Effects of Instructional Style on Problem-Solving Creativity

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ABSTRACT: This study sought to determine the impact of 2 differing instructional approaches on creative problem-solving performance. Eighty-two college students completed a novel structure-building task after receiving algorithmic instruction (providing a rote, step-by-step algorithm for building a sample structure), heuristic instruction (demonstrating the same techniques in a more flexible form), or no instruction. All participants viewed the same sample structure before beginning the task. It was hypothesized that algorithmically instructed students would exhibit less exploratory behavior and lower levels of creativity than students receiving heuristic instruction. No specific hypotheses were made concerning the problem-solving creativity of students in the no-instruction condition. Results suggest that the type of instruction that students received influenced their perceptions of the task, their behaviors during the task, and their final solution to the structure problem. Students receiving algorithmic instruction exhibited greater confidence and speed when building their structures than did other students. However, they were significantly less likely to engage in exploratory behavior or to deviate from the sample structure than were students receiving heuristic instruction. Although there was no main effect of instruction condition on the judge-rated creativity of these structures, a significant interaction between instruction type and participants' attempts to replicate the sample structure was predictive of the structure's creativity. Theoretical and practical implications of these and other results are discussed.

The development of problem-solving ability has traditionally advocated the instruction of such basic skills as reading, writing, and mathematics (Glaser, Pellegrino, & Lesgold, 1978), there has been an increasing emphasis in more recent years on the importance of promoting general thinking and reasoning skills that enhance students' ability to solve novel and unusual problems (Bransford, Arbitman-Smith, Stein, & Vye, 1985; Fuson, 1992; Lipman, 1985). In an age in which powerful computers have redefined the ways in which we approach problems, "children now need to be problem solvers and problem posers, not just calculators" (Fuson, 1992, p. 55). As accumulating evidence has demonstrated that problem-solving strategies can be taught in the context of formal education, at least within specific domains, questions have arisen concerning the optimal methods to teach such strategies to students (Lampert, 1992; Voss, 1989).

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Several learning theories suggest that the way in which information is taught and cognitively organized later influences the manner in which that information can be used (Bransford, Sherwood, Vye, & Rieser, 1986; Bransford, Vye, Kinzer, & Risko, 1990; Wickelgren, 1979). Furthermore, it has been proposed that the methods used to teach problem solving within a particular domain can have important effects on the flexibility and conceptual understanding of information in that domain (Mayer & Greeno, 1972; Mayer, Stiehl, & Greeno, 1975; Voss, 1989). It appears, therefore, that the way in which problem-solving strategies are taught may influence students' subsequent ability to understand and apply this information. Thus, educators are now faced with the considerable task of identifying those instructional styles that will optimize students' retention and flexible utilization of problem-solving skills.

One critical aspect of problem solving, an aspect that may be considerably influenced by the manner in which information is acquired and organized, is creativity. Although it has been largely neglected in the education literature, creativity is fundamental to the process of problem solving. In fact, classical definitions of creativity make little distinction between creative thinking and problem solving (Barron, 1955; Bernard, 1954; Runco, 1994). According to these definitions, creativity is exhibited when an individual solves a problem in a way that is novel and appropriate (or valuable). Moreover, a number of the cognitive processes thought to hinder or facilitate creativity have also been shown to influence the ability to solve problems. One such process is functional fixity (also known as functional fixedness), defined as the difficulty that people experience when attempting to think about and use objects in unconventional ways (Duncker, 1935/1945). A related concept is that of cognitive set, in which cognitive rigidity causes people to view a particular type of problem as having one specific kind of solution without allowing for alternative strategies and explanations (Anderson, 1983; Luchins, 1942). In this context, breaking set is used to describe the consideration and exploration of new approaches to a problem.

Just as functional fixity and cognitive set impede creative thought, they also obstruct students' ability to solve problems for which they have not been specifically trained, problems that call for flexibility, unconventional thinking, and the ability to relate novel aspects of the problem to familiar skills and ideas (Woolfolk & Nicolich, 1980). These novel problems, extending beyond the realm of trained problem solving, present the greatest challenge to teachers and students alike (Fuson, 1992; Griffin, Case, & Capodilupo, 1995). Clearly, it is impossible for educators to anticipate, much less introduce, every type of problem that students will encounter in their lives. It is therefore necessary to identify a method of instruction that will enable students not only to solve familiar problems well, but also to approach new problems in a way that will facilitate appropriate, valuable solutions (Gutstein & Romberg, 1995; Perkins, 1990).

There are a number of theories indicating that the nature of domain-relevant information and the way in which it is stored can make an important difference in creative performance. Psychologists typically define two types of approaches that may be used to solve a problem (e.g., Hilgard & Bower, 1975; McGraw, 1978). The algorithmic approach to problem solving follows specific steps or rules along a straightforward path to a clearly defined goal. The heuristic approach, on the other hand, utilizes problem-solving strategies that are more general, flexible, and exploratory in nature. A particular problem-solving task may be approached and solved according to rote response algorithms or through general, heuristic approaches.

The value of problem-solving strategies taught in the form of broad, conceptual heuristics, as opposed to more narrow, context-specific algorithms, appears to depend on the context and aim of instruction. Studies by Mayer and his colleagues (Mayer & Greeno, 1972; Mayer et al., 1975) have shown that instruction emphasizing computation through the use of a formula can lead to greater skill in solving problems similar to those previously practiced, whereas instruction emphasizing conceptual understanding more often leads to knowledge that allows greater flexibility of use by the student and is more applicable in new contexts. Other studies have noted that students who learn principles in a single, restricted subject area experience significantly less difficulty during initial learning than do students who learn these principles in a more general context that is not subject specific (e.g., Bransford, 1979). However, these studies also indicated that students receiving instruction that is not specific to a single context are better able to apply their knowledge in a wider variety of domains than are students who learn the con-
the concepts within the framework of a single or restricted context (Bransford, 1979; Nitsch, 1977).

