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Autonomy-Supportive Teaching Algorithm Which Fosters Independent Learners

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Abstract

After being taught by teachers, learners often need to work independently in new situations. However, a teaching strategy that most efficiently fosters independent learning remains elusive. In this study, we developed a novel experimental paradigm to compare various teaching strategies. In addition, we formalized autonomy-supportive teaching and constructed an autonomy-support algorithm that estimates learners' mental states and aims to enhance both learners' competence and autonomy. In the experiment, participants were taught through different teaching algorithms depending on the experimental conditions, after which they independently worked on a new set of tasks. Our results demonstrate that compared to the all- and no-teach algorithms, the autonomy-support algorithm enhances learners' engagement while being taught and enhances performance when learners independently work on a new set of tasks. Our findings contribute to the existing observational and interventional research on education by providing rigorous evidence in an experimentally controlled setting.

Keywords: autonomy; instruction; motivation; pedagogy; performance; teaching

Introduction

Teaching is one of the fundamental building blocks of human society. People teach others not only in schools, but also in other educational settings. Parents teach their children at home and mentors teach mentees in the workplace. Successful teaching gives ability to learners to solve a novel problem efficiently, even when the solution needs to be explored independently. For example, a mentor teaches a mentee how to cook French cuisine, who then replicates the cooking style taught by the mentor. In a few years, the mentee independently opens new restaurants in different areas, and tries to adapt to local preferences and ingredients. Can the mentee cook different cuisines well independently? The mentor should teach mentees considering that the mentees will eventually cook different cuisines on their own in future. The goal of the present study is to examine the teaching strategy that can lead to better performance among learners when they subsequently work independently, in a new situation.

All-Teach and No-Teach Strategies

There are several teaching strategies. The simplest approach is to teach everything. Many studies have shown that instructions and direct advice enhance task performance (Biele, Rieskamp, & Gonzalez, 2009; Rosedahl, Serota, & Ashby, 2021). For example, in a concept-learning task, learners who received verbal instructions regarding the optimal strategy performed better than those who did not receive any instructions (Rosedahl et al., 2021). However, excessive instructions or advice may worsen performance when learners work independently. Direct instructions on use of a machine ensures that learners follow the instructed method only and are less likely to explore a new method (Bonawitz et al., 2011). Moreover, students who perceive their teacher as controlling (e.g., giving a learner an answer immediately) tend to be less autonomous and have lower academic performance (Grolnick, 2016).

Another simple approach is to teach nothing. If teachers do not teach at all, the learners have maximum opportunities to work on a task by themselves. However, it is inefficient to work without being taught when a task is too difficult for learners; they often have limited time and cannot master their skills without being taught. Moreover, repeated failures can cause learners to give up (Hiroto & Seligman, 1975).

Autonomy-Supportive Teaching Strategy

In the field of educational psychology, researchers have been investigating the development of autonomous learners and have proposed the theory of autonomy-supportive teaching (Reeve & Cheon, 2021; Ryan & Deci, 2017), which includes instructional behaviors. For example, autonomy-supportive teachers give learners the time they need to work at their own pace, and also give helpful hints when the learners seem stuck. Such autonomy-supportive behaviors emerge when the learner's perspective is considered (Reeve & Cheon, 2021), such as trying to understand their needs and gauge their understanding of the material. In other words, taking the learners' perspective enables autonomy-supportive behavior in teachers. Many observational and interventional studies have shown that learner perceived autonomy-supportive teaching is positively related to intrinsic motivation (interest and enjoyment) and engagement (Reeve, 2016), which in turn is positively related to academic performance (Lerner, Grolnick, Caruso, & Levitt, 2022).

However, almost all studies on autonomy support have used surveys, observation, or interventions as methodology. Surveys and observational research cannot provide strong causal inference for teaching strategies, and school interventions cannot test this effect in controlled settings. Although in a recent study (Reeve et al., 2022), autonomy

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support was experimentally manipulated using verbal instruction (e.g., asking teacher participants to understand the learner's perspective and be supportive), this manipulation was weak and ambiguous. Possibly because of that, the study did not find any statistically significant effect of autonomy-support on the learners' performance. Precise manipulation is required by formalizing teaching strategies and removing verbal ambiguity (Guest & Martin, 2021).

