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Motivational factors in online learning
(extended summary)

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Introduction

Online learning has the potential to democratize education. It can be much more than a smart strategy on the part of educational institutions worldwide. It can fundamentally change the way we think about and conduct education.

In the last two decades alone, online learning has evolved from being an exotic supplement to classroom instruction, reserved to the few technical savvy instructors, to being an extensively used medium for delivering education. Recent data from extensive surveys in America, Europe and Asia show that both corporate and higher education decision-makers consider online learning a critical strategic asset for their institutions. Over 7 million undergraduate students enrolled in at least one online course. Almost one third of corporate training in America being delivered electronically. It is now self-evident that this type of education delivery system is critical for both public and private institutions.

Under such circumstances, there is a dire need for empirically based guidelines and best practices, and there are many studies conducted in this area, especially on how contextual, design and learner characteristics interact to affect learning and performance. Meta-analyses published on the topic of online learning show it is at least as effective if not more so, compared to classroom instruction. They also pinpoint some critical aspects of instructional design that can significantly increase student performance.

However, there is still a dark side to online learning. Students enrolled in online courses still have significantly higher attrition rates compared to traditional, classroom students. Many of them drop out or fail to pass examinations. Some theorists in the field proposed alternative explanations for this phenomenon. Mostly, they gravitate around higher levels of self-determination, and implicit lack of instructor guidance and peer support. When learning online, students have more control over how and how much they learn. In order to succeed, they need to be more adept at self-regulation, they need higher levels of motivation, and better use of learning strategies.

Therefore, high attrition rates, higher self-determination, and extant accounts of online students self-regulatory behaviors and beliefs, suggest we need to do more to understand their motivation and to identify ways of enhancing it. So far, we have mostly emphasized cognitive aspects of online learning and instructional design. Very little has been done to isolate motivational aspects of online learning, how they impact performance, and most importantly, what we can do to enhance them.

This thesis presents the results of a research program focused on the motivational side of online learning. Its core purpose was to identify aspects of online students' motivation, based on theory and previous research, to explore how they may affect academic performance, and to propose and test several types of instructional interventions targeted at enhancing motivation.

Chapter 1. Online learning: scope and effectiveness

The use of computers and the Internet to deliver learning experiences to students both in academia, and organizations increased dramatically in the last decade. Especially in the US, but also in Europe and Asia, online learning has become a realistic alternative to face-to-face classroom learning, or at least it is used to complement the classic approach.

The proportion of academic leaders who report that online learning is critical to their institution's long term strategy has grown from 48,8% in 2002 to 70,8% in 2014 (Allen & Seaman, 2015).

The number of students in the United States that access at least one online course has risen from 2.4 million in 2004 (Allen & Seaman, 2006) to 7.1 million in 2013 (Allen & Seaman, 2015). And although the United States are usually trend-setters in learning and development, the growth rate (approximately 4%) is not even among the top 10 worldwide (Adkins, 2013), according to a global market analysis conducted by Ambient Insight. Surprisingly, this report puts Romania in the fourth place (after India, China, and Malaysia) in terms of market growth, with a 38% estimated growth rate for 2010-2015.

Moreover, the overall growth in eLearning adoption is not limited to universities. For example, a survey of member organizations of the American Society of Training and Development's benchmarking service showed the percentage of companies using technology-delivered training increased from 8% in 1999 to 27% in 2004, and about 75% of the technology-delivered courses in 2004 were online (Sugrue & Rivera, 2005).

Online learning effectiveness

Survey results presented above suggest that online learning is adopted by more and more universities and companies worldwide. But is it effective and efficient in developing student knowledge and skills?

Currently, there are several meta-analyses comparing online with classroom instruction (e.g. Zhao, Lei, Lai & Tan, 2005; Means et al., 2009; Sitzmann et al., 2006). Zhao et al. (2005) conducted a meta-analysis to compare the effectiveness of distance education courses (i.e. courses where the instructor and students are physically separated) to face-to-face courses and found no difference in the overall effectiveness of the two delivery settings.

Means et al. (2009) showed that classes with online learning (whether completely online or blended) produce stronger student learning outcomes than do classes with solely face-to-face instruction. The mean effect size for all 51 contrasts was 0.24 with $p < .001$.

When comparing purely online courses with face-to-face instruction, the mean effect was 0.14, which was statistically significant ($p < .05$). On the other hand, when blended conditions (with classroom learning complemented by online learning) was compared with face-to-face instruction alone, the main effect size was 0.35 ($p <.001$). The authors also show that the difference in effect size between online vs classroom and blended vs classroom is significantly smaller.

On the other hand, **Sitzmann et al.'s (2006)** meta-analysis differentiated between effects on declarative knowledge and procedural knowledge. Their analysis showed online learning to be 6% more effective than classroom instruction (CI) for teaching declarative knowledge. However, there was no difference between the two means of instruction regarding procedural knowledge. Moreover, results indicated that trainees were equally satisfied with the two delivery media.

All in all, we now have sufficient data to conclude that online learning can be as effective as classroom learning, if not more effective under certain circumstances. Moreover, extant research suggests some pathways to enhance learning by means of instructional design. Although they might also impact student motivation by making the materials to be learned more attractive, these studies have little to offer in answering instructors' and decision makers' worries that online learning leads to more attrition, and that students are not motivated or disciplined enough to optimally benefit from online courses.

In order to address these concerns, however, we first need a more thorough understanding of classic theories of motivation with extensive applications for learning contexts. Next, we will present the most important motivational theories in education: expectancy-value theory, social-cognitive theory, and theories about interest.