Recent extensions of this work have suggested that algorithmic instruction may hinder problem-solving ability by imparting computational skill at the expense of conceptual understanding. Research in mathematics and the sciences has shown that students who are taught to solve problems with formulas may face considerable difficulty when they are required to reason without the use of algorithmic “props” (e.g., Niaz, 1995). Furthermore, students instructed with an emphasis on conceptual understanding have been found to outperform students instructed by more rote, traditional methods on problem-solving tasks involving both learned and related concepts (Griffin et al., 1995; Mayer, 1987). These findings have led increasing numbers of education researchers to call for a shift from largely memorization-based algorithmic instruction to classroom approaches promoting the conceptual understanding of interconnections between different components and types of problems (Carpenter & Moser, 1984; Fuson, 1992; Niaz, 1995; Sawrey, 1990).

Having observed that problem-solving flexibility is heightened in students who are instructed within broad rather than specific contexts, and with an emphasis on conceptual rather than computational understanding, theorists have raised two related conjectures: first, that knowledge organized according to general principles is more valuable and applicable than specific collections of facts in a narrow domain (Wickelgren, 1979), and second, that teaching individuals specialized strategies applicable only to a specific class of tasks places restrictions on generality (Dansereau, 1985). Knowing what we do about the detrimental effects of functional fixity and cognitive set on creative performance, it follows that problem-solving information learned and organized according to broad heuristics should yield more creative solutions than information learned in the form of rote algorithms. As Voss (1989) suggested, “A major characteristic of a good problem solver is flexibility ... One does not acquire problem-solving skill by learning to use steps 1 to 4 (whatever they may be) whenever a problem arises” (p. 285). Nevertheless, despite these propositions, there has been a paucity of carefully controlled studies to offer empirical evidence favoring heuristic over algorithmic styles of instruction in the enhancement of problem-solving ability and creativity.

This study utilized a novel problem-solving task—structure building—to compare the effects of algorithmic and heuristic instructional methods on the creative performance of college students. This experiment was designed to test the hypothesis that individuals will solve a problem more creatively in a given domain if they are taught using general, adaptable heuristic principles rather than context-specific, structured algorithms. It was hypothesized that, compared to those instructed algorithmically, individuals instructed in a heuristic fashion would be more likely to exhibit cognitive flexibility, original use of structure materials, and exploratory behavior, resulting in more creative solutions to the structure-building problem. In addition, it was hypothesized that algorithmically instructed individuals would experience greater functional fixity and rigidity of set than individuals instructed heuristically. We expected that algorithmic instruction would engender a simplified, narrowed, guideline-focused view of the task, leading to diminished experimentation with novel ideas and little deviation from the provided algorithm.

Although a number of theories propose that, all else being equal, an individual possessing skills in a given domain will more likely be creative than an individual who does not possess such skills (e.g., Amabile, 1983), the hypotheses of this study suggest that acquiring skills for certain tasks by means of algorithmic instruction may in fact be more detrimental to student creativity than receiving no instruction at all. To test these hypotheses and to determine the effects of instruction on structure creativity and on students' ability to fulfill the requirements of the task, a no-instruction control group was included in the study. It was hypothesized that the control group would either evidence lower levels of creativity than participants in each of the instruction groups, as previous theories would suggest, or achieve levels of creativity intermediate between the algorithmic group and the heuristic group, indicating that algorithmic instruction can be more damaging to creativity on certain tasks than a complete absence of instruction. The two instruction groups were expected to exhibit differences in creativity, whereas learning and retention of problem-solving techniques were expected to be identical between these experimental groups. Both instruction groups were expected to display greater mastery of structure-building techniques than the no-instruction control group.
Method

Participants

Participants in the experiment were 82 undergraduate students at Brandeis University (22 men and 60 women) enrolled in Introductory Psychology either at the time of the study or during the preceding semester. Students were recruited via sign-up sheets or direct telephone solicitation for a study entitled "The Structure-Building Activity." They received either course credit or $5 in exchange for their participation.

Problem-Solving Task

The structure-building activity was selected as the experimental task because it met several important criteria. First, it was important that the chosen task be unfamiliar to university students, because the experimental manipulation depended on direct control of the amount and type of task-specific instruction received by each participant. As a laboratory-developed task designed to differ from tasks with which participants might be familiar, the structure activity fulfilled this requirement of novelty. A second criterion called for a task that could be taught and completed under controlled conditions in a relatively brief period of time. Previous laboratory studies employing the structure activity have indicated that although participants rate the task as challenging, it can be completed even without instruction within 15 min (Ruscio, Whitney, & Amabile, 1998; Whitney, Ruscio, Amabile, & Castle, 1995). A third criterion required a task for which instruction could be delivered in either an algorithmic or a heuristic fashion, and for which both algorithms and heuristics could be employed. The open-ended, flexible nature of the structure activity made it easily adaptable to either form of problem instruction and solution. Finally, to test the hypotheses of the study, it was essential that the selected problem yield solutions whose creativity could be reliably judged by independent raters, as well as a sufficiently broad range of creativity scores across students. Prior research has indicated that the structure activity meets these requirements (Ruscio et al., 1998; Whitney et al., 1995).

Materials

Participants were given the following materials to incorporate into their structures: seven paper cups (2.5-in. diameter at the top), three pieces of blue yarn (16 in. long), five toothpicks, three wooden skewers (10 in. long), five plastic drinking straws, and 11 jumbo paper clips (2 in. long). Odd numbers of materials were used to deter the students from constructing symmetrical structures, thereby increasing the difficulty of the task. Participants were also provided with tools that could be utilized in building the structures: tape, scissors, and a ruler (marked at 15 in., for checking the height of the structure).

Instruments

After building their structures, all students completed a task questionnaire concerning their impressions of and feelings about the task. Participants in the algorithmic and heuristic conditions also completed a video questionnaire containing three measures. The first of these measures assessed students’ impressions of the instructional video that they had seen, whereas the second addressed their feelings and thoughts while watching the video. The third measure, an informational questionnaire, contained specific questions about techniques shown in the videos to verify that both experimental groups did indeed learn, and were able to recall, the same amount of structure-related information.

Instructional Videos

In designing the videos, our goal was to present the same amount of information and instruction to the two experimental groups while varying the manner in which that information was presented. Steps were taken to assure that the algorithmic and heuristic videos were equal in length (12 min) and that each illustrated precisely the same techniques. The narrator used the same total number of words in both videos. In addition, phrases in the script directly requesting participation, such as those asking students to refer to the structure materials laid out before them, occurred equally in both videos. In both videos, participants were taught by the same instructor, whose structure-building demonstrations were de-
scribed in a running commentary by the narrator. This
instructor was introduced by the off-camera narrator as
an expert at the structure-building activity, much in the
same way that a teacher might be regarded as an expert
or knowledgeable authority by students in the context of
classroom instruction.

