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Relationships among individual task self-efficacy, self-regulated learning strategy use and academic performance in a computer-supported collaborative learning environment

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This study investigates relationships between self-efficacy, self-regulated learning strategy use and academic performance. Participants were 96 undergraduate students working on projects with three subtasks (idea generation task, methodical task and data collection) in a blended learning environment. Task self-efficacy was measured with self-reports administered during each subtask. Learning strategies were assessed by counting each instance of strategy use as it occurred in peer-to-peer conversations typed into a computer software system. Results showed that for each subtask, learners with higher task self-efficacy had higher task performance. Those who used more learning strategies on each subtask also had higher performance. In turn, high performance was associated with high self-efficacy on subsequent subtasks. Surprisingly, results showed that task self-efficacy and learning strategy use were not significantly related during any subtask. Overall, results imply that task self-efficacy, learning strategy use and past performance are important predictors of task performance.

Keywords: academic performance; self-efficacy; self-regulation

The rapidly changing nature of today’s environment affects the knowledge, skills and abilities that individuals must strive to attain in order to utilise new technologies. For example, jobs are increasing in complexity (e.g. becoming more knowledge based and technologically rooted; Goldstein & Ford, 2002). In order for organisations to increase the potential of each employee, opportunities for self-directed learning must be provided in addition to formal training programmes (Goldstein & Ford, 2002). To obtain the full benefit from learning experiences, individuals must engage in self-regulated learning.

To be self-regulated, learners must have high self-efficacy toward the task, have commitment to goals (learning/academic) and utilise learning strategies (Zimmerman, 1989). While learners may have a repertoire of learning strategies from which to choose, their use is dependent on motivational elements. One motivational variable, self-efficacy, is a person’s belief in his or her capability to accomplish a task (Bandura, 1997). Self-efficacy is found to affect motivational and self-regulatory processes during training (Kozlowski et al., 2001) and enhance learning outcomes and performance (Salas & Cannon-Bowers, 2001). The purpose of this study is to closely examine the relationships between task self-efficacy,

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self-regulated learning strategy use and performance on a variety of tasks in a blended face-to-face and computer-supported collaborative learning (CSCL) environment. Our research objectives include the study of self-efficacy as a predictor, mediator and outcome of academic performance and the use of self-regulated learning strategies over a series of tasks. To assess these relationships, we explore: (1) how self-efficacy impacts strategy use and performance; (2) how self-efficacy might play a mediating role between past performance and future strategy use; and (3) how future self-efficacy might be affected by strategy use and performance on a previous task.

Studying learning in a blended learning environment is especially important as educational programmes incorporate the use of technology inside and outside of the classroom. Studies have focused on collaborative work in different types of learning environments. In comparing online collaboration to face-to-face collaborative settings, Lee and Tsai (2011) found that in an internet-based environment, students perceived higher levels of collaboration, self-regulated learning capabilities and experience in information seeking. Spending at least 7–14 h a week on an internet-based learning environment related to higher self-regulated learning and higher perceptions of collaborative behaviour. The current study contributes to the literature on self-regulated learning in CSCL environments by examining the potential role of task self-efficacy in the learning process. These relationships are studied through the collection of qualitative and quantitative data during three distinct learning project tasks in an academic setting.

**Self-efficacy**

Self-efficacy is integral to self-regulation. Self-efficacy is the perception that one can perform a given task with success (Bandura, 1977). It reflects the motivation to apply skills that are learned (Sookhai & Budworth, 2010). Self-efficacy can be conceptualised at both trait and state levels. Generalised self-efficacy is stable, trait-like and refers to one’s perceptions that he or she can effectively perform across a variety of tasks and situations (Chen, Gully, Whiteman, & Kilcullen, 2000). Task self-efficacy is malleable, state-like and refers to the perceptions that one can succeed at a specific task. Self-efficacy is multifaceted, varies from domain to domain, and should be measured according to specific tasks and contexts (Bandura, 1997). Specific, contextualised measures should provide more predictive power than global measures (e.g. generalised self-efficacy; Bandura, 1977), therefore, state (e.g. task) self-efficacy is examined in the current study. Given the nature of the construct, self-efficacy can be a predictor, mediator and outcome of other variables.

Self-efficacy is important to study because performance is affected by both capabilities as well as beliefs in one’s ability to successfully accomplish a task (Bandura, 1997). The application of what people know and the skills that they have are influenced by self-efficacy. It is important to study self-efficacy’s role in the learning process because it can act as a predictor, mediator and an outcome of performance. To the extent that task self-efficacy is malleable, educators should be interested in knowing what factors may influence self-efficacy. If feedback about past performance is a strong predictor of future self-efficacy, educators should make an effort to provide timely constructive feedback. Self-efficacy toward a task may influence the number of learning strategies utilised, so finding ways to build high self-efficacy become important because learning strategy utilisation is likely to influence performance.
Self-efficacy predicts learning strategies

Self-efficacy is found to predict a number of behaviours. According to Bandura (1999), individuals with high self-efficacy have more interest in what they do, set challenging goals, have higher goal commitment and believe that shortcomings can be overcome. Individuals with low self-efficacy tend to avoid challenges, have lower goal commitment and view shortcomings as being due to personal deficiencies.

Self-efficacy is crucial to self-regulated learning (Zimmerman, 1989). Self-efficacy predicts the use of learning strategies (Brunstein & Glaser, 2011; Hong & Park, 2012; Wu, Lowyck, Sercu, & Elen, 2012; Zimmerman & Martinez-Pons, 1990). Self-efficacy helps influence decision-making, effort, reactions to setbacks and stress (Bandura, 1991). Self-efficacy positively significantly predicts learning strategies related to goal setting such as self-set goal level (e.g. Fu, Richards, & Jones, 2009; Locke, Frederick, Lee, & Bobko, 1984; Phillips & Gully, 1997) and upward goal revision (Tolli & Schmidt, 2008). Self-efficacy toward the ability to self-regulate one’s behaviour relates positively to efficacy for academic achievement (Zimmerman & Bandura, 1994; Zimmerman, Bandura, & Martinez-Pons, 1992). High academic self-efficacy predicts greater use of learning strategies (Zimmerman & Martinez-Pons, 1990), including cognitive strategies, monitoring, time management and environmental structuring (Pintrich & Schrauben, 1992). Other self-regulatory functions influenced by self-efficacy include monitoring, use of cognitive strategies, self-set goal difficulty level, goal commitment and interest in a task (Bandura, 1991).

Self-efficacy predicts performance

There are robust findings suggesting that self-efficacy is a significant predictor of past and future performance (e.g. Aguayo, Herman, Ojeda, & Flores, 2011; Bandura & Wood, 1989; Fast et al., 2010; Phillips & Gully, 1997; Seijts & Latham, 2011). Specifically, self-efficacy is a significant positive predictor of academic performance (Bandura, 1997; DiBenedetto & Bembenutty, 2013; Richardson, Abraham, & Bond, 2012). As tasks change and increase in difficulty, self-efficacy has the ability to predict training performance over and beyond what is predicted by past training performance (Kozlowski et al., 2001).

Learning strategies are often mediators between personal factors (e.g. self-efficacy) and performance (Pintrich, 2000). High self-efficacy positively predicts the amount of deep-processing learning strategies which predict academic performance (Diseth, 2011; Sins, van Joolingen, Savelbergh, & van Hout-Wolters, 2008). Other research has examined task strategies and their relationships to self-efficacy and performance. Task strategies are defined as a collection of methods and procedures implemented to achieve task objectives (Campbell, 1991). Laboratory studies measuring task strategy development often conduct pilot tests or examine previous studies to pre-determine a set of effective strategies (e.g. Seijts & Latham, 2011; Thompson, Payne, Horner, & Morey, 2012). While task strategies are different than learning strategies, there are commonalities among the two constructs. Both sets of strategies involve cognitive processing and a selection of tactics relevant to achieving the task at hand. In a laboratory study focusing on the specific task strategies, Seijts and Latham found that self-efficacy was significantly and positively related to performance on the task, and that task strategy development mediated this effect.
Given that learning strategies and task strategies can act as mediators between self-efficacy and performance, a similar partially mediated model is proposed with learning strategies. See Figure 1.

Hypothesis 1: Self-regulated learning strategy use in a CSCL environment partially mediates the relationship between task self-efficacy and task performance.

