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RESEARCH ARTICLE

Self-regulation of motivation when learning online: the importance of who, why and how

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Abstract Successful online students must learn *and* maintain motivation to learn. The Self-regulation of Motivation (SRM) model (Sansone and Thoman 2005) suggests two kinds of motivation are essential: Goals-defined (i.e., value and expectancy of learning), and experience-defined (i.e., whether interesting). The Regulating Motivation and Performance Online (RMAPO) project examines implications using online HTML lessons. Initial project results suggested that adding usefulness information (enhancing goals-defined motivation) predicted higher engagement levels (enhancing experience), which in turn predicted motivation (interest) and performance (HTML quiz) outcomes. The present paper examined whether individual interest in computers moderated these results. When provided the utility value information, students with higher (relative to lower) individual interest tended to display higher engagement levels, especially when usefulness was framed in terms of personal versus organizational applications. In contrast, higher engagement levels continued to positively predict outcomes regardless of individual interest. We discuss implications for designing optimal online learning environments.

Keywords Self-regulation of motivation · Interest experience · Online learning · Utility value · Engagement · Individual interest · Goals-defined motivation · Experience-defined motivation

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Computer-based learning environments (CBLEs) allow individuals to actively engage in and regulate learning activities. Active engagement has long been recognized as important for sustained learning (e.g., Dewey 1913; McKeachie et al. 1978), and learning online would thus appear to be particularly beneficial for promoting motivated learning. However, the same characteristics (e.g., self-paced, self-directed) allow individuals to choose to disengage, engage at a minimal level, or "click through" the options without actually processing them. In the Sloan Consortium's 2006 study of online teaching in U.S. higher education (Allen and Seaman 2006), 63% of Chief Academic Officers viewed the dependence on students' abilities to sustain motivation as a critical barrier to greater adoption of this medium.

Models of self-regulated learning include an important role for motivational processes, such as self-efficacy beliefs (Pintrich 2000), and these models have been applied more recently to CBLEs (Azevedo 2005; Perry and Winne 2006; Winters et al. 2008). Although conceptually the models acknowledge the importance of motivation, empirically the research has focused primarily on how features of the CBLE support or affect cognitive and behavioral aspects of self-regulated learning (e.g., goal setting, monitoring, knowledge acquisition) (Zimmerman and Tsikalas 2005). This work also emphasizes how CBLEs lend themselves to measurement of self-regulatory processes "online" (Schraw 2010; Winne 2010). These include the potential to measure "traces" of self-regulated learning (e.g., whether text was highlighted), and how these traces map onto learning outcomes (e.g., comprehension).

Although motivation is essential to learning no matter the context, it is particularly critical when learning online, where whether students engage the material, how, and how long, is entirely within their control (e.g., Sansone et al. 2002). In this case, the computer based learning environment is not one part of a class, but encompasses the entire class. Others are not present to prompt and guide self-regulation (e.g., on how to monitor progress), which Azevedo and colleagues have shown results in better self-regulation than when students are left on their own (Azevedo et al. 2008). Thus, successful online students must learn the material, and must maintain motivation to learn the material, on their own.

The present paper uses the Self-regulation of Motivation (SRM) model to guide the examination of whether and how motivational processes work over time in the process of learning online. The SRM model suggests that it is not sufficient to examine whether students have the necessary *level* of motivation to learn the material. The focus only on level assumes that motivation has a linear effect on learning outcomes (i.e., more motivation predicts better learning). In contrast, the SRM model proposes that the type of motivation as well as level is important to consider, because what motivates students when they begin learning might not be the same once engaged. Moreover, the model assumes that an important regulatory task is to regulate motivation as well as cognition and behavior. Strategies for regulating motivation might be considered effective by students, but not by educators, if strategy use results in students needing to spend more time on the task to demonstrate similar knowledge levels. Similar to research measuring traces of metacognitive processes when learning within CBLEs (e.g. Azevedo et al. 2010), therefore, our research attempts to measure traces of motivational self regulation.

