativity_aut_cond1 +
  Zcreativity_design_cond1 +
  Zcreativity_rpp_cond1 +
  Zcreativity_titles_cond1
#X
ZinhibitionLV =~
  Zstroop + Zflanker + Zsimon
#direct effect, c'
creativity_examplesLV ~ c*ZinhibitionLV
#mediator
holistic_conformity_examplesLV ~ a*ZinhibitionLV
creativity_examplesLV ~ b*holistic_conformity_examplesLV
#path a
pathA := a
```

```
#path b
pathB := b
#indirect effect
indirect := a*b
#direct effect
direct := c
#total effect
total := c + (a*b)
pathC_total := direct + indirect
#prop mediated
propmediated := indirect/total
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit)
parameterEstimates (fit, ci = T, level = .95)
```

#11E.

```
model <- '
#M
conformity_examplesLV =~
  Zconformity_alien_cond1 +
  Zconformity_aut_cond1 +
  Zconformity_design_cond1 +
  Zconformity_rpp_cond1 +
  Zconformity_titles_cond1
#Y
creativity_examplesLV =~
  Zcreativity_alien_cond1 +
  Zcreativity_aut_cond1 +
  Zcreativity_design_cond1 +
  Zcreativity_rpp_cond1 +
  Zcreativity_titles_cond1
#X
ZefLV =~
  Zstroop +
  Zflanker +
  Zsimon +
  Zkeeptrack_average +
  Znback_average +
  Zlocalglobal_switch_minus_sameRT +
  Zcolorshape_switch_minus_sameRT
#direct effect, c'
creativity_examplesLV ~ c*ZefLV
#mediator
```

```
conformity_examplesLV ~ a*ZefLV
creativity_examplesLV ~ b*conformity_examplesLV
#path a
pathA := a
#path b
pathB := b
#indirect effect
indirect := a*b
#direct effect
direct := c
#total effect
total := c + (a*b)
pathC_total := direct + indirect
#prop mediated
propmediated := indirect/total
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit)
parameterEstimates (fit, ci = T, level = .95)
```

#11F.

```
model <- '
#M
conformity_examplesLV =~
  Zconformity_alien_cond1 +
  Zconformity_aut_cond1 +
  Zconformity_design_cond1 +
  Zconformity_rpp_cond1 +
  Zconformity_titles_cond1
#Y
creativity_examplesLV =~
  Zcreativity_alien_cond1 +
  Zcreativity_aut_cond1 +
  Zcreativity_design_cond1 +
  Zcreativity_rpp_cond1 +
  Zcreativity_titles_cond1
#X
ZinhibitionLV =~
  Zstroop +
  Zflanker +
  Zsimon
#direct effect, c'
creativity_examplesLV ~ c*ZinhibitionLV
#mediator
```

```
conformity_examplesLV ~ a*ZinhibitionLV
creativity_examplesLV ~ b*conformity_examplesLV
#path a
pathA := a
#path b
pathB := b
#indirect effect
indirect := a*b
#direct effect
direct := c
#total effect
total := c + (a*b)
pathC_total := direct + indirect
#prop mediated
propmediated := indirect/total
'
fit<- sem(model, data = mydata, fixed.x = F)
summary(fit)
parameterEstimates (fit, ci = T, level = .95)
```

Appendix D: SPSS Script

	RQ	Model	Code
Primary	#1: Did participants generate ideas that were more creative in the Examples condition than in the No Examples condition?		1A
	#2: Does EF predict Creativity in the No Examples condition?	Original	2A
		3 Factor	2B
		Inhibition	2C
	#3: Does EF predict Creativity in the Examples condition?	Base	3A
		3 Factor	3B
		Inhibition	3C
	#4: Does EF predict Creativity differently in the Examples condition than it does in the No Examples condition?	Base	
		3 Factor	
		Inhibition	
	#5: Does EF predict the difference between Creativity in the No Examples condition and the Examples condition?	Base	4A
		Inhibition	4C
Secondary	#6: Was the Conformity Effect demonstrated?	Base/ Inhibition	6A – 6F
	#7: Does EF predict Conformity in the No Examples condition (baseline level of Conformity)	Base	CF: 7A HC: 7B Combined: 7C
		3 Factor	CF: 7D HC: 7E Combined: 7F
		Inhibition	CF: 7G HC: 7H Combined: 7I
	#8: Does EF predict Conformity in the Examples condition?	Base	CF: 8A HC: 8B Combined: 8C
		3 Factor	CF: 8D HC: 8E Combined: 8F
		Inhibition	CF: 8G HC: 8H Combined: 8I
	#9: Does Conformity predict Creativity in the No Examples condition?	Base	CF: 9A HC: 9B Combined: 9C

	#10: Does Conformity predict Creativity in the Examples condition?	Base	CF: 10A HC: 10B Combined:10C
	#11: Does Conformity mediate the relation between EF and Creativity?	Base	
		Inhibition	

