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Predicting Task Persistence within a Learning-by-Teaching Environment

Cristina DUMDUMAYA[ab*], Ma. Mercedes RODRIGO[a]
[a]*Department of Information Systems and Computer Science, Ateneo de Manila University, Philippines*
[b]*Institute of Computing, University of Southeastern Philippines, Philippines*
*cedumdumaya@usep.edu.ph

Abstract: We attempted to model task persistence, a student attribute reflecting one's dispositional need to complete difficult tasks in the face of frustration, within a learning by teaching intelligent tutoring system (ITS) called SimStudent. We used the interaction logs of 32 students from the Philippines to develop a Naïve Bayes model to detect task persistence. Using forward feature selection, an optimized set of predictors was derived. Out of 11 candidate features, those that significantly predicted task persistence were time on task, time spent on resources after failure, number of re-attempts to unsolved problems, and proportion of difficult problems attempted.

Keywords: Task persistence, intelligent tutoring systems, Learning-by-Teaching, SimStudent

1. Introduction

Task persistence refers to the continuation of a goal-directed action in spite of obstacles, difficulties and discouragement (DiCerbo, 2016). Persistence, a facet of conscientiousness, describes a category of student actions (e.g., focusing on tasks, believing in one's own capacity to succeed, and making an effort to overcome challenges) that requires sustained thinking and decision making (Clarke, Cheeseman, Roche, and van der Schans, 2014). Persistence does not only involve one's initial drive to do a task. More importantly, persistence necessitates the ability to maintain that momentum regardless of the challenges that might hinder task success. Thus, a persistent individual unceasingly exerts effort and finds alternative approaches to accomplish difficult tasks instead of giving up.

Persistence has been shown to predict academic achievement (DiCerbo, 2014) and other life outcomes (Kautz, Heckman, Diris, Ter Weel, and Borghans, 2014). For many of these outcomes, the predictive power of persistence on student's success rivals cognitive abilities (Kautz et al., 2014) suggesting that developing student persistence is as important as nurturing their cognitive skills. Previous accounts stated that cognitive aptitude only reveals how much intellectual promise a student possess but does not specify the degree to which the student utilizes his potential (Borghans, Duckworth, Heckman, and Weel, 2008). In a problem solving task, student's success or failure is often influenced by his persistence on the task, as much as his mathematical abilities (Lester, Garofalo and Kroll, 1989). Thus, gaining insights on how students' attain success necessitates understanding of both the cognitive and non-cognitive variables that influence students' academic achievement. Furthermore, studies have shown that non-cognitive skills, including persistence, are critically vital for the 21st century workforce however employees seemed to be deficient on these skills (American Management Association, 2012; Cator and Adam, 2013). Hence, the need to develop these critical skills in children while they are still in the academe.

This work attempts to create a predictive model for student task persistence within a Learning by Teaching (LBT) environment called SimStudent, to be discussed in full in Section 3. We sought answers to these questions:

1. What features predict student task persistence?
2. How well do these features predict student task persistence?

This study may contribute towards applying data mining approaches to predict task persistence using behavioral data collected from students' utilization of a computer-based learning environment (CBLE). Persistence in task is an important factor, besides general metal ability, influencing attainment in working life and the academe. Predicting which student will likely persist in academic tasks and identifying the behavioral features that may influence student's persistence in a task could provide insights to educational technology designers on what student actions should be nurtured to ensure persistence in academic tasks. This could consequently serve as basis in formulating design guidelines for educational systems to encourage persistence among students and incorporating interventions to induce learners to persist in difficult tasks and to develop positive behaviour towards learning.

2. Learning by Teaching

This study will be explored within the context of a learning-by-teaching intelligent tutoring system (ITS). LBT is a pedagogical methodology where students learn by actively participating in their own learning (Martin and Kelchner, 1998). When students are actively learning, they are involved in the learning process not only by listening to the teacher or reading a text but in discussions and actual tasks (e.g., problem solving) resulting in deeper and fuller understanding, and stronger connection and commitment to both the learning materials and task goal.

