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Prior Knowledge Influence on Self-Explanation Effectiveness When Solving Problems: An Exploratory Study in Science Learning

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This exploratory study presents the outcomes of using self-explanation to improve learners' performance in solving basic chemistry problems. The results of the randomized experiment show the existence of a moderation effect between prior knowledge and the level of support self-explanation provides to learners, suggestive of a synergistic effect for learning. The results also suggest the existence of a threshold level of prior knowledge necessary for self-explanation-based cognitive strategies to become effective. As validation, this study also confirms prior findings that show that, given the right settings, learners can benefit significantly from using self-explanation while solving problems.

Although you may not have experienced it yourself, it is likely that you have heard colleagues voicing their concerns about difficulties they have teaching key theoretical concepts to students in a way that makes these concepts "stick." This lack of understanding significantly impairs students' ability to understand future content, because these concepts act as gateways for the understanding of major topics in every field (e.g., Land, Meyer, & Smith, 2008). If we are to look through the lens of a domain map, these conceptual misunderstandings prevent learners from making the appropriate connections between other concepts within the domain (e.g., Bernhard, Carstensen, & Holmberg, 2011). For this reason, these concepts need to be covered until learners reach a level of understanding that allows them to make sense of the material they learn and deepens their understanding as they move forward.

To comprehend the material taught, students need to: (a) relate new concepts to knowledge they already possess, and (b) use prior knowledge to understand these new concepts and synthesize new knowledge. When students struggle with concepts they learn, instructors will typically attempt to remedy the situation using a variety of methods at their disposal. For example, they can discuss the concept in class, in groups, or in one-on-one sessions, or they can direct students to look at supplementary resources. Regardless of the method chosen, instructors typically tend to follow threads of coherent reasoning based on their direct (e.g., questions and answers) or indirect (e.g., homework, projects) interaction with their students. Unfortunately, an instructor is rarely available at the precise moment when a student needs help understanding a concept or a theoretical model. This often forces students to rely on a variety of cognitive strategies they have mastered to make sense of the material they study.

From the range of learning strategies that have the potential to support learners' conceptual understanding and learning, self-explanation (e.g., Chi & Bassok, 1989) stands out as a cognitive strategy reported to have significant impact on both the learners' ability to relate new ideas to prior knowledge and to help with the synthesis of new knowledge (e.g., Bielaczyc, Pirolli, & Brown, 1995). However, very little research focuses on understanding how prior knowledge impacts the effectiveness of self-explanation-based cognitive strategies. To address this gap, we designed this exploratory study to investigate whether self-explanation has the same effect over the entire range of prior knowledge learners might have. More specifically, the focus of this study was on the moderating effect (Baron & Kenny, 1986) prior knowledge might have on the effectiveness of using cognitive support strategies based on self-explanation when solving chemistry problems.

Based on our teaching experience as well as conversations with engineering and STEM faculty at a Midwestern school of engineering, we decided to localize our study as early in the program of study as possible. Therefore, we chose to focus on an introductory chemistry module taught during a summer program to the incoming freshmen interested in speeding up their integration into the college academic life.

Theoretical Foundations

The term "self-explanation" or "self-generated explanation" (Chi, Bassok, Lewis, Reinmann, & Glaser, 1989) refers to the explanation a learner generates on his or her own as opposed to the explanation(s) provided by an external source (e.g., instructor, book). This is a domain-independent strategy that can be used across domains and age groups with the capability to provide significant improvements in learners' performance. That is, once learned, a cognitive strategy based on self-explanation is reusable and adaptable from one context to another and, more importantly, from one domain to another.

Self-explanation is thought to be more effective than explanations provided by others or gathered by the learner from other sources (e.g., textbooks) because (a) it requires learners to actively elaborate their prior knowledge, thus triggering more constructive learning processes; (b) it is usually very well targeted to the learner's specific problem; and (c) it is always available exactly when and where the learner needs it. In science education, reported gains attributed to the use of cognitive strategies based on self-explanation are overwhelming, with self-explainers sometimes performing twice as well as non-self-explainers (Kastens & Liben, 2007). VanLehn, Jones, and Chi (1992) propose three possible explanations for why self-explanation works. First, self-explanation seems to persuade learners to detect and fill gaps in their own knowledge. Second, self-explanation seems to help learners to abstract solutions and procedures from the initial context in which they were generated to a more general description of the problem. Third, it seems to induce an analogical enhancement, a richer elaboration of the example or case, facilitating later analogical problem solving.