```
* Encoding: UTF-8.
*1A.
        T-TEST PAIRS=creativity_cond1 WITH creativity_cond0 (PAIRED)
          /ES DISPLAY(TRUE) STANDARDIZER(SD)
          /CRITERIA=CI(.9500)
          /MISSING=ANALYSIS.
*1B.
        T-TEST PAIRS=creativity_alien_cond1 creativity_titles_cond1
        creativity_rpp_cond1
            creativity_design_cond1 creativity_aut_cond1 WITH
        creativity_alien_cond0 creativity_titles_cond0
            creativity_rpp_cond0 creativity_design_cond0 creativity_aut_cond0
        (PAIRED)
          /ES DISPLAY(TRUE) STANDARDIZER(SD)
          /CRITERIA=CI(.9500)
          /MISSING=ANALYSIS.

*2A.
          REGRESSION
          /DESCRIPTIVES MEAN STDDEV CORR SIG N
          /MISSING LISTWISE
          /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
          /CRITERIA=PIN(.05) POUT(.10)
          /NOORIGIN
          /DEPENDENT Zcreativity_cond0
          /METHOD=ENTER Zef.

*2B.
        REGRESSION
          /DESCRIPTIVES MEAN STDDEV CORR SIG N
          /MISSING LISTWISE
          /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
          /CRITERIA=PIN(.05) POUT(.10)
          /NOORIGIN
```

```
  /DEPENDENT Zcreativity_cond0
  /METHOD=ENTER Zinhibition Zswitching Zupdating.
```

*2C.

```
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Zcreativity_cond0
  /METHOD=ENTER Zinhibition.
```

*3A.

```
  REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Zcreativity_cond1
  /METHOD=ENTER Zef.
```

*3B.

```
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Zcreativity_cond1
  /METHOD=ENTER Zinhibition Zswitching Zupdating.
```

*3C.

```
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Zcreativity_cond1
  /METHOD=ENTER Zinhibition.
```

*5A.

```
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Zcreativity_diff
  /METHOD=ENTER Zef.
```

*5B.

```
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Zcreativity_diff
  /METHOD=ENTER Zinhibition.
```

*6A.

```
T-TEST PAIRS=cf_cond1 WITH cf_cond0 (PAIRED)
  /ES DISPLAY(TRUE) STANDARDIZER(SD)
  /CRITERIA=CI(.9500)
  /MISSING=ANALYSIS.
```

*6B.

```
T-TEST PAIRS=cf_alien_cond1 cf_titles_cond1 cf_rpp_cond1
    cf_design_cond1 cf_aut_cond1 WITH cf_alien_cond0 cf_titles_cond0
    cf_rpp_cond0 cf_design_cond0 cf_aut_cond0 (PAIRED)
  /ES DISPLAY(TRUE) STANDARDIZER(SD)
  /CRITERIA=CI(.9500)
  /MISSING=ANALYSIS.
```

*6C.

```
T-TEST PAIRS=holistic_conformity_cond1 WITH
holistic_conformity_cond0 (PAIRED)
  /ES DISPLAY(TRUE) STANDARDIZER(SD)
  /CRITERIA=CI(.9500)
  /MISSING=ANALYSIS.
```

*6D.

```
T-TEST PAIRS=holistic_conformity_alien_cond1
holistic_conformity_titles_cond1 holistic_conformity_rpp_cond1
    holistic_conformity_design_cond1 holistic_conformity_aut_cond1 WITH
```

```
holistic_conformity_alien_cond0 holistic_conformity_titles_cond0
   holistic_conformity_rpp_cond0 holistic_conformity_design_cond0
holistic_conformity_aut_cond0 (PAIRED)
  /ES DISPLAY(TRUE) STANDARDIZER(SD)
  /CRITERIA=CI(.9500)
  /MISSING=ANALYSIS.
```

*6E.