In the algorithmic video, the instructor was shown
building a particular structure from start to finish in a
series of rote, specific steps and stages. Each new tech-
nique was introduced as a step in the straightforward
path toward the solution of the problem: a completed
structure meeting all of the task requirements. Students
were encouraged by the narrator to pay close attention
to the techniques demonstrated on the video, as well as
to the steps taken by the instructor to complete the
structure. The structure that was chosen for this dem-
stration was based on several structures that had
been rated by judges in an earlier study as highly cre-
ative. This creative model offered a means to present
participants with a broad base of problem-solving
techniques, while at the same time avoiding an artifi-
cial deflation of students' creativity scores in the algo-
rithmic condition.

The heuristic video included demonstrations of the
same techniques appearing in the algorithmic video.
However, rather than following a logical stepwise pro-
gression, this video presented individual techniques
loosely grouped according to functional similarity.
There were three general functional categories: alter-
ing materials, combining pieces, and achieving struc-
tural stability. This approach was taken in order to
organize an otherwise haphazard presentation of infor-
mation. However, the techniques were not placed into
a specific and meaningful order within these broad cat-
egories, nor were they depicted in the context of a par-
ticular structure. The heuristic approach to problem
solving defines no clear and identifiable path to solu-
tion; therefore, although participants in this condition
were presented with information and techniques to aid
in the completion of their task, they were given no
straightforward algorithm to guide them. Instead, they
were encouraged to observe the techniques demon-
strated on the video and to think of original ways to use
these and other techniques to construct their own struc-
tures. These students were not shown a complete or
partially completed structure during the demonstration
portion of their video.

To permit comparison between all structures cre-
ated in the study, it was essential that participants in the
heuristic and control groups be exposed to the same
sample structure shown in the algorithmic video. For
this reason, a 12-sec video clip depicting the completed
algorithmic structure was added to the end of the algo-
rithmic and heuristic videos and was also shown to par-
ticipants in the control condition, who did not view an
instructional video, after their 12-min planning ses-
son. (See the Procedure section for further discussion
of the experimental protocol.) To students in the algo-
rithmic condition, the video clip was introduced as a fi-
nal view of the finished structure constructed in the
video. To students in the heuristic and control condi-
tions, the clip was introduced as an opportunity to view
one example of a finished structure using the available
materials. All participants viewed this video segment
immediately before building their structures.

Design

Students were randomly assigned to one of the three
experimental conditions (algorithmic instruction, heu-
sitic instruction, or no-instruction control), and steps
were taken whenever possible to ensure that proce-
dures across the three conditions were identical. Only
instructions pertaining directly to the experimental
manipulation were varied across conditions. Equal
time was provided in all conditions for explanation and
completion of tasks, and the experimenter remained
blind to experimental condition until the manipulation
was introduced.

Procedure

All students took part in individual, hour-long ses-
sions with the same female experimenter. In a brief in-
troduction, participants were informed that they would
have 15 min to build "an interesting, free-standing
structure at least 15 inches tall and incorporating all of
the available materials." Because we wished to assess
the effect of condition on participants' self-motivated
proclivity toward creativity, no explicit mention was
made of creativity in the task instructions. However,
permission for creativity was implicitly given through
use of the word interesting. To promote close attention
to the instructional videos and satisfactory completion
of the task, participants were told that very few
Brandeis University students who had participated in
the structure-building activity during the previous year had been able to both meet the height requirement of the task and use all of the materials in the allotted time. Participants were then informed that because of the difficulty of the structure-building activity, they would be given the opportunity to prepare for the task before building their structures.

At this stage in the procedure, the instructions for the three groups diverged, and the experimenter was informed of participants’ experimental condition. Students in the algorithmic condition were told that they would view a video depicting a structure being built step by step, from start to finish, by the person who had developed the structure task. They were asked to pay close attention to the information presented on the video. Students in the heuristic group were told that they would view some basic structure-building techniques demonstrated by the developer of the structure task. They were asked not only to pay attention to the video, but also to imagine new ways in which the materials could be used in their structures. Students in the control condition did not receive instruction for the task. Previous research has indicated that simply having time to think about the structure-building activity before engaging in it improves creative performance on the task (Whitney et al., 1995). Thus, it appeared that the most appropriate control group for the study was one that would not receive instruction for the task, yet would be exposed to the structure materials for the same amount of time as it took to watch the instructional videos. Participants in this group were therefore told that they would be given the opportunity to look over the materials and to plan their structures before beginning the task. Although they had 12 min to think about the materials and the structure-building activity, just as did students in the algorithmic and heuristic conditions, students in the control condition were not provided with suggestions or techniques for the task. In all conditions, structure materials were laid out in front of the students, with instructions not to touch the materials until the building period began. The experimenter then left the room for 12 min while participants either watched one of the instructional videos or looked over the structure materials.

After this 12-min session was over, all students viewed a video clip of the finished sample structure. The experimenter then asked the students to build any structure that they wished, so long as it met the criteria of the task. Participants were asked for their permission to be videotaped while building their structures; all consented to being videotaped during the task. The experimenter left the room as the students began working.

After 15 min, the experimenter reentered the room and asked the students to stop building, whether or not they had completed their structures. All participants then completed the task questionnaire, with participants in the algorithmic and heuristic groups also completing the additional video questionnaire. After the students were debriefed and had left the laboratory, the experimenter measured the height of the finished structure, recorded the number of remaining unused pieces, and photographed the structure from two different angles so that it could be rated on creativity at a later date. Seven structures were dropped from the study, either because they were not free-standing and could not be photographed or because photo developing errors rendered their pictures unfit for rating. Of these structures, one was dropped from the algorithmic condition and three were dropped from each of the heuristic and control conditions. These proportions did not differ significantly by group, $\chi^2(2, N = 82) = 1.07$, ns. Seventy-five structures remained for subsequent evaluation.