**Self-efficacy as a mediator**

State self-efficacy often acts as a mediator of the relationships between individual differences and behaviour (e.g. Chen et al., 2000; Kuhl, 1985; Phillips & Gully, 1997; Pintrich, 2000). Self-efficacy has been found to mediate (fully) the relationship between role stressors (i.e. role ambiguity and role overload) and role performance such that role stressors are not detrimental to performance for individuals with high self-efficacy (Lindberg & Wincent, 2011).

Efficacy beliefs play a mediating role in predicting academic performance from factors like cognitive ability, educational attainment, gender and academic attitudes (Bandura, 1997). Self-efficacy also is a mediator between past performance and future use of analytic strategies (Bandura & Wood, 1989); past performance positively predicted subsequent self-efficacy perceptions which led to an increase in strategy use on the next task. Feedback about past performance can influence one’s future self-efficacy as individuals continue to work on a project. Past experiences shape future self-efficacy perceptions (Bandura, 1997). Receiving feedback about a previous experience (e.g. performance) is then likely to influence self-efficacy perceptions. For example, feedback about failure on an anagram task led to a significant decrease in task self-efficacy and future performance (Smith, Kass, Rotunda, & Schneider, 2006). DiBenedetto and Bembenutty (2013) call for future research to examine the effect of past performance feedback on self-efficacy.

Moreover, not only do individuals respond to performance discrepancies, but also, they are proactive in creating discrepancies through goal setting. There are open feedback loops in the triadic model of self-regulation. This implies that individuals can be proactive in self-regulation or they can choose to self-regulate in reaction to feedback (Bandura, 1999; Zimmerman, 2000). Given the important role that feedback plays in the self-regulation process, we predict that past performance feedback will predict future use of learning strategies directly and through its influence on subsequent self-efficacy perceptions. See Figure 2.


Figure 1. Task self-efficacy as a predictor. Learning strategies partially mediate the relationship between task self-efficacy and task performance.
Self-efficacy as an outcome
State self-efficacy is malleable and can change over time in response to various factors. Self-efficacy perceptions stem from four sources: mastery experiences (e.g. successfully overcoming obstacles), vicarious experiences (e.g. watching people viewed as similar to yourself succeed at a task), social persuasion (e.g. encouragement from others) and physical and emotional states (e.g. strength, anxiety; Bandura, 1999). Self-efficacy perceptions also can be shaped by goal type. Proximal goals are shown to increase mastery of mathematical skills and self-efficacy perceptions, while students with distal goals or no goals have lower self-efficacy perceptions (Bandura & Schunk, 1981). Successful past performance is found to increase efficacy perceptions (e.g. Bandura & Wood, 1989; Elias & MacDonald, 2007).

Past research supports the notion that strategies affect performance and that past performance affects future task self-efficacy. We expect to find similar relationships in this study. However, researchers have yet to examine the relationship between learning strategy use and future task self-efficacy. We predict that learning strategy use on a previous task will predict self-efficacy on a subsequent task. See Figure 3.

Hypothesis 3: Past performance in a CSCL environment will partially mediate the relationship between self-regulated learning strategy use and task-specific self-efficacy.

Method
Participants
Participants were recruited from an undergraduate computer science course offered three different semesters \( (n = 26) \), and from an undergraduate social psychology course offered two different semesters \( (n = 70) \) at a small private Midwestern university, yielding a total sample size of 96. The psychology and computer science classes were chosen because they used the same CSCL software for semester-long team-based projects. Participants were 22 years old on average, 53% were female, 68% were White and 58% were seniors. Most teams contained three students \( (n = 22) \), and a few teams had two students \( (n = 3) \) or four students \( (n = 6) \).
Materials

Task self-efficacy

Self-efficacy toward each project task was measured by the Personal Efficacy Beliefs Scale (Riggs, Warka, Babasa, Betancourt, & Hooker, 1994). An example item is, ‘I have confidence in my ability to do the project’. The response scale was 1 = Strongly Disagree to 7 = Strongly Agree. The reported internal consistency of the scale was $\alpha = 86$. The observed internal consistencies were .82, .85 and .88 for each of three project tasks, respectively.

We asked participants to rate their individual task self-efficacy and provide demographic information in an online survey. Students reported self-efficacy a total of three times, once during each task. We emailed survey links to each student during the middle of each task because individuals must have knowledge of task demands before they can accurately judge their efficacy toward a task (Bandura, 1997).

System data

Students utilised a computer educational software programme, Software Engineering REwards for BRainstorming Online (SEREBRO; Gamble et al., 2009; Jorgenson, Hale, & Gamble, 2011) during project completion which kept a record of each task activity (e.g. discussion posts to teammates, uploaded files). SEREBRO archived all student comments made in a team forum. The conceptual basis and rationale for using SEREBRO was to provide an asynchronous network that promotes creativity during project task endeavours. The programme facilitates project-based interactions outside of the classroom, enhances creativity, and is an avenue for knowledge sharing and feedback seeking. By design, SEREBRO records all activity generated within the system and maintains a conversation ‘tree’ of all text-based comments to which students can refer over the course of the project. SEREBRO’s main feature consists of a forum where students can initiate brainstorms and elaborate on team members’ ideas.

Performance data

From the instructors we obtained each student’s individual grades on three subtasks, the overall project and course grade. The use of academic performance as an indicator of feedback learning has been established in previous research (e.g. Colquitt & Simmering, 1998). In the current study, students obtained individual grades based on their personal performance after each task (students did not receive a group grade). All students were asked to review and incorporate feedback in future tasks. Knowledge of performance is a critical component of learning and facilitates development of self-efficacy and strategy use.

Procedure

As a part of their psychology or computer science coursework, students enrolled in an in-seat face-to-face course completed a team project throughout a 16-week semester. Students discussed the project with team members each week, often daily, in a CSCL environment. Discussions were monitored daily by a teaching assistant to
ensure the participation and collaboration of each team member as they worked together to complete their joint tasks. Students discussed each of their subtasks in separate areas of a discussion forum. Students were not instructed to discuss learning strategies.

The tasks

The projects observed in this study were a required portion of the class curriculum. The psychology team project involved conducting a naturalistic observation on a topic in social psychology with three major subtasks (Idea Generation, Method, Data Collection). Naturalistic observation studies by definition are studies where researchers collect data by observing people in a field setting (e.g. park, store), not in an artificial laboratory setting (Kimmel, 2004). The first task involved brainstorming topic ideas and conducting literature reviews. The second task was methodical in that students developed a detailed method for conducting the study. Finally, the third task consisted of data collection in a field setting. An example study is the observation of motorists’ prosocial behaviour toward roadside beggars.

The computer science team project involved developing a computer software product for clients. The first subtask was creative in that students designed software products with relevant and innovative features to meet client needs. The second subtask was methodical in nature and involved the development of a software architecture document, an analysis of the product’s design, and continual development and initial testing of the prototype. The third subtask included collecting data and information from Beta testers in order to identify product ‘bugs’, and preparation for a transition of the product to the customer. For example, products include the development of password cracking software and the creation of a mobile phone application.

Content analysis

Student communication with teammates and instructors occurring within the SERE-BRO forum was content analysed by two trained raters for learning strategy use. Krippendorff’s $\alpha$ estimates from .80 to .99 were observed, yielding high inter-rater reliability for each learning strategy within each task. See Table 1 for a list of learning strategies and their frequency of use. To understand the magnitude of learning strategy use for each student, we counted and totalled every instance of strategy use during task completion. For example, a student who set goals three times, evaluated work six times and sought social assistance twice would have a total strategy score of 11 for that task.

Partial mediation analyses

To assess the partial-mediation hypotheses, we used the SOBEL macro developed by Preacher and Hayes (2004) which is a computational tool for estimating the indirect effect of $X$ on $Y$ through $M$ to formally test the significance of the indirect effect both parametrically and non-parametrically, while simultaneously providing the output relevant to assessing mediation with the Baron and Kenny (1986) criteria. It has the capability to bootstrap the sampling distribution of $ab$ and derive a confidence
interval with the empirically derived bootstrapped sampling distribution. The bootstrapped estimate of the indirect effect is similar to the point estimate computed from the conventional regression analysis of the raw data. The analyses were run with 5000 bootstrap resamples.
Results

Standard scores

Data cases were sorted into five classes (i.e. three Psychology classes and two Computer Science classes) and standardised z-scores were computed for learning strategies and grades. Sorting cases in this way allowed for the control of differences in total posts and learning strategies based on the specific class in which students were enrolled. This was important to control because computer science students used the software system to a greater extent than psychology students, which influenced the frequency of learning strategy use. Further, there was a significant difference in posts and total learning strategies used between classes within the psychology discipline. A Welch’s one-way ANOVA indicated that class membership predicted total strategy use, $F(4, 34.09) = 14.58, p < .001, \omega^2 = .36$. Class membership explained 36% of the variance in total learning strategy use. Grades were standardised by class to control for differences in grading procedures, instruction and course requirements. Standardised z-scores also were computed for task self-efficacy based on course membership. Because computer science students used the system more frequently than psychology students, Table 2 shows descriptive statistics by course (i.e. Psychology and Computer Science); correlations are displayed using standardised scores for the whole sample.

Relationships among task self-efficacy, learning strategy use and performance

With Hypothesis 1, we proposed that learning strategy use would partially mediate the relationship between task self-efficacy and performance. This hypothesis was tested for each project task. We examined the bootstrap results for the indirect effect with 95% confidence intervals for Task 1 (point estimate = .03, CI = [−.05, .13]), Task 2 (point estimate = .02, CI = [−.01, .07]) and Task 3 (point estimate = .01, CI = [−.02, .06]). All of these confidence intervals contained zero, therefore the reduction was not significant. Hypothesis 1 was not supported. Table 3 shows the coefficients for the mediation model. It can be seen that task self-efficacy had a significant positive total effect on performance during all three tasks. On Tasks 1 and 2, learning strategy use had a significant positive effect on performance even after controlling for task self-efficacy. On Tasks 2 and 3, task self-efficacy maintained its significant positive effect on performance even after controlling for learning strategy use.

Hypothesis 2 proposed that self-efficacy would partially mediate the relationship between prior performance and learning strategy use. First, we tested the indirect effect using performance at Task 1, and task self-efficacy and learning strategy use during Task 2 (point estimate = .02, CI = [−.02, .06]). Second, we tested this hypothesis with performance at Task 2, and task self-efficacy and learning strategy use during Task 3 (point estimate = .02, CI = [−.04, .08]). Both of these confidence intervals contained zero, therefore the reduction was not significant. Hypothesis 2 was not supported; see Table 3. Performance at Task 1 had a significant positive effect on learning strategy use and self-efficacy during Task 2. Task self-efficacy during Tasks 1 and 2 did not partially mediate the relationship between past performance and learning strategy use on the same task. There was no significant relationship between task self-efficacy and learning strategy use.
Table 2. Correlations between self-efficacy, strategy use and performance.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Psychology M</th>
<th>SD</th>
<th>Computer Science M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 T1 task self-efficacy</td>
<td>4.91</td>
<td>.85</td>
<td>4.69</td>
<td>.82</td>
</tr>
<tr>
<td>2 T2 task self-efficacy</td>
<td>5.01</td>
<td>.88</td>
<td>5.19</td>
<td>.76</td>
</tr>
<tr>
<td>3 T3 task self-efficacy</td>
<td>5.02</td>
<td>.95</td>
<td>5.13</td>
<td>.78</td>
</tr>
<tr>
<td>4 T1 strategy use</td>
<td>19.60</td>
<td>14.60</td>
<td>120.12</td>
<td>78.92</td>
</tr>
<tr>
<td>5 T2 strategy use</td>
<td>19.19</td>
<td>21.11</td>
<td>86.92</td>
<td>72.30</td>
</tr>
<tr>
<td>6 T3 strategy use</td>
<td>13.49</td>
<td>17.65</td>
<td>62.15</td>
<td>101.00</td>
</tr>
<tr>
<td>7 T1 performance</td>
<td>82.04%</td>
<td>.22</td>
<td>41.23%</td>
<td>.08</td>
</tr>
<tr>
<td>8 T2 performance</td>
<td>82.39%</td>
<td>.27</td>
<td>41.38%</td>
<td>.08</td>
</tr>
<tr>
<td>9 T3 performance</td>
<td>80.39%</td>
<td>.28</td>
<td>41.28%</td>
<td>.37</td>
</tr>
</tbody>
</table>

Note: Psychology n = 70, Computer Science n = 26. Pearson’s correlation coefficient, one-tailed test. T1 = Task 1 (Idea Generation), T2 = Task 2 (Method), T3 = Task 3 (Data Collection). \( * p < .05; ** p < .01 \).
Hypothesis 3 proposed that prior performance would partially mediate the relationship between prior learning strategy use and task self-efficacy on a subsequent task. First, we tested the indirect effect using learning strategy use and performance on Task 1, and task self-efficacy during Task 2 (point estimate = .09, CI = [−.00, .22]). Second, we tested this hypothesis with learning strategy use and performance on Task 2, and task self-efficacy during Task 3 (point estimate = .06, CI = [−.00, .16]). Both of these confidence intervals contained zero, therefore the reduction was not significant. Hypothesis 3 was not supported; see Table 3. Learning strategies on a task significantly and positively predicted performance during the same task. Performance on Task 2 significantly predicted task self-efficacy on Task 3 while controlling for learning strategy use during Task 2.

Discussion

The primary purpose of this study was to examine relationships between self-efficacy, learning strategies and performance. We designed this study in a way that allowed us to assess self-efficacy during three distinct, yet related project tasks in a blended learning environment (i.e. face-to-face and computer-supported interactions) while measuring learning strategy use during each task. Surprisingly, task self-efficacy was not significantly related to learning strategy use during any task. Without significant relationships between task self-efficacy and learning strategy use, we did not find support for the partial mediations as proposed. However, other interesting findings emerged from the analyses. While many studies support that one’s belief in his or her ability to accomplish a task with success is positively related to performance (e.g. Nurittamont, 2012; Wu et al., 2012), we decided to take it a step further to assess not only if task self-efficacy would be related positively to performance, but also if task self-efficacy would influence strategy use, and if

Table 3. Results of partial mediation analyses of the relationships between self-efficacy, learning strategies and performance.

<table>
<thead>
<tr>
<th></th>
<th>Total Effect of X on Y</th>
<th>Effect of X on M</th>
<th>Effect of M on Y, controlling for X</th>
<th>Direct Effect of X on Y, controlling for M</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>b</td>
<td>t</td>
<td>b</td>
<td>t</td>
</tr>
<tr>
<td>Hypothesis 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Task 1</td>
<td>.17†</td>
<td>1.70</td>
<td>.07</td>
<td>.70</td>
</tr>
<tr>
<td>Task 2</td>
<td>.19†</td>
<td>1.89</td>
<td>.12</td>
<td>1.31</td>
</tr>
<tr>
<td>Task 3</td>
<td>.33**</td>
<td>3.54</td>
<td>.05</td>
<td>.60</td>
</tr>
<tr>
<td>Hypothesis 2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tasks 1–2</td>
<td>.18†</td>
<td>1.85</td>
<td>.19†</td>
<td>1.81</td>
</tr>
<tr>
<td>Tasks 2–3</td>
<td>.03</td>
<td>.33</td>
<td>.32**</td>
<td>3.09</td>
</tr>
<tr>
<td>Hypothesis 3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tasks 1–2</td>
<td>.10</td>
<td>.89</td>
<td>.48***</td>
<td>4.70</td>
</tr>
<tr>
<td>Tasks 2–3</td>
<td>.18</td>
<td>1.61</td>
<td>.21†</td>
<td>1.92</td>
</tr>
</tbody>
</table>

strategy use would lead to higher performance. We believed that this high performance would then lead to an increased sense of task self-efficacy on future tasks, and a continued high use of learning strategies.

Results showed that for each task (i.e. Idea Generation, Method, Data Collection), individuals with higher task self-efficacy had higher task performance. Those who used more learning strategies on each task also had higher performance. This high performance was associated with high self-efficacy on the next task (i.e. higher performance on the creative task was associated with higher self-efficacy on the methodical task; higher performance on the methodical task was associated with higher self-efficacy on the final data collection task). High performance on the creative task also was positively and significantly related to strategy use on the next methodical task. Individuals who performed poorly on the first creative task tended to use a low amount of learning strategies on the second methodical task, while high performers tended to use a high amount of learning strategies.

In sum, higher task self-efficacy and learning strategy use were associated with higher task performance, and higher task performance related to higher task self-efficacy (and sometimes higher strategy use) during subsequent tasks. Task self-efficacy is important for high performance, but achieving optimal success is more than just believing that one can perform successfully; effort has to be exerted by using strategies. The use of learning strategies during a brainstorming/creative task helps learners achieve task success because there is less structure in the beginning of a project and the use of different types and kinds of strategies helps learners explore the task and examine a multitude of directions in which to proceed. The use of learning strategies also helps learners attain high performance when tasks are more methodical and during data collection and implementation stages of a project. Even structured tasks require the execution of learning strategies. While the tasks may be more structured, there is still an element of learning because these tasks, while methodical, are not yet routine to the learners. Therefore, learning strategies play a role in predicting performance for tasks that are structured as well as for creative and unstructured tasks. This study shows that task self-efficacy and learning strategy use are important for a variety of tasks.

Results also demonstrate significant relationships between past performance feedback and future learning strategy use and task self-efficacy. This finding supports the ideas of Clark (2012) who states that feedback is essential to the development of self-regulated learning strategies among students, and that feedback also has the potential to impact self-efficacy (Clark, 2012; Dweck, 1999). Results from the current study explain why some learners may consistently perform poorly; once knowledge of poor performance is obtained, task self-efficacy may decrease along with the desire to use learning strategies. Conversely, high performers may be motivated to continue to use many learning strategies and experience an increase in task self-efficacy for future tasks. The key is to break this cycle for poor performers.

Instructors should identify poor performers, teach them task-specific learning strategies and prompt learning strategy use during task completion. Feedback should be used to further enhance self-regulated learning (Nicol & Macfarlane-Dick, 2006). Instructors should provide constructive feedback along with a grade so that poor performers can identify targeted areas for improvement.

Interestingly, task self-efficacy was not significantly related to learning strategy use, preventing the ability to find support for the hypotheses, which in part, suggested that self-efficacy and learning strategy use would be positively related.
There are several possible explanations for why self-efficacy and learning strategy use were not related. Individuals with high self-efficacy toward the task may not have used many learning strategies because they were confident about their task understanding and did not need to explore or engage in multiple learning strategies. Perhaps they used only a few effective strategies, while low performers used a myriad of strategies that were irrelevant or ineffective. It could also be that individuals with low self-efficacy compensated by using more strategies in an effort to perform well on the learning task.

Limitations and future directions
Measuring learning strategies through peer communication may have failed to capture all the learning strategies that students used, as students likely did not verbalise all learning strategy use within the system. Students were not prompted to mention learning strategy use; learning strategies were derived from conversations with teammates. Had they been prompted to mention learning strategy use, students may have communicated a higher amount of learning strategies used outside of the CSCL environment (e.g. strategies used when collecting data out in the field). It is likely that strategies were used that were not reported in conversations. Future research should incorporate multiple assessments of strategy use to capture a more complete picture of the strategies that learners use. Questionnaires should measure how often students used each strategy during specific tasks, not whether they know how to use the strategies or whether they have ever used the strategies. Think-aloud protocols are another observational method. This method asks participants to describe what they are thinking while they work on a task. This method also can be used to capture metacognition (i.e. thinking about thinking).

Perhaps in collaborative settings, there is a boundary condition such that the relationship between self-efficacy and learning strategy use is only likely to be significant in a setting where learners work on individual tasks. Perceptions of collective efficacy may mask one’s self-efficacy perceptions in predicting learning strategy use. It could be that self-efficacy matters after taking into account nesting; with whom one works likely makes a difference in the learning strategies that an individual learns and uses in their presence (observational learning; Bandura, 1986). Further, personality may play a role in who is likely to communicate personal strivings and learning strategy use to others. Introverted individuals may not share as much personal learning strategy use with teammates as extroverted members share. Future research should examine the relationship between self-efficacy and learning strategy use in collaborative environments by also considering the role of collective efficacy and personality (e.g. extraversion, introversion).

This study was set in a group context. The task was structured such that students generated ideas, planned and executed a research project while collaborating and interacting using an idea-management software. Thus, any project-associated learning occurred primarily in this context. However, the project outcomes were evaluated individually. Given this structure, we were primarily interested in exploring what happens to individual task self-efficacy in this environment as a predictor, mediator and outcome in relation to performance. Exploring social group learning is warranted and is a question for future research.

While the current study focused on learning strategy use at the individual level, Järvelä and Hadwin (2013) suggest that researchers create methods to understand
self-regulation, co-regulation and shared regulation (e.g. developing shared goals) in CSCL environments (see Winne, Hadwin, & Perry, 2012). In addition to the regulation of tasks, learners need to regulate their interactions with others in a CSCL environment (Saab, 2012; Saab, van Joolingen, & van Hout-Wolters, 2012). Delfino, Dettori, and Persico (2008) found that learning strategies focused at the social level (e.g. setting goals for the group) were more prevalent than those focused at the individual level (e.g. setting goals for oneself) in a virtual learning environment. Though these learning strategies were aimed at the group, the learning strategy itself was initiated by an individual. Further, to the extent that a team member directed learning strategies at the group (e.g. set group goals), individual teammates may not have needed to engage in these particular learning strategies. External factors such as peer pressure or highly structured tasks or procedures may affect one’s autonomy and ability to self-regulate (Hughes, 2003). The learner has the opportunity to make most of the decisions regarding their learning. Providing learners with more autonomy will create a space where self-regulatory skills will be required, and hence also provide the opportunity to develop them further. This task was structured as a group-based project to facilitate autonomous learning under guidance from instructor and teaching assistant. Future research should examine the impact of external influences on self-regulation.

**Contributions**

This study contributes to current literature in four main ways. First, this study focuses on measuring individuals’ learning strategies while students participate in a longitudinal project in a blended face-to-face and CSCL environment. This environment added a unique element to the context in which learners interacted with each other to complete the project. Blended learning environments are now being used extensively in education and organisations, yet little research has studied the learning strategies that are used in this context. Second, we assessed learning strategies as an event instead of using self-report measures to capture learner perceptions regarding their use of learning strategies. This is an objective way to measure strategy use, and researchers have been calling for studies that examine learning strategies through events (Winne & Perry, 2000) and observational methods (Ziedner, Boekaerts, & Pintrich, 2000). Third, the current study also contributes to the literature by taking task type into consideration when examining strategy use. Task type is linked to self-regulated learning as learning strategies are contingent on the task. Low or non-significant relationships between self-reported learning strategy use and course grades may be due to different types and amounts of learning strategy use required by each task (Credé & Phillips, 2011). Fourth, relationships between self-efficacy, learning strategies and performance are clarified by examining the potential role of task self-efficacy in the learning process in a CSCL environment. Given that self-regulated learning is contextual, it was important to study the possible influences and outcomes of learning strategy use for different task types in a blended learning environment.

Future research could examine learner interest in the task or material, as studies show that interest is related to learning strategy use (Cleary & Chen, 2009) and task performance (Reeve & Jang, 2006). Additionally, studies can expand the observation of learning strategies to include other types of tasks than the tasks examined here. This may include repetitive or familiar tasks, tasks with different amounts or types
of consequences for poor performance, or highly autonomous tasks. The examination of learning strategies with different tasks in different environments would expand what we know about self-regulation in different contexts.

**Conclusion**

This study focused on the role of self-efficacy in relationship to academic performance and self-regulated learning strategy use. (1) As a predictor, self-efficacy significantly and positively predicted performance, but not strategy use; (2) As a potential mediator, self-efficacy was predicted by past performance, but self-efficacy did not predict strategy use; (3) As an outcome, self-efficacy on the data collection task was predicted by past performance on the methodical task, but learning strategy use did not predict self-efficacy.

The common finding among all hypotheses is that self-efficacy and learning strategy use were neither related within the same task, nor between tasks. A lack of this relationship precluded us from finding full support for our hypotheses. However, what we can learn from this study is that past performance predicts future self-efficacy and learning strategy use. We also found support for the idea that both self-efficacy and learning strategy use predict performance uniquely, albeit self-efficacy and learning strategy use are unrelated.

Using the findings from this study, instructors and trainers can understand better the factors that influence performance while encouraging learners to effectively self-regulate their behaviour. A continuous need to develop competencies places a strong need for lifelong learners and self-directedness (Bandura, 1997). Learning is a lifelong process that, at times, must be self-regulated. Learning is not limited to a formal, traditional, classroom or training environment; much learning in life occurs in spontaneous, informal and social contexts. Individuals who take the initiative to improve their knowledge and skills will be more prepared for the dynamic world in which we live.

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**References**