LBT has many aspects that contribute to improved learning, namely: structuring, taking responsibility and reflecting on processes and outcomes (Biswas, Segedy, and Bunchongchit, 2016). Teaching is an open-ended and self-directed process that charges tutors with the selection of the most appropriate material or the best strategy to stimulate learning. Preparation for the actual task of teaching requires the tutor to check whether he has sufficient domain knowledge to perform the task effectively. This action supports and trains one's meta-memory functions (Schneider, 2008). As consequence of his judgments and adjustments, the tutor gains better understanding of the material and becomes more equipped for the task. The actual teaching also invokes the critical factors of learning. As the tutor interacts with the tutee (e.g., receiving questions, providing feedbacks), the tutor is reorganizing his own domain knowledge. Communicating with the tutee allows the tutor to reflect on the queries made, and assess and restructure his own understanding when necessary. Finally, effective teaching requires the tutor to monitor and evaluate task outcomes. These actions will possibly guide the tutor in deciding whether a different strategy must be adopted to improve the outcomes of the task (Kirkegaard, Gulz, and Silvervarg, 2014).

With the goal of harnessing such benefits, several works have explored the use artificial intelligence in pedagogical approaches through virtual peers or teachable agents to support student learning. One of these systems is Betty's Brain (Biswas, Segedy, and Bunchongchit, 2016). Betty's Brain leverage the LBT paradigm to get the students to read about a science topic and construct a causal model of a phenomena to promote learning. The classroom experiments on Betty's Brain demonstrated the effect of LBT on student performance and learning behaviour (e.g., Kinnebrew, Mack, and Biswas, 2013).

3. SimStudent

SimStudent (Matsuda, Barbalios, Zhao, Ramamurthy, Stylianides, and Koedinger, 2016) is an ITS based on the LBT pedagogical approach. SimStudent, a virtual teachable agent, learns procedural skills inductively from the examples given by a human tutor as they solve a linear equation problem. SimStudent attempts to solve a problem one step at a time, occasionally asking the human tutor about the correctness of each step or requesting for a demonstration. From the feedback and demonstrations, SimStudent generates production rules that represent the skills learned.

SimStudent was first used in a classroom experiment in 2011 and has undergone several revisions. For this study, we utilized a version that provides the human student with adaptive assistance on how to proceed with the tutoring task. When the human tutor requests for assistance, an embedded metatutor agent provides one of the four types of help: (a) *quiz assistance* to suggest when students should take the quiz and why, (b) *problem selection assistance* to suggest what problem students to present next and why, (c) *resource assistance* to suggest when students should review a particular resource and why, and (d) *impasse recovery assistance* to suggest a problem restart or to give a new problem when students are stuck for a predetermined amount of time. Aside from the adaptive scaffold the system provides, the human tutor can utilize an array of learning resources (e.g., worked-out examples, step-by-step quiz solution, introduction video, unit overview, and problem bank) to support the activation of self-regulatory processes. These resources aid tutors in setting up their goals by learning what the task is all about, planning strategies by understanding the subject domain, teaching their tutee, and assessing their own understanding and performance.

SimStudent have been used in several studies, for example, to examine the implications of prior knowledge on student learning (Rodrigo, Ong, Bringula, Basa, Cruz, and Matsuda, 2013). The data utilized in this work was previously analyzed to investigate the effects of scaffolding and prior knowledge on students' performance (Dumdumaya, Banawan, Rodrigo, Ogan, Yarzebinski, and Matsuda, 2017). Also, a cross-cultural analysis on how students customize an agent's appearance across regions in the United States and the Philippines was conducted using the same dataset which findings emphasized learners' profile diversity (Yarzebinski, Dumdumaya, Rodrigo, Matsuda, and Ogan, 2017). The results of these works suggest the importance of taking into account learners attributes (e.g., skills, attributes and behaviors) when designing interventions in CBLEs to nurture students, both in cognitive and non-cognitive aspects.

4. Data Collection and Preprocessing

Our dataset came from an experiment involving 32 students interacting with SimStudent. The data was collected from eighth-grade or 2nd year high school students with age ranging from 12 to 15 years old. Seventeen students were from Krus na Ligas National High School (KNLHS), a public junior high school in Quezon City; 11 were from Ateneo de Davao University (AdDU) in Davao City; and 4 from the University of the Cordilleras (UC) in Baguio City, both are private universities in the Philippines. Participation to the experiment was voluntary. Parental consent and child assent were obtained prior to the experiment. No compensation was given to the participants of the experiment.

Prior to tutoring their SimStudent, the students took a pre-test to assess their proficiency in solving linear equations. They then started tutoring their SimStudent for 3 consecutive days, for 40 minutes each day. The complete structure of the study was discussed elsewhere (Dumdumaya et al., 2017).