The effect of self-explanation has been investigated by numerous researchers on subjects taught in a variety of conditions and tasks. For example, Chi and Basok (1989) studied its influence on problem-solving in physics while Pirolli and Recker (1994) looked at computer programming. Lin and Lehman (1999) looked at experimental design while Kastens and Liben (2007) looked at map reading activities. Existing research documents the effectiveness of self-explanation based strategies across a variety of conditions. For example, Diderjean and Cauzinille-Marmèche (1997) studied its effectiveness when self-explanations are spoken aloud compared to when they happen only in one's head, and Aleven and Koedinger (2002) looked at it from the perspective of written versus type expression media. It also has been documented that self-explanation based strategies help with (Aleven & Koedinger, 2002) and without (Chi et al., 1989; Chi, De Leeuw, Chiu, & Lavancher, 1994) feedback on the correctness of the explanation.

From a theoretical perspective, self-explanation was studied in the context of gap-filling (Chi & Bassok, 1989; Lin & Lehmann, 1999; VanLehn et al., 1992), mental model revision (DeLeeuw & Chi, 2003), conflict detection and resolution during knowledge integration (Chi et al., 1994), and error detection and self-correction respectively (Kastens & Liben, 2007). By construct, scholars have looked at schema formation and case-based reasoning (Didierjean & Cauzinille-Marmèche, 1997), analogical enhancement (Reinmann & Neubert, 2000), visual/verbal integration (Aleven & Koedinger, 2002), construction of new knowledge (Chi et al., 1989; DeLeeuw & Chi, 2003; Wong & Lawson, 2002), connection of principles to action (Lin & Lehmann, 1999), and situational model building (Kintsch, 1994).

Looking at self-explanation as a domain-independent strategy, Nathan, Mertz, and Ryan (1994) found that it works better for conceptual reasoning while providing only marginal advantage for procedural contexts. The same study also suggests that a decrease in performance occurs when cognitive load increases, such as is the case for solving complex problems.

Bielaczyc et al. (1995) show that self-explanation is a strategy most high-performance students use, for example, when linking current concepts to prior knowledge. In their studies, they found that the effectiveness of the strategy depends on the learners' domain-general and domain-specific knowledge, the comprehensiveness of the problem being studied, and the state of the students' evolving understanding.

It has also been found that performance improved with either guiding students through the self-explanation process (e.g., Bielaczyc et al., 1995) or prompting them to self explain (Chi et al., 1989). Therefore, tutoring is an area where self-explanation-based cognitive strategies can be used successfully. While some studies on self-explanation show that most learners do not spontaneously use self-explanation (Conati & VanLehn, 2000), other studies suggest that learners seem to start self-explaining more effectively when they are guided or prompted to do so (Bielaczyc et al., 1995). This suggests that self-explanation is capable of improving the effectiveness of the tutoring sessions in problem solving through more intense conceptual engagement of the students. As an example, Chi (1996) successfully used strategies involving self-explanation in tutoring students to solve mechanics problems. In this case, the tutor's actions that prompted the co-construction of knowledge (which includes self-explanation) proved to be both beneficial in achieving deep learning and capable of helping learners overcome misconceptions. Therefore, providing the tutees with support and opportunities will help them successfully construct answers on their own.

The use of self-explanation-based cognitive strategies proved also to be beneficial in online environments. One of the attempts in using an online environment to scaffold the use of self-explanation was undertaken by Atkinson, Renkl, and Merrill (2003), who asked learners who were solving problems about probabilities to specify the principle(s) that applied to the problem they were working on. In this case, a surprisingly simple procedure—prompt the participants to choose the principle underlying the problem from a drop-down box—produced medium to strong effects on both near and far transfer tasks. These are only two example of how self-explanation was used successfully in online environments to improve learners' performance. The interventions used in both cases are simple. What was important for success was the way these interventions were implemented to support learners' effective use of self-explanation strategies.

