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Motivation matters: Interactions between achievement goals and agent scaffolding for self-regulated learning within an intelligent tutoring system

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ABSTRACT

In this study, we examined the influence of achievement goals and scaffolding on self-regulated learning (SRL) and achievement within MetaTutor, a multi-agent intelligent tutoring system. Eighty-three ($N = 83$) undergraduate students were randomly assigned to either a *control* or *prompt and feedback* condition and engaged in a 1-h learning session with MetaTutor to learn about the human circulatory system. Process and product data were collected from all participants prior to, during, and following the session. MANCOVA analyses revealed that students in the *prompt and feedback* condition deployed more SRL strategies and spent more time viewing relevant science material compared to students in the *control* condition. Results also revealed a significant interaction between achievement goals and condition on achievement outcomes, such that learners adopting a dominant performance-approach demonstrated higher achievement in the *prompt and feedback* condition. Findings are discussed in relation to the role of motivation in self-regulated learning within computer-based learning environments. Implications for the design of pedagogical agents are also discussed.

1. Introduction

Do pedagogical agents foster self-regulated learning processes and achievement? What role does motivation play in the effectiveness of agent scaffolding? Should instructional supports adapt to learners' achievement goals? Despite the potential advantages of embedding prompts and feedback within hypermedia environments to foster self-regulated learning (Azevedo, 2009, 2015; Azevedo, Feyzi-Behnagh, Duffy, Harley, & Trevors, 2012), there is a need for research to examine the impact on students' learning processes and achievement using both process and product data (Azevedo et al., 2013; Bannert, Reimann, & Sonnenber, 2014). Moreover, few studies have explored the interactions between motivation and instructional supports within these types of computer-based learning environments (Moos, 2014; Moos & Marroquin, 2010).

Although models of self-regulated learning (e.g., Boekaerts, 2011; Efklides, 2011; Pintrich, 2000, 2004; Winne & Hadwin, 2008; Zimmerman, 2011) and interactive tutoring feedback (e.g., Narciss, 2008) indicate that motivational orientation is a critical factor in learners' use of self-regulatory strategies and responsiveness to scaffolding, these theoretical claims have not received empirical scrutiny within computer-based learning environments. For example, it may be the case that agent scaffolding and learners' achievement goals both relate directly to self-regulated learning and achievement. It may also be the case the there is an interaction between the two; that is, that the effectiveness of scaffolding will vary according to the type of achievement goal adopted. For instance, it is not clear whether learners who aim to improve their personal competence (i.e., mastery-approach) benefit differently from scaffolding compared to learners who strive to outperform their peers (i.e., performance-approach) or how this impacts their achievement within computer-based learning environments.

In the present study, we aim to address these gaps by drawing on frameworks of self-regulated learning (e.g., Winne & Hadwin, 2008) and achievement motivation (e.g., Elliot & Murayama, 2008) to examine the impact and interactions between pedagogical agent scaffolding and achievement goals within MetaTutor, a multi-agent hypermedia-based intelligent tutoring system designed to help students learn about the human circulatory system. This study extends previous work by responding to calls to: (1) collect trace data in real-time to examine the deployment of self-regulatory strategies (Azevedo et al., 2013; Winne &

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Azevedo, 2014); (2) examine the effectiveness of pedagogical agent scaffolding on learning outcomes using an experimental design (Heidig & Clarebout, 2011); and (3) investigate motivational facets of self-regulated learning in addition to cognitive and metacognitive processes within computer-based learning environments (Moos, 2014; Moos & Marroquin, 2010; Moos & Stewart, 2013).

Findings from this research have important implications for the advancement of self-regulated learning models and the design of computer-based learning environments by providing insights into the role of learner characteristics, such as achievement goals. In the following sections, we provide theoretical background and a review of the literature on self-regulated learning, instructional scaffolding, and achievement motivation within computer-based learning environments. The introduction closes with the goals of the current study.[1]

1.1. Self-regulated learning

Theories of self-regulated learning (e.g., Boekaerts, 2011; Pintrich, 2000; Winne & Hadwin, 2008; Zimmerman & Schunk, 2011) are commonly employed as a guiding framework to understand the nature of student learning. Broadly speaking, self-regulated learning (SRL) refers to the self-initiated management of thoughts, feelings, and behaviors, which are used to achieve specific learning goals (Zimmerman, 2001, 2011). Research has demonstrated that in order to achieve positive learning outcomes, students must engage in effective SRL processes, such as planning and setting goals, selecting and monitoring learning strategies, and evaluating comprehension of the material (e.g., Azevedo & Feyzi-Behnagh, 2010; Azevedo et al., 2012, 2013; Greene & Azevedo, 2010; Winne & Perry, 2000).

These SRL processes are particularly important within computer-based learning environments where students must carefully regulate several aspects of their learning given the potential of these environments to be open-ended, non-linear, and information-rich (Azevedo et al., 2013; Bannert & Mengelkamp, 2013; Opfermann, Scheiter, Gerjets, & Schmeck, 2013). For example, within hypermedia environments, information is presented in multiple formats (e.g., texts, diagrams, animations) and contains hypertexts that allow learners to self-direct the sequencing and duration of content viewed. As such, learners must make decisions about which information to attend to, for how long, and in what order.

As Moos (2009) has argued, the nature of these environments can place high demands on limited cognitive resources, which may thwart learning. Indeed, research has demonstrated that students typically do not self-initiate a high degree of SRL processes and often struggle when learning about complex topics or ill-structured problems (Azevedo et al., 2012; Kinnebrew, Biswas, Sulcer, & Taylor, 2013; Opfermann et al., 2013). This lack of effective regulation limits the potential learning gains of educational tools aimed at promoting deep comprehension of complex topics, such as science (Graesser & McNamara, 2010). As a result, researchers have developed a variety of computer-based learning environments, including hypertext, multi-media, hypermedia, and intelligent tutoring systems, that are designed to promote, support, and detect SRL (e.g., Azevedo & Aleven, 2013; Azevedo et al., 2012; Biswas, Jeong, Kinnebrew, Sulcer, & Roscoe, 2010; Graesser, Chipman, King, McDaniel, & D'Mello, 2007; Lajoie et al., 2013; Lester, Mott, Robinson, & Rowe, 2013; Winne & Nesbit, 2009). In the following section we discuss how scaffolding embedded within these systems can influence SRL and achievement.

1.2. Instructional scaffolds

Instructional scaffolding refers to support or guidance provided by an agent or tool that allows learners to participate in a task that would otherwise be too challenging to effectively complete (Belland, 2014). In the context of computer-based learning environments designed to promote self-regulated learning for science education, scaffolds have typically focused on promoting regulation of cognitive processes (Devolder, van Braak, & Tondeur, 2012). Recently, these systems have also integrated scaffolds and design features to promote metacognition (e.g., Azevedo et al., 2012) and motivation (D'Mello, Chauncey-Strain, Olney, & Graesser, 2013; D'Mello, Lehman, & Graesser, 2011; Mayer, 2014). Scaffolding can take several forms, including: hints, prompts, feedback, illustrations, or interactive features (Devolder et al., 2012). For example, within MetaTutor (Azevedo et al., 2012, 2013), learners have access to an embedded SRL palette that contains a number of strategies that can be selected to self-initiate self-regulatory processes Taub, Azevedo, Bouchet, & Khosravifar, 2014). These include cognitive strategies (e.g., taking notes, writing a summary, making an inference) and metacognitive strategies (e.g., activating prior knowledge, evaluating content relevancy, assessing understanding and knowing).

To further promote effective learning, researchers have embedded pedagogical agents within computer-based environments to adaptively scaffold SRL by providing timely instructional prompts and or feedback (e.g., Azevedo et al., 2012, 2013; Biswas et al., 2010; D'Mello et al., 2013; Graesser & McNamara, 2010; Lester et al., 2013; Poitras & Lajoie, 2014).[2] Within MetaTutor (Azevedo et al., 2013), agents are designed to scaffold cognitive and metacognitive processes by providing prompts and feedback in response to learners' goals, behaviors, self-evaluations, and progress. For instance, learners receive prompts at various points to set sub-goals for learning, monitor understanding and feelings of knowing, activate prior knowledge, and deploy learning strategies. Learners also receive feedback as they create sub-goals (e.g., too broad or too narrow), write summaries (e.g., too long or too short), view content (e.g., relevant or irrelevant to sub-goal), progress toward their goals (e.g., sufficiency of content coverage), and assess understanding (e.g., calibration between quiz result and self-evaluation).

These types of environments are garnering evidence that pedagogical agents can effectively promote self-regulated learning (Azevedo et al., 2012, 2013). For example, Trevors, Duffy, and Azevedo (2014) found that within MetaTutor, agents significantly reduced shallow-level note-taking (e.g., verbatim copying) for low prior knowledge learners, which was found to be a maladaptive learning strategy. Despite these potential benefits, limited research has directly examined the effectiveness of agent scaffolding for SRL to promote achievement. One major limitation in research examining the impact of pedagogical agents is the lack of experimental design and control groups (Heidig & Clarebout, 2011). In addition, there is a need for research to attend to the role of learner characteristics, which likely impact the effectiveness of scaffolding (Devolder et al., 2012). Although research has demonstrated that prior knowledge has an influential role within agent-based environments (e.g., Taub et al., 2014; Trevors, Duffy, & Azevedo, 2014), one learner characteristic that has received inadequate attention within computer-based learning environments is achievement goal motivation (Moos & Marroquin, 2010).

[1] Given the diversity of research on computer-based learning environments, we focus our review on scaffolding and motivation within CBLEs designed to promote self-regulated learning.

[2] For further information regarding variations in agent features and scaffolding design, see Azevedo, 2014; Azevedo & Hadwin, 2005; Graesser & McNamara, 2010; Heidig & Clarebout, 2011; Tien & Osman, 2010).

1.3. Achievement goal motivation

Achievement goal theory (Ames, 1992; Ames & Archer, 1988; Hulleman, Schrager, Bodmann, & Harackiewicz, 2010) provides a useful framework for understanding students' motivation for achievement tasks. Achievement goals are considered a facet of motivation given that they provide a purpose or focus for the task and, as such, guide students' learning behaviors and performance by setting the standards with which to evaluate success (Elliot & Murayama, 2008; Linnenbrink & Pintrich, 2001). According to this framework, students who adopt a mastery-approach goal focus on developing competence and skills, whereas students with a performance-approach goal focus on outperforming their peers (Elliot & McGregor, 2001; Elliot & Murayama, 2008).[3] Despite its well-established relations to adaptive learning variables, a mastery-approach goal does not consistently predict achievement (see Harackiewicz, Barron, Pintrich, Elliot, & Thrash, 2002; Senko, Hulleman, & Harackiewicz, 2011; Senko & Miles, 2008). In fact, some research has shown that students who adopt a performance-approach goal supersede students with a mastery-approach goal on performance measures (e.g., Harackiewicz, Barron, Carter, Lehto, & Elliot, 1997; Harackiewicz, Barron, & Elliot, 1998; Hidi & Harackiewicz, 2000). One possible explanation for this pattern is that mastery-approach students jeopardize their performance by spending more time on content they find interesting rather than balancing their study efforts to cover all to-be-tested material, whereas those adopting a performance-approach may use more strategic tactics (Senko & Miles, 2008).

Findings from studies using computer-based learning environments provide further evidence that the relationship between achievement goals, SRL processes, and achievement is mixed. For instance, in some cases mastery-approach goals are positively related to SRL processes (e.g., Bernacki, Brynes, & Cromley, 2012) and achievement (e.g., Bernacki, Aleven, & Nokes-Malach, 2014), whereas in other cases, they are negatively related to SRL (e.g., Nesbit et al., 2006; Vaessen, Prins, & Jeuring, 2014) and unrelated to achievement (e.g., Moos & Azevedo, 2006). Although the learning environments in these studies contained tools that could be used to initiate SRL processes, they did not contain animated agents specifically designed to promote SRL. In the current study we expand on previous work by examining how achievement goals relate to agent scaffolding designed to promote self-regulated learning. In the following section we discuss how these variables (scaffolding, motivation, SRL processes, and achievement) can be brought together within a self-regulated learning framework.

1.4. Theoretical framework

To illustrate how achievement goals and scaffolding may jointly influence learning and achievement, we draw on Winne and Hadwin's (2008) four-phase model of self-regulated learning (COPES).[4] According to the COPES model, there are four phases of learning, which are weakly sequenced and recursive: (1) task definition; (2) goal setting and planning; (3) enactment; and (4) adaptation. Activation of achievement goals are likely to be most salient during the first two phases of learning: (1) task definition (achievement goals influence the perception of the task); (2) planning and goal setting (achievement goals influence the specific goals and plans for the task), whereas agent scaffolding is likely to be more salient during the last two phases of learning: (3) enactment (agent prompts influence the strategies and tactics deployed); and (4) adaptation (agent feedback influences evaluations of learning and strategy use as acceptable or unacceptable). However, we also argue that the achievement goals activated in earlier phases, are likely to influence the responsiveness to agent scaffolding by way of conditions, operations, products, evaluations, and standards (COPES).

For example, during the task definition phase learners may reflect upon prior experience to determine whether the purpose of the task is to improve their understanding of the topic (i.e., mastery-approach) or to outperform other students (i.e., performance-approach). During the planning and goal-setting phase those who adopt a mastery-approach for the learning session may formulate a plan to use strategies that will help them to gain a deeper understanding of content. Those who adopt a performance-approach may devise a plan to use strategies that will help them to outperform other learners. During the enactment and adaptation phases, learners who adopted a mastery-approach may spend more time elaborating on ideas for a limited amount of content. Their responsiveness to agent prompts will depend on whether they feel suggested strategies will help to promote deeper understanding. Their responsiveness to feedback will depend on whether they consider the evaluations to convey information about personal growth. In contrast, learners who adopted a performance-approach may spend more time ensuring that they cover a broader range of to-be-tested material during the learning session. Their responsiveness to agent prompts will depend on the extent to which they feel suggested strategies will help them to outperform their peers. Their responsiveness to feedback will depend on the extent to which they consider evaluations to convey information about their competence relative to others. Collectively, these differences in goals, strategies, and reactions to agent scaffolding, will impact performance on the post-test. As these examples (and the underlying theory) illustrate, an interaction may occur between achievement goals and agent scaffolding. In the following section we discuss the goals of the current study, as guided by this framework.

1.5. The current study

Based on limitations in previous work, there is a need for research that: (1) employs experimental designs to test the effectiveness of pedagogical agents on SRL and achievement; (2) uses both process (e.g., log files) and product data (e.g., post-tests) to measure behaviors as they unfold in real time; (3) examines motivational constructs (in particular achievement goals) as a factor in the effectiveness of scaffolding; and (4) tests these relations within the context of adaptive computer-based environments designed to scaffold SRL and promote achievement.

Motivation is not only activated in response to the learning environment but is also activated *prior* to engaging in the learning environment. In particular, the achievement goals that students adopt based on previous experiences, values, and beliefs, can influence the way they approach the learning task, the strategies they deploy, and arguably the extent to which they benefit from scaffolding. Moreover, given that there is disagreement in the literature about whether a performance-approach or mastery-approach goal is more adaptive, there is a need to empirically examine differences in behaviors and performance between these two goals in particular. As such, the purpose of this study was threefold: (1) to test the effectiveness of pedagogical agents' scaffolding (instructional prompts and feedback versus control condition) on learners' self-regulated learning (cognitive and metacognitive strategies) and achievement (performance on post-test); (2) to test the relationship between achievement goals

[3] In this study we focused exclusively on mastery-approach and performance-approach goals given that avoidance goals are typically considered less adaptive, whereas it remains unresolved as to whether a mastery-approach or performance-approach goal is ideal.

[4] For detailed descriptions of the COPES model and our theoretical perspective that SRL be treated as an event that can be detected, traced, and modeled see Azevedo, Moos, Johnson, & Chauncey, 2010; Azevedo et al., 2012, 2013; Winne & Hadwin, 1998, 2008.

(mastery-approach versus performance-approach), self-regulated learning, and achievement; and (3) to test for an interaction between agent scaffolding and achievement goals on self-regulated learning and achievement. We conducted this research within MetaTutor, an intelligent tutoring system designed to help students learn about the human circulatory system by scaffolding cognitive and metacognitive self-regulatory processes. Accordingly, the research questions are as follows: (1) what influence does agent scaffolding and achievement goals have on learning processes within MetaTutor? and (2) what influence do agent scaffolding and achievement goals have on achievement within MetaTutor? The following section outlines the methods used to address these questions.

2. Methods

2.1. Participants

Eighty-three[5] undergraduate students (64% females) participated in the study. The sample had a mean age of 21.0 (SD = 2.8) and mean GPA of 3.2 (SD = 0.6). The majority of students were in their second year of study (36.9%) followed by fourth-year students (22.6%), third-year students (20.2%), and first-year students (17.9%) from a large North American public university. Participants represented a variety of disciplines. Specifically, 9.5% were arts majors, 9.5% were science majors, 34.5% were math or engineering majors, 22.6% were social science majors, and 10.7% were business majors. Approximately 42.9% of participants had some prior experience with biology-related topics (e.g., the circulatory system), although most of these students (22.6%) had only taken one topic-relevant course.

2.2. Learning environment

The MetaTutor learning environment (Azevedo, 2009; Azevedo, Cromley, Moos, Greene, & Winters, 2011; Azevedo et al., 2010, 2012, 2013) is an adaptive, multi-agent hypermedia learning environment designed to teach students about the human circulatory system and how to self-regulate their learning. It is also used to measure cognitive, affective, motivational, and metacognitive (CAMM) self-regulatory processes deployed during learning. MetaTutor presents 41 pages of human circulatory-system content through texts and diagrams (Azevedo et al., 2010, 2012). The underlying assumption of MetaTutor is that students should regulate key cognitive, affective, metacognitive, and motivational (CAMM; Azevedo et al., 2010) processes in order to learn about complex and challenging science topics.

Embedded within the MetaTutor learning environment is a timer (which indicates the time remaining during the learning session), an SRL palette where learners can interact with the agent to initiate learning strategies (e.g., write content summaries, make metacognitive judgments, take notes, evaluate relevancy of content, activate prior knowledge), as well as an overall learning goal, sub-goals, and a table of contents (see Fig. 1). The non-linear, self-paced structure of the environment allows learners to access content and navigate to new pages by selecting a subtopic from headings located in the table of contents or by using the navigational buttons at the bottom of the screen to progress forward or backward. To help participants more easily approach the learning task, they are asked to create two subgoals, displayed within a progress bar directly below the overall learning goal. Four pedagogical agents (Gavin, Pam, Mary, Sam), displayed in the upper right section of the screen, are each responsible for specific tasks: Gavin the Guide is responsible for providing learners with information about system features and the layout to help them navigate through the environment. Pam the Planner is responsible for helping students to set appropriate subgoals (based on a predefined set of subgoal options), Mary the Monitor helps learners evaluate their understanding during the learning session. Finally, Sam the Strategizer is responsible for facilitating students' use of learning strategies (either self-initiated or agent-generated prompts). These agents are activated throughout the learning session and are adaptive to learners' responses and actions; however, their specific actions and responses vary according to the experimental condition (described in more detail below). Overall, the prompts and feedback from agents are designed to scaffold learners' self-regulatory learning processes and understanding of the content. MetaTutor also includes a dialogue history box where participants can access their previous interactions with the PAs (e.g., feedback regarding sub-goals). Additionally, an electronic notepad is available during the session where participants can take notes and have access to them at all times, except during the posttest.

During the 1-h learning session with MetaTutor, we collected the following data from each participant log files that provide a time-stamped record of learner interactions and navigation behaviors (e.g., number of times visiting relevant pages, amount of time visiting pages and diagrams, number of times SRL palette is selected, agents-learner dialogue), self-report measures to assess motivations for learning with MetaTutor, as well as pretest and posttest data to assess prior knowledge, learning gains, and comprehension of material.

[5] The complete sample for this study consisted of 100 students; however, 17 participants were excluded from analyses, as given the nature of our research objectives we were interested in examining only those students with a dominant mastery-approach or dominant performance-approach goal.

2.3. Materials/measures

2.3.1. Demographics

Demographic information, including age, gender, ethnicity, GPA, university enrollment, year in university, university major, and prior experience with human biology content was obtained from all participants.

2.3.2. Achievement Goal Questionnaire (AGQ)

The Revised AGQ (Elliot & Murayama, 2008) is a 12-item self-report questionnaire that assesses four achievement goal dimensions: (a) mastery-approach, (b) mastery-avoidance, (c) performance-approach, and (d) performance-avoidance using Elliot and McGregor's (2001) 2×2 framework (see Appendix A for items). Items were adapted to assess students' motives for the MetaTutor learning task. Participants were asked to indicate the degree to which each item was characteristic or true of them using a 7-point Likert scale. A sample item for the mastery-approach subscale was: "my aim is to completely master the material presented during this learning session." A sample item for the performance-approach subscale was: "my goal is to perform better than the other student participants." Learners' dominant goal was determined based on the highest sub-scale score for each individual. Reliability estimates (Cronbach's alpha) for these subscales were moderate to high (ranging from .72 to .90).

2.3.3. Comprehension measures

2.3.3.1. Prior knowledge. The pretest and post-test both consisted of 25 multiple-choice items (see Appendix B for sample items). Two equivalent forms of the tests were created using 50 items and were counterbalanced across participants. Each of the multiple-choice questions included four foils: a distractor, near-miss, thematic, and correct answer alternatives. Both versions of the tests included text-based (based on one sentence in the content) and inferential items (required participants to integrate the information from two sentences within the content). The pre-test was used to assess prior knowledge of the circulatory system and was treated as a

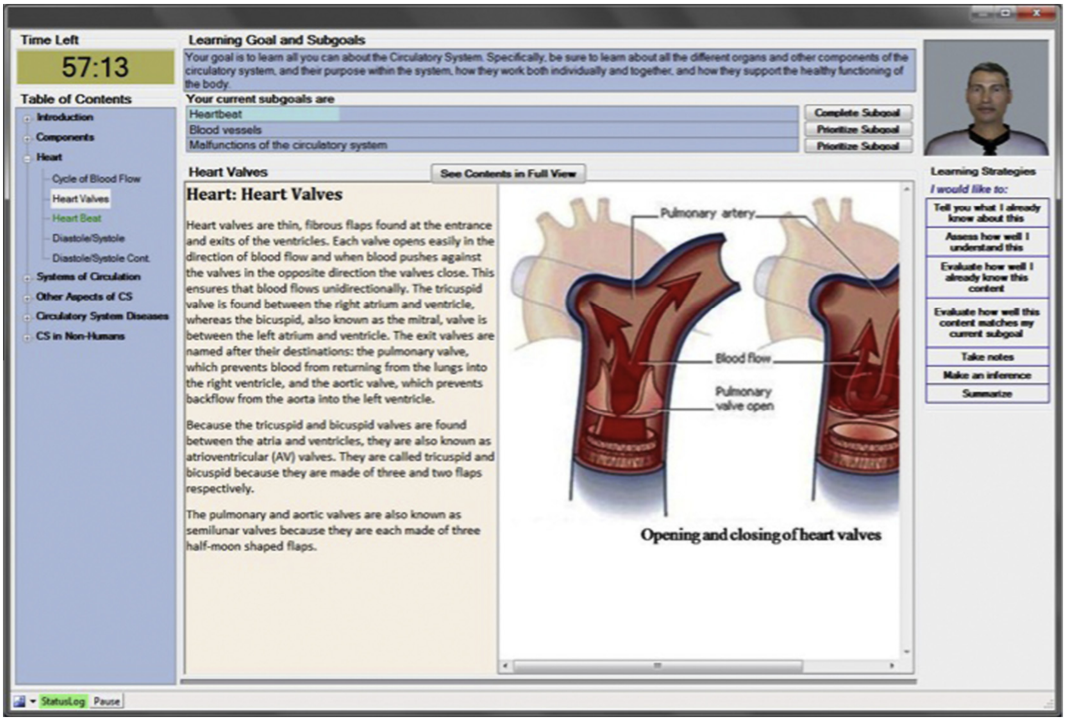

Fig. 1. Screenshot of the MetaTutor interface (Azevedo et al., 2013).

covariate in analyses. The posttest was designed to assess participants' knowledge about the human circulatory system after participating in a 1-h learning session with MetaTutor (see below for more details about how this was used to assess achievement).

2.3.3.2. Achievement. Three variables were created to assess participants' achievement: *overall post-test score* (number of questions answered correctly), *sub-goal relevancy score* (percentage of post-test questions relevant to selected sub-goals that were answered correctly), and *learning gains* (change in score from pre-to-posttest). Together, these variables provide a more sensitive measure of comprehension, which is important given that achievement measures should take into account the self-paced nature of the learning environment and differences in prior knowledge by including adaptive measures of achievement that reflect the material that each learner chose to spend time learning, as well as each learner's individual growth in knowledge and understanding, in addition to more traditional measure of achievement that capture the breadth of material considered by experts to be important for comprehension of the topic.

2.3.4. Learning process measures

2.3.4.1. Self-regulatory strategies. Log file data was extracted to determine the number of times that learner's deployed self-regulatory learning strategies based on the number of times the strategies were activated (this includes user-generated from selecting the palette and agent-prompted activation of strategies).[6] A mean score was obtained based on the total number of instances of: note-taking, summaries, monitoring progress toward goal, content evaluation, judgments of learning, feelings of knowing, planning, and prior knowledge activation.

2.3.4.2. Time viewing relevant pages. Log file data was also mined to determine the total time each participant spent viewing material in MetaTutor (i.e., pages and diagrams of the human circulatory system) that was relevant to their current activated sub-goal (i.e., whether the material was related to the sub-goal topic). Together, these two variables (self-regulatory strategies and time viewing relevant pages) provide a measure of students' use of cognitive and metacognitive monitoring and regulation throughout the learning session as they indicate that the learner is deploying cognitive/metacognitive strategies, monitoring the relevancy of the content, and regulating which material they give attention to.

2.4. Procedure

Participants were randomly assigned to either a prompt and feedback (PF) condition ($N = 39$) or a control (C) condition ($N = 44$). The two conditions differed in the nature, detail, and amount of guidance provided by the agents. In both conditions the PAs instructed participants to set two sub goals, be mindful of their overall learning goal, and either accepted or rejected participants' proposed sub goals. In the PF condition, students received prompts to deploy specific SRL strategies (e.g., write a summary, assess the relevancy of the content, take notes, assess their understanding, re-read sections of the text) and were given feedback regarding the accuracy and quality of their use. The timing of prompts were dictated by several factors, including the time that the learner spent viewing a particular page, the relevancy of that page, time spent working on a sub-goal, and number of pages visited. In the control (C) condition, learners did not receive prompts or feedback (i.e., no qualitative evaluation of their behaviors or strategy use) from agents, although participants in this condition were still provided access to the SRL palette to initiate a process.

The study consisted of two parts: day one (30 min) and day two (2 h), which were separated by a maximum of three days or completed on the same day separated by a break of 1 h to avoid participant fatigue. During day one, students completed a pretest and demographic questionnaire. All participants completed the session individually using a desktop computer. During day two, students

[6] This is considered a proxy for the enactment of SRL processes during learning.

participated in the learning session using MetaTutor (1 h) and completed a posttest on the human circulatory system (20 min). Prior to beginning the learning session, students completed the Achievement Goal Questionnaire. At the beginning of the session, a video tutorial demonstrated how to think-aloud and students were provided with an overview of the learning environment features (i.e., how to use the different components, navigate the system). A research assistant was present throughout the entire session and reminded participants to verbalize their thinking if they were silent for more than 3 s (based on Azevedo et al. (2010) and Ericson and Simon (1993)). After 30 min into the learning session, participants were given the opportunity to take a 5-min break. Following the learning session, participants completed a post-test. At the end of the study, all participants were debriefed and compensated with $10 per hour.

3. Results

3.1. Preliminary analysis

Assumptions of homogeneity of variance and homogeneity of covariance matrices were met, as Levene's Test of homogeneity and Box's *M* were not significant ($p > .05$) (indicating the assumption was not violated). Sample sizes in all cells were greater than the number of dependent variables for each multivariate analysis, as recommended by Tabachnick and Fidell (2007).

3.2. Multivariate and post hoc analyses

Two Multivariate Analysis of Covariance (MANCOVA) were conducted to test for main effects of experimental condition (*prompt and feedback* versus *control*) and achievement goal motivation (mastery-approach versus performance-approach) on learning processes (SRL strategies and time on relevant pages) and achievement (overall post-test score, sub-goal relevancy score, and learning gains), as well as to test for interaction effects. Two separate MANCOVAs were conducted as correlation analyses revealed that the relationships between learning process variables and achievement variables were not significant (see Tabachnick & Fidell, 2007). Furthermore, the variables within each category are conceptually related. Accordingly, dependent variables were grouped into one of two categories: *learning processes* or *achievement*. Table 1 presents correlations among all dependent variables.

The first MANCOVA for *learning processes* revealed that there was a significant main effect of experimental condition, Pillai's Trace = .24, $F(2,77) = 12.25$, $p < .01$, partial $\eta^2 = .24$, but no significant effect for the prior knowledge covariate, Pillai's Trace = .00, $F(2,77) = .06$, $p > .05$, $\eta^2 = .00$, achievement goal, Pillai's Trace = .05, $F(2,77) = 2.02$, $p > .05$, $\eta^2 = .05$, or interaction effect, Pillai's Trace = .02, $F(2,77) = .59$, $p > .05$, $\eta^2 = .02$. As demonstrated in Fig. 2, follow-up univariate and post hoc analyses revealed that there was a significant effect of condition on time on relevant pages, $F(1,78) = 20.62$, $p < .01$ with the *prompt and feedback* group spending significantly more time viewing relevant pages than the *control* group ($p < .05$). As demonstrated in Fig. 3, there was also a significant effect of condition on SRL strategies, $F(1,78) = 5.50$, $p < .05$ with participants in the *prompt and feedback* group using the SRL palette significantly more than those in the *control* condition ($p < .05$). Means and standard deviations for learning processes across condition are displayed in Table 2.

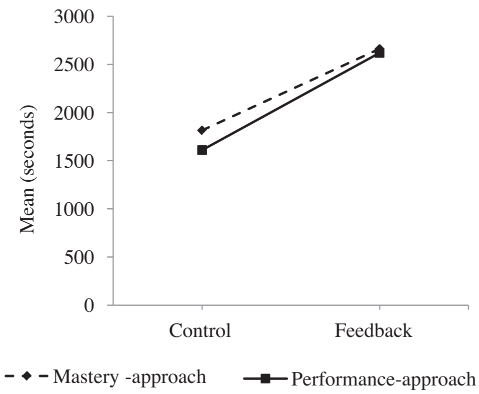

Fig. 2. Main effect of experimental condition on time viewing relevant pages.

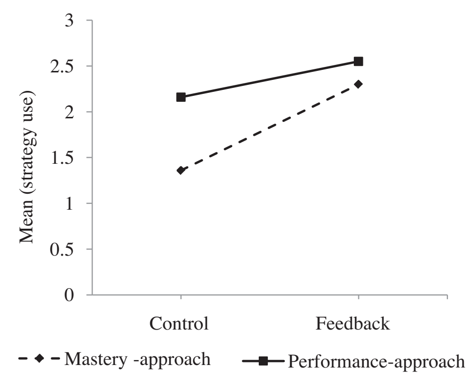

Fig. 3. Main effect of experimental condition on self-regulatory strategies.

The second MANCOVA for achievement revealed that there no significant main effect for achievement goal, Pillai's Trace = .01, $F(2,77) = .20$, $p > .05$, partial $\eta^2 = .01$, or experimental condition, Pillai's Trace = .02, $F(2,77) = .71$, $p > .05$, partial $\eta^2 = .02$. However, there was a significant effect of prior knowledge covariate, Pillai's Trace = .52, $F(2,77) = 42.19$, $p < .01$, partial $\eta^2 = .52$ and a significant interaction effect between condition and achievement goal, Pillai's Trace = .09, $F(2,77) = 3.82$, $p < .05$, partial $\eta^2 = .09$. Follow-up univariate analysis revealed that there was a significant interaction effect on: sub-goal relevancy scores $F(1,78) = 7.74$, $p < .01$, and approaching significance for both learning gains, $F(1,78) = 3.88$, $p = .05$, and post-test scores, $F(1,78) = 3.88$, $p = .05$. As

Table 1
Correlations between learning processes and achievement measures.

	Overall post-test score	Learning gains	Sub-goal relevancy score	Time on relevant pages (s)	SRL strategies
Overall post-test score	–	.21	.86**	.00	−.01
Learning gains	–	–	.10	.14	.07
Sub-goal relevancy score	–	–	–	−.05	−.01
Time on relevant pages (s)	–	–	–	–	.24*
SRL strategies	–	–	–	–	–

* $p < .05$.
** $p < .01$.

Table 2
Means and standard deviations for learning processes across condition.

Learning processes	Condition	
	Control	Prompt/feedback
SRL strategies	1.48 (1.09)	2.37 (0.97)
Time on relevant pages (s)	1782.69 (806.26)	2650.36 (642.03)

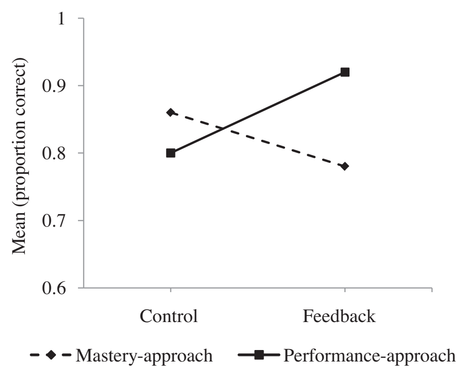

Fig. 4. Interaction between condition and achievement goals on sub-goal relevancy score.

demonstrated in Fig. 4, post hoc analyses on sub-goal relevancy scores revealed that performance-approach learners in the *prompt and feedback* condition demonstrated higher achievement scores compared to performance approach learners in the *control* condition ($p < .05$) and mastery-approach learners in the *prompt and feedback* condition ($p < .05$). In contrast, mastery-approach learners showed no significant difference in achievement across conditions, although descriptive statistics suggest that these mastery-approach learners fared better in the *control condition* than *prompt and feedback*. Means and standard deviations for achievement measures across condition for each achievement goal are displayed in Table 3.

4. Discussion

The purpose of this study was to examine whether pedagogical agents' scaffolding (instructional prompts and feedback) would impact learners' self-regulated learning processes and achievement in MetaTutor. We also aimed to better understand the interaction between agent scaffolding and learners' achievement goals. Specifically, we examined whether the dominant achievement goal adopted by learners moderated the impact of agent scaffolding. We discuss our results and the implications of these findings in the following sections.

4.1. Impact of agent scaffolding and achievement goal motivation

Results from this study demonstrate that agents' prompts and feedback within a computer-based learning environment foster learning behaviors such as increased use of SRL strategies and time viewing relevant material during the learning session. Regardless of achievement goal, learners' in the *prompt and feedback* condition demonstrated significantly more SRL strategy use. However, the results also suggest that these scaffolds are not sufficient to improve comprehension and achievement outcomes, as we did not find a significant difference between the *prompt and feedback* and *control* condition on performance measures. To understand why scaffolding for SRL did not improve performance, we draw on the findings from the motivational variable.

The agents in MetaTutor were designed to promote cognitive and metacognitive self-regulation; however, our findings suggest that motivation (in particular, achievement goal motivation) also plays an integral role. More specifically, students' dominant achievement goal interacted with the scaffolds they received, such that those with a performance-approach excelled in the *prompt and feedback* condition compared to the *control* condition, whereas those with a mastery-approach did not improve with scaffolding and the pattern suggests that they may fare better (or at least no worse) without these supports. Thus, it appears that instructional prompts and feedback may impact learning and achievement differently depending on the motivational orientation of the learner, which prompts us to ask: what accounts for these differences? It may be the case that learners adopting a mastery-approach goal, who are typically more intrinsically motivated, find the scaffolding intrusive and controlling. Research has shown that learner perceptions of goal structures (e.g., Cho & Cho, 2014), connectedness (e.g., Shea, Li, & Pickett, 2006), and autonomy support (e.g., Benita, Roth, & Deci, 2014) play a role in the effectiveness of instructional information and scaffolding. For example, Benita et al. (2014) found that perceived autonomy support influenced the relationship between achievement goals and psychological outcomes (e.g., interest, enjoyment engagement), such that mastery goals were adaptive only when learners perceived higher autonomy support. Similar to our findings, Carr, Luckin, Yuill, and Avramides (2013) also found that learners adopting a mastery-approach did not benefit from scaffolding within an intelligent tutoring system to the same extent as performance-approach learners. They speculated that it might be the lack of challenge inherent in the scaffolding that undermines mastery-approach learners' interest. Performance-approach learners, in contrast, may respond positively to prompts that help them to tailor their learning efforts and achieve higher test scores than their peers. They may also respond positively to agent scaffolding if they consider obliging to prompts and feedback to be an opportunity to demonstrate their superior competence relative to their peers. Returning to Winne and Hadwin's (2008) model of self-regulated learning, this implies that agent scaffolding, which can be considered a task condition that impacts success, may be a perceived as a *resource* for performance-approach learners' and a *constraint* for mastery-approach learners.

If these perceptions of the agent can help to explain the differences in performance between mastery-approach and performance-approach learners, then what is the underlying mechanism? One possibility is the role of emotions. For instance, if mastery-approach learners hold negative perceptions toward agents this may lead to negative emotions (e.g., anger, disgust), which can tax cognitive resources and interfere with higher-order processes that require sustained effort. In contrast, if performance-approach learners hold positive perceptions toward agents this may lead to positive

Table 3
Means and standard deviations for achievement across condition and achievement goal.

Achievement measures	Control		Prompt/feedback	
	Mastery ($N = 37$)	Performance ($N = 7$)	Mastery ($N = 28$)	Performance ($N = 11$)
Overall post-test score	21.32 (2.71)	20.14 (6.01)	19.68 (4.36)	22.18 (2.79)
Learning gains	2.24 (3.24)	1.00 (1.41)	2.11 (3.17)	3.09 (3.18)
Sub-goal relevancy score	0.86 (0.12)	0.80 (0.21)	0.78 (0.17)	0.92 (0.08)

emotions (e.g., curiosity, gratitude) that free up cognitive resources and allow for higher-order cognitive processes that enhance achievement (Pekrun & Perry, 2014). These reactions to agents may also influence willingness to deploy learning strategies (e.g., note-taking) or monitor understanding (e.g., judgment of learning). Another possibility is that learners differed in whether or not they attended to agents' prompts and feedback in the first place. If they ignored the agent and directed attention elsewhere, then we would expect this to impact their likelihood of responding to scaffolding. To test these whether these possible explanations account for differences in achievement, however, further work is needed to closely examine learners' attention, perceptions, and reactions to agent scaffolding.

4.2. Conclusions and implications

Overall, this study contributes to the emerging body of research that draws on both process and product data to examine self-regulated learning for conceptually-rich domains within hypermedia environments (Azevedo & Aleven, 2013; Azevedo, Taub, & Mudrick, 2015; Azevedo et al., 2010). The findings from this study provide evidence of the effectiveness of pedagogical agents and highlight the importance of considering motivation in relation to cognitive and metacognitive processes from both a theoretical and practical standpoint. Based on these results, we recommend that computer-based pedagogical agents be designed to assess students' achievement goals and adapt scaffolding accordingly throughout the learning session. It may also help to provide learners, particularly those with a mastery-approach, with greater autonomy by offering control over the type and frequency of prompts/feedback they receive (Scheiter & Gerjets, 2007; White & Frederiksen, 2005), or by allowing them to view their interactions with the system using an open learning model (Bull & Kay, 2013). If the learner perceives the source of regulation to be external rather than internal, then a social-cognitive framework would suggest that a social-to-self graduated movement of self-regulation could help to promote autonomy or more volitional forms of guidance (Deci & Ryan, 2011; Ryan & Deci, 2000; Zimmerman & Tsikalas, 2005). As Belland (2014) notes, scaffolding should be a dynamic process, which also involves a process of fading and transfer of responsibility (Belland, 2014). Moreover, as Moos (2014) notes, although design of pedagogical agents has largely focused on scaffolding cognitive and metacognitive processes, there is a need to embed motivational supports as well. Guidelines and frameworks for integrating motivation into instructional scaffolds are beginning to emerge (e.g., Belland, 2013) and calls have been made to develop "systems that care" (du Boulay et al., 2010, p. 197) that provide motivationally-sensitive and affect-aware intelligent tutoring systems (Carr et al., 2013; du Boulay, 2011; Rebolledo-Mendez, Luckin, & du Boulay, 2011). Indeed, several computer-based learning environments have integrated features to detect, trace, model, and support motivational and affective processes (e.g., D'Mello et al., 2011; Rebolledo-Mendez et al., 2011).

4.3. Limitations

In this study, students' self-reported achievement goals were used to identify mastery or performance dominant learners; thus, we were not able to ensure that sample sizes were equal across all cells (achievement goal and experimental condition). However, as previously indicated, appropriate preliminary analyses and statistical tests were conducted. Furthermore, by focusing exclusively on comparisons between mastery-approach and performance-approach goals we were able to directly address a pressing debate in the motivation literature surrounding the value of adopting mastery-approach versus performance-approach goal. However, it also required that we limit our sample size, which may have reduced the effect size or likelihood of detecting statistical significance. Alternate statistical analysis could be explored in future work. For example, median split analysis may help to retain a larger sample size by including participants with varying degrees (e.g., high/low) and combinations of achievement goals (e.g., performance-avoidance and mastery-avoidance) employed during learning rather than focusing on the dominant goal adopted. This approach would allow for the inclusion of students who pursue multiple achievement goals at one time (see Harackiewicz et al., 2002). Despite these limitations, we feel the approach we employed provides a much-needed person-centered analysis of learners' achievement goals (Tuominen-Soini, Salmela-Aro, & Niemivirta, 2011). In the following section we discuss the contributions of this study and future directions to expand upon this line of research.

4.4. Future directions

To expand on our findings, future research should closely examine relations between achievement goals and affective reactions to pedagogical supports. This may also involve testing whether interventions aimed at detecting and scaffolding emotion and motivation regulation address the challenges we have raised (see Azevedo et al., 2015). In addition, teasing apart the relative contribution of each agent would help to clarify whether learner's reactions to prompts and feedback vary according to unique role of each agent.

Analysis of qualitative differences in learners' deployment of specific strategies would also provide further information about differences in the nature of students' approach to learning (e.g., sophisticated [e.g., making inferences] versus less-sophisticated [e.g., maintenance rehearsal] and user-versus agent initiated strategy use) as previous research has demonstrated that strategy use varies not only in the quantity (e.g., frequency and volume of content) but also the quality (e.g., copying verbatim versus inference generating (e.g., Trevors et al., 2014). Similarly, testing the relative contribution of each self-regulated learning strategy using data mining techniques and profile analyses would help us to determine which specific strategies or sub-sets of behaviors accounted for greater variance in learning outcomes (Winne & Baker, 2013).

We also suggest that future studies administer achievement goal measures at various points during learning and following the post-test to assess the stability of learners' achievement goals over time (see Fryer & Elliot, 2009; Muis & Edwards, 2009; Tuominen-Soini et al., 2011). According to Winne and Hadwin's (2008) model of self-regulated learning, achievement goals may change at different phases of learning based on changes in task conditions (e.g., instructional supports), evaluations (e.g., interpretation of quiz results), and standards (e.g., criteria used to determine success or failure). Thus, a fine-grained analysis of achievement goals at multiple time-points would allow researchers to test multiple pathways and the recursive nature of self-regulated learning by examining whether learners' achievement goals vary in strength as they evaluate their progress and receive more information about the nature of the learning environment (Bernacki, Nokes-Malach, & Aleven, 2013; Bernacki et al., 2014). It may also be worth examining other facets of motivation (e.g., self-efficacy, intrinsic motivation) in relation to achievement goals. In a similar vein, finer-grained analysis should also be employed for outcome measures, such as examining differences between post-test scores for questions that emphasize inference generation compared to rote memorization, as recent research suggests that mastery-approach goals may predict better performance on more cognitively complex post-test questions, such as those that assess knowledge transfer (e.g., Carr et al., 2013). Finally, we contend that researchers continue to include process measures when examining self-regulated learning, as this type of data is ideal to capture the temporal and dynamic nature of self-regulation and to advance our understanding of the role of multiple regulatory processes involved in learning. The findings from this study demonstrate that motivation is indeed an important variable to include in these future analyses.

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Appendix A

A.1. Adapted achievement goal questionnaire (Elliot & Murayama, 2008)

1. My aim is to completely master the material presented during this learning session.
2. I am striving to do well compared to other student participants.
3. My goal is to learn as much as possible.
4. My aim is to perform well relative to other student participants.
5. My aim is to avoid learning less than I possibly could.
6. My goal is to avoid performing poorly compared to other student participants.
7. I am striving to understand the content of this learning session as thoroughly as possible.
8. My goal is to perform better than the other student participants.
9. My goal is to avoid learning less than it is possible to learn.
10. I am striving to avoid performing worse than other student participants.
11. I am striving to avoid an incomplete understanding of the material.
12. My aim is to avoid doing worse than other student participants.

Appendix B

B.1. Sample pre-test and post-test items (Azevedo et al., 2013)

1. Nicotine causes arteries to constrict. What might happen if Mr. Smith, whose coronary arteries are partially blocked by plaque, smokes cigarettes?
   A. The arteries might completely constrict and lead to a heart attack.
   B. The diameter of the arteries might increase in response to the nicotine.
   C. The nicotine might enlarge the arteries and repair the damage.
   D. The nicotine might affect his breathing.
2. What is the effect of the clotting process?
   A. Bleeding is stopped and damaged blood vessels are repaired.
   B. Antibodies are released to fight infection.
   C. Waste products are picked up from the body.
   D. Undigested food is eliminated.
3. The American Heart Association recommends that about 25% of a person's daily calories should come from fat. Mr. Spencer's diet is 40% fat. What situation may result from this?
   A. The increase of plaque buildup in his arteries.
   B. An increase in the size of his heart.
   C. Increased blood clotting.
   D. Poor antibody production.
4. What might happen in a disease when alveoli are stiff and not very flexible?
   A. It might be more difficult for gas exchange to occur.
   B. They might not be connected to the bronchial tubes.
   C. They might not be surrounded by capillaries.
   D. It might be easier to send fats to the liver.
5. What are the tiny air sacs that are found at the end of the branches of the bronchial tubes?
   A. Alveoli.
   B. Capillaries.
   C. Lungs.
   D. Glands.

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