Product Assessment

Participants' structures were judged by five psychology graduate students following the guidelines of the consensual assessment technique (Amabile, 1982). Due to the novel nature of the structure task and the absence of expert raters in this domain, graduate students were selected to serve as judges for the task. Previous research on the consensual assessment technique has demonstrated that, on tasks that do not require high levels of domain-relevant skill, evaluative judgments made by nonexperts are fairly consistent with those of expert judges (Amabile, 1996).

Judges were recruited via department-wide flyers and participated in individual, independent rating sessions. To become familiar with the structure-building activity and prepare for judging, raters were given the instructions for the structure task and were then asked to build a structure of their own. After experiencing this building process, judges were shown photos of participants' structures and were asked to rate the
structures relative to one another according to their own subjective definitions of creativity. Each judge viewed the structures in a different randomized order, making ratings on a 7-point Likert scale ranging from 1 (low creativity) to 7 (high creativity). Judges were kept blind to the existence of the three different experimental conditions, and structures from the three groups were mixed randomly in the viewing order. As in previous investigations utilizing the consensual assessment technique, interjudge agreement was computed using the alpha coefficient (Amabile, 1996). In this study, the interrater reliability of judges’ creativity ratings was .87.

To increase our understanding of possible effects obtained in the study, assessments were also made of participants’ overall strategy in the structure-building activity—the extent to which their structure was similar to the sample. Thus, after rating the creativity of the students’ structures, judges were shown a picture of the sample structure built in the algorithmic video, the structure seen by all participants before engaging in the structure-building task. Judges were then asked to assess the similarity of each participant’s structure to the sample structure. Similarity ratings were made on a 7-point Likert scale ranging from 1 (not at all similar) to 7 (very similar) and yielded an interjudge reliability (alpha) of .88.

**Behavioral Coding**

Development of a scheme for coding students’ videotaped structure-building behaviors began with an already-existing behavioral scheme previously designed for the structure activity (Ruscio, Whitney, & Amabile, 1998). This coding scheme had been developed through an iterative process, in which coders revised the coding categories through application and redefinition until a set of behavioral measures was developed that could be reliably identified. Data collected with this initial scheme were examined, and items that were highly correlated with others or found to be nonpredictive of creative performance were dropped from the coding system. Items specific to this study were added (see later), and the scheme as a whole was refined by two coders, both highly familiar with the structure task, through repeated practice and definition using videotapes of several pilot participants.

The final coding scheme contained 14 items, including nine process ratings made on 7-point Likert scales and five behavioral ratings utilizing frequency counts. (See Appendix for a list of coding categories and definitions.) Coding of each 15-min structure-building session was performed in five segments, with ratings made every 3 min while the videotape was paused. Both coders viewed the algorithmic and heuristic instructional videos before beginning the coding process, enabling them to distinguish between techniques presented on the videos and strategies that the students developed themselves. Blind to the experimental condition of the participants that they watched, coders independently rated 12 students’ building sessions. Interrater reliability (alpha coefficients) computed for the coding items ranged from a low of .61 to a high of .97, with a median of .77. As adequate reliability had been established, one of the coders went on to code the remaining video segments.

**Prediction-Specific Measures**

Several questionnaire and coding items were utilized to address the hypotheses outlined earlier in this article. Functional fixity and cognitive set were operationalized as participants’ adherence to the standard with which they had been provided. The degree of adherence was assessed both by judges’ ratings and by students’ own reports of the similarity of their structures to the sample structure shown. Additional measures of functional fixity and cognitive set were provided by the video coding categories of mimicking and applies technique—same, which assessed identical replication of the sample structure and use of structural techniques in the same general manner as that shown on the videos, respectively. The use of exploratory behaviors, novel strategies, and inventive solutions to problems was assessed primarily with the coding category exploration, as well as with the category applies technique—different, which focused on the application of taught structural techniques to different materials in new ways. Finally, structure creativity was represented by the averaged creativity ratings of the expert judges. The remaining measures included factors that were thought to be related to instructional style, but for which no specific hypotheses had been formulated. These items were examined in an exploratory fashion during data analysis.
Results

To determine whether students in the algorithmic and heuristic instruction conditions truly learned the same amount of structure-related information from their respective videos, a manipulation check was performed by comparing the total scores of the two groups on the information questionnaire. This written quiz, asking detailed questions about techniques demonstrated in both videos, was given to participants in the two instruction conditions. The quiz included such questions as, "What were the three different things that [the instructor] did with unbent paper clips?" and "[The instructor] used skewers most often in combination with which material?"

Independent-sample t tests performed on students' scores revealed no significant differences between conditions, t(48) = .69, ns, a result that remained constant even after test items with low variability were omitted and the analysis was recomputed using only high-variability items, t(48) = 1.00, ns. Based on these results, it was concluded that the instructional videos shown to the algorithmic and heuristic groups did not differ in the amount of information they presented or in the amount of information that was retained by participants.

Creativity

An initial one-way analysis of variance (ANOVA) revealed no significant differences between conditions on structural creativity, F(2, 72) = 0.49, ns. Because we suspected that the effect of instruction on creativity might have depended on the structure-building strategy that participants chose, we conducted further analyses to explore this possibility. Thus, a subsequent ANOVA was performed, using both condition and judge-rated similarity (divided at the median into groups of high and low similarity to the sample structure) as the independent variables (see Table 1). This ANOVA uncovered a significant interaction, F(2, 69) = 4.03, p = .022; neither main effect was statistically significant. Correlations computed between creativity and similarity scores within each condition help to explain this interaction. Structures produced by students in the algorithmic condition were rated as more creative the more similar they were to the sample; the correlation between creativity and similarity in that condition was strong and positive, r(23) = .43, p = .033. In the heuristic condition, on the other hand, structures were rated as more creative the less similar they were to the sample structure; in this condition, creativity and similarity had a strong negative relationship, r(23) = -.57, p = .003. No statistically significant relation was found between creativity and similarity in the control condition, r(23) = -.01, ns.

Figure 1 graphically depicts these relations by representing individual regression lines for each condition on a single graph. The slopes of the algorithmic and heuristic lines were significantly different (z = -3.68, p = .001), as were the slopes of the heuristic and control lines (z = -2.13, p = .033). The difference between the slopes of the algorithmic and control lines was not statistically significant (z = 1.54, ns). These results suggest that the relationship between instruction type and

![Figure 1. Similarity to the sample structure regressed on creativity in the algorithmic, heuristic, and control conditions.](image-url)
creativity depended on the strategy that the student employed in the structure-building task.