```
T-TEST PAIRS=conformity_cond1 WITH conformity_cond0 (PAIRED)
  /ES DISPLAY(TRUE) STANDARDIZER(SD)
  /CRITERIA=CI(.9500)
  /MISSING=ANALYSIS.
```

*6F.

```
T-TEST PAIRS=conformity_alien_cond1 conformity_titles_cond1
conformity_rpp_cond1
   conformity_design_cond1 conformity_aut_cond1 WITH
conformity_alien_cond0 conformity_titles_cond0
   conformity_rpp_cond0 conformity_design_cond0 conformity_aut_cond0
(PAIRED)
  /ES DISPLAY(TRUE) STANDARDIZER(SD)
  /CRITERIA=CI(.9500)
  /MISSING=ANALYSIS.
```

*7A.

```
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Zcf_cond0
  /METHOD=ENTER Zef.
```

*7B.

```
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Zholistic_conformity_cond0
  /METHOD=ENTER Zef.
```

*7C.

```
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Zconformity_cond0
  /METHOD=ENTER Zef.
```

*7D.

```
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Zcf_cond0
  /METHOD=ENTER Zinhibition Zswitching Zupdating.
```

*7E.

```
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Zholistic_conformity_cond0
  /METHOD=ENTER Zinhibition Zswitching Zupdating.
```

*7F.

```
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Zconformity_cond0
  /METHOD=ENTER Zinhibition Zswitching Zupdating.
```

*7G.

```
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
```

```
  /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Zcf_cond0
  /METHOD=ENTER Zinhibition.

*7H.
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Zholistic_conformity_cond0
  /METHOD=ENTER Zinhibition.

*7I.
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Zconformity_cond0
  /METHOD=ENTER Zinhibition.

*8A.
  REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Zcf_cond1
  /METHOD=ENTER Zef.

*8B.
  REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Zholistic_conformity_cond1
```

```
/METHOD=ENTER Zef.

*8C.
REGRESSION
/DESCRIPTIVES MEAN STDDEV CORR SIG N
/MISSING LISTWISE
/STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT Zconformity_cond1
/METHOD=ENTER Zef.

*8D.
REGRESSION
/DESCRIPTIVES MEAN STDDEV CORR SIG N
/MISSING LISTWISE
/STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT Zcf_cond1
/METHOD=ENTER Zinhibition Zswitching Zupdating.

*8E.
REGRESSION
/DESCRIPTIVES MEAN STDDEV CORR SIG N
/MISSING LISTWISE
/STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT Zholistic_conformity_cond1
/METHOD=ENTER Zinhibition Zswitching Zupdating.

*8F.
REGRESSION
/DESCRIPTIVES MEAN STDDEV CORR SIG N
/MISSING LISTWISE
/STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT Zconformity_cond1
/METHOD=ENTER Zinhibition Zswitching Zupdating.

*8G.
REGRESSION
```

```
        /DESCRIPTIVES MEAN STDDEV CORR SIG N
        /MISSING LISTWISE
        /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
        /CRITERIA=PIN(.05) POUT(.10)
        /NOORIGIN
        /DEPENDENT Zcf_cond1
        /METHOD=ENTER Zinhibition.

*8H.
        REGRESSION
        /DESCRIPTIVES MEAN STDDEV CORR SIG N
        /MISSING LISTWISE
        /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
        /CRITERIA=PIN(.05) POUT(.10)
        /NOORIGIN
        /DEPENDENT Zholistic_conformity_cond1
        /METHOD=ENTER Zinhibition.

*8I.
        REGRESSION
        /DESCRIPTIVES MEAN STDDEV CORR SIG N
        /MISSING LISTWISE
        /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
        /CRITERIA=PIN(.05) POUT(.10)
        /NOORIGIN
        /DEPENDENT Zconformity_cond1
        /METHOD=ENTER Zinhibition.

*9A.
       REGRESSION
        /DESCRIPTIVES MEAN STDDEV CORR SIG N
        /MISSING LISTWISE
        /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
        /CRITERIA=PIN(.05) POUT(.10)
        /NOORIGIN
        /DEPENDENT Zcreativity_cond0
        /METHOD=ENTER Zcf_cond0.

*9B.
       REGRESSION
        /DESCRIPTIVES MEAN STDDEV CORR SIG N
        /MISSING LISTWISE
        /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
        /CRITERIA=PIN(.05) POUT(.10)
```

```
  /NOORIGIN
  /DEPENDENT Zcreativity_cond0
  /METHOD=ENTER Zholistic_conformity_cond0.