The interactions of each participant with SimStudent were tracked and automatically recorded into a file. The raw interaction logs had 58 features, comprised of nominal and numeric data that captured students' actions, agents and system responses and all other related information totaling more or less 120 minutes. The interaction events included actions to prepare for the task, the actual tutoring actions, and post tutoring actions. The log file records specific parameters such as attempt identifier (e.g. UserID, sessionID), timestamp, the specific action taken (e.g., entered a problem, explained a hint, demonstrated a step, and viewed example solution), results (e.g., correct action and incorrect action), problem category (i.e., OneStep (one step equation), TwoStep(two step equation), BothSides (equation with variables on both sides)). From the logged information, we derived the feature set used in the study.

As a preprocessing step, we first removed incomplete records (i.e., participants with incomplete and invalid data), segmented students' interaction records into sessions, translated session logs into observational attribute vector, and distilled and summarized features. A session refers to a sequence of events commencing from the time the student initiates the program learning environment (PLE) until the student closes the PLE. A student could have none to multiple tasks or problem attempts within a session. From the 32 students, 129 sessions were obtained containing on average 817.20 (SD =512.08) transactions.

5. Feature Variables

Eleven candidate features were explored as variables that influence task persistence within a LBT environment. They were categorized as follows:

(1) Engagement- Student engagement have been consistently linked to persistence (Gentry, 2014; Jung and Lee, 2018). Croxton (2014) underscored the impact of interactivity in student persistence suggesting the need of providing learning environments that allow students to engage in the learning process through active collaborations with peers, mentors, and the course content to encourage persistence. Based on previous works (Cocea and Weibelzahl, 2007; Lloyd, Heffernan, and Ruiz, 2007; Zhang, Cheng, He, and Huang, 2003), we quantified engagement using the following features:

(a) Tasks attempted (TaskAttempts) - the number of problems tutored within a session.

(b) Time spent on task (TimeOnTask) - the average time (in seconds) a student spent tutoring problems within a session, regardless of the outcome. This was computed as total time on tutoring problems over total number of problems tutored.

(c) Time spent on resources (TimeResources) - the average time (in seconds) spent viewing learning resources during the entire session (including prior, during and post task events). It was computed as total time spent on resources over the number of access to resources.

(d) Time spent on Hints (TimeOnHints) - the average time (in seconds) spent on given hints.

(e) Time spent by students on resources prior to task (TimePriorTask) – task preparation is indicative of broader patterns of development in relation to becoming independent, self-regulated and persistent learner. We investigated this feature using the average time spent on resources to prepare for the task which was computed as total time spent on resources prior to first problem tutored over the number of resources accessed prior to first problem tutored.

(f) Number of bottom level hints explored (NumOfBottomHints) - the number of instances when students delved deeper into given hints to normalize confusion and to reflect on one's strategies and actions when confronted with challenges.

(g) Proportion of followed hints (%FollowedHints) - the percentage of hints followed by students, computed as the number of hints followed over the total number of hints provided.

(2) Self-efficacy - Self-efficacy has been found to influence student's persistence (Bandura, 1997; Lent, Brown, and Larkin, 1984). Self-efficacy refers to one's personal belief that he is capable of completing tasks successfully. As emphasized in previous works, self-efficacy impacts student's problem or task choice (Mcquiggan, Mott, and Lester, 2008) and help-seeking behavior (Nelson and Ketelhut, 2008; Williams and Takaku, 2011). In this work, we quantified self-efficacy using the following features:

(h) Number of reattempts to unsolved problems (NumOfReattempts) - the average number of re-attempts to a problem after a failed submission or being stuck in a step for a long time.

(i) Proportion of Difficult problems attempted (%DiffProblemsAttempted) - the percentage of attempts to tutor equations having variables on both sides. This was computed as the number of target problems attempted over the total problems attempted.

(j) Time spent on resources after failure (TimeResourcesAfterFailure) - the average time spent by the student viewing learning resources after an incorrect problem submission or being stuck in a step for a long time.

(k) Time spent on resources after an incorrect step - the average time spent by the student viewing learning resources after committing a mistake in a specific problem step.

6. Methodology

6.1 Coding

Students who are persistent believe that their intelligence is malleable, and can be developed through hard work, good strategies and input from others. They are unafraid to take on difficult mathematical problems as they look at these tasks as opportunities to cultivate their abilities. In contrast, those who are not persistent believe that intelligence is an unchangeable attribute. Hence, they avoid challenging tasks and exhibit helpless response to challenges (Suh, Graham, Ferrarone, Kopeinig, and Bertholet, 2011).