Self-regulation of motivation model

The Self-regulation of Motivation (SRM) model (Sansone and Thoman 2005) suggests that considering students to be "motivated" or "unmotivated" blurs the distinction between two kinds of motivation that are embedded in self-regulation over time. The first kind, and the type typically discussed in self-regulation models, is defined in terms of achieving goals or outcomes. The more that students value a particular goal (e.g., learning HTML) and expect to achieve it (e.g., believe they have the efficacy to reach this goal), the more motivated they will be to put in the time and effort to reach that goal, use strategies that they believe will aid that goal, and evaluate their progress in terms of that goal (e.g., Eccles and Wigfield 2002; Linnenbrink and Pintrich 2000).

The SRM model (see Fig. 1) proposed that in addition to this goals-defined motivation, motivation defined in terms of the experience (i.e. whether interesting and involving) is also critical for sustained engagement. Goals-defined motivation may be essential in directing initial choice of tasks (e.g., choosing to access the online lesson as opposed to watching TV), and initial actions once engaged in a learning task (e.g., reading the text on the lesson page). However, these actions also affect the experience while working on the lesson. For example, if the lesson text is interesting and engaging versus monotonous and dry, the same action (reading required text) will result in different experiences. Moreover, subsequent actions ("maintenance actions") may be in service of reaching goals *or* in service of making the experience more interesting, particularly over a longer time period. For example, when someone clicks on optional links in a lesson, this action may be motivated by the desire to attain the goal of learning about the topic (goals-defined motivation). However, this action might also be motivated by the desire to break up the monotony of reading text on a screen (experience-defined motivation).

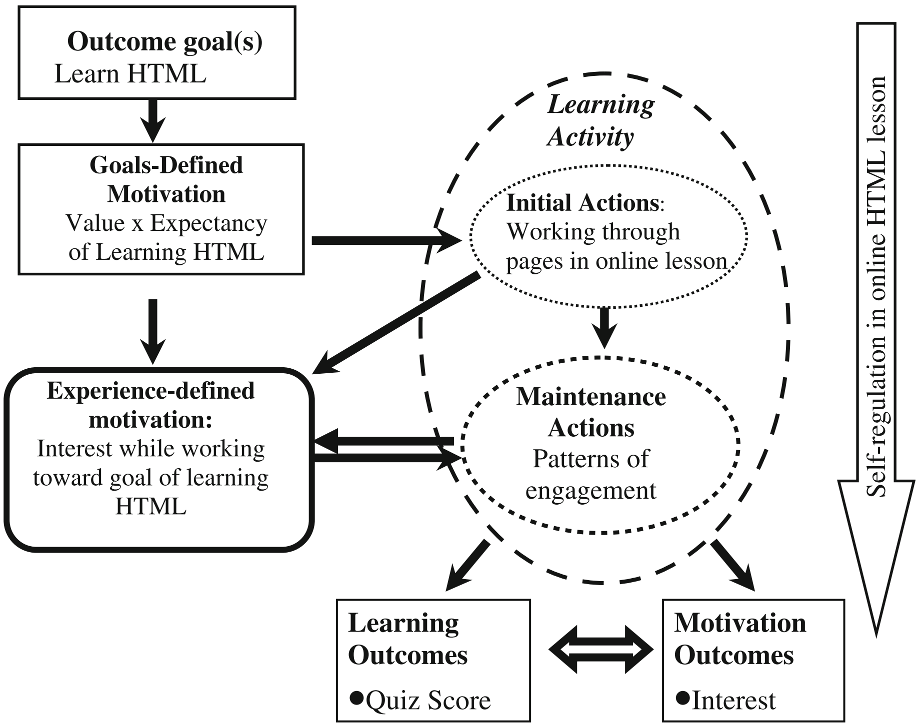

Fig. 1 Self-regulation of Motivation model as applied to learning HTML online

Even if motivated by the desire to learn about the topic (i.e., regulation in service of the goal), by breaking up the monotony, the action might also make the learning experience more interesting and thus promote continued motivation to work on the lesson. Conversely, if the same action were instead motivated by the desire to break up the monotony (i.e., regulation in service of the experience), by choosing to access additional material, students might also come to learn more.

Moreover, research by Sansone and colleagues (Sansone et al. 1992, 1999) suggests that there may be a sequential relationship between goals-defined and experience-defined motivation. When students worked on a repetitive task in the lab, they were more likely to engage in actions that made the experience more interesting (e.g., varied the procedure) when they had first been told that there were good reasons (e.g., health benefits) to persist at the boring task. Thus, students were more likely to exert the extra effort to do the things that made the experience more interesting when given a reason to value persistence (Smith et al. 2009).

Application to learning online

The SRM model suggests that although the degree of initial goals-defined motivation is important, its effect on motivation and performance outcomes may not be direct, but depend on its relationship to students' actions while working on the online learning task. In other words, enhancing students' motivation to reach learning goals might affect motivation and performance outcomes because it affects whether and how students attempt to make the experience of learning more interesting and involving. Interventions to make students more "motivated" to learn the material may thus depend on whether and how this goals-defined motivation enhances, detracts from, or has no effect on, the experience. From this perspective, when students engage in actions (e.g., click on interesting links) because they make the experience more interesting, this may not reflect ineffective self-regulation, in contrast to how other researchers categorize these actions (e.g., Salmerón et al. 2010). Rather, over the longer term, these actions may allow greater persistence and re-engagement of the material (Sansone 2009).

The Regulating Motivation and Performance Online (RMAPO) project was developed to begin to examine the implications of the SRM model for online learning. For this project, Sansone and colleagues created for the lab an online lesson on HTML that was based on lessons used in a real online programming class. As a first step, they varied only the initial description of the lesson such that it just described the skills to be learned (control), or enhanced goals-defined motivation by adding reasons to value learning these skills. In particular, the lesson description explicitly made connections between the skills and how they could be used to create personal web pages or to create business and organizational web pages. Initial results (Sansone et al. 2010) suggested that adding utility value did not directly affect motivation (interest) and performance (quiz on HTML knowledge) outcomes. Rather, as compared to the control, the added utility value was associated with more active engagement while working on the lesson, as measured by the frequency with which students manipulated and modeled HTML codes in optional examples and exercises. Mid-level engagement (modeling only) predicted higher quiz scores, and higher level engagement (manipulating and modeling) predicted greater interest at the end of the 1½ h session.

These results suggested that the added utility value information was beneficial for motivation and learning outcomes, in line with models that suggest that enhancing value leads to greater motivation and performance (Hulleman and Harackiewicz 2009). However, the added utility value was associated with better outcomes because it was associated with higher levels of engagement with optional examples and exercises, suggesting that the experience while learning was a critical mediator of the effects (Sansone and Thoman 2005). These results also show the importance of tracing motivational processes in CBLEs over time. Specifically, the online environment allowed for different levels of interaction with the optional examples and exercises, and the different levels were differentially related to learning and interest.

Do individual differences in interest matter?

These initial results suggested that adding explicit connections between the material and its potential use in real life could turn “unmotivated” students into “motivated” ones. However, their results were obtained without examining differences in initial motivations that students might have brought to the learning situation. In the present paper, we examined whether the previously found results changed if we took into account individual interest in computers (Hidi and Renninger 2006). Students with well-developed individual interests in a topic or area have greater knowledge about the subject, value the topic area, and find engaging related material interesting and enjoyable. They are more likely to make their own connections between the new material and what they already know and value, and voluntarily spend time and effort to learn more, build skills, and engage in related activities (Krapp and Lewalter 2001; Renninger et al. 2004; Schiefele 1996).

For the present case, previous research suggests at least two alternative ways in which preexisting individual interest in computers might affect motivation and performance outcomes. One alternative is that students who come to the lesson with greater interest in computers may display greater knowledge and interest regardless of added utility information, because the learning task is relevant to their interests and they make the connections on their own. Regardless of the value manipulation, then, they might show greater motivation and greater learning at the end of the lesson compared to those with lower interest. The second alternative is that rather than affecting outcomes as a main effect, preexisting interest may be associated with greater responsiveness to added utility value manipulations (Durik and Harackiewicz 2007). That is, students with higher individual interest in computers may be more receptive to the added value information, and find the experience more interesting because of the added utility value (Durik and Harackiewicz 2007).

These opposing predictions only address the potential influence of preexisting individual interest on *outcomes*. However, there are also potentially opposing predictions for how individual interest in computers might affect the *process*, particularly in terms of patterns of engagement. Although previous research has not distinguished between goals-defined and experience-defined motivation when examining individual interest within the self-regulatory process, the distinction might matter.