Other Teaching Strategies

In cognitive science, various teaching strategies have fostered learning. For example, tests foster learners to remember more content than additional studies of the same content, which is called the testing effect (Roediger III & Karpicke, 2006). Expectations for tests also enhance long-term retention (Szpunar, McDermott, & Roediger, 2007). Thus, a teaching-then-testing strategy encourages learners to consolidate memory of the content, and the learners are more likely to use the content when they work independently in a new situation. In addition, research on self-regulated learning has shown that monitoring one’s own thinking and regulating learning processes enhances academic performance (Mega, Ronconi, & De Beni, 2014; Pintrich, 2004; Zimmerman, 1998). Thus, by letting learners decide whether or when they ask teachers questions, learners can accurately monitor their understanding and work more efficiently in a new situation independently.

The Present Study

Which of the teaching strategies leads to the best performance, especially when learners subsequently need to work independently in a new situation? Despite many theories and findings on teaching strategies, to the best of our knowledge, no study has experimentally tested this important question. It is challenging to compare teaching strategies across different studies based on existing findings because previous studies have used different tasks, set differing control conditions, and measured varied outcomes. The effectiveness of various strategies must be compared in the same setting (Hameiri & Moore-Berg, 2022).

The present study aims to formalize teaching strategies that extract the essence of previous findings and to systematically compare the effectiveness of teaching strategies by developing an experimental paradigm. Inspired by computational studies that formalize the decision-making processes in teaching (Bridgers, Jara-Ettinger, & Gweon, 2020; Ho, Cushman, Littman, & Austerweil, 2019), we experimentally manipulated autonomy-supportive teaching by constructing a computational algorithm. As the first step, we developed an autonomy-support algorithm and compared it with no- and all-teach algorithms.

Experiment

Experimental Task As a task that requires learners to explore uncertain environments and form new concepts, we employed a type of conceptual learning task: a category learning task (Zeithamova et al., 2019). During the task, learners are presented with a stimulus in each trial and asked to classify it into one of the two categories. The task consists of two sessions: an exploration and a generalization session. In the exploration session, the learners receive feedback for each response (i.e., correct or not). By repeating classification and feedback, the learners form an association between stimuli features and their categories, and pay attention to the features that are relevant to classification (Kruschke, 1992; Love, Medin, & Gureckis, 2004; Nosofsky, 1986). Subsequently, the learners integrate information across stimuli and form the category rules (Bowman & Zeithamova, 2018). The generalization session tests whether the learners find the category rules. In this session, learners are shown new stimuli without feedback and are asked to classify them using the same category rule as in the exploration session.

Overview of Autonomy-Support Algorithm The fundamental strategy of our autonomy-support algorithm is based on the theoretical research on autonomy support (Reeve & Cheon, 2021; Ryan & Deci, 2017). This research proposes that the essence of autonomy-supportive teaching is to (1) take the learners' perspectives and support their competence (e.g., giving helpful hints when learners seem stuck); and (2) take learners' perspectives and support their autonomy (e.g., letting the leaners work at their own pace). Our autonomy-support algorithm takes the learners’ perspective (e.g., level of understanding, the time required by a learner to master a task, etc.) by calculating the learners’ responses; it aims to enhance the learners’ competence by enabling them to master a task, and enhances their autonomy by maximizing the opportunity for learners to think on their own. Particularly on the category task, the autonomy-support algorithm (1) estimates a learner's accuracy of classification and partially teaches items that learners cannot find the category-relevant features of (i.e., enabling them to master the task); and (2) estimates the number of trials required by a learner to master a task to a certain level and delay the start of teaching until then (i.e., maximizing the opportunity for learners to think on their own). These features of the algorithm are considered effective in enhancing the learners' competence and autonomy, which leads to higher intrinsic motivation of the category task. Subsequently, the learners are likely to independently perform better in the exploration and generalization sessions.

Hypothesis We had two hypotheses. (1) Performance during the independent exploration and generalization sessions in the autonomy-support condition would be better than that in the no- and all-teach conditions. (2) The effect of autonomy-support on performance would be mediated by self-reporting intrinsic motivation measured after the teaching sessions.

Methods

Participants We recruited 172 participants from the United Kingdom using the Prolific Research Platform (M_{age} = 35.42 years, SD = 7.99, range = 20 to 49; 75 female, 94 male, 1 did not answer). Before recruitment, the necessary sample size was estimated using G*Power (Faul, Erdfelder, Lang, & Buchner, 2007). As this was the first attempt to investigate the effect of an autonomy-support algorithm using the category learning task, we estimated a medium effect size (f) of .25 for comparing the three conditions on between-participant design and set power at .80 and alpha level at .05. The results of the power analysis indicated that 159 participants were required to obtain a statistically significant effect. Two participants were excluded for failing attention checks; therefore, our final sample size consisted of 170 participants. Participants were randomly assigned to three conditions: 66, 53, and 51 to the no-teach, all-teach, and autonomy-support conditions, respectively. The number of participants did not differ statistically significantly across the conditions ($p > .310$).

Materials We created four types of creature stimuli (Figure 1) based on previous category-learning studies (Bowman & Zeithamova, 2018; Bozoki, Grossman, & Smith, 2006; Rosedahl & Ashby, 2018). Each creature contained eight items. An individual item had three features (e.g., crest, foot, and tail, which varied among items in a bird type). Items were divided into two categories: red and blue. Each category has prototypical features (e.g., the foot of the red category has three nails, whereas the foot of the blue category has one nail). The items were categorized according to the number of features relevant to the categories. This rule was followed for classification of the items into categories.

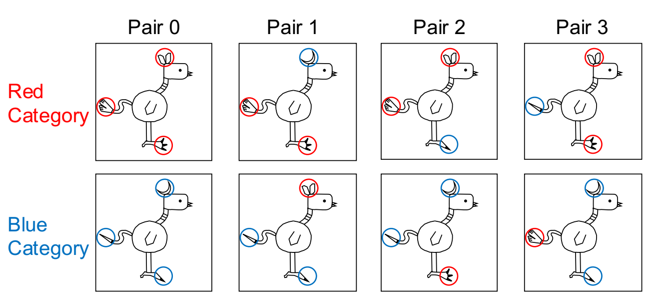

Figure 1: Example of stimuli. The features that are relevant to each category are circled with each category's color.

Procedure The experiment was conducted online using jsPsych (de Leeuw, 2015). The task consisted of five sessions: three teaching sessions, an independent exploration session, and an independent generalization session (Figure 2). Four types of creatures were randomly assigned to one of the three teaching sessions or to a set of independent sessions (exploration and generalization). In each trial, an item was presented for a maximum of two seconds, and participants were asked to indicate their response with a keyboard press at their own pace. Items were ordered pseudo-randomly, such that each item presented once in a set, and no more than three items from the same category were presented consecutively (Bowman & Zeithamova, 2018).

In the teaching sessions (Figure 2; Upper part), participants classified each of the eight items of a creature 15 times (8 items × 15 times = 120 trials per teaching session). After each classification, participants received feedback regarding whether their answer was correct or wrong. In each trial, the algorithm for each condition decided whether a hint was required (Figure 2). If an item's feature was associated with the red category, it was marked with a red circle. If an item's feature was associated with the blue category, it was marked with a blue circle. After the three teaching sessions, participants were asked to rate their intrinsic motivation on the category task.

In the independent sessions (Figure 2; Bottom part), the participants classified items of another type of creature without any hints. In the independent exploration session, participants classified each of the eight items of a creature 15 times (8 items × 15 times = 120 trials). They were asked to attempt learning of the creature's category rule based on feedback. In the independent generalization session, the participants classified the same eight items and forty novel items of the same kind as those in the independent exploration session (8 items + 40 items = 48 trials). The forty items in the generalization session were slightly different from those in the independent exploration session and had additional features. During the generalization session, the participants did not receive any feedback. They were asked to use the same category rule as that in the independent exploration session.

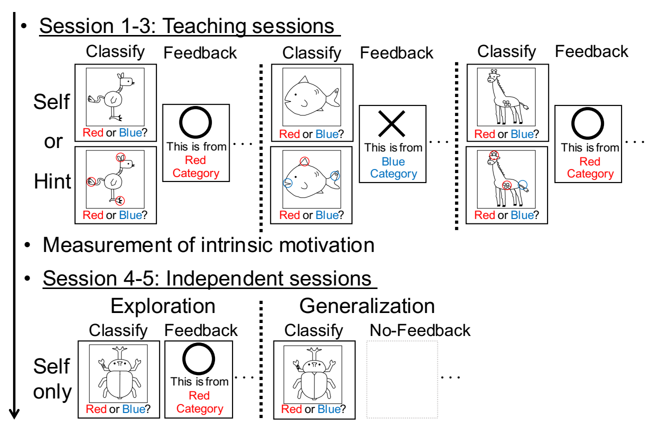

Figure 2: Procedure of the experiment.

Experimental Conditions Depending on the conditions, the algorithm for the hint timing differed in the teaching sessions. The independent exploration and generalization sessions were the same across all conditions.

No-Teach and All-Teach Algorithms The no-teach algorithm never gave participants a hint. The all-teach algorithm gave participants a hint of every trial (three relevant features were highlighted by red and/or blue circles).

Autonomy-Support Algorithm The autonomy-support algorithm estimated the learner's accuracy of classification and partially taught what the learners could not understand. The algorithm divided the eight items into four-item pairs based on the features of the creature (Pair 0 to Pair 3 in Figure 1). At the beginning of the first teaching session, the algorithm provided a hint on the first two trials of each pair and then allowed the participants to solve the remaining six trials by themselves, without any hint. Using the responses of these six trials, the algorithm calculated the accuracy (e.g., five correct responses ÷ six trials = .83 accuracy), which was interpreted as the participant's level of understanding of the task. Based on this estimation, the algorithm decided whether to provide hints. If the accuracy was .80 or higher, the algorithm assumed that the participant had mastered the item pair and allowed them to perform the task by themselves. The algorithm then calculated the accuracy again, using the responses of consecutive trials without a hint (e.g., seven trials). The algorithm repeated this calculation and allowed the participant to perform the task by themselves, as long as the accuracy was .80 or higher. If the accuracy was lower than .80, the algorithm provided a hint for the next two trials. This procedure was repeated, leaving participants by themselves without a hint of six trials, and the accuracy was calculated again using the responses of these six trials. The algorithm estimated the classification accuracy by the participants in the same way during the second and third sessions.

In the second and third sessions, the algorithm estimated the number of trials necessary for a learner to master a task to a certain level and delayed the start of providing the first hint. Using the response data in the first teaching session, the algorithm calculated the number of trials that participants needed to achieve an accuracy rate of .80, for every four-item pairs. For example, 6 trials were needed to obtain .80 accuracy on pair 0, 14 trials on pair 1, 30 trials on pair 2, and 16 trials on pair 3. The number of these trials was added, and the total number of necessary trials was calculated (66 trials); this total number was considered as the necessary time. Based on the estimation of the necessary time, the algorithm determined when to provide hints in the second teaching session. The algorithm calculated the number of self-trials by subtracting the number of necessary trials (e.g., 66) from the total number of trials in a session (e.g., 120 – 66 = 54). At the beginning of the teaching session, the algorithm allowed participants to perform the task independently without hints on the number of self-trials (e.g., 54 trials). At the beginning of the third teaching session, the algorithm estimated the necessary time using response data from the second teaching session and delayed the start of teaching accordingly.

Measurement To measure performance, the classification accuracy in the independent exploration and generalization sessions were calculated by averaging the responses for each session. As a measure of intrinsic motivation, four items from the Intrinsic Motivation Inventory (Ryan, 1982) were used as self-report measures (e.g., "I thought the task was very interesting"; Cronbach's $\alpha = .93$). Participants responded on a scale of 1 (*strongly disagree*) to 7 (*strongly agree*).

Data Analysis To examine the main effects of conditions on accuracy in the independent exploration and generalization sessions, we conducted a two-way ANOVA. The independent variables were conditions (between participants) and sessions (within participants), and the dependent variable was accuracy in five sessions (three teaching sessions, an independent exploration session, and an independent generalization session). Mediation analysis was conducted using the bootstrap method on an R package: *mediation* (Tingley, Yamamoto, Hirose, Keele, & Imai, 2014). The experimental design was represented by dummy coding (Cohen, Cohen, West, & Aiken, 2003). The autonomy-support condition was chosen as the reference condition, and two dummy codes were created: autonomy vs. no-teach code (autonomy-support condition = 0, no-teach condition = 1, all-teach condition = 0), and autonomy vs. all-teach code (autonomy-support condition = 0, no-teach condition = 0, all-teach condition = 1). The first code contrasted the autonomy-support and no-teach conditions, whereas the second code contrasted the autonomy-support and all-teach conditions. For this analysis, 10,000 bootstrap samples with replacements were used. All analyses were performed in the R programming environment (R Core Team, 2022).

Results and Discussion

Main Results Figure 3 shows the means of accuracy of the teaching sessions, the independent exploration session, and the independent generalization session. Two-way ANOVA showed that the interaction effect between condition and session was statistically significant ($F(2,167) = 43.44$, $p < .001$). Not surprisingly, in the teaching sessions, the simple effects of condition were statistically significant (ps < .001), and accuracy in the all-teach condition was higher than that in the autonomy-support (ps < .001) and no-teach (ps < .001) conditions.

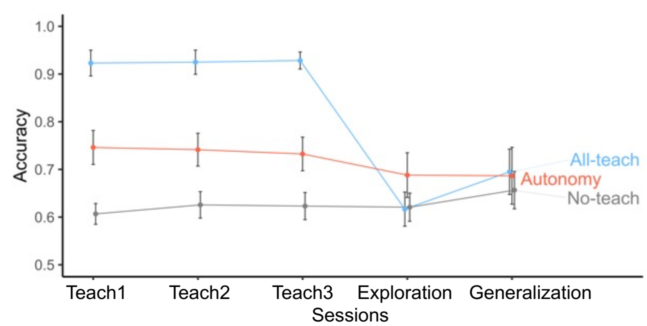

Figure 3: Means on accuracy of each session across conditions. Error bars represent the 95% confidence interval of the mean.

Importantly, in the independent exploration session, the simple effect of condition was statistically significant ($F(2,167) = 4.276$, $p = .015$), and accuracy in the autonomy-support condition was higher than that in the no-teach ($p = .033$) and all-teach ($p = .033$) conditions (Figure 4a). Simple effect tests of session showed that in the no-teach condition, the accuracy of the independent exploration session did not statistically significantly differ from that of the teaching sessions ($ps > .217$). Thus, the difference among conditions in the independent exploration session can be interpreted as a positive effect of the autonomy-support algorithm rather than a negative effect of fatigue and boredom in the no-teach condition. However, in the independent generalization session, the simple effect of condition was not statistically significant ($F(2,167) = 0.725$, $p = .486$), contrary to our hypothesis.

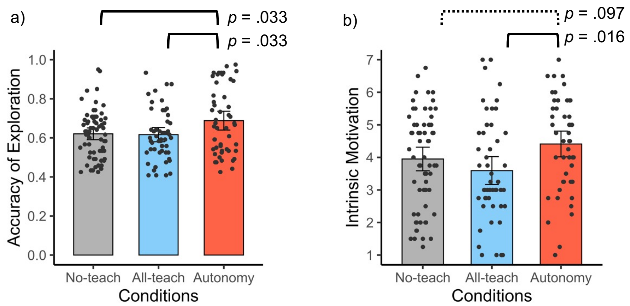

Figure 4: Means on accuracy of the independent exploration session and intrinsic motivation across conditions. Error bars represent the 95% confidence interval of the mean. Dots in the figure represent value for each participant.

Mediation by Intrinsic Motivation We examined whether intrinsic motivation mediated the effect of the autonomy-support algorithm on the accuracy of the independent exploration session. First, we examined the effect of condition on intrinsic motivation. ANOVA showed that the main effect was statistically significant ($F(2,167) = 3.984$, $p = .020$). Intrinsic motivation in the autonomy-support condition was statistically significantly higher than that in the all-teach ($p = .016$) condition, whereas there was no statistically significant difference between the autonomy-support and no-teach conditions ($p = .097$) (Figure 4b). Second, the correlation between intrinsic motivation and accuracy in the independent exploration session was weak and not statistically significant ($r = .147$, $p = .056$). In contrast to this hypothesis, intrinsic motivation was not a mediator of the positive effect of the autonomy-support algorithm on performance in the independent exploration session.

Mediation by Engagement We explored the reason for enhanced accuracy with the autonomy-support algorithm in the independent exploration session. First, we calculated the correlation between accuracy in the independent exploration session and reaction time in the teaching sessions. The correlation coefficient was positive and moderate ($r = .363$, $p < .001$). Longer reaction time may suggest that participants observed a stimulus more carefully and considered categorization. Therefore, reaction time may be interpreted as engagement in the category task.

Second, we calculated the means on reaction time across conditions (Figure 5) and examined the effect of condition on reaction time by conducting a two-way ANOVA (condition × session). We found that the interaction effect between condition and session was statistically significant ($F(2,167) = 4.435$, $p < .001$). The simple effects of condition in the teaching sessions were statistically significant ($ps < .010$), and in the second and third teaching sessions, reaction time in the autonomy-support condition was longer than that in the all-teach ($ps < .011$) and no-teach conditions ($ps < .011$). However, the simple effects of the condition in the independent exploration session were not statistically significant ($p = .624$). These results suggest that the autonomy-support algorithm enhanced the participants' engagement, specifically during the teaching sessions. Finally, mediation analysis was conducted. The results showed that the indirect effects of reaction time were statistically significant (standardized partial regression coefficient $\beta = -.059$, 95% CI [-.129, .001], $p = .047$ for autonomy vs. no-teach code; $\beta = -.138$, 95% CI [-.231, -.063], $p < .001$ for autonomy vs. all-teach code). This suggests that the autonomy-support algorithm enhances engagement during teaching sessions, which in turn enhances performance in the independent exploration session.

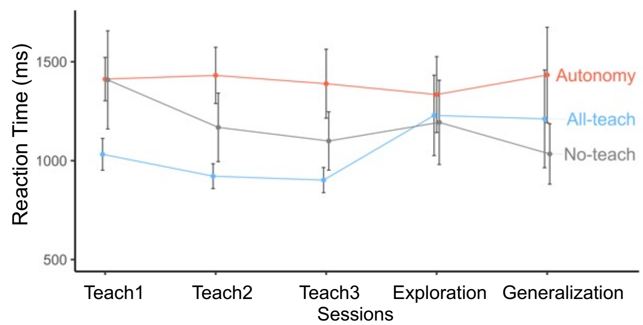

Figure 5: Means on reaction time of each session across conditions. Error bars represent the 95% confidence interval of the mean.

General Discussion

In the present study, we developed a novel experimental paradigm that allowed us to systematically compare various teaching strategies. In addition, based on autonomy-supportive teaching in the educational psychology literature, we implemented autonomy-supportive teaching as an algorithm and examined its effect on learners' performance.

Our results demonstrate that the autonomy-support algorithm led to longer reaction time during the teaching sessions, which likely reflects the greater task engagement of learners. This result is in line with previous correlational research on the association between perceived autonomy support and academic engagement (Reeve, 2016). More importantly, the autonomy-support algorithm enhanced learners' performance in the independent exploration session. According to the theories of category learning (Kruschke, 1992; Love et al., 2004; Nosofsky, 1986), as learners repeat classifying stimuli and getting feedback many times, learners find that some features are particularly relevant for classification (e.g., the foot of bird stimuli in our study). In our experiment, learners were shown relevant features as a hint in the teaching sessions, and learners in the autonomy-support condition were more engaged in the sessions. Thus, learners in the autonomy-support condition may learn to identify relevant features. Then, in the independent exploration session, learners may find relevant features of different types of creatures' stimuli more quickly, which in turn would enhance performance.