Our research was developed to target the same characteristics. In our study we used prompting questions to elicit self-explanation at different stages in the learner's path toward the solution. The challenge was to find: (a) how to construct these questions so that they were not leading directly to the solution, and (b) how to time them to produce the expected effect, the occurrence of self-explanation.

Instructional Context

As mentioned earlier, based on our own teaching experience and following conversations with engineering and Science, Technology, Engineering, and Mathematics (STEM) faculty, we decided to localize our study as early in the program of study as possible. Originally looking at freshman courses we found an even better opportunity: a three-week intensive summer program designed for incoming freshmen.

Incoming students often face difficulties in moving from learning strategies they used in high school to strategies that are effective for learning in college. These difficulties seem to be more apparent in engineering and science programs where abstract knowledge and the skills needed to master it are critical to achieving academic success. Among these difficulties, students face a major challenge to build and successfully use deep reasoning skills. In the long run, failure to address this challenge at an institutional level results in poor student retention, which, in turn, contributes to a decrease in the attractiveness of engineering and science programs. In response, a Midwestern college of engineering offers incoming students the opportunity to enroll in a three-week summer program focused on the transition from high school to college instruction. For incoming students, this program provides an excellent opportunity to learn about coursework expectations in mathematics, chemistry, and English, as well as about campus life and community involvement. Increasing enrollment in this summer program is evidence of its positive impact for incoming students. In addition, the program provides the students with the opportunity to earn three credit hours towards their academic degree.

Of the three modules mentioned above, we decided to focus our study on the introductory chemistry module. The objective of this module was to engage students in a comprehensive study of general principles of chemistry. The module emphasizes chemical nomenclature, periodicity of elements, chemical reactions and stoichiometry, chemical bonding, and possible applications. For this module, students work on homework assignments, take pop quizzes and formal examinations, and are graded for their performance.

Research Questions

The main objective of this research study was to investigate if self-explanation has the same effect over the range of prior knowledge levels learners had when they enrolled in the course. While, as previously explained, existing research studies suggest that the use of self-explanation has a significant positive impact on the learners' performance, we wanted to discover whether this strategy had a positive impact on students' performance specifically in solving chemistry problems. The research questions were:

1. Does the use of self-explanation as cognitive support strategy increase learners' performance when solving basic chemistry problems?
2. How does the effectiveness of self-explanation as a cognitive support strategy relate to the level of self-reported prior knowledge?

Methods and Methodologies

Participants

At the time of this study, 80 incoming freshmen were enrolled in the intensive summer preparatory program. The task for this study, designed together with the course instructor, asked the students to solve a short chemistry problem. While this group of future engineering students was expected to have a certain level of knowledge in the field of chemistry, to ensure equal training that would allow them to address the task, we scheduled this study at the end of the chemistry track in the summer program.

Participation was voluntary and rewarded with extra points towards their chemistry section grade. Fifty-two students completed all the required tasks. No outliers were found and normality was a strong assumption for the group (one-sample Kolmogorov-Smirnov test shows $p > 0.05$ for all continuous variables).

Research Design and Procedure

A two-group between-subjects completely randomized experimental design was used in this study (Keppel, 1991). Each participant was randomly assigned to one of two experimental conditions, control or treatment. The experiment was conducted using a web-based research instrument designed and developed by the researchers for this study. The web application automatically assigned the participants to one of the two experimental groups. Of the 52 students who completed all of the required tasks, 29 students were in the control group and 23 students in the treatment group.

The participants in both groups were asked to solve the chemistry problem described below:

> Adrenaline, also referred as epinephrine, is a sympathomimetic monoamine that is produced by the adrenal gland. This stress hormone, when secreted into the bloodstream, rapidly prepares the body for action in emergency situations. It increases heart rate and stroke volume, dilates the pupil, and constricts arterioles in the skin and gastrointestinal tract while dilating arterioles in skeletal muscles. It elevates the blood sugar level by increasing catabolism of glycogen to glucose in the liver, and at the same time begins the breakdown of lipids in fat cells.

The students in the control groups were asked to answer the following question: "Given that adrenaline contains three oxygen moles, 13 hydrogen moles, nine carbon moles, and one nitrogen mole, which is its chemical formula?"