Posttask Questionnaires

A factor analysis was performed on all video questionnaire items, which were standardized prior to their combination into factors. This analysis uncovered three factors with eigenvalues greater than 1.00 and reliabilities greater than .50 (see Table 2). Subsequent examination of these factors included all items that loaded onto the factors in the original analysis. The first of these three factors, labeled Video Value, had an internal reliability (Cronbach’s alpha) of .85 and included five of the video questionnaire items in which participants reported the extent to which they (a) considered the instructional video helpful, (b) considered the instructional video interesting, (c) tried to build a structure similar to the sample structure on the video, (d) concentrated on memorizing the instructions being taught while watching the video, and (e) believed they would not have built as good a structure if they had not first watched the video. The second factor, labeled Admire, had an alpha of .62 and included three items in which participants reported the extent to which they (a) perceived the instructor as skilled, (b) liked the sample structure, and (c) felt distracted by thoughts unrelated to the task while watching the video (reverse-scored). The third factor, labeled Impede, had an internal reliability of .53 and included two items from the video questionnaire: (a) feeling that ideas were hindered by the video, and (b) developing new ideas for the structure while watching the video (reverse-scored).

As these factors were relatively uncorrelated with one another (mean $r = .27$) they were subjected to univariate analyses. Independent-sample $t$ tests comparing the two instruction conditions revealed statistically significant differences between groups on two of the factors. Compared to those in the heuristic condition, students in the algorithmic condition were more likely to endorse the items underlying Video Value, $t(48) = 2.17$, $p = .035$, and Impede, $t(48) = 3.22$, $p = .002$. The two conditions did not differ significantly on the factor Admire, $t(48) = 1.14$, $ns$.

<table>
<thead>
<tr>
<th>Item</th>
<th>Video Value</th>
<th>Admire</th>
<th>Impede</th>
</tr>
</thead>
<tbody>
<tr>
<td>Found Video Helpful</td>
<td>.91</td>
<td>.13</td>
<td>.15</td>
</tr>
<tr>
<td>Not as Good Without Video</td>
<td>-.77</td>
<td>-.08</td>
<td>.01</td>
</tr>
<tr>
<td>Found Video Interesting</td>
<td>.73</td>
<td>.30</td>
<td>.08</td>
</tr>
<tr>
<td>Concentrated on Instructions</td>
<td>.71</td>
<td>-.04</td>
<td>.07</td>
</tr>
<tr>
<td>Tried to Replicate Sample Structure</td>
<td>.70</td>
<td>.11</td>
<td>.42</td>
</tr>
<tr>
<td>Liked the Sample Structure</td>
<td>.20</td>
<td>.81</td>
<td>-.01</td>
</tr>
<tr>
<td>Distracted During Video</td>
<td>.06</td>
<td>-.70</td>
<td>-.06</td>
</tr>
<tr>
<td>Perceived Instructor as Skilled</td>
<td>.50</td>
<td>.63</td>
<td>-.01</td>
</tr>
<tr>
<td>Ideas Hindered by Video</td>
<td>.28</td>
<td>-.13</td>
<td>.77</td>
</tr>
<tr>
<td>Developed New Ideas During Video</td>
<td>-.03</td>
<td>-.17</td>
<td>-.75</td>
</tr>
<tr>
<td>Planned Own Structure During Video</td>
<td>-.10</td>
<td>-.12</td>
<td>.25</td>
</tr>
<tr>
<td>Felt Anxious About Building Structure</td>
<td>.06</td>
<td>.13</td>
<td>-.41</td>
</tr>
<tr>
<td>Percentage of Variance</td>
<td>32.6</td>
<td>13.5</td>
<td>10.8</td>
</tr>
<tr>
<td>Reliability (Cronbach's a)</td>
<td>.85</td>
<td>.62</td>
<td>.53</td>
</tr>
</tbody>
</table>

Means (Standard Deviations)

- **Algorithmic** ($n = 25$)
  - Admire: $M = .23$, $SD = .77$
  - Impede: $M = .34$, $SD = .87$

- **Heuristic** ($n = 25$)
  - Admire: $M = -.23$, $SD = .76$
  - Impede: $M = -.34$, $SD = .63$

$t(48) = 2.17$*, 1.14, 3.22**

*Note: $N = 50$. Italicized entries in each column reflect the items that loaded onto the corresponding factor. Loadings shown were obtained with a varimax rotation. The factors captured a total of 56.9% of the variance in the questionnaire items.

*p < .05. **p < .01.
Video-Coded Behaviors

Before the behavioral coding variables were entered into a second factor analysis, log transformations were employed to alleviate the skewed distributions of a few variables. All variables were then standardized so that they could be combined into factors. A factor analysis performed on these behavioral items yielded four factors with eigenvalues greater than 1.00 and reliabilities greater than .50 (see Table 3); one factor contained only a single item and therefore could not be assessed for reliability. Analyses examining the four reliable factors utilized all items that loaded onto the factors in the original analysis. The first of the factors, labeled Decorate, had an internal reliability (Cronbach’s alpha) of .94 and included two coding categories: time spent on aesthetics and time spent on stability (reverse-scored). The second factor, labeled Imitate, had an alpha of .72 and included three coding items: mimicking, applies technique—same, and exploration (reverse-scored). The third factor, labeled Secure, had an alpha of .70 and included three behavioral items: confidence, pace, and progress. The fourth factor, labeled Insecure, had an alpha of .66 and was comprised of three coding variables: difficulty, self-initiated backtracks, and non-initiated backtracks.