*9C.
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Zcreativity_cond0
  /METHOD=ENTER Zconformity_cond0.

*10A.
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Zcreativity_cond1
  /METHOD=ENTER Zcf_cond1.

*10B.
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Zcreativity_cond1
  /METHOD=ENTER Zholistic_conformity_cond1.
*10C.
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Zcreativity_cond1
  /METHOD=ENTER Zconformity_cond1.
```

Appendix E: Results Summary

RQ	Type	Model	Figure	β
#1: Did participants generate ideas that were more creative in the Examples condition than in the No Examples condition?	Latent			
	Observed		3	
#2: Does EF predict Creativity in the No Examples condition?	Latent	Base	4	0.42 [0.20, 0.63]
		Improved	5	0.41 [0.22, 0.60]
		3 Factor	6	Inhibition: 0.61 [-0.37, 1.59] Switching: 0.33 [-0.67, 1.33] Updating: -0.12 [-0.93, 0.69]
		Inhib.	7	0.40 [0.20, 0.59]
	Observed	Base		-0.11 [-0.26, 0.04]
		3 Factor		Inhibition: 0.26 [0.11, 0.41] Switching: 0.01 [-0.16, 0.18] Updating: 0.05 [-0.10, 0.21]
		Inhib.		0.19 [0.06, 0.32]
#3: Does EF predict Creativity in the Examples condition?	Latent	Base	8	0.31 [0.08, 0.54]
		3 Factor	9	Inhibition: 0.10 [-2.50, 2.69] Switching: -0.26 [-1.45, 0.94] Updating: 0.26 [-2.33, 2.85]
		Inhib.	10	0.34 [0.13, 0.54]
	Observed	Base		-0.16 [-0.31, -0.01]
		3 Factor		Inhibition: 0.08 [-0.08, 0.23] Switching: -0.13 [-0.31, 0.03] Updating: -0.04 [-0.19, 0.12]
		Inhib.		-0.10 [-0.04, 0.24]
#4: Does EF predict Creativity differently in the Examples condition than it does in the No Examples condition?	Latent	Base	11	0.10 [-0.12, 0.32]
		Improved	12	0.08 [-0.11, 0.28]
		Inhib.	13	0.07 [-0.13, 0.26]
	Observed	Base	14	
		3 Factor	14	
		Inhib.		
#5: Does EF predict the difference between Creativity in the No Examples condition and the Examples condition? Does the presence or absence of examples moderate the relation between EF and Creativity?	Latent	Base	15	-0.28 [-0.71, 0.15]
		Inhib.	16	-0.18 [-0.57, 0.21]
	Observed	Base	17A	-0.02 [-0.17, 0.12]
		Inhib.	17B	-0.11 [-0.24, 0.02]
#6: Was the Conformity Effect demonstrated?	Latent			
	Observed	Base/ Inhib.	18A - C	

<table>
<tr><th>RQ</th><th>Type</th><th>Model</th><th>Figure</th><th>β</th></tr>
<tr><td rowspan="6">#7: Does EF predict Conformity in the No Examples condition (baseline level of Conform</td><td rowspan="3">Latent</td><td>Base</td><td>CF: 19
HC: 22
Comb.: 25</td><td>CF: 0.26 [0.06, 0.46]
HC: -0.45 [-0.66, -0.23]
Combined: 0.29 [0.08, 0.51]</td></tr>
<tr><td>3 Factor</td><td>CF: 20
HC: 23
Comb.: 26</td><td>CF:
Inhibition: 0.40 [-4.40, 5.19]
Switching:-0.43 [-3.11, 2.25]
Updating: -0.07 [-4.89, 5.75]
HC:
Inhibition: -0.62 [-2.40, 1.15]
Switching: 0.59 [-0.57, 1.75]
Updating: 0.20 [-1.52, 1.92]
Combined:
Inhibition: 0.54 [-0.82, 1.91]