An alternative explanation for the performance results in the independent exploration session might be that the all-teach and no-teach algorithms might have decreased learners' performance. For example, learners in the all-teach condition worked on an easy task with a hint at every trial during the teaching sessions. Thus, they might have expected the task in the independent exploration session to be easy and could have concentrated less. In addition, learners in the no-teach condition worked on difficult tasks without hints of any trial in the teaching sessions and might have been tired. Thus, they might have lacked mental resources during the independent exploration session. However, in the no-teach condition, performance in the teaching sessions did not statistically significantly differ from performance in the independent exploration session, which indicates that the no-teach condition is the baseline. Performance in the all-teach condition did not statistically significantly differ from that in the baseline no-teach condition. In addition, there was no statistically significant difference in the reaction time during the independent exploration session among the three conditions, suggesting that task engagement did not differ across the conditions. Therefore, the result concerning the independent exploration session can be attributed to the positive effect of the autonomy-support algorithm.

In contrast to our hypothesis, in the independent generalization session, there was no statistically significant difference in performance among the conditions. The reason for this result may be that the teaching sessions were more like the exploration session than the generalization session. Previous research suggests that forming a category rule requires learners to integrate information across stimuli (Bowman & Zeithamova, 2018). In our experiment, although learners had the opportunity to learn the identification of relevant features of stimuli using hints given by the algorithm, they did not have the opportunity to learn integration and generalization of information regarding stimuli in the teaching sessions. Therefore, in future experiments, it would be important and interesting to test, whether the autonomy-support algorithm enhances performance in the independent generalization session when generalization was also included in the teaching sessions.

We developed a new experimental paradigm to identify the teaching strategy that leads to the best performance among learners. Recent studies in social science have compared various online interventions and identified the most effective interventions for social problems (e.g., prejudice and intergroup conflicts) (Hameiri & Moore-Berg, 2022). However, there is little research using this approach for critical problems in the educational context, which may be because it requires considerable time and resources to conduct many teaching strategies in schools or workplaces. In our experimental paradigm, teaching strategies are formalized by judging whether to give learners a hint, and are represented as algorithms by changing when to give a hint. Conducting our experimental paradigm online enables us to compare various teaching strategies in a cost-effective manner to determine the most effective strategy.

Limitations and Future Directions

Despite the positive contributions of this study, some limitations suggest directions for future research. First, the positive effect of the autonomy-support algorithm can be explained as the testing effect. Previous findings show that the teach-then-test method encourages learners to remember content (Roediger III & Karpicke, 2006; Szpunar et al., 2007). The autonomy-support algorithm provided a hint on the first two trials (i.e., teach), and then allowed the participants to solve the remaining six trials without any hint (i.e., test). This may have encouraged learners to consolidate their memory of the association between features and categories in the teaching sessions, and learners may have recalled the association in a better way in the independent sessions. Teach-then-test algorithm, which gives a hint at several trials and lets one at next several trials in the teaching sessions, may enhance learners' performance in the independent exploration session.

Second, it is unclear whether algorithms are needed to take learners' perspective and decide when to provide a hint. The theory of self-regulated learning shows that monitoring one's own thinking and regulating learning processes enhances academic performance (Mega et al., 2014; Pintrich, 2004; Zimmerman, 1998). By simply letting learners decide whether they get a hint at every trial in the teaching sessions (self-pace algorithm), the learners may monitor their understanding more accurately and pay attention to stimuli' features more efficiently. By comparing the effectiveness of these algorithms to the autonomy-support algorithm, we address these possible confounding factors and test the best strategy for enhancing learners' performance when they work independently in a new situation.

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