As with the questionnaire factors, these factors shared relatively low intercorrelations (mean $r = -.08$) and were thus subjected to univariate tests (one-way ANOVAs). The first analysis, examining Decorate across conditions, yielded no significant differences between groups, $F(2, 71) = 0.79$, ns. A second ANOVA revealed a significant effect of condition on Imitating, $F(2, 71) = 16.52$, $p < .0001$. Post hoc comparison of means using the Student Neuman–Keuls (SNK; Howell, 1997) procedure indicated that stu-

<table>
<thead>
<tr>
<th>Variable</th>
<th>Decorate</th>
<th>Imitate</th>
<th>Secure</th>
<th>Insecure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time on Aesthetics$^a$</td>
<td>.95</td>
<td>-.08</td>
<td>.01</td>
<td>-.04</td>
</tr>
<tr>
<td>Time on Stability$^a$</td>
<td>-.94</td>
<td>.11</td>
<td>-.10</td>
<td>.13</td>
</tr>
<tr>
<td>Mimicking$^a$</td>
<td>-.12</td>
<td>.90</td>
<td>.07</td>
<td>-.21</td>
</tr>
<tr>
<td>Applies Technique—Same$^b$</td>
<td>.03</td>
<td>.83</td>
<td>.03</td>
<td>-.00</td>
</tr>
<tr>
<td>Exploration$^a$</td>
<td>.38</td>
<td>-.54</td>
<td>.07</td>
<td>.13</td>
</tr>
<tr>
<td>Confidence$^a$</td>
<td>.08</td>
<td>.01</td>
<td>.87</td>
<td>-.08</td>
</tr>
<tr>
<td>Pace$^a$</td>
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<td>.07</td>
<td>.73</td>
<td>.22</td>
</tr>
<tr>
<td>Progress$^a$</td>
<td>.35</td>
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<td>.53</td>
<td>.01</td>
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<tr>
<td>Noninitiated Backtrack$^b$</td>
<td>-.04</td>
<td>-.02</td>
<td>.08</td>
<td>.84</td>
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<tr>
<td>Difficulty$^a$</td>
<td>-.33</td>
<td>-.21</td>
<td>-.35</td>
<td>.72</td>
</tr>
<tr>
<td>Self-Initiated Backtrack$^b$</td>
<td>.07</td>
<td>-.14</td>
<td>.17</td>
<td>.67</td>
</tr>
<tr>
<td>Time on Height$^a$</td>
<td>-.01</td>
<td>-.21</td>
<td>.11</td>
<td>-.07</td>
</tr>
<tr>
<td>Applies Technique—Difference$^b$</td>
<td>.13</td>
<td>-.24</td>
<td>.41</td>
<td>-.06</td>
</tr>
<tr>
<td>Checks Height$^b$</td>
<td>.05</td>
<td>-.16</td>
<td>-.07</td>
<td>.05</td>
</tr>
</tbody>
</table>

### Table 3. Behavioral Coding Factor Analysis and One-way Analyses of Variance

<table>
<thead>
<tr>
<th>Variable</th>
<th>Decorate</th>
<th>Imitate</th>
<th>Secure</th>
<th>Insecure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage of Variance</td>
<td>19.6</td>
<td>17.9</td>
<td>14.2</td>
<td>9.6</td>
</tr>
<tr>
<td>Reliability (Cronbach’s $\alpha$)</td>
<td>.94</td>
<td>.72</td>
<td>.70</td>
<td>.66</td>
</tr>
</tbody>
</table>

### Means (Standard Deviations)

<table>
<thead>
<tr>
<th></th>
<th>Decorate</th>
<th>Imitate</th>
<th>Secure</th>
<th>Insecure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algorithmic ($n = 25$)</td>
<td>-.16 (.88)</td>
<td>.60 (.92)$^1$</td>
<td>.39 (.67)$^1$</td>
<td>-.27 (.74)$^1$</td>
</tr>
<tr>
<td>Heuristic ($n = 25$)</td>
<td>-.02 (.82)</td>
<td>-.15 (.53)$^2$</td>
<td>-.17 (.80)$^2$</td>
<td>-.01 (.61)$^2$</td>
</tr>
<tr>
<td>Control ($n = 24$)</td>
<td>.19 (1.19)</td>
<td>-.47 (.44)$^3$</td>
<td>-.23 (.76)$^3$</td>
<td>.29 (.87)$^3$</td>
</tr>
</tbody>
</table>

$F(2, 71)$ = 0.79

### Note:

$N = 74$. Italized entries in each column reflect the variables that loaded onto the corresponding factor. Loadings shown were obtained with a varimax rotation. The factors captured a total of 61.3% of the variance in the process measures. Within each column, means sharing superscripts did not differ significantly at the .05 level using the Student Neuman–Keuls (Howell, 1997) post hoc procedure.

*Likert scale. $^aFrequency count.

* $p < .05$. ** $p < .01$. *** $p < .0001$. 

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Students in the algorithmic group were significantly more likely to exhibit behaviors that imitated the video than were students in either the heuristic or control groups. A third ANOVA revealed a significant effect of condition on Security, $F(2, 71) = 5.19, p = .008$. SNK comparison of means uncovered the same pattern of differences across conditions as with the previous factor; participants taught algorithmically were more likely to display behaviors labeled Secure than participants in either the heuristic or control groups. A fourth ANOVA yielded a significant effect of condition on Insecurity, $F(2, 71) = 3.51$, $p = .035$. Computation of the SNK statistic indicated that students in the control group were more likely to exhibit behaviors termed Insecure than were students in the algorithmic group. No significant differences were found between either of these conditions and the heuristic group, which had a mean that fell between those of the control and algorithmic groups.

One objective of this study was to determine whether the type of instruction that individuals received influenced their ability to implement learned techniques in new contexts. In other words, to what extent were algorithmically instructed students able to deviate from the algorithm that they were taught, to apply these techniques in novel contexts within their own structures rather than in precisely the same manner that they were learned? To answer this question, the coding variables mimicking and applies technique—same were correlated within each condition. Recall that whereas mimicking represented direct imitation of the structural algorithm, applies technique—same reflected the frequency with which taught techniques were used in the structure, whether or not they were used in the same structural context that was shown in the algorithm. The resulting correlations were .84, .52, and .50, respectively, for the algorithmic, heuristic, and control conditions. Tests of significance performed between these independent correlations yielded statistically significant differences between the algorithmic and heuristic conditions ($z = 2.15, p = .016$) and between the algorithmic and control conditions ($z = 2.22, p = .013$). In other words, when participants in the algorithmic condition utilized the structure techniques shown in the video, they were more likely to use them in a mimicking fashion than were participants in the heuristic and control conditions, suggesting that algorithmically instructed individuals experienced greater rigidity of set and functional fixity than those in the other groups.