While the participants in the control group were only prompted to answer the question, those in the treatment group were asked, before having the opportunity to provide an answer to the above question, to answer three guiding questions:

1. What type of chemical compound is adrenaline?
2. How does belonging to this type of chemical compounds influence the way chemical formulae are written?
3. How do you write the formula for this type of compound?

These questions were developed in collaboration with the instructor and were aimed at engaging the participants' self-explanation behavior. They were intended to emulate the causal structures an expert would activate when answering this type of questions. Previous studies (e.g., Bielaczyc et al., 1995) have shown this type of guiding questions to be effective in engaging students in self-explanation behavior.

After having the opportunity to provide an answer to the chemistry question, the participants in both treatment and control groups were asked to indicate: (a) how confident they were that their answer was correct, and (b) how familiar they were with the field of organic chemistry. To answer the above self-evaluation questions, students were provided with a virtual slider that could be placed anywhere between 0 (*low*) and 100 (*high*). The rationale behind the decision to use self-reported prior knowledge (second research question) is presented below when the independent variables included in this study are described. Finally, the participants were asked several questions related to their individual learning characteristics as well as demographic information.

Dependent Variables

Two categories of measures were used in this study. The first category included measures of students' performance and the associated confidence that the answer they provided was correct. The performance was measured as a binary outcome, where a value of 0 was assigned to an incorrect answer and a value of 1 to a correct one. In addition, participants' confidence in the correctness of their answer was generated as a continuous variable ranging between 0 (*low* or *no confidence*) and 100 (*complete confidence*). To control for the students "guessing" the correct answer and to better reflect the strength of their mental model of the problem they were asked to solve, an adjusted performance score was computed combining the binary score (0 or 1) with the self-reported confidence levels as follows:

- Adjusted Performance = (-1) * Confidence when answer is incorrect + 100
- Adjusted Performance = Confidence when the answer is correct + 100

That is, the dependent variable (i.e., Adjusted Performance) was always positive, with a range from 0, when the participant answered the question incorrectly but indicated that s/he was certain that the answer was correct, to 200, when the participant answered the question correctly and was also certain that the answer s/he provided was correct.

The second category of dependent variables was aimed at determining if the two groups, control and treatment, had similar individual characteristics. Motivation and academic efficacy were measured using an instrument adapted from Midgley, Kaplan, Middleton, Maehr, Urdan, and Anderman (1998). For these constructs, a 5-point Likert scale was used, with the final value computed as the mean of all items included in the scale. This final value varied from 1 (*low*) to 5 (*high*) for each construct.

Independent Variables

The two independent variables used were the participant assignment to the experimental group and respectively self-reported prior knowledge of chemistry. The experimental group variable has two levels, one for each of the two experimental conditions. The self-reported prior knowledge of chemistry was collected as a continuous variable ranging from 0 (*low* or *no prior knowledge*) to 100 (*high familiarity*) with the field.

Researchers' opinions on the validity of self-reporting in assessing one's own knowledge are divided. While an objective assessment of prior knowledge would have been preferable, the limitations of this study, such as the short time students had available to complete this module and limited possibilities to include more extensive testing within it, prevented us from using a more objective measure for this variable. The students participating in this research worked through almost all of the course content, had homework to do, solved problems, and took tests, all activities for which they received feedback from their instructor. In this context we expected that the self-reported prior knowledge would account not only for the opinion about self, but also for the feedback from the instruction and peer assessment. This decision is also supported by existing research studies and meta analyses which report, for example, that no consistent over- or underestimation was found in self-assessment (e.g., Boud & Falchikov, 1989) and that broad agreement between self-assessment and objective knowledge can be observed (e.g., Ackerman, Beier, & Bowen, 2002).

Table 1 summarizes the statistical characteristics of the continuous variables included in this study.

Results and Interpretation

Group Homogeneity

One-way ANOVA analysis with one between-groups factor was used to test the homogeneity of the two experimental groups. No statistically significant differences were found between students' learning characteristics in the two experimental groups as measured by academic efficacy, $F(1,49) = 1.16$, $p = .29$, motivation goal orientation, $F(1,49) = .63$, $p = .43$, and self-reported prior knowledge of chemistry, $F(1,50) = 2.54$, $p = .12$. Therefore, the two randomly created groups can be considered to share similar entry-level learning characteristics.

Chi-Square Tests

To study the impact the use of self-explanation based cognitive strategies has on learners' performance on solving chemistry problems, a chi-square test was initially run for the dependent variable in its categorical form. The analysis shows that significantly more participants in the treatment group, those who were prompted to self-explain, answered correctly when compared to the participants in the control group, $X^2(1, N = 52) = 6.32$, $p < .05$. This result provides firm support for an improvement in learners' performance when they use self-explanation while solving chemistry problems.

Logistic Regression Analysis

Looking at the raw categorical data, logistic regression analysis (Bewick, Cheek, & Brown, 2005; Hosmer & Lemeshow, 2000) was used to study the moderating effects of prior knowledge on the effectiveness of using self-explanation based cognitive strategies. The results of this analysis, shown in Table 2, suggest the existence of an interaction effect between the treatment condition (use of self-explanation) and self-reported prior knowledge, thus warranting a finer-grained analysis using the adjusted score (continuous data).

Regression Analysis

We used linear regression analysis to examine how the self-explanation impact on performance relates to prior knowledge as reported by the learners. The adjusted score was the dependent variable, the treatment condition was the categorical variable treated as dummy variable (coded with 1 for the treatment group and 0 for the control group), and self-reported prior knowledge of chemistry was the moderating variable. The analysis focused on the moderating effect prior knowledge has on the relationship between the adjusted score and the treatment condition. The reason for choosing the adjusted score for this analysis is its ability to enhance the value of a categorical true or false answer to account for the students' confidence in the validity of the answer they provided and thus better reflect the strength of their mental model of the concepts foundational to their problem solving.

The bivariate correlations revealed the treatment condition as being the only significant predictor for the adjusted score ($r = 0.37$, $p < 0.05$). In a first step the adjusted score was regressed on the treatment and the self-reported level of chemistry knowledge. The resulted regression equation accounted for 15% of the variance in the adjusted score, $F(2,49) = 4.16$, $p < 0.05$. Only the treatment condition variable had a significant beta weight ($\beta = 0.39$, $p < 0.05$).

In a second step, the interaction between the treatment condition (use of self-explanation) and the self-reported prior knowledge of chemistry was introduced as a predictor. Mean centered values for self-reported chemistry knowledge were used in the analysis. The results show that the interaction term between the treatment condition and self-reported prior knowledge of chemistry explained a significant increase in the adjusted score, $\Delta R^2 = 0.16$, $F(1,48) = 11.06$, $p < 0.05$. Therefore, we can conclude that prior knowledge of chemistry, as reported by the participants, is a significant moderator of the relationship between the experimental condition and the adjusted score (Table 3).

Table 1
Means, Standard Deviations, and Pearson Correlations for Continuous Variables

	M	*SD*	1	2	3	4
1. Adjusted Performance Score	111.22	73.75	–	.29*	.29*	0.01
2. Academic Efficacy	4.12	.58		–	.52**	0.14
3. Motivation Goal Orientation	3.93	.64			–	-0.02
4. Self-reported Prior Knowledge	44.78	37.01				–

Note: * p < .05, ** p < .01

Table 2
Results of the Logistic Regression Analysis

Predictor	β	SEβ	Wald X^2	*df*	*p*	e^{β}
Constant	-0.691	.390	3.140	1	.076	.501
Treatment condition (1) by Self-reported prior knowledge (1)	1.480	.522	8.024	1	.005**	4.393
Total			X^2	*df*	*p*	
Overall model evaluation Likelihood ratio[b]			10.578	1	.001**	
Goodness of fit Hosmer & Lemeshow test[c]			1.328	1	.249	

Note. [a] The analysis was conducted using SPSS's Binary Logistic Regression with backwards elimination process. The elimination process continued until the most parsimonious model was reached. The significance level was set at 0.05. Cox and Snell R^2 = 0.191, Nagelkerke R^2 = 0.255. The elimination process took place in three steps. The model significance was 0.006 in the first step, 0.003 in the second step, and 0.001 in the third step. [b] p < 0.05 means there is adequate fit of the data to the model, meaning that at least one predictor is significantly related to the response variable. [c] A finding of non-significance indicates that the model adequately fits the data. ** p < 0.01.

Table 3
Summary or Regression Analysis

	Beta Weights	
Predictor	β	*t*
Treatment (A)	.41	3.35**
Self-reported prior knowledge (B)	-.26	-1.59
A * B	.54	3.33**
Model Summary	R^2 = .31**	

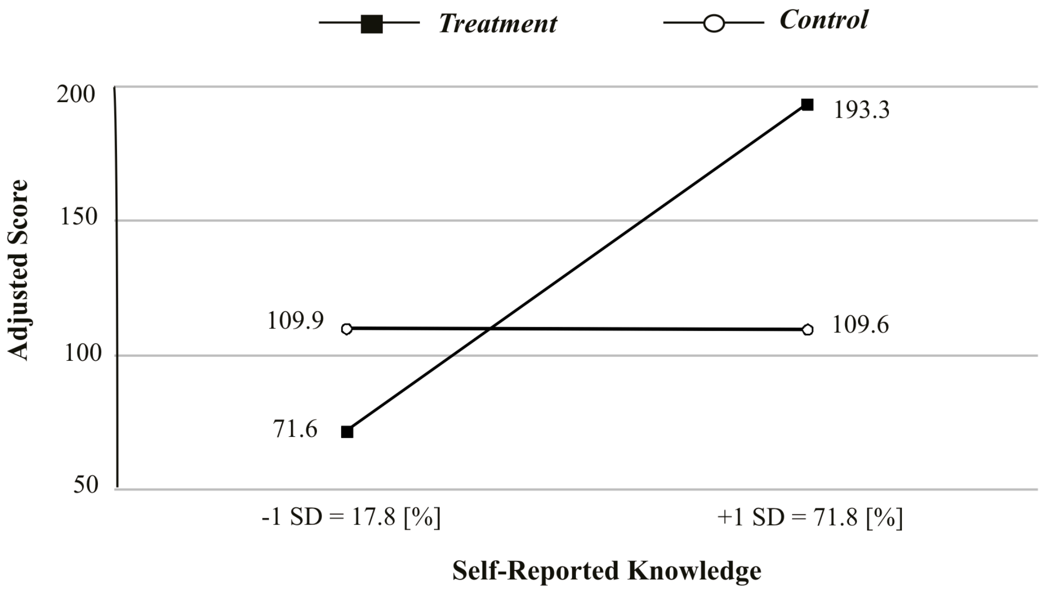
The unstandardized simple slope of adjusted score for the treatment group was +1.55 and the unstandardized simple slope for the control group was -0.71. The simple slope analysis (Aiken & West, 1991) indicated that the positive slope for the treatment group was statistically significant, $t(48) = 3.01 > t_{cr}(40) = 2.707$, $p < 0.01$, while the negative slope of the control group was not statistically significant (Figure 1).

As a domain-independent cognitive strategy that allows learners to relate new ideas to knowledge they already possess so that they can understand new concepts and synthesize new knowledge, self-explanation, or self-generated explanation, refers to the explanation a learner generates on his or her own as opposed to the explanation provided by an external source. It is a reusable cognitive strategy that can be utilized across domains and age groups, capable of producing significant improvements in learner performance. It actively triggers constructive learning processes, better targets the problem, and is always available when needed. Self-explanation works by persuading learners to detect and fill gaps in their knowledge, by helping them abstract solutions and procedures from the current context, and by facilitating analogical problem solving.

Discussion and Implications

With little research on understanding how prior knowledge affects the effectiveness of self-explanation-

Figure 1
Moderating Effect of Self-Reported Prior Knowledge on the Effectiveness of Using Self-Explanation as Cognitive Support Strategy



based cognitive strategies, this study was focused on better understanding the moderating effect prior knowledge has on the effectiveness of using cognitive support strategies based on self-explanation when solving chemistry problems. The results of this study confirm prior findings showing that learners can benefit from using self-explanation. They also show that there is a moderating effect of prior knowledge on the effectiveness of self-explanation for chemistry problem-solving.

The interaction between prior knowledge of chemistry and the effectiveness of self-explanation seems to be twofold. On one hand, the higher the self-reported knowledge of chemistry, the more powerful the effect of self-explanation is. That is, the use of strategies based on self-explanation tends to help learners better incorporate their prior knowledge in their current activities by "forcing" them to consider it when on task.

On the other hand, for these strategies to be effective, learners need to reach a certain level of prior knowledge, a threshold. That is, when the students have little prior knowledge of the domain, using self-explanation seems to hinder performance rather than help learners. The explanation of the existence of a threshold, as suggested by this study, could be related to the fact that while learners might have an understanding of the disparate concepts that would allow them to make sense of the new information they encounter, they are not yet aware of the relationships among these concepts. That is, students might understand the concepts individually, but they cannot yet link them together. Therefore, when learners attempt to self-explain, they search for similar situations, concepts, or processes in their prior knowledge in order to construct new knowledge or solve new problems. When there is a weak prior knowledge foundation, the entire process falters. Unfortunately, the number of participants and the extent of this study prevented us from performing a more fine-grained analysis. It is for future research to investigate in more depth the nature and level of this prior knowledge threshold that makes self-explanation-based cognitive strategies effective.

There are implications for the instructional design process in finding a threshold from which the use of self-explanation becomes effective. That is, while self-explanation can be used to increase the effectiveness of, for example, tutoring and review sessions or short transfer problems through more intensive cognitive engagement of the students during the various learning activities, it should not be suggested or introduced too early in the learning cycle. It would be therefore advisable to use other cognitive support tools and methods capable of helping learners in the early stages of the learning process, to bring them to the level of knowledge that would make the use of self-explanation effective.

Also, since self-explanation is a domain-independent cognitive strategy, the upside is that once learned, students would probably attempt to use it in other fields and apply it to other problems. The downside is that while progression through the curriculum will improve learners' domain-general knowledge, domain-specific knowledge is still needed to make self-explanation work, which might render the strategy ineffective when learners are just beginning to study a domain. Therefore, the instructional design process needs to account for such tendency and implement safeguards that would keep learners away from using this strategy until appropriate.

In essence, our findings suggest that when implementing self-explanation-based strategies in the classroom, the first step should be a thorough assessment of the learners' prior knowledge. Based on this assessment the instructor can then decide how to introduce self-explanation-based cognitive strategies. For example, when asking the students to solve a new type of problem, the instructor can start by providing students with more specific guiding questions. Typically, good guiding questions will compel students to start by reviewing the relevant content needed to solve the problem rather than directly starting to solve that problem. After the students get a grasp on how it works, the instructor can start implementing general prompts aimed at eliciting the self-explanation behaviors, and he or she can ask the students to use these prompts on their own whenever they have to solve a problem. The long-term goal is for the students to be able to activate self-explanation strategies on their own when facing tasks requiring solving problems.

Another possible strategy is to have the instructor introduce self-explanation by using a constrained argumentation structure. That is, students will use predesigned prompts to help them build an argument for their path to the solution. Therefore, with this strategy the predesigned argumentation prompts are what elicit students' self-explanation behavior.

Unfortunately, as prompts to self-explain are highly dependent on the topic and field of study, there is no universal recipe for how to design them, especially in the initial stages of introducing this strategy. The prompting questions can range from general (e.g., "What theory or theories might be involved in finding the solution?" "What principles should be used in the context of this problem?") to specific questions, similar to those we used in this study (e.g., "What type of chemical compound is adrenaline?" "How does belonging to this type of chemical compounds influence the way chemical formulae are written?"). It is ultimately the instructor's task to find the best way to elicit the self-explanation behavior, depending on both students' range of prior knowledge and the specific elements of the field of study.

Nevertheless, if the objective is, aside from helping students be better problem-solvers in a certain area, to help them learn a strategy that they could use in the future to solve problems, we suggest using a progression approach. That is, the instructor will start with simple and focused questions when a topic or problem type is new, and he or she will gradually move towards generic questions later on in the instructional process. Using this approach, in the initial stages students will have the opportunity to learn the benefits of using this strategy while in the final stages they will learn how to generalize it to other fields of study.

Looking forward, future research should take a closer look at the nature and level of the threshold level in prior knowledge that makes self-explanation-based cognitive strategies effective. It should also look at how various characteristics of the elicitation prompts (e.g., focus, atomicity, concept versus process targeting) influence learners' performance. For example, in science and engineering, where question asking is frequently used in classroom-based activities, research could look at the effect of generic versus specific prompts or at how timing of the questions could affect the strategy's effectiveness.

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