We operationally defined students who are "persistent in task" to be students who attempted to tutor linear equation problems in progressing level of difficulty. For example, the student started with OneStep problem, then tutored a TwoStep problem and/or a problem having variables on both sides (BothSides) in succession, or students who attempted to tutor difficult problems only within the session regardless of task outcomes. Using a visualization of the students' action sequences (see Figure 1), we coded 1 to indicate that the student exhibited task persistence in a session and coded 0 otherwise. We used the annotated data as ground truth.

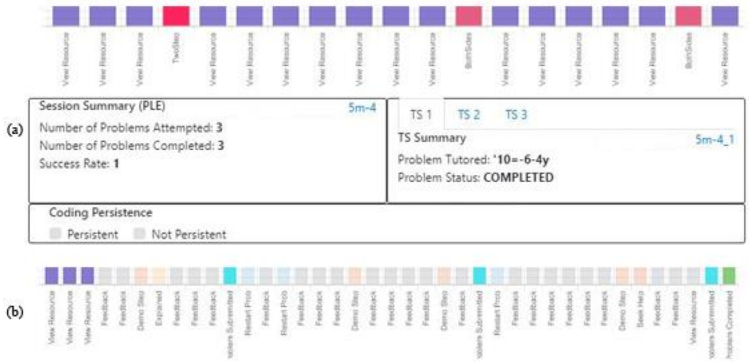

Figure 1. Example of a visualization of student actions sequences: (a) action sequences within a session, (b) action sequences within a problem task.

6.2 Modeling and Validation

We used Naïve Bayes algorithm to detect task persistent behavior from interaction logs of students. Naïve Bayes is a probabilistic classifier, meaning that for student session *s*, the classifier returns the class *c'* out of all classes $c \in C$ which has the maximum posterior probability given the session parameters. An advantage of the naive Bayes classifier is that it requires a small amount of training data to estimate the parameters (means and variances of the variables) necessary for classification (Bhardwaj and Pal, 2012). Since Naïve Bayes assumes independence among predictors, only the variances of the variables for each class need to be determined and not the entire covariance matrix. In spite of their naive design and apparently simplified assumptions, Naïve Bayes classifiers have been used in many complex real-world situations (e.g., Parthiban, Rajesh, and Srivatsa, 2011), and in educational data mining (e.g., Ahmed and Elaraby, 2014).

Prior to modeling, the most relevant attributes of the feature set were selected using forward selection (Ren, Qiu, Fan, Cheng, and Philip, 2008). Forward selection exhaustively search for the best subset of features that optimized the prediction model's performance by progressively incorporating variables into larger and larger subsets in iterations, starting with a NULL model until a stopping criteria is met. The stopping criteria was when there is no more increase in the classifier performance.

Model performance was evaluated using 10-fold cross validation. In cross validation, data is randomly subdivided into subsets, in this case, ten. One subset is isolated for use as testing data and the remaining serve as training data. In successive iterations, the model is run with each subset serving as testing data to ensure that each student's data was entirely either in the testing set or the training set which minimizes bias in calculating classification accuracy. The classifier was evaluated using two performance metrics: accuracy and Cohen's Kappa (Cohen, 1960). Accuracy is simply the ratio of correctly predicted observation to the total observation. Cohen's Kappa assesses whether the predictor is better than chance in recognizing which sessions implicate persistence behavior. A Kappa of 0 indicates that the predictor performs at chance, and a Kappa of 1 indicates that the predictor performs perfectly.

7. Results and Discussion

7.1 Predictors of Task Persistence

We derived a Naïve Bayes model predicting a binary variable, whether the student is persistent or not in his task. An optimized feature selection process selected 4 attributes among the 11 candidate features as predictors of student task persistence. These variables were associated with engagement and self-efficacy.

How long students tutored a problem (*TimeOnTask)* was linked to student task persistence, as with Jung & Lee(2018). Students who demonstrated persistence in their task spent higher amount of time on task compared to those who did not persist *(P_{Mean}=342.29, P_{SD}=206.57 vs. NP_{Mean}=245.92, NP_{SD}=263.90, t(127)=2.26, p=0.03)* corroborating previous works (e.g., Morris & Finnegan, 2008). This could mean that one characteristic of a persistent individual is to stick to the task of overcoming problems until they figure things out. Engagement in task for longer periods of time allows students to process instructions more deeply which help in achieving their goals. As persistence is linked closely with sustained attention or the ability to focus attention on task for extended periods of time (DiCerbo, 2014), hence the amount of time invested by a student in a task could be indicative of the degree of persistence he will likely demonstrate as he tries to attain his goal.