Chapter 2. Theories of motivation

There are numerous theories explaining students' motivation for learning. We have selected expectancy-value theory, social-cognitive theory and interest theory, as they are the most established, well-researched and validated. Also, they are mostly complementary and can be integrated, as we will show when we discuss Keller's (1983) ARCS model. Finally, we selected these three theories because they allow us to explore avenues for intervention and improvement of student motivation.

Expectancy-value theory

According to the expectancy-value theory of achievement motivation (Wigfield & Eccles, 2000), expectancy and value are the most proximal determinants of performance and choice. **Task value** refers to a person's belief that a certain task is valuable to oneself, and tends to predict the decision to pursue it further or not. Task value was defined by Eccles & Wigfield (1995) as the extent to which learners find a task interesting, important and/or useful.

Attainment value is defined as the importance of doing well on a task, and is related to confirmation of self-worth. Eccles (2006) postulated that people's attainment value comes from perceiving the task as instrumental in meeting needs and personal values that are central to one's self-definition.

Interest, or **intrinsic value**, is defined as the inherent pleasure one gets from engaging in an activity, or as the subjective interest in the content of a task. Eccles (2006) relates intrinsic value with Csikszentmihalyi's (1988) concept of *flow*, but also with *situational interest*, defined as a state of emotional and attentional arousal determined by the interaction between personal and task characteristics.

Extrinsic or **utility value** is defined as the usefulness of a task for the individual in terms of their short- and long-term goals. According to Eccles (2006), utility value is determined by how well a task fits into an individual's goals and plans.

A fourth and final component of task value is **cost**, which is conceptualized in terms of the negative aspects of task involvement, including time and effort needed to succeed, and the lost opportunities that may result. It also includes performance anxiety and fear for both failure and success.

On the other hand, expectancy for success was defined as beliefs about how well one will do on upcoming tasks (Wigfield & Eccles, 2000). Although similar to Bandura's concept of self-efficacy, expectancy for success was defined and measured as domain, rather than activity specific, thus being more general than self-efficacy.

For the purposes of our research studies, we focus mostly on utility value. With the exception of Eccles & colleagues' initial measure, researchers found it hard to differentiate between attainment and utility by means of factor analysis. On the other hand, intrinsic value overlaps significantly with situational interest, both conceptually and operationally.

Social cognitive theory

Bandura (1986) defined self-efficacy as "people's judgments of their capabilities to organize and execute courses of action required to attain designated types of performance" (p. 391). He hypothesized that self-efficacy affects the choice of learning tasks, goal setting, and amount of effort, emotions, achievement and persistence. According to Bandura (1977), people who have low self-efficacy for accomplishing a specific task may avoid it, while those who believe they are capable are likely to participate. Moreover, individuals who feel efficacious are hypothesized to expend more effort and persist longer in the face of difficulties than those who are unsure of their capabilities (Bandura, 1997).

Moreover, there are certain theoretical and psychometric considerations regarding self-efficacy that are essential for our endeavor. Zimmerman (2000) suggested self-efficacy is characterized by level, generality, and strength. Self-efficacy level depends on task difficulty, generality refers to transferring self-efficacy beliefs across different tasks and activities, and self-efficacy strength is one's confidence in their ability to execute an action.

Bandura (2006) suggested measuring strength of self-efficacy instead of level alone. As mentioned above, level of self-efficacy is associated with task difficulty. That is, when the more a student believes he can learn, the higher self-efficacy level is. However, Bandura contends researchers should compute the probability of successful performance as a function of the strength of perceived self-efficacy, which is the product of level and confidence. "*This* *micro level analysis retains the predictive value of variations in strength, because efficacy strength incorporates efficacy level as well as gradations of certainty."*(Bandura, 2006, p. 314).

Theories about interest

Interest was described by Krapp (2002) as a relational construct that consists of a relationship between a person and an object. What distinguishes interest from other motivational concepts is its content specificity (Krapp & Prenzel, 2011). "One cannot simply have an interest: one must be interested in something" (Gardner, 1996, p. 6). Therefore, interest must always have an object, which can be a thing, a topic, a subject-matter or an abstract idea, or, as Krapp & Prenzel (2011) put it, "a certain part of a cognitively represented environment". (p. 7).

Silvia (2001) argued that interest serves longer term goals of adaptation, such as cultivating knowledge and promoting diversified skills and experience and that interest develops through a process of magnification: repeated experience with qualitatively similar input. He also conceptualizes situational interest as an emotion, with typical facial expression, physiological parameters, subjective experience, specific behaviors and objectives (Silvia, 2005).

Especially in the context of academic learning, the literature differentiates between situational and individual interest. The first is considered a temporary state determined by the features of a situation. It is characterized by focused but relatively effortless attention, increased cognitive functioning, curiosity, and affective involvement (Renninger & Hidi, 2011; Schiefele, 2009). Individual interest is a set of relatively stable valence beliefs regarding a certain domain or subject area. Although it is theorized to have an affective component, this concept overlaps considerably with intrinsic task value (Schiefele, 2009).

A further differentiation was made between triggered and maintained situational interest. While triggering interest describes the induction of attention and arousal for a short term, maintained interest refers to students' perception of subject content as being relevant to their daily lives.

For the purposes of this study, we focus exclusively on situational interest, and especially triggered situational interest. We do this for two reasons. First, it is almost impossible to differentiate, conceptually and opperationally, perceived value from individual, and even maintained situational interest. Value is, by definition, a part of these types of interest. And second, one of the most important objectives for our research program was to provide empirically tested methods for enhancing motivation. As mentioned above, individual interest is a more stable, trait-like characteristic of learners, making it less susceptible to modification by means of instructional design.

The ARCS Model

Self-efficacy, task value, and interest are three of the most reliable predictors of learning effort, academic performance and persistence, in both classroom and online learning contexts.

However, the theories behind each of these concepts superimpose on each other, making it difficult to develop a measure of all three of them. Keller's (1983) ARCS model draws on previous academic motivation theory and helps to delineate between concepts, making it especially well-suited for diagnosis and design purposes. Moreover, it was conceived from the very beginning with application to distance learning in mind.

In short, the ARCS model suggests that a student's level of effort is determined by his or her curiosity (Attention), perceived Relevance of the course and Confidence for successful learning. Therefore, students will learn when their interest is stimulated by new or surprising information, humor or other characteristics of the course (i.e. high situational interest). Their motivation will be promoted when they see a clear connection between course content and their own objectives (i.e. high utility value). Finally, students will exert effort to learn when they believe they can succeed in the learning endeavor (i.e. high self-efficacy).

Based on this macro-model of motivation, as he called it, Keller (2010) went further to propose several instructional design strategies for capturing and maintaining attention, establish relevance and improve learner confidence.

Getting and maintaining attention

Attention getting strategies include ways of triggering situational interest, stimulating an attitude of inquiry and maintaining attention by incorporating variability. Triggering situational interest, or perceptual arousal, as Keller calls it, refers to reflexive reactions to stimuli. It can be obtained by changes in voice level, presenting surprising information, humor, or using events that introduce incongruence or conflict. This type of situational interest is usually short lived, but can be maintained by stimulating inquiry. Instructional designers are encouraged to create problematic situations that can be resolved only by information seeking behavior. Case studies and guided discovery are specific techniques that fall into this category.

Another way to get and maintain attention is the variation of form and content delivered. Using the same tone of voice or the same sequence of events during a course can become boring, and students will sooner or later tune out. However, if the instructor varies in tone of voice, uses different types of activities, and varies the sequence during the course, students are more likely continue paying attention to the message and the learning content.

Establishing relevance

The most straightforward way to influence perceived utility is to emphasize how the course content is connected to learner's goals and needs. Creating a logical link between content and goals is easier to do when we have a practical course, but can also be done with introductory or fundamental courses. However, when no link can be created with students' professional or personal goals, relevance can still be supported by appealing to fundamental needs, like autonomy, competence, and relatedness. One way to do this is to allow students to make their own choices about what or how to learn. In other words, they should have to possibility to control their learning, thus making it more meaningful and intrinsically rewarding.

Finally, perceived usefulness or relevance can be enhanced by connecting instructional materials with students' beliefs, interests and previous experience. Especially for adult learners, such a link can be a powerful proxy for motivation.

Building confidence

The first thing any instructor should do in order to enhance her students' confidence or self-efficacy is to specify what is expected from the student and what the course objectives are. Not knowing what to expect breeds anxiety and limits confidence.

The most important determinant of self-efficacy is previous mastery experience. That is why it is important to offer students opportunities for success early in the course. Hence, designers should take into consideration the level of previous knowledge, and develop tasks that start from a fairly low level of challenge and move quickly enough to more and more challenging tasks.

Self-efficacy can also be enhanced by vicarious experiences or verbal persuasion. Teachers can present cases of similar students who took the same course, were exposed to pretty much the same tasks and were able to do it. Using examples or case studies with similar models of behavior and using verbal encouraging can also support the development of self-efficacy.

Chapter 3. Measuring motivation for online learning

Before being able to study how certain variables (in our case situational interest, perceived utility and self-efficacy) influence outcomes, we need to make sure we have the right instruments to measure them. That is why we have identified questionnaires that were previously used to measure these variables in online learning environments.

There are two measures of motivational concepts developed specifically for research in distance or online learning. The first is Keller's Instructional Material Motivational Survey (IMMS), which was developed to measure the dimensions of the ARCS model (i.e. Attention, Relevance, Confidence and Satisfaction). However, the IMMS does not measure motivation per se. Instead, the scales ask participants to rate the motivational value of instructional materials. Moreover, items were developed in the early 1990s, and need significant rewarding and adaptation for the use with contemporary, interactive, multi-media online courses (e.g. The quality of the writing holds my attention).

The other measure of motivational factors is Artino and McCoach's (2008) Online Value and Self-Efficacy Scale (OLVSES). This instrument was developed specifically to measure perceived value and self-efficacy in the context of online learning.

Although OLVSES is reported to have good psychometric qualities and does measure self-efficacy and task value, it is not fit for our purposes for several reasons. First, it does not differentiate between situational interest and perceived value. The Task Value scale includes items measuring perceived importance of content (i.e. attainment value), perceived relevance for one's goals (i.e. utility value), and interest or intrinsic value, defined as pleasure derived from engaging in learning. Based on the theoretical accounts presented above, we wanted to differentiate between interest and value, and isolate their individual effects on effort and performance.

On the other hand, we considered existing self-efficacy scales, including the one from Artino & McCoach's (2008) OLVSES to be too general, making them a less then optimal predictor for performance, according to Pajares (1996, 1997). They were worded to refer to self-paced online courses in general, and not to a certain course in particular. Also, any progressive difficulty is missing from this scale, and according to Bandura's (2006) guidelines, self-efficacy strength (defined as a combination of confidence and level of self-efficacy) is preferable as a predictor of effort and performance.

In conclusion, we decided to design and develop a new instrument for the measurement of situational interest, perceived utility, and self-efficacy that would better differentiate between the three variables. It would also take into account Bandura’s (2006) suggestions and show good psychometric quality. Next, we present our first study, conducted exactly for the development and psychometric assessment of this new measure.

Study 1. Measuring motivational aspects of online learning

Purpose of the study

The purpose of the first study was to develop a new measure of motivational factors that theory and previous research show to be good predictors for learners’ satisfaction, performance, and persistence in online learning. We drew on extant literature and previously developed measures for both classroom and distance learning.

Objectives

This study was aimed, primarily, at developing a measure for perceived value, situational interest and self-efficacy that could be used in both self-paced and blended learning contexts, regardless of course length and types of content used.

Our second goal was to offer initial assessment of the new measure’s psychometric qualities, especially in terms of internal consistency and factor structure.

In order to meet our goals, we developed further criteria for the new measure. First, the items should refer to a course, and not a certain domain of knowledge or a single specific learning experience. This would make it more versatile because online learning can have so many forms, lengths and complexities.

Second, we wanted to be able to use this measure in academic and organizational domains, with students, and employees. So the wording and item content should be appropriate for both.

Third, from a theoretical point of view, it’s important to differentiate the three motivational concepts shown to best predict learning outcomes. That is why we chose to focus on situational (and not individual) interest, on utility value (and not intrinsic or attainment), and on self-efficacy.

Finally, we intended to develop a measure that is easily administered due to a small number of items. This would make it very useful not just for research but also for practical diagnosis and evaluation of student motivation, leading to further calibration of instructional design elements.

Method

Participants

We used a convenience sample of 134 first and second-year psychology students. Of these, 112 (83%) were female. Participation was voluntary, but students were rewarded with academic credit.

Scale development

We have developed three scales to measure situational interest, perceived utility, and self-efficacy for a specific online or blended course. We decided to only include a utility value scale and not an intrinsic and attainment value scales because intrinsic value items superimpose greatly on situational interest items. On the other hand, attainment value and utility value items loaded on a single factor in all but the initial instrument developed by Eccless et al. (1993) (see also Artino & McCoach, 2008, for similar issues).

The situational interest scale includes two items adapted from Linnenbrinck-Garcia et al.'s (2010) scale of triggered situational interest and one new item created by the authors. This scale was developed for classroom learning (e.g. I enjoy coming to lecture.). We adapted the items to fit an online or blended learning course (i.e. I enjoy this course.). One of the adapted items was reverse coded.

The utility scale includes four items, of which one is reverse coded. Three of the items were adapted from the MSLQ (Pintrich et al., 1991), and we added one new item (i.e. The information in this course are not helpful for me).

For these two scales, participants were asked to rate how much they find themselves in agreement with each affirmation. They were presented with a 5-point Likert scale, ranging from *completely disagree* to *completely agree*.

The self-efficacy scale was developed according to Bandura's (2006) guidelines. It consists of 10 items of progressive difficulty (e.g. I can learn 10% of the ideas presented in this course; I can learn 20% of the ideas presented in this course). Participants were asked to use a

10 point scale to assess their confidence in learning a certain amount of information from the target course. Therefore, we combine confidence or certainty with efficacy level, resulting in a measure of self-efficacy strength which was a weighted average of scores obtained for each of the 10 items.

Procedure

The study was conducted in the laboratory. Participants were scheduled in groups of 9 to 12 to take part in a two-hour course on academic project writing at an undergraduate level. The course was developed by the first and third authors for the purpose of this study and consisted of several video lectures on different aspects and stages of preparing an academic paper. Students were instructed to log on to a computer in the laboratory and go through the entire course. After that, they could take the motivation to learn survey. Then, they could immediately take the performance test or they could take more time to learn. They were told they could take the test at any time, but their leaning time was limited to two hours.

Both the questionnaire and the test were delivered online, as part of the course and data were recorded using a Learning Management System (LMS), and then exported to Excel for further processing. Descriptive and reliability analysis was conducted using SPSS. Confirmatory factor analysis (CFA) was conducted using Amos.

Results

Confirmatory factor analysis (CFA)

CFA was conducted on the four utility items and three situational interest items. We did not include the self-efficacy items into the analysis as the structure of this third measure CFA unnecessary and inapplicable in this case.

We showed χ^2 to be significant ($p < .0001$). However, under small sample size conditions, χ^2 is not an adequate model fit index. NFI, on the other hand, is the practical criterion of choice for decades, and Bentler (1990) revised it to take into account sample size, thus resulting the CFI. Both NFI and CFI were lower than the .95 cut-off for well-fitted models (Hu & Bentler, 1999).

Therefore, we examined the modification indices (MI), and identified potential cross loadings. MIs suggested regression paths between the first and third situational interest items on the one hand and the fourth utility item, on the other hand. Taking into consideration this potential cross-loading and the fact that eliminating the fourth utility item would not affect content validity of the scale, we decided to eliminate this item and run a second analysis. Though χ^2 remained significant ($p < .05$), both NFI and CFI rose above the .95 cutoff. The RMSEA declined to .10 which suggests an improvement in model fit.

Reliability analysis

We ran a reliability analysis for all of the three scales, retaining the three item version of the utility scale. Cronbach's alpha was .84 for the situational interest scale, .80 for the utility scale, and .91 for the self-efficacy scale.

Conclusions

This study resulted in the development of a 16-item measure of motivational aspects of learning that is adapted and easy to use in the context of online and blended learning. Based on current theoretical considerations and previous empirical research, we proposed a 3-item situational interest scale, a 4-item utility value scale and a 10-item self-efficacy scale. All three variables are known predictors of satisfaction, task persistence and academic performance. Moreover, they are all dimensions of motivation that can be markedly impacted by means of instructional design (for more details, see Keller, 2010).

Also, we have obtained acceptable goodness-of-fit indices and factor loadings once we eliminated one of the initial items. Reliability was surprisingly high for such small number of items in each scale.

However, there are some limitations that should be taken into consideration by future research. First, the sample size is barely sufficient for the purposes of the study. This allows only of initial validation of the factor structure. Future studies should try to replicate our results on larger samples. Also, we have use psychology undergraduates involved in an academic writing course. Similar analyses should be run on data from different background students enrolled in other types of online or blended learning courses.

Finally, we did not address the issue of criterion-related validity. Further validation of our measure is required with a focus on its utility for predicting criterion measures such as student achievement emotions, use of self-regulated learning strategies, learner satisfaction and academic performance.

Chapter 4. Predictive value of motivational factors for satisfaction, persistence, and academic achievement

Pintrich & De Groot (1990) argued that "knowledge of cognitive and metacognitive strategies is usually not enough to promote student achievement; students must also be motivated to use the strategies as well as regulate their cognition and effort" (p. 33). In general, research in traditional classrooms has consistently found moderate to strong positive relations between students' motivational engagement, their use of self-regulatory strategies, and, ultimately, their academic achievement and overall satisfaction (Pintrich & De Groot, 1990; Pintrich, 1999).

Compared to the abundance of research data on the predictive value of task value, self-efficacy and interest for learner satisfaction, persistence, and academic achievement, similar research in the context of online learning is rather scarce. However, extant data is mostly encouraging, showing that these motivational factors could partially explain the above mentioned outcome variables. For example, several studies have shown that task value beliefs positively predict students' metacognition and use of learning strategies (Artino & Stephens, 2009; Hsu, 1997), academic performance and satisfaction (Lee, 2002), and future enrollment choices (Artino, 2007, 2008). Also, Artino (2009) reported that learners with career aspirations directly related to the course content were more likely to report greater perceptions of task value and greater use of metacognitive control strategies, compared to learners with no related career aspirations.

Moreover, self-efficacy was shown to predict learning strategy use (Joo, Bong, & Choi, 2000; Artino & Stephens, 2009), satisfaction (Lim, 2001; Liaw, 2008), persistence (Artino, 2007), and academic performance (Hsu, 1997; Joo et al, 2000; Wang & Newlin, 2002). Efficacious students used more learning strategies, experienced higher satisfaction and higher likelihood of taking future online courses, and had superior academic performance.

As far as interest for learning tasks is concerned, even fewer studies are available. One of them was conducted by Sun & Rueda (2012) and found situational interest and self-regulation to be significantly correlated with the three types of engagement. That is, students who found the course interesting, or captivating, used more learning strategies (cognitive engagement) and invested more effort to learning (behavioral engagement). These results are echoed by Jones (2010) who found that situational interest was higher for online learners compared to face-to-face learners. More importantly, situational interest predicted effort, satisfaction with the instructor and the course, but also achievement, measured by the number of points received on four different exams during the semester.

Study 2. Direct and indirect effects of situational interest, utility value and self-efficacy on academic performance

Objective and hypotheses

The purpose of this study was to test a predictive model based on these previously presented results.

We contend that all three motivational variables have a direct effect on performance, but also an indirect one. We expect all indirect effects to be mediated by level of effort invested by students in learning, and by the use of self-assessment, which is, according to present date research the most effective learning strategy (Dunlosky et al, 2011).

We went out to test this model (Figure 2) in an ecological environment, guided by the following hypotheses:

1. Utility value, situational interest, and self-efficacy have direct positive effects on performance.
2. Utility value, situational interest, and self-efficacy have direct positive effects on students' effort to learn.
3. Utility value, situational interest, and self-efficacy have direct positive effects on students' use of self-evaluation learning strategies.
4. Effort and self-evaluation partially mediate the effect of utility value on performance.

Method

Participants

Participants were 432 pharmacists (42%) and pharmacy assistants (58%) taking part in a year-long online learning program comprising 18 different technical courses on different diseases, their diagnosis and options for recommendation in the pharmacy. Although taking the courses was mandatory as part of their continuous education program, taking part in the study was voluntary.

Measurement instruments

Motivational aspects

Situational interest, utility value, and self-efficacy were measure using the Motivational Aspects of Online Learning Scales (MAOLS), developed in the first study.

Self-evaluation

Barnard and her colleagues (Barnard et al., 2008; Lan et al, 2004; Barnard et al., 2009) developed a 24 item scale with a 5-point Likert response format, named the Online Self-regulated Learning Questionnaire (OSLQ). For the purpose of this study we selected self-evaluation, a three-item scale from the OSLQ, using a 5-point Likert-type response format, with values ranging from strongly disagree (1) to strongly agree (5). Also, the original wording of the items referred to online learning in general. However, we were not interested in the generic use of learning strategies, but if such strategies are used more in a specific course as a direct effect of students' contextual interest, perceived utility and self-efficacy about that one course. Therefore, we adapted the items to fit to our purposes. For example, the item *I ask myself a lot of questions about the course material when studying for an online course* became *When learning for this course, I asked myself a lot of questions about the material in order to verify my understanding.*

Effort and performance

In the context of classroom instruction, where students can be observed or monitored, effort to learn is usually measured either by the duration of time allocated to learning. This is either self-reported or observed by the instructor or the researcher. However, self-reported effort is unreliable, especially if it requires thinking back over a longer period of time (in our case, over a month), and direct observation was not an option in our context. Therefore, we opted for measuring effort as the number of times students accessed one of the course pages.

Regarding knowledge testing, students had a 20 minutes window to complete 15 questions based exclusively on the content of the course. Questions were developed by the same professional pharmacists who developed the course.

Procedure

We collected data in a 3 months interval (May to July 2015), using questionnaires, log data, and a knowledge test, all of which related to their learning of one of the 18 courses. Each of them had access to this course of a one month interval.

Situational interest, self-efficacy, and perceive utility scales became available to them one week into the course, and they were instructed to not complete these scales until they have took at least 3 of the 12 sections of the course. Using log data regarding student access, we ensure this condition was met in order for students to have a clear image about course format and content before they report on their motivation.

One week before their access expired, learners were invited to complete the Online Self-Regulated Learning Questionnaire (OSRLQ), before taking a 15 question knowledge test. For the purpose of this study, we were only interested in the Self-Evaluation scale of the OSRLQ.

All instructions were presented automatically and data from participants were collected the same way, through a Learning Management System (LMS) software.

Results

Data analysis

For the purpose of the SEM analysis, we decided to parcel items from the self-efficacy scale in order to minimize its potential overweight on a particular variable in the model. In our case, a parcel was comprised by the weighted average of three or four items. Given that items were of progressive difficulty, we decided to aggregate them so that the overall difficulty of each parcel would be relatively equal to the others. This procedure is likely to reduce measurement error by using fewer observed variables and to ensure the assumption of multivariate normality, which was, as we mentioned, our case (Bandalos, 2002).

Internal reliability of the scales proved to be adequate, especially considering the small number of items for three of the scales.

Regarding normality of our data sample, results showed that all kurtosis values (beta 2) were smaller than 7, indicating a relatively normal univariate distribution for all observed variables (West et al., 1995). Mardia's normalized estimate of multivariate kurtosis was 3.978. According to Bentler (2005), values smaller than 5.00 are indicative of normally distributed data.

All correlational coefficients were in the expected direction, ranging from small to medium. All motivational aspects positively correlated significantly with effort, self-evaluation, and performance. The highest correlate for performance was self-evaluation.

Assessment of the measurement model

Before testing the full structural model, in order to test our hypotheses, we conducted an assessment of the measurement model, by running a confirmatory factor analysis using AMOS 21. The first row of Table 4 presents the goodness of fit indices for the measurement model, suggesting a good fit between the proposed model and the collected data. An NFI, TLI and CFI indices equal or above .95 are considered to suggest a well-fitted model. RMSEA however, is above .05, which suggests a marginally adequate model. However, RMSEA is one of the goodness-of-fit indices that are sensitive to sample size (Byrne, 2010).

Factor loadings ranged from .51 to 1.01, indicating the adequate validity of all factors in the measurement model (Hair, Anderson, Tatham & Black, 1992).

Structural model and hypotheses testing

Once we ensured the measurement model fits our current data and the factor structure was confirmed, we move to testing our hypothesized model. Goodness-of-fit indices suggest a marginally adequate fit to the data, with NFI and TLI at .94, CFI at .96, and RMSEA at .07.

Next we look at the standardized estimates for each prediction. Our first hypothesis was that situational interest, utility value, and self-efficacy would all exert direct and positive effects on student performance. Results support these hypothesized direct effects of motivational aspects on student performance. The highest direct effect was from utility value ($\beta = .399$, $CR = 6.319$; $p < .001$), followed by situational interest ($\beta = .298$, $CR = 5.022$, $p < .001$) and self-efficacy ($\beta = .170$, $CR = 3.816$, $p < .001$).

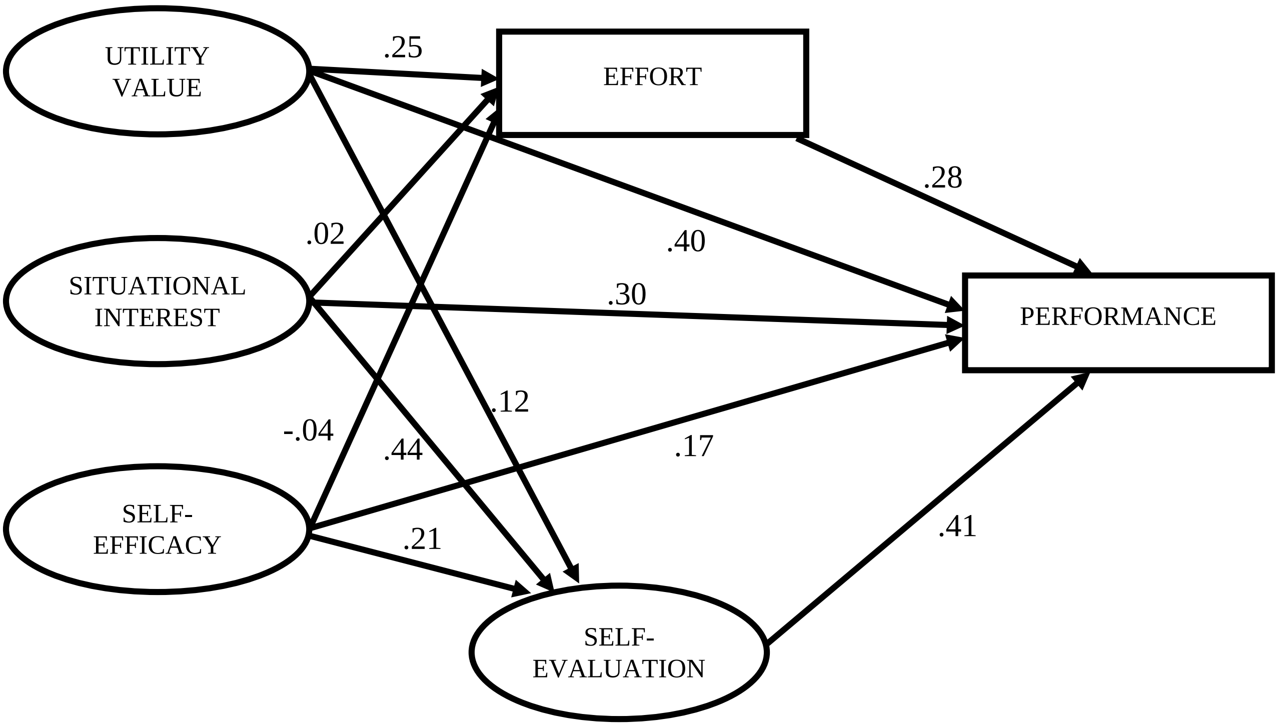
Our second hypothesis referred to the direct, positive effects of motivational aspects on student effort. Here, results offered only partial support. Utility value proved to have a significant direct effect on effort ($\beta = .255$, $CR = 3.789$, $p < .001$). However, effort was not influenced by situational interest ($\beta = .02$, $CR = .365$, $p > .10$), nor by self-efficacy ($\beta = -.043$, $CR = -.862$, $p > .10$).

Regarding the direct effects of motivational aspects on self-evaluation (our third hypothesis), we also obtained only partial support from our results. If self-efficacy ($\beta = .21$, $CR = 3.884$, $p < .001$) and situational interest ($\beta = .443$, $CR = 5.982$, $p < .001$) did show a direct effect on self-evaluation, the coefficient for utility value was not statistically significant ($\beta = .115$, $CR = 1.584$, $p > .10$).

In order to test our fourth hypothesis regarding the mediating role of effort and self-evaluation for the impact of motivational aspects on performance, we used the percentile bootstrap method to calculate the upper and lower bounds and the statistical significance of the total, direct, and indirect effects. In running the analysis, we have set the number of bootstrapping samples at 2000, and the bias-corrected confidence intervals at 95 (which implies a margin of error of .05).

Results further supported our first three hypotheses, with all three motivational aspects having a positive and significant direct effect on performance. More importantly, these results suggest they also have positive and significant *indirect* effects, mediated by effort and self-evaluation. More specifically, perceived utility impacts performance both directly ($\beta = .280$, $p < .005$), and indirectly ($\beta = .255$, $p < .01$). Similar patterns can be observed for self-efficacy, with a direct effect ($\beta = .17$, $p < .005$), but also an indirect effect on performance ($\beta = .076$, $p < .01$), and for situational interest, with a direct effect on performance ($\beta = .298$, $p < .005$), but also an indirect effect ($\beta = .189$, $p < .005$).

Figure 4. Structural model (simplified)



A closer look at the mediators suggests that the indirect effects of perceived utility value on performance are exerted through students' effort to learn. On the other hand, self-efficacy and situational interest have indirect effects on performance mostly mediated by the use of effective learning strategies, in this case self-evaluation. The effects of perceived utility on self-evaluation, and those from self-efficacy and situational interest to effort were found to not be statistically significant. Hence, according to Barron & Kenny's (1983) criteria, we could not confirm effort as a mediator for the effects of self-efficacy and situational interest on performance, nor could we confirm self-evaluation as a mediator for the effects of utility value on performance.

Discussion

Based in theory and previous research we proposed an explanatory model, According to this model, academic performance is influenced both directly by value, self-efficacy, and situational interest, but also indirectly, through exerted effort to learn and self-evaluation as a proven-to-be-effective learning strategy. Moreover, according to it, we put forward four different hypotheses. Goodness-of-fit indices suggested our model fits the data well. However, of all hypothesized paths, the ones from value to self-evaluation, from self-efficacy to effort, and from situational interest to effort proved to be statistically non-significant. Therefore, our results fully supported our first hypothesis: value, self-efficacy, and situational interest will have direct effects on academic performance. The second and third hypotheses received only partial support. Effort was only affected by utility value, but not self-efficacy or situational interest. For the third hypothesis, the situation was reversed: self-evaluation during learning was only affected by self-efficacy and situational interest, but not utility.

Although there is substantial support for the predictive value of self-efficacy for student effort to learn, our data showed no such effect. One possible explanation can be found in one of the early works of Bandura (1977) who contended that self-efficacy strength is not necessarily linearly related to choice behavior (e.g. the choice to exert more effort). Keeping in mind that our results show that higher levels of self-efficacy lead to higher levels of performance, it is possible that in the specific case of our participants, task difficulty did not require extensive effort from their part, thus impairing the potentially linear relationship between self-efficacy and effort.

On the other hand, Artino and his colleagues (Artino, 2009; Artino & Stephens, 2009) consistently found a positive relation between task value and use of metacognitive and learning strategies. From a correlational stand point, we have found similar results: utility value correlated significantly with self-evaluation. However, when direction was added to this relationship in the form of path analysis, the relationship remained positive, but it was much smaller and no longer statistically significant. One possible explanation was that there are one or more other variables that explain the covariation between value and strategy use.

Finally, our results showed situational interest to be a very strong predictor for strategy use and performance, but not for effort. As for the predictive value of situational interest for performance in an online course, our results are in synch with previous online learning research (e.g. Sun & Rueda, 2010; Jones, 2010), that also found a positive relationship between situational interest and performance in online courses. Both the direction and the magnitude of the relationship is encouraging as it is possible that this motivational aspect does play a more important role in online learning than in its more traditional counterpart, which is classroom learning.

On the other hand, our results divert from previous studies in what the predictive value of situational interest for student effort is concerned. Here, we have a similar situation to that of value and self-evaluation, in that situational interest does have a positive correlation with student effort, but path analysis yielded a much lower estimate, which was also not statistically significant. In this case, it is possible that the third variable here is value, which explains the covariation, but lack of predictive effect between situational interest and effort.

There is, however, a methodological aspect that comes to bear on the predictive value and implications of situational interest. As we have mentioned above, we have recorded the number of times the students accessed any particular page or content that was part of this course and used it as a measure of effort. We decided not to use a self-report measure of effort for reasons related to social desirability. Also, we have deemed duration of access to be an unreliable measure of effort, as students did not learn in a controlled environment and it was very well possible that they would open a certain page and leave it open for an indefinite period of time, while their attention was focused on something else. It is however, possible that some students did access the course and its content on fewer occasions, but spent a larger amount of time on it. This limitation is mitigated by the lack of an alternative and by the fact that the course content was highly fragmented and, even if students had fewer learning sessions for longer periods of time, they would still have to actually click more times in order to navigate the course content, compared to those who spent less time learning.

Overall, there are three important contributions this study brings to the theory and practice of educational psychologists and online instructional designers.

First, we brought together three of the most well-researched motivational variables and tested their direct and indirect effects on student performance. Previous research focused on value or self-efficacy or both, but mostly ignored situational interest. We have proposed and tested a model where all three variables have shown strong effects on student performance.

Second, we insisted on how motivation impacts performance, with tremendous implications for practice. We have shown perceived utility leads to academic performance through effort, and that self-efficacy and situational interest also influence performance, but by means of learning strategy use. More research should be devoted to explaining how motivation works to impact performance. However, our results inform both motivational theory, but also instructional design practice. When faced with low performance due to insufficient engagement in learning tasks, instructors should focus on enhancing perceived utility or relevance of the content and tasks. On the other hand, if they wish to encourage students to use more effective learning strategies in order to succeed in online learning, they should focus mostly on enhancing self-efficacy and situational interest.

Finally, our study was conducted in a highly ecological setting. Participants were adult learners taking part in a year-long professional development program. Therefore, our results are that more valuable for instructors conducting similar courses.

Chapter 5. Enhancing motivation to learn

Thus far, we went through a descriptive approach to motivation in online learning. Then we took an explanatory and predictive approach to the same topic, and showed how motivational aspects influence online performance, by means of effort and learning strategy use. Finally, we focus on actually establishing causation and testing if perceived utility, self-efficacy and situational interest can be enhanced by specific interventions. We take an in depth look at previous intervention research and try to further our understanding of how motivation for online learning can be enhanced and to what effect.

Traditionally, research on **interest-enhancement** focused on text characteristics and their manipulation. Its results suggested that situational interest is increased by text coherence, identification with characters, suspense, concreteness, and imageability of salient text segments also increase situational interest (Wade, 1992; Anderson et al, 1987; Jose &

Brewer, 1984; Sadoski et al, 1993). More recent classroom interventions targeted on situational interest have been successful in improving reading comprehension (e.g. Guthrie et al., 2006), teacher ratings of student motivation (e.g. Guthrie et al., 2006), performance on writing tasks (e.g. Hidi et al., 2002), self-efficacy (e.g. Hidi et al, 2002), and interest (Hidi et al, 2002).

Significantly more research was conducted on **value-enhancement interventions** in the classroom. Most of these interventions used either a presentation of the potential benefits of learning the content, or asked students to write a brief text about how the course material was useful or relevant to them or someone they knew (e.g. Durik et al., 2014; Hulleman et al., 2010; Hulleman & Harackiewicz, 2009; Harackiewicz et al, 2012). These interventions have been found to positively impact a number of outcomes, including: course-related interest, future interest in course-related careers, future course enrollment, perceptions of utility value for the subject area, and increased expectancies for success.

In the traditional motivation to learn literature, there are a few evidence-based suggestions that are recurrently made to teachers for **building students' self-efficacy**. The most prominent of them is using moderately difficult tasks that are not too difficult, not too easy for a student's current level of ability, and progressively increasing the difficulty over time (Linnenbrink & Pintrich, 2003; Stipek, 1998). A second strategy teachers can use is peer models. Giving students examples of people they find themselves to be similar with can help build their self-efficacy. Finally, teachers are encouraged to provide frequent, focused and task specific feedback in order to guide students, but also to persuade them of their ability (see Good & Brophy, 2003 and Salend, 2001).

Research on motivational enhancement in online learning

When shifting our attention to motivational interventions in the context of online learning, we find fewer studies conducted. Most of them resulted from doctoral studies and did not focus on a single component of learning motivation. Instead, they combined several specific strategies into a single intervention intended to improve motivation in general. One exception from this rule is a study conducted by Naime-Diