Expectations of Technology: A Factor to Consider in Game-Based Learning Environments

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Abstract. This study investigates how students' prior expectations of technology affect overall learning outcomes across two adaptive systems, one game-based (iSTART-ME) and one non-game based (iSTART-Regular). The current study (n=83) is part of a larger study (n=124) intended to teach reading comprehension strategies to high school students. Results revealed that students' prior expectations impacted learning outcomes, but only for students who had engaged in the game-based system. Students who reported positive expectations of computer helpfulness at pretest showed significantly higher learning outcomes in the game-based system compared to students who had low expectations of computer helpfulness. The authors discuss how the incorporation of game-based features in an adaptive system may negatively impact the learning outcomes of students with low technology expectations.

Keywords: Artificial Intelligence, student expectations, learning, motivation, educational technology, game-based features.

1 Introduction

The field of Artificial Intelligence in Education (AIED) promotes the design of so-phisticated learning environments that adapt to students' individual learning needs and abilities [1]. Recently, AIED developers have begun to investigate the relation between students' expectations, engagement, and learning outcomes within these educational learning environments [2-3]. These systems can vary widely in terms of complexity, user control, and interface features, each of which may affect outcomes differently based on students' prior perceptions. For example, incorporating game-based elements within a system has a positive impact on students' perception of a system [4]. Although previous work has shown that game-based features impact students' affect, relatively little work has investigated how these components interact with students' prior expectations to impact overall learning outcomes. To gain a deeper understanding of these relations, this study examines how the impact of students' prior expectations of technology on immediate and long-term learning outcomes depends on whether they engage with a game-based or non-game educational system.

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1.1 Perceptions and Expectations within Technology

We expect the influence of students' attitudes toward technology to be a crucial factor in developing a more complete understanding of user affect and engagement within educational systems [2], [5]. In line with this assumption, the Technology Acceptance Model (TAM) is a model that accounts for how students' attitudes toward technology potentially impact their behaviors within a system [3], [6]. The key notion underlining this model is that students' expectations of a system's usefulness and ease of use are good predictors of their acceptance of the system [6].

Researchers have also begun to investigate how perceptions of technology relate to student motivation and performance within Intelligent Tutoring Systems (ITSs) [5], [2]. For instance, Jackson et al. (2009) found that students' prior expectations of computers' helpfulness predicted their ratings of the ITS after training. Similarly, Corbett and Anderson (2001) found that students' posttest perception of their experience was significantly related to the amount of help (i.e., feedback) they received from an ITS during training. These few studies are in line with the TAM model, providing preliminary evidence that students' expectations and perceptions of technology impact the way in which they view and interact with an ITS. Additional work is clearly needed to better understand these relations and to further investigate how learning goals (e.g., reading strategies, math skills, writing strategies) are affected by system characteristics and students' prior expectations.

1.2 Game Features within Technology

One recent question regarding interactive learning environments has regarded the effects of games and game-based features [7- 8]. Integrating game-based features into a system is typically intended to improve students' engagement and interest while completing target tasks. For example, previous research has indicated that incorporating game-like elements can positively impact students' enjoyment, engagement, and motivation [4], [8]. Providing interactive elements within a system affords students a high locus of control over their individual learning paths as well as increases personal investment and identification with a system [4]. Similarly, research has shown that the inclusion of game-based elements is positively related to increases in student engagement [8]. Leveraging these and similar results, researchers have developed game-based learning environments that incorporate game-based elements into ITSs. This study utilizes two different learning environments (game vs. non-game) to examine how the interaction between system features and prior expectations impacts students' learning outcomes.

1.3 iSTART

The Interactive Strategy Training for Active Reading and Thinking (iSTART) tutor is a traditional ITS designed to enhance students' reading comprehension skills. iSTART focuses on improving students' content comprehension through the use of reading comprehension strategies, including self-explanation [9]. Students who use self-explanation strategies are more successful at problem solving, generating inferences and developing a deeper overall understanding of the meaning of the text [10].

The iSTART system includes three modules: introduction, demonstration, and practice. During the introduction module, three animated agents (a teacher and two students) discuss the concept of self-explanation and how it can be combined with the additional iSTART reading strategies: comprehension monitoring, predicting, paraphrasing, elaborating, and bridging. After the agents discuss each reading strategy, students are given short quizzes intended to formatively assess their understanding of the previously discussed strategies. In the demonstration module, students watch as two animated agents (one teacher and one student) apply various strategies to science texts. Students are then asked to specify which strategy was used in each example. Finally, in the practice module students are given two science texts and asked to apply self-explanation and comprehension strategies to target sentences. A teacher agent then provides each student with formative feedback designed to improve the quality of the self-explanations.

iSTART also contains an extended practice module, called Coached Practice, that begins immediately after students complete the first three phases (see Figure 1 for screenshot). This module functions in the same manner as the first two practice texts (i.e., students generate self-explanations and receive formative feedback). iSTART's extended practice phase is designed to provide a prolonged interaction across weeks or months and allows students to develop mastery by applying the iSTART strategies across a range of texts.

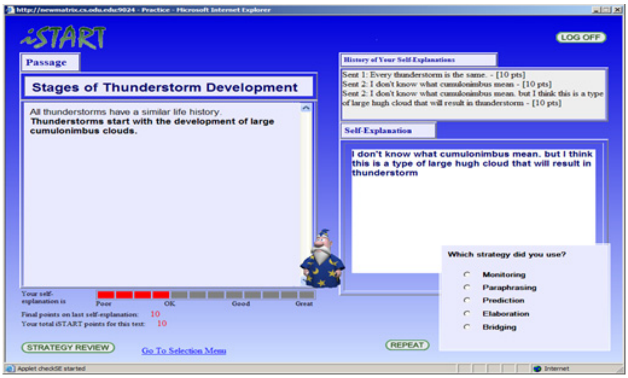

Fig. 1. Screen shot of the Coached Practice Module

The iSTART system provides feedback about strategy usage through an algorithm that assesses the quality of students' generated self-explanations. This feedback algorithm assesses students' self-explanations utilizing a combination of word-based measures and latent semantic analysis (LSA), [11]. The scores range from 0 to 3, describing a range of explanation quality from very poor (e.g., irrelevant, too short) to very good (i.e., incorporating information about the text or prior knowledge at a global level).

1.4 iSTART-ME

Studies with iSTART have demonstrated significant improvements for students' reading comprehension across time [12]. However, the repetitive nature of the extended practice module can occasionally result in student disengagement [13]. iSTART-ME (Motivationally Enhanced) was designed to address this problem by incorporating game-based elements into the original extended practice module [12]. The design and elements incorporated into iSTART-ME were based on previous research indicating a positive relation between specific mechanisms and their effects on motivation, engagement, and learning [14].

Both of the iSTART systems (iSTART-ME and iSTART-Regular) provide identical training through the first three modules: introduction, demonstration, and practice. The difference between the two systems occurs in the extended practice module, where iSTART-ME introduces game-based elements. Within iSTART-ME, the ex-tended practice module is controlled through an interactive selection menu where students can choose to self-explain new texts, personalize features within the interface, or play mini-games (see Figure 2). In addition, this menu allows students to view their advancement in the system through personal progress screens. These screens update students on their achievement level, number of points, and trophies earned within the system.

Students earn points in the system by interacting with three different types of generative practice: Coached Practice, Showdown, and Map Conquest. Coached Practice is a non-game-based method of practice, and is the same environment used within iSTART-Regular extended practice. In addition, Showdown and Map Conquest incorporate the same self-explanation assessment algorithm within two different game environments. As students engage with these generative practice environments, they accumulate more points within the system and subsequently progress to higher achievement levels.

Fig. 2. Screen Shot of iSTART-ME Menu

Students' earned points also serve as currency (iBucks), which they can use to purchase incentives within the system. Students have four options on how to spend their earned iBucks. The first three options allow the user to personalize their experience by customizing an avatar, selecting a new tutor agent, or applying new color themes to the overall interface. All three of these options provide students with control over the environment through a variety of choices.

The fourth option for spending iBucks allows students to select and play one of six mini-games. Each mini-game allows students to engage in play while still practicing reading comprehension strategies from the system. After students complete each mini-game, they are given a score based on their performance and, if applicable, a trophy. Students can accumulate trophies throughout their time in the system and view them at any time through their personal progress screens on the main interface menu. The iSTART-ME system has been found to increase students' motivation and engagement over time, while remaining equally as effective at training students to use self-explanation strategies as the original iSTART system [15].

2 Methods

Participants in this study included 83 high-school students from a mid-south urban environment. The sample included in the current work is a subset of 124 students who participated in a larger study that compared learning outcomes across three conditions: iSTART-ME, iSTART-Regular, and no-tutoring control. This study solely focuses on the students who were randomly assigned to the game (iSTART-ME) and non-game (iSTART-Regular) conditions.

The current study consisted of 11-sessions in which all students completed a pre-test, 8 training sessions, a posttest, and a delayed retention test. During the first session, students completed pretest measures that assessed individual differences in motivation, attitudes toward technology, prior self-explanation ability, and prior reading comprehension ability.

During the following 8 sessions, students completed the initial strategy training (~2 hours) and then spent the remainder of their time interacting with the extended practice module in either iSTART-Regular or iSTART-ME. In contrast to previous work [5], [16], all students were exposed to similar types of feedback as they progressed through the systems, with iSTART-ME providing a small amount of additional modeling and implicit feedback through examples and rewards. Session 10 included a posttest that incorporated measures similar to the pretest. The eleventh session occurred 1 week after the posttest. In this session, students completed a retention test that contained measures similar to the pretest and posttest (i.e., self-explanation ability and attitudinal measures).

At pretest, students provided ratings on their expectations of and attitudes towards technology. To assess prior expectations of technology, each student indicated the relative importance of the following statement, "I expect computer systems to be helpful," for related work see [2]. This rating was on a scale from 1 (strongly disagree) to 6 (strongly agree), and is the only pretest measure of students' expectations of computer helpfulness. Students' reading comprehension ability was assessed using the Gates-MacGinitie Reading Test [17]. Self-explanations were scored using the automated iSTART assessment algorithm.

3 Results

This study investigates how students' prior expectations of technology relate to learning outcomes from two learning environments. We first examined how individual differences influenced performance within these two systems (game and non-game) by examining the relation between students' pretest rating of prior expectations and pretest, posttest, and retention measures of learning outcomes (self-explanation quality). Analyses indicated no relation between expectations and students' self-explanation quality at pretest or posttest (see Table 1). However, these correlations revealed that students' prior expectations of system helpfulness had a significant positive relation with their self-explanation quality on the retention test.

Table 1. Correlations between Prior Expectations and Learning Outcomes across Conditions

Dependent Measure	Prior Expectations of Helpfulness
Pretest Self-Explanation Scores	.181
Posttest Self-Explanation Scores	.078
Retention Self-Explanation Scores	.247*
*$p < .05$; ** $p < .01$	

The positive relation between prior expectations and retention self-explanation scores suggests that students' expectations may impact long-term learning outcomes. Additionally, we were interested in assessing how these long-term impacts may vary as a function of condition. A second set of correlations examined the relation of prior expectations and learning outcomes in the two conditions separately (see Table 2). These results indicated that students assigned to the non-game condition (iSTART-Regular) did not demonstrate a significant relation between prior expectations and learning outcomes. However, students in the game condition (iSTART-ME) showed a significant positive correlation between their prior expectations of helpfulness and their retention self-explanation scores. These findings suggest that the long-term effects may be due to the characteristics of a system (e.g. interface and game features), rather than the content and domain being covered (i.e., both systems covered the same content and used the same assessment algorithm).

Table 2. Correlations between Prior Expectations and Learning Outcomes

Non-Game (iSTART-Regular)	Prior Expectations of Helpfulness
Posttest Self-Explanation Scores	- .127
Retention Self-Explanation Scores	- .062
Game (iSTART-ME)	
Posttest Self-Explanation Scores	.274
Retention Self-Explanation Scores	.473 **
*$p < .05$; ** $p < .01$,	

Table 2 shows a significant positive relation between students' prior expectations and retention outcomes for students in the game condition. Further examining this relation, a hierarchical linear regression found that for students in the game condition, prior expectations was a significant predictor of retention outcomes, over and above pretest self-explanation scores, $F(1,38) = 10.67$, $p < .05$, $R^2=.37$. Specifically, after controlling for pretest self-explanation scores ($\beta = .381$, $p < .05$), students' prior expectations ($\beta=.394$, $p<.05$, $R^2=.15$) significantly predicted retention self-explanation outcomes.

To investigate the potential impact of individual differences on learning outcomes across systems, two separate 2 x 2 mixed-factor ANOVAs compared the self-explanation performance at posttest and retention for the two expectation groups (low vs. high, using a median split on prior expectations) as a function of condition (game vs. non-game). These statistical analyses revealed no significant interactions between expectation group and condition for posttest self-explanation scores, $F(3,79)=1.04$, $p=.376$, but a marginally significant interaction between expectation group and condition for retention self-explanation scores, $F(3,79)=2.632$, $p=.056$.

Follow-up analyses were conducted to examine the potential effects within each condition. A one-way ANOVA on the posttest outcomes within the game condition demonstrated that students with low expectations performed marginally worse on posttest self-explanation than students with high expectations, $F(1,38)=3.19$, $p=.08$ (see Figure 3). Additionally, on the retention outcomes, students with low expecta-tions generated significantly worse self-explanations than students with high expecta-tions, $F(1,38)= 6.579$, $p<.05$ (see Figure 4). A similar ANOVA on the non-game con-dition found that there were no significant differences between the low and high ex-pectations groups for posttest self-explanation scores, $F(1,38)=.040$, $p=.85$ (see Figure 3) or retention self-explanation scores, $F(1,41)=.003$, $p=.95$ (see Figure 4).

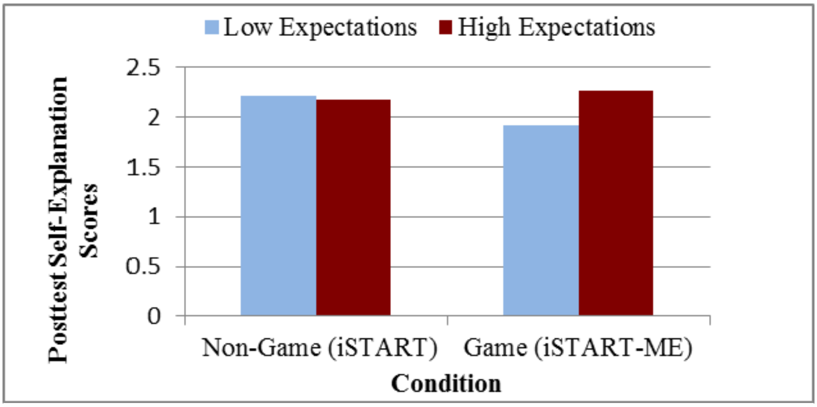

Fig. 3. Mean Posttest Self-Explanation Scores per Condition

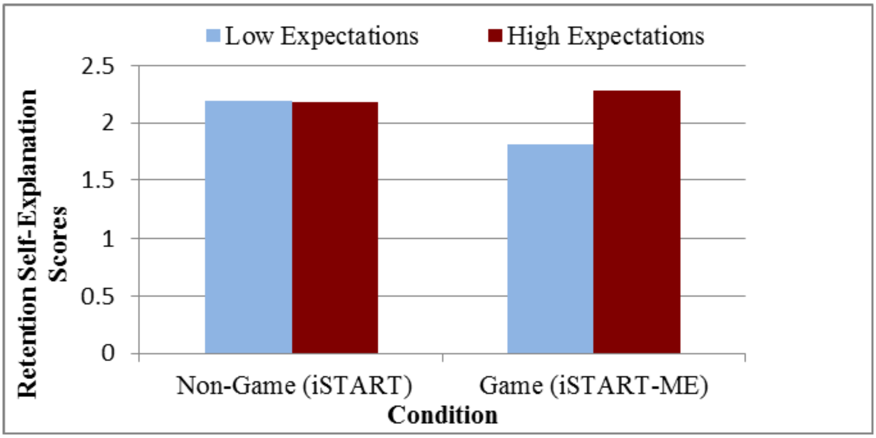

Fig. 4. Mean Retention Self-Explanation Scores per Condition

The null results for the non-game condition indicated that students' prior expectations did not impact overall learning outcomes. In contrast, results for the game condition indicated that students with low expectations of technology performed significantly worse at retention compared to students with high expectations of technology. These findings indicate that the influence of students' expectations on long-term learning outcomes may vary as a function of system characteristics

4 Conclusions and Implications

The current study investigated how system characteristics influence the impact of students' prior expectations on immediate and long-term learning outcomes. The results presented here indicate that overall skill retention is significantly affected by an interaction between students' prior expectations and characteristics of a system. These findings build upon two different bodies of work; the importance of students' perceptions and expectations [2], [3], [6] and the impact of game-based features in ITSs [7-8].

Our results are congruent with the Technology Acceptance Model; specifically, students' expectations of the helpfulness of the system impacted their interactions with the system [6]. Students in the game condition who reported low expectations of computer helpfulness showed lower long-term learning outcomes compared to students who had high expectations of computer helpfulness. However, this relation did not emerge within the non-game condition. Students with low expectations may have disliked the added level of complexity that accompanies the incorporation of game elements, while students with higher prior expectations may have viewed the added game-based features as helpful toward achieving the learning objectives.

In the current study, the primary difference between conditions was that one was a game-based ITS (iSTART-ME) and the other was a non-game-based ITS (iSTART-Regular). Although the non-game system does incorporate some game features (e.g., points and a qualitative feedback bar), these features are fixed and no other options are offered to the student. In contrast, the game-based system offers many features. iSTART-ME expands upon the features in iSTART-Regular by allowing users to choose to interact with multiple practice environments, mini-games, personalized characters, changeable pedagogical agents, and editable background themes.

It is important to note that iSTART-Regular does include some game-based fea-tures, which indicates that incorporating one or two game features is not sufficient to contribute to the overall effect on learning outcomes. Instead, the current study may suggest that the variety of game-based features within iSTART-ME required students to interact more within the system; therefore, their prior expectations may have played a bigger role in overall learning outcomes. However, future work is needed to investigate how specific features (e.g., variety, choice, and control) may be influencing the impact that students' prior expectations have on their learning outcomes. Additionally, studies are planned that will examine the efficacy of these systems within ecological settings.

The current findings demonstrate that students' prior expectations can impact learning and that these effects may be more likely when users are engaged in systems with game-based elements. These results are especially important for AIED developers who are implementing game-based features into systems. These elements are intended to engage students' interest in the learning environment. However, individual differences in prior expectations of technology may impact the effectiveness of the features.

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