Consistent with the results that linked self-efficacy and persistence (Miller, Behrens, Greene, & Newman, 1993), this work also found an evidence associating self-efficacy and student task persistence. Percentage of difficult problems attempted *(%DiffProblemsAttempted)*, number of reattempts to a problem *(NumOfReattempts)*, and time spent on resources after failure *(TimeResourcesAfterFailure)* were selected as predictors of task persistence.

Persistence is specifically important in problem solving task. Unlike simple calculations that generally requires carrying out a single operation (e.g., OneStep linear equation problems), solving difficult linear equation problems includes several steps, such as carrying out mental transformations and building mental models, and selecting and applying a series of appropriate strategies (e.g., add, subtract, divide and multiply) to solve a problem. The feature selection process revealed that student's problem choice is a marker of persistence. Students who exhibited persistence have higher percentage of attempts to difficult problems than those who are non-persistent (*P_{Mean}=0.26, P_{SD}=0.40 vs. NP_{Mean}=0.01, NP_{SD}=0.06, t(127)=5.35, p<0.001*). This finding characterizes persistent individuals as challenge takers. This class of students demonstrate strong confidence in their abilities by seeing difficult problems as opportunities they can control and manage through their skill. According to Dweck and Leggett (1988), students with high self-efficacy persist through difficult tasks as they consider difficult problems as challenges to be mastered rather than threats to be avoided. Conversely, individuals who have low sense of self-efficacy tend to shy away from difficult situations (Bouffard-Bouchard, 1990). Their goal commitment is weakened by negative self-cognition and negative affect and they tend to concentrate on personal deficiencies and obstacles rather than how to perform tasks successfully. As a result, they either skip difficult tasks or search for less challenging alternative activities.

For persistent individuals, initial failure is just a cue to work harder. In this work, we found that *NumOfReattempts* to a problem is an indicator of task persistence as previously defined in (Ventura and Shute, 2013). Collins (1984) emphasized that children with high self-efficacy demonstrate greater effort and persist longer in reworking incorrect problems. In this case study, students who demonstrated persistence in their task re-attempted initially failed problems more frequently than non-persistent learners *(P_{Mean}=0.54, P_{SD}=1.06 vs. NP_{Mean}=0.14, NP_{SD}=0.48, t(127)=2.81, p=0.005).* Re-attempts to task could be a manifestation of student's beliefs in his own ability to control essential dimensions of learning as a coping mechanism to the challenges and the negative affect he might experience when trapped in learning impasses (Bhanji and Delgado, 2014). Thus, we could infer that an "if failed-reattempt" strategy could be one's approach to correct mistakes while staying the course. This action shows the dependency of one's perceived ability to regulate facets of learning and his persistence on the task.

A key construct relating to student's persistence on a task is their personal perceptions of competence related to their ability to seek for help when it's needed. As found in this work, *TimeResourcesAfterFailure* is a predictor of task persistence. When facing a challenge or initial failure, persistent students tend to explore different strategies to be able to continue on the same path and to avoid negative outcomes (Narciss, 2004). Help seeking after failure (e.g., viewing resources after an incorrect submission) is an approach to continue with the task and elude another failure. As emphasized by Jõgi and Kikas (2016), persistent students are adaptive help seekers which manifests the influence of self-efficacy to student persistence. Highly efficacious individuals feel empowered to succeed, thus they utilize strategic approaches to complete the tasks and to sustain their efforts when difficulties are encountered. Self-efficacy acts on a broader level through more effective use of metacognitive and self-regulated learning strategies (Pintrich and Zusho, 2002). For example, when facing failure, a persistent student reflects on his performance, evaluates his domain understanding, and then regulates his strategy when necessary (i.e., seek direct or indirect help), which in turn influences his decision to persist in a task. Previous research have reported that highly efficacious students demonstrate better help-seeking behavior (e.g., Nelson and Ketelhut, 2008), however, this work revealed that while students who demonstrated persistence spent more time exploring learning resources after a failure than those who showed non-persistence, their mean difference is not significant at all *(P_{Mean}=21.77, P_{SD}=85.15 vs. NP_{Mean}=3.52, NP_{SD}=20.11, $t(127)=1.76$, $p>0.05$).* This means that contrary to findings showing that students with low self-efficacy avoid seeking help (e.g., Ryan, Gheen, and Midgley, 1998), the students in the present study were relatively active help seekers as well. It has been suggested that help seeking may serve multiple purpose (Nelson-Le Gall and Gumerman, 1984). Besides, adaptive help-seeking, it is also possible that students just seek help merely for task completion (i.e., seeking help without comprehension or mastery as an objective) or to avoid the task altogether (e.g., by gaming the system (d Baker, Corbett, Roll, Koedinger, Aleven, Cocea, Hershkovitz, de Caravalho, Mitrovic, and Mathews, 2013). Such cases demonstrate maladaptive help seeking behaviour which results to low persistence in task (Dweck, 1986). Help seeking is a multifaceted process in which students have to make decisions on whether to ask for help, what type of help to ask for, and from whom to ask for help (Schunk and Meece, 2012) that combines aspects of both cognitive and social interactions (Ryan, Gheen, and Midgley, 1998). Help seeking behavior is what discriminates a persistent from a non-persistent student (Kennedy, Sheckley, and Kehrhahn, 2000). While adaptive help seekers enjoy exerting effort, in pursuit of task mastery, by seeking for help when faced with setbacks and failures, maladaptive help seekers are inclined to demonstrate negative affect and negative self-cognition when faced with adversities (Dweck, 1986; Ahn, Teeters, Wang, Breazeal, and Picard, 2007). Their self-doubts and negative self-cognition seemed to weaken their commitment to the task. Rather than finding ways to overcome the challenge, maladaptive help seekers focus on personal inadequacies and on task difficulty that will possibly result to diminished ability of an individual with low self-efficacy to use strategic information seeking to efficiently control his learning experience.

7.2 Validation

The machine learned model was validated using 10-fold cross validation. The confusion matrix (see Table 1) shows the performance of the model in predicting the incidence of persistence and non-persistence in tasks. The model's class precision (how good the model is at avoiding false positives) is 88.89% while its recall or sensitivity (how good the model is at avoiding false negatives) is 44.44%. The model's overall accuracy is 74.42% with a Kappa rating of 0.435 indicating that the predictor was 43.5% better than chance in recognizing which sessions involve persistence behavior.

Table 1

Confusion Matrix

Predicted	Actual	
	Persistent	Not Persistent
Persistent	24	3 (false positives)
Not Persistent	30 (false negatives)	72

8. Conclusion, Contribution and Future Work

The goal of this work was to identify the factors that may detect student persistence in peer tutoring task. We found that student's engagement, denoted by average time on task, and self-efficacy, represented by average number of reattempts to a task, average time spent on resources after a failure, and proportion of difficult problems attempted, are factors that influenced persistence as reported in previous studies (Jung and Lee, 2018; Lent, Brown, and Larkin, 1984). This means that students who tend to persists on a task spend more time working on the task in spite of challenges and failures. Moreover, students who attempt challenging problems, re-attempt a failed or unsolved problem, and take time to review resources after a failed step have the tendency to exhibit greater degree of persistence.

The combination of Naive Bayes classification with forward feature selection identified the most efficient predictors for the given target attribute, although an increase in classification accuracy and kappa rating would have been more gratifying.

Aside from contributing to the existing literature on task persistence, this study has presented the predictor variables of student task persistence within an intelligent tutor for Algebra in the context of Learning by Teaching. The model derived in this work will possibly help designers of computer-based learning environments in determining and integrating interventions that would be beneficial in developing persistent behavior in students which is an attribute considered vital for long term success.

Previous works have shown that persistence is likely influenced by one's affective states (e.g., Ahn et al., 2007). Unfortunately, affect as a predictor of persistence was not explored in this study. As a future work, we will investigate whether affective states indeed influence an individual's decision to persist or abandon a task.

In Palaoag, Rodrigo, Andres, Andres, and Beck (2016), the markers of persistence were found to indicate not only productive persistence but wheel spinning, a case of unproductive persistence (Kai, Almeda, Baker, Shechtman, Heffernan, and Heffernan, 2017). Hence, as part of our future work, we will attempt to distinguish productive persistence from unproductive persistence to gain further understanding about these constructs in the context of a learning by teaching environment.

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