Another objective of this study was to evaluate the assertion that individuals instructed heuristically would demonstrate greater exploratory behavior and original use of structure materials than those instructed algorithmically. To test this hypothesis, a one-way ANOVA, with condition as the independent variable, was performed on the single behaviorally coded exploration variable. Results revealed a significant effect of condition on exploration, $F(2, 71) = 4.24, p = .018$. Post hoc comparison of means using the SNK procedure indicated that students in the heuristic group exhibited significantly more exploratory, curious, and experimenting behaviors during the structure task than did students in either the algorithmic or control groups.

Solving the Problem

Although creativity was the primary variable of interest in this study, other components of problem solving were also assessed to more fully examine the effects of instruction on students' problem-solving performance. Recall that the requirements of the structure-building activity called for participants both to use all available materials and to achieve a structural height of at least 15 in. in the allotted time. A test of association was conducted to test the relation between instruction condition and successful completion of the height requirement. Achievement of this requirement was measured by a dichotomous height variable separating participants who met or exceeded the height requirement from those who failed to do so. This analysis revealed that participants in the two instruction conditions were more likely to solve the height problem of the structure task than were those in the no-instruction control condition, $\chi^2(1, N = 75) = 5.11, p = .024$. There was no significant difference between the algorithmic and heuristic conditions on this variable.

A second test of association was conducted using a dichotomous variable differentiating students who used all of the structure materials from students who failed to do so. No differences were found between conditions on this variable, $\chi^2(1, N = 75) = 1.33, ns$.

Discussion

This study compared two approaches to instruction—algorithmic and heuristic—and their subsequent
effects on students' construction of creative solutions to a novel problem. Results of the study indicated that participants in the two instruction groups learned and retained the same amount of task-related information and were equally successful in meeting the requirements of the task. However, as predicted, the type of instruction had great bearing on students' reactions to the instructions, their approach to the structure-building task, and their resulting products—although these effects were considerably more complex than anticipated.

This experiment did not uncover the straightforward relationship between instruction type and creativity that was predicted. Instead, creativity and similarity to the presented sample were differentially related in the three conditions, despite the judges' ignorance of these conditions as they made the ratings. In the algorithmic condition, participants' structures were rated as more creative the more closely they replicated the structural example. By contrast, in the heuristic condition, participants' structures were rated as more creative the less similar they were to the example. There was no relation between creativity and structural similarity in the control condition.

These results suggest that algorithmic instruction was more effective than heuristic instruction in enhancing problem-solving performance when students attempted to mimic a presented example. This effect can be clearly seen in the display of regression lines in Figure 1 where, at high levels of similarity to the sample structure, structures built in the algorithmic condition received markedly higher creativity scores than structures constructed in the other two conditions. However, when students deviated from the standard to produce a novel product, algorithmic instruction seemed to create a liability. At low levels of similarity to the sample—reflecting participants' attempts to diverge from the example and produce original structures of their own design—creativity scores for structures produced in the algorithmic condition were noticeably poorer than those for structures produced not only in the heuristic condition, but in the control condition as well. This pattern suggests that students may find it more difficult to generate novel solutions when they are instructed algorithmically than when they receive no instruction at all. In a general sense, these findings are consistent with those found by Mayer and his colleagues (Mayer & Greeno, 1972; Mayer et al., 1975) in studies demonstrating that, although students taught in a single, specialized context experienced less difficulty with an identical problem-solving task than students taught more general principles, they experienced significantly more difficulty on a related but different problem for which they had not been given an algorithm. Our study further suggests that algorithmic instruction could present even more obstacles for independent, creative problem solving than a complete lack of information or instruction in the problem domain. A little information can indeed be a dangerous thing—if it is learned in a rigid, algorithmic fashion, and if novelty is the goal.

Measures of students' self-reported perceptions of the task, as well as their actual problem-solving behaviors, provide some clues about the mechanisms by which these effects might have occurred. Participants in the algorithmic condition were more likely to perceive the instructional video as helpful and interesting and to report attempts to memorize the instructions presented on the video. Examination of these students' structure-building behaviors revealed that they were far more likely to copy the provided example than were students in the heuristic or control groups. Moreover, when participants in the algorithmic condition applied techniques that they had learned from the video, they were more likely to do so in a fashion that directly imitated the sample structure. These students exhibited greater confidence and a faster work pace than students in the other two conditions, attributable perhaps to the fully modeled problem-solving approach and the clearly outlined solution with which they were provided. However, these students were less likely to generate and implement novel solutions to the structure problem than were those in the heuristic condition.

Participants themselves seemed to realize the restrictive effect of the algorithmic instructional video on their ability to generate new ideas for the task; they were less likely to report developing new ideas for their structures while watching the video and were more likely to feel that their ideas were hindered by the video. It is interesting to note that participants in the algorithmic condition recognized these limitations, while at the same time embracing the instructional algorithm, attempting to replicate what they saw, and believing that they would not have built as good a structure if they had not first watched the video. Thus, as predicted, algorithmic instruction seems to have led to greater functional fixity than heuristic instruction. By contrast, heuristic instruction seems to have led to...
increased exploratory behavior and flexible experimentation with the task materials. Moreover, students in the heuristic condition tended to use learned techniques in a less rigid fashion and were more likely to attempt problem-solving strategies that had not been explicitly taught to them.

Why, then, was there no main effect of condition on judge-rated creativity? This surprising finding may be an artifact of the precaution we took to render the structures comparable across experimental conditions. Just prior to the structure-building activity, all students were shown an identical sample structure, the same structure that was built in considerable detail on the algorithmic video. To avoid artificially deflating the creativity of participants in the algorithmic condition, we chose a highly creative structure for this sample (as assessed by judges in previous studies using this activity). The judges in this study did not see the sample before assessing the creativity of the participants’ structures and, indeed, were not told that participants had been shown the sample. Thus, they were unaware of the extent to which similar elements in students’ structures had not actually been conceived by the students themselves.

Perhaps it should not be surprising, then, that the judges tended to rate as highly creative those structures in the algorithmic condition that replicated the sample structure. These participants had learned precisely how to build a structure that previous judges had viewed as especially creative. However, participants in the heuristic condition had not learned in detail how to construct this particular complex structure, although they had learned the relevant techniques. This may explain why, to the extent that students in this condition attempted to replicate the sample structure, their results were disappointing and tended to receive lower creativity ratings from the judges.