Switching: -0.51 [-1.47, 0.45]
Updating: -0.20 [-1.56, 1.16]</td></tr>
<tr><td>Inhib.</td><td>CF:21
HC: 24
Comb.: 27</td><td>CF: 0.25 [0.07, 0.43]
HC: -0.33 [-0.54, -0.12]
Combined: 0.29 [0.10, 0.48]</td></tr>
<tr><td rowspan="3">Observed</td><td>Base</td><td></td><td>CF: 0.02 [-0.14, 0.17]
HC: 0.003 [-0.04, 0.04]
Combined: 0.01 [-0.15, 0.15]</td></tr>
<tr><td>3 Factor</td><td></td><td>CF:
Inhibition: 0.19 [0.03, 0.34]
Switching: -0.03 [-0.20, 0.15]
Updating: -0.004 [-0.16, 0.15]
HC:
Inhibition: 0.14 [-0.001, 0.29]
Switching: -0.05 [-0.21, 0.11]
Updating: -0.09 [-0.24, 0.05]
Combined:
Inhibition: 0.20 [0.05, 0.35]
Switching: -0.03 [-0.20, 0.14]
Updating: -0.04 [-0.19, 0.12]</td></tr>
<tr><td>Inhib.</td><td></td><td>CF: 0.13 [0.00, 0.27]
HC: 0.08 [-0.05, 0.20]
Combined: 0.13 [-0.001, 0.26]</td></tr>
</table>

RQ	Type	Model	Figure	β
#8: Does EF predict Conformity in the Examples condition?	Latent	Base	CF: 28 HC: 31 Comb.: 34	CF: 0.09 [-0.12, 0.30] HC: 0.26 [0.02, 0.50] Combined: 0.18 [-0.04, 0.40]
		3 Factor	CF: 29 HC: 32 Comb.: 35	CF: Inhibition: 0.48 [-1.91, 2.88] Switching: -0.05 [-1.40, 1.30] Updating: -0.38 [-2.81, 2.06] HC: Inhibition: 0.60 [-2.02, 3.21] Switching: 0.07 [-1.06, 1.19] Updating: -0.32 [-2.91, 2.28] Combined: Inhibition: 0.47 [-1.96, 2.91] Switching: 0.02 [-1.21, 1.26] Updating: -0.30 [-2.70, 2.10]
		Inhib,	CF: 30 HC: 33 Comb.: 36	CF: \0.05 [-0.12, 0.22] HC: 0.15 [-0.07, .37] Combined: 0.08 [-0.12, 0.27]
	Observed	Base		CF: 0.00 [-0.01, 0.01] HC: 0.00 [-0.05, 0.05] Combined: 0.07 [-0.08, 0.23]
		3 Factor		CF: Inhibition: 0.09 [-0.07, 0.24] Switching: -0.07 [-0.24, 0.11] Updating: -0.08 [-0.23, 0.08] HC: Inhibition: 06 [-0.09, 0.22] Switching: 0.04 [-0.14, 0.21] Updating: -0.09 [-0.24, 0.07] Combined: Inhibition: 0.08 [-0.08, 0.24] Switching: -0.03 [-0.21, 0.16] Updating: -0.09 [-0.25, 0.07]
		Inhib.		CF: 0.10 [-0.04, 0.23] HC: 0.06 [-0.07, 0.20] Combined: 0.08 [-.05, 0.22]
#9: Does Conformity predict Creativity in the No Examples condition?	Latent	Base	CF: 37 HC: 38 Comb.: 39	CF: 0.44 [0.28, 0.61] HC: -0.41 [-0.61, -0.20] Combined: 0.46 [0.27, 0.64]
	Observed	Base		CF: 0.30 [0.18, 0.43] HC: 0.25 [0.12, 0.38] Combined: 0.29 [0.16, 0.41]
#10: Does Conformity predict Creativity in the Examples condition?	Latent	Base	CF: 40 HC: 41 Comb.: 42	CF: -0.12 [-0.30, 0.06] HC: -0.05 [-0.28, 0.18] Combined: -0.14 [-0.33 0.05]
	Observed	Base		CF: 0.15 [0.20, 0.29] HC: 0.09 [-0.04, 0.22] Combined: 0.13 [0.00, 0.27]
#11: Does Conformity mediate the relation between EF and Creativity?	Latent	Base	CF: 43A HC: 44A Comb.: 45A	CF: NS HC: NS Combined: NS
		Inhib.	CF: 43B HC: 44B Comb.: 45B	CF: NS HC: NS Combined: NS
	Observed	Base	CF: 43C HC: 44C	CF: NS HC: NS

			Comb.: 45C	Combined: NS
		Inhib.	CF: 43D HC: 44D Comb.: 45D	CF: NS HC: NS Combined: NS