For example, because students with greater individual interest in the topic presumably expect the material to be useful and interesting, they might have less need to regulate the experience once they begin. Their motivation and performance at the end of the lesson may thus be less dependent on their actions during the lesson. Alternatively, individual interest might work to make students more likely to do the lesson in ways that make the experience more interesting and useful (e.g., explore what happens when you change the HTML codes in the examples). In this case, students with individual interest might display greater self-directed exploration, but only if and when they see the activity as relevant to their interest and the activity provides opportunities for exploration (Azevedo 2006).

The potential increased sensitivity to interest-relevance also implies that students with higher individual interest might be *less* likely to engage the activity at high levels if they do not see the activity as relevant or if the activity is structured in ways that do not allow them to explore as they wish (see Renninger et al. in press). An implication for the present study is that although Sansone et al. (2010) found that the added utility value information was associated with similar patterns of engagement regardless of whether the information was framed in terms of personal or organizational applications, it is possible that the area of application might matter to students with different levels of individual interest in computers.

Present study

In the present paper, we utilize data from the RMAPO project to examine whether motivational differences that students bring to the learning situation change how they regulate their interest and learning online. We focus on individual interest in computers, measured prior to the online HTML lesson, and examine whether this individual difference moderates whether and how added utility value manipulation affects the online learning process.

Methods

Participants

Undergraduates ($n = 108$, 70% female, 77% white) were recruited using the Psychology subject pool in exchange for course credit. Their mean age was 24 (range 18–67 years) and their mean reported GPA was 3.3 (range 1.33–4.00). Participants were recruited over the course of two different semesters. Three participants did not complete the entire set of interest measures at the end of the study, and therefore were excluded from these analyses.

Procedure

As part of the larger RMAPO Project, the first portion of the study involved completing an online survey that included a variety of questions assessing background information and individual differences, including questions assessing individual interest in computers. Upon survey completion, participants were assigned a time to come into the lab to complete the in-person portion of the study.

The lab was set up to resemble a typical on-campus computer lab. Upon arrival, participants were assigned to a computer workstation where they were to evaluate an online lesson in HTML programming. This lesson was created by adapting and combining several lessons from an actual beginner's course in HTML programming taught at the University of Utah.

The "computer lab attendant" (actually a research assistant) gave general instructions for accessing the online lesson, and reiterated the information in the lesson introduction that informed participants that they could take bathroom breaks or get up to get a drink during the 90 min session. Participants were also told that the "lab attendant" would not be able to help with any content-related problems, but was available if they had problems with the computer (e.g., if the computer froze). The "lab attendant" then went back to a separate workstation that clearly did not allow him or her to see participants as they worked on the lesson. This was our effort to create an environmental analog to students working on an actual online course, where their actions would not be monitored and how they used their time was up to them.

Once students had logged in, the computer displayed a brief lesson description in which was embedded the utility value manipulation. Students were randomly assigned to read one of three versions of the lesson description. In the control group, the lesson was described just in terms of learning HTML (neutral condition; $N = 37$). In the other two conditions, the lesson was described either in terms of learning HTML to create a personal webpage (personal application; $N = 33$), or in terms of learning HTML to create a webpage for a business or organization (organizational application; $N = 35$).

In all three conditions, the HTML skills to be learned (e.g., text positioning, inserting images) were described identically. The differences appeared only in the examples of how they could use these skills. In the neutral condition, the use of these skills was described in a generic way (e.g., will allow you to insert an image on a web page). In the personal applications condition, the use of these skills was described in terms of personal web pages (e.g., will allow you to insert a picture of you and your family on your personal web page), whereas in the organizational applications condition, the use of these same skills was described in terms of business or organizational web pages (e.g., will allow you to insert an image of a company's product on the business' web page). Besides these differences in initial framing of the lesson, all other materials were identical between conditions.

After reading the initial descriptions, participants answered several items assessing their understanding of the instructions and expectations for the lesson, and then the actual lesson began. The first few pages of the lesson instructed participants about the use of optional examples and exercises. The buttons to access these examples and exercises were displayed at various points on the main lesson pages. When participants clicked on one of these buttons, a new window would open up, displaying sample HTML code. While these materials were not required to complete the lesson and the assignment at the end of the lesson, they were introduced as tools students could use to actually see what HTML code looks like, and how HTML code can be used to create and change what a web page looks like.

After 90 min of working on the lesson and lesson assignment (whether or not participants had completed the assignment), a post-lesson questionnaire appeared on the screen in place of the browser window. After they completed the questionnaire, the final screen thanked participants for their time and confirmed the amount of credit that they had earned.

Measures

Individual interest in computers was assessed by three items in the online survey completed prior to the in-lab portion of the study. Participants rated their knowledge, interest and value of computers, using 1 (very low) to 5 (very high) scales. Responses were combined to create an individual interest measure ($\alpha = .70$). Anticipated interest ("How interesting do you think the lesson will be?") and anticipated usefulness ("How useful do you think learning the material in this lesson will be?") were measured by one item each, assessed after participants read the instructions but prior to beginning the lesson, using 1 (not at all interesting/useful) to 5 (very interesting/useful) scales.

We assessed use of the optional examples and exercises in three different ways. At the first level, we assessed the number of times that participants simply accessed the examples or exercises across the entire lesson (Degree Accessed). Once participants opened the example or exercise window, they then had two further options. They could click on a “model” button that would open a second window that showed how the sample code affected the web page, and/or they could click on the “change” button that would open a second window that would allow them to manipulate the sample code and model the effects of those changes on the web page. As a measure of the second or mid-level of engagement, therefore, we assessed the number of times that participants clicked on the “model” button across the entire lesson (Degree Modeled). As a measure of the third and highest level of engagement, we assessed the number of times that participants clicked on the “change” button across the entire lesson (Degree Manipulated/Modeled).

Learning was assessed by a short multiple choice quiz in the post-lesson questionnaire (Quiz Score). The quiz was comprised of questions about HTML code that had been taught in the lesson (e.g., “what happens when you place a
 tag at the end of a line of text?”, “How many rows in a table will the following line of code create?”). Possible scores ranged from 0 to 15.

Finally, Lesson Interest was assessed in the post-lesson questionnaire, where participants rated how much they agreed with each of five statements (e.g., “I would describe this lesson as very interesting”, “I enjoyed doing this lesson very much”) using 1 (Strongly Disagree) to 5 (Strongly Agree) scales. These items were combined ($\alpha = .88$), with possible scores ranging from 5 to 25.

Results

Analyses overview

A regression model was created that included two orthogonal contrast codes for the manipulation of utility value: *Value added versus No value added* (+1 for Personal and Organizational conditions, −2 for Control condition), and *Personal versus Organizational Value* (+1 for Personal, −1 for Organizational, 0 for Control conditions). These two contrasts comprised the model previously tested and reported in Sansone et al. (2010). For the present paper, we added to this model the main effect of individual interest in computers (centered), and the interactions between each of the contrasts and individual interest. We report whether and how the inclusion of individual interest in computers changed or moderated previous results that did not take into account preexisting differences in individual interest. To interpret any significant interactions, predicted values were generated from the regression equations using the contrast codes and scores 1 SD above and below the mean to represent typical high and low scorers on the measure of individual interest in computers.

Did individual interest moderate the effects of the manipulation on anticipated usefulness and anticipated interest prior to working on the lesson?

When the model was regressed on anticipated usefulness, the previously found main effect of the Value added versus No value added contrast remained ($t(100) = 3.52$, $p = .00$, $b = .23$, $SE = .06$). However, this main effect was qualified by a significant interaction with individual interest ($t(100) = 2.41$, $p = .02$, $b = .08$, $SE = .03$). Predicted values indicated that the increase in anticipated usefulness when provided utility value information was even greater when individuals had higher individual interest (Lower individual interest: No value added, $\hat{Y} = 3.30$, Value added, $\hat{Y} = 3.52$; Higher individual interest: No value added, $\hat{Y} = 2.68$, Value added, $\hat{Y} = 3.79$).

When the model was regressed on anticipated interest, there were marginally significant main effects of both contrasts, suggesting that students anticipated greater interest when utility value information was added ($t(100) = 1.86$, $p = .07$, $b = .12$, SE $= .07$), and when the added value was described in terms of organizational as opposed to personal applications ($t(100) = -1.74$, $p = .08$, $b = -.21$, SE $= .12$). However, there was a significant interaction between individual interest and the Personal versus Organizational Value contrast ($t(100) = 2.30$, $p = .02$, $b = .16$, SE $= .07$). Predicted values indicated that the preference for organizational versus personal applications was true only for students lower in individual interest in computers (Lower individual interest: Personal application, $\hat{Y} = 2.41$, Organizational application, $\hat{Y} = 3.41$; Higher individual interest: Personal application, $\hat{Y} = 3.21$, Organizational application, $\hat{Y} = 3.04$).

Individual interest thus appeared to be important in terms of influencing students' expectations prior to beginning the lesson. However, differences in individual interest did not directly predict expected usefulness or interestingness. Rather, individuals higher in individual interest expected the material to be more useful primarily when provided the added utility value information, and anticipated greater interest when the information was framed in terms of personal rather than organizational applications. We next examined whether individual interest influenced how individuals actually did the lesson, in terms of the degree to which they accessed the optional examples and exercises, and the degree to which, once they accessed them, they chose to model and manipulate the HTML codes in the examples and exercises.

Did individual interest moderate the effects of the utility value manipulation on patterns of engagement?

When the model was regressed on Degree Accessed, neither condition contrast was significant (as found previously). There was a new interaction between individual interest and the Value added versus No value added contrast ($t(102) = 2.03$, $p = .04$, $b = 5.83$, SE $= .29$). Predicted values indicated that when utility value information was added (no matter whether framed in terms of personal or organizational applications), individuals higher in individual interest accessed the examples and exercises more frequently (Lower individual interest: No value added, $\hat{Y} = 25.80$, Value added, $\hat{Y} = 22.74$; Higher individual interest: No value added, $\hat{Y} = 22.16$, Value added, $\hat{Y} = 25.64$).

We next examined whether individual interest influenced how students interacted with the examples and exercises after they accessed them. When the model was regressed on the degree to which students Modeled the HTML code, the previously found main effect of the Value added versus No value added contrast remained ($t(102) = 3.70$, $p = .00$, $b = 2.04$, SE $= .55$). This main effect was qualified by a marginally significant interaction with individual interest ($t(102) = 1.77$, $p = .08$, $b = .51$, SE $= .29$), such that the added utility value information was associated with greater modeling especially by students higher in individual interest (Lower individual interest: No value added, $\hat{Y} = 11.09$, Value added, $\hat{Y} = 14.31$; Higher individual interest: No value added, $\hat{Y} = 7.65$, Value added, $\hat{Y} = 16.66$).

When the model was regressed on the degree to which students Manipulated/Modeled the HTML codes, the previously found main effect of the Value added versus No value added contrast remained ($t(102) = 2.71$, $p = .01$, $b = 3.42$, SE = 1.26). However, there was also a new, marginally significant interaction between the Personal versus Organizational Value contrast and individual interest ($t(102) = 1.88$, $p = .06$, $b = 2.38$, SE = 1.26). Predicted values indicated that individuals higher in individual interest manipulated/modeled the code more when the potential utility was framed in terms of personal rather than organizational applications, whereas individuals lower in individual interest showed the reverse pattern (Lower individual interest: Personal application, $\hat{Y} = 23.67$, Organizational application, $\hat{Y} = 31.06$; Higher individual interest: Personal application, $\hat{Y} = 32.02$, Organizational application, $\hat{Y} = 21.5$).

Did individual interest moderate the relationships between the patterns of engagement and motivation and performance outcomes?

The previously found relationships between the three measures of engagement and Lesson Interest and Quiz Scores remained the same when individual interest in computers was taken into account (either as a main effect or in interaction with each of the three engagement behaviors). That is, regardless of individual interest in computers, the degree to which students simply accessed the examples and exercises did not predict either outcome. In contrast, greater Manipulated/Modeling of the code in the examples and exercises predicted greater lesson interest, and greater Modeling and greater Manipulated/Modeling of the code predicted higher quiz scores. There were no direct effects of individual interest in these models.

Discussion

Individual interest in computers did not directly affect motivation and performance outcomes, nor did it directly affect students' patterns of engagement during the lesson. Rather, individual interest tended to amplify the effects of utility value information in promoting use of optional examples and exercises. Rather than the added utility value information being unnecessary for students who approached the lesson with greater individual interest in the topic, the explicit connections to how the material could be used were even more influential.

These results suggest that preexisting individual interest in computers tended to influence the process by making students more active in how they used the online lesson, particularly when the initial framing of the lesson made explicit connections for how the skills could be used in real life. When provided information that enhanced goals-defined motivation, therefore, students with higher individual interest were even more likely to regulate the experience, whether or not that was the initial intent of their actions. These results suggest that individual interest may increase the importance of the situational experience while working toward the goals, rather than making the experience less important.

The results also suggest that the type of utility value information might matter when taking into account the students' degree of individual interest in computers. For example, when averaged across individual differences, the added utility value had similarly positive effects on patterns of engagement whether framed in terms of personal or organizational applications. However, this was not the case when individual interest in computers was considered. Individuals higher in individual interest expected the material to be more interesting, and tended to become engaged at higher levels (greater degree of manipulating and modeling the sample HTML codes), when the value was framed in terms of personal rather than organizational applications. In attempts to promote greater motivation for online students, these results suggest that explicitly providing potential connections between the material and real life might backfire if the connections are not ones relevant to students' already established interests in the topic (Renninger et al. in press). In contrast, when there was little preexisting interest, the explicit connections to how individuals could use the skills in real life were more motivating when framed in terms of potential work applications. For these students whose interests make them less likely to voluntarily engage in computer-related activities, framing usefulness in terms of personal applications is liable to make them even less likely to explore optional material on their own.

Limitations

Although we have examined the effects of adding utility value to the description of an online HTML programming lesson in the lab, we have not actually examined the effects in the context of a real online course. The lesson in our study lasted only 90 min, and so it is important to ask whether the beneficial effects of providing information about how the skills could be used would actually translate to better learning and interest when learning takes place throughout an entire semester-long course.

In addition, although the participants in our study were undergraduates, they participated in the study as a way of earning credit in their psychology class, and the ostensible goal of their participation was to "evaluate" the lesson. This is not the same situation as when a student chooses to enroll in an entire class where they receive grades on performance, and so it is possible that our results are limited in their ability to generalize. The potential differences are important in interpreting the present findings.

Design implications

The Self-regulation of Motivation model suggests that to make students more "motivated" when learning online, one should take into account both goals-defined and experience-defined motivation, and the relationship between them. This perspective has important implications for how we choose to design online lessons. For example, if the present lesson, based on material drawn from a real online class, had not been designed to include opportunities for the higher and more interesting levels of engagement while learning (i.e., modifying and modeling sample HTML codes), the added utility value might not have had any impact on motivation and performance outcomes. The implication of this finding may be especially critical for situations when learning progress depends mostly on students' own regulation, as is the case when learning takes place entirely online. These results suggest that the lack of integrated opportunities for exploration and "playing" with the new material could result in poorer outcomes even when students begin with a high degree of motivation to learn the material.

This perspective also suggests the possibility of an opposite problem. If students do explore and play with new material, there is the potential that they will spend less time on material that will be tested. In this case, students' actions may make the experience of learning more interesting in the short term, but may negatively impact scores on externally defined criteria that assess learning (Harp and Mayer 1998; Garner et al. 1989; Sansone 2009). As a result, in the longer term the actions may come at a cost to both learning and motivation outcomes. This means that simply adding optional features to online lessons will not necessarily be beneficial for both motivation and learning outcomes. Rather, there may sometimes be trade-offs between designing a lesson to maximize self-directed motivation and designing a lesson to maximize the amount of novel material to which students would be exposed. By conceptualizing students' actions as being directed by goals-defined *and* experience-defined motivation, however, our approach provides guidelines for identifying critical parameters when designing features that can promote long term learning as well as the motivation to learn.

Furthermore, our present results suggest that although overall the nature of the utility value did not matter, this was not the case when we took into account students' interests coming into the lesson. This suggests that to optimize sustained learning over time, it may be beneficial to design online environments in such a way that the applications of what is being learned can be tailored to individuals' interests. These latter findings suggest the possibility of "personalizing" learning activities in terms of motivational enhancements (Cordova and Lepper 1996), which may be easier to implement in online learning contexts. Although researchers and educational designers have noted the potential benefits of personalizing instruction in terms of students' background knowledge and expertise (e.g., Butcher and Sumner in press), our research suggests that incorporating students' motivational backgrounds may also be key for optimizing learning online.

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