These speculations raise intriguing theoretical questions about the fundamental nature and definition of creativity. As noted earlier, creativity is generally defined in the literature as a novel solution that is appropriate for the problem at hand. Novelty can only be assessed relative to work that has already been done on a problem, and thus can be accurately evaluated only by judges who are familiar with the domain of the problem and with previous solutions produced in that domain. The consensual assessment of creativity (Amabile, 1982) requires that judges be thus informed before evaluating the creativity of a set of products.

However, although judges in this study were familiar with the task itself, they lacked familiarity with key elements of the domain in which students had operated: an understanding that students had all seen the same sample structure, and a knowledge of the sample’s appearance. Although elements of this sample had been viewed as highly creative by previous judges when they were first conceived, we argue that an imitation of this sample cannot be considered truly creative, much as a painstaking reproduction of a master work in painting would not be considered creative by experts who know it to be a copy. Thus, although those students in the algorithmic condition who imitated the example tended to receive high marks for “creativity,” their work would not be regarded as such by traditional definitions of creativity. Certainly, in the real world, creative responses are not those that closely mimic an existing product or solution.

Although this study offers preliminary insight into the influence of instruction on problem-solving creativity, it also raises a number of questions that remain unanswered. For example, it is unclear to what extent heuristic and algorithmic instruction for a task within a particular domain might impact performance on a novel task in that domain. Following the work of Bransford (1979), this question of generalizability could be addressed by assessing students’ creative performance on a task that is conceptually similar to, but physically different from, a task for which they receive instruction. Such a study would explore the consequences of training in which the existing sample is not one that participants can directly replicate. Second, recent research on the training of statistical reasoning found that although broad, formal training and example-specific training had an equally positive effect on statistical reasoning, a composite training program including both types of training resulted in significantly better reasoning than either type of training alone (Fong, Krantz, & Nisbett, 1993). These results suggest that students instructed both algorithmically and heuristically may produce the most creative solutions of all. Future research could determine whether or not this is indeed the case, as well as whether the order in which instruction types are used has any bearing on the creativity of resultant solutions. Third, because there is evidence for a positive relationship between intrinsic motivation toward a task and creative performance on that task, it would be useful to determine the extent to which heuristic
and algorithmic instruction styles differentially influence students’ intrinsic motivation for a task.

Generalizability of this study is limited by the relatively simple nature of the structure-building task and by participants’ very brief exposure to the instruction sets. However, given that such limited exposure produced observable group differences in task approach, perception, and behavior, it is conceivable that prolonged exposure to different instructional styles may have a considerable, long-lasting impact on students’ problem-solving skill. Further investigation is needed to extend these findings to precollege student populations and to problem-solving tasks that are more complex in nature. Furthermore, additional research is needed to ascertain the extent to which algorithmic and heuristic instruction styles influence student problem-solving behavior in classroom settings.

This study suggests several important implications for the selection of optimal instructional styles to teach problem-solving skills. As discussed earlier, the unpredictable nature of real-world problems mandates that individuals be prepared to generate novel solutions for problems that they have never before encountered, using previously learned problem-solving techniques in new and flexible ways. Such demands require instruction that not only promotes ready responses to known problems, but that also fosters an approach to problem solving that results in innovative and resourceful solutions. Findings of this study suggest that although algorithmic, step-by-step instruction may facilitate problem-solving confidence and solutions requiring exact duplication of a standard, it is less likely to lead to experimentation with original ideas and more likely to create dependence on a provided algorithm. In fact, when algorithmically instructed students attempt to deviate from an algorithm to explore novel problem-solving strategies, they are less likely to produce creative results than students who are instructed heuristically or who are not instructed at all. This study indicates that heuristic methods may yield mediocre results when individuals endeavor to duplicate a complex standard in the absence of algorithmic instruction. However, when students taught with a heuristic approach pursue their own ideas rather than attempting to mimic an available model, they are more likely than un instructed or algorithmically instructed individuals to reach creative solutions. Thus, if the goal of problem-solving instruction is to enable students to utilize existing skills in an independent, flexible, and innovative manner when faced with novel problems, the heuristic approach to instruction appears to be the most likely to succeed.

References


teaching (pp. 53–187). Hillsdale, NJ: Lawrence Erlbaum Associates, Inc.


Appendix

Presented in the following are the coding categories and definitions employed in the behavioral video coding of participants' structure-building segments. Items followed by an (L) were coded using 7-point Likert scales; items followed by an (F) were coded using frequency counts.

- **Confidence:** Participant’s apparent confidence in his or her ability to complete the task successfully; working in an assertive and relaxed manner without panicking, worrying, or becoming upset or overwhelmed by the task. (L)
- **Difficulty:** Amount of difficulty encountered by the participant in meeting the task requirements, handling the materials, or following through on an idea or plan. (L)
- **Progress:** Amount of progress made by the participant in a given segment toward completing the structure and meeting the requirements of the task. (L)
- **Exploration:** Curious, exploratory behavior toward the materials or the structure; trying out different ideas, searching for novel ways in which to use the materials, working experimentally rather than according to a predetermined plan. (L)
- **Pace:** The speed at which the participant works; a slow-to-fast gradient of working rate. (L)
- **Mimicking**: Extent to which the participant attempts to copy the exact process used to build the sample structure shown on the videos. (L)
- **Work on aesthetics**: Amount of work devoted to making the structure aesthetically appealing. (L)
- **Work on stability**: Amount of work devoted to maintaining structural integrity and stability. (L)
- **Work on height**: Amount of work devoted to increasing structural height. (L)
- **Self-initiated backtracks**: Participant takes apart the structure, removes materials from the structure, or initiates any other type of structural backtracking. (F)
- **Non-initiated backtracks**: Structure falls down or falls apart without initiation from the participant; materials fall off the structure. (F)
- **Checks height**: Participant uses a ruler to check the height of the structure. (F)
- **Applies technique—same**: Participant utilizes a technique as it was presented on the videos, applying it in any structural context. (F)
- **Applies technique—different**: Participant applies a technique presented on the video in a novel manner or with different materials than those used by the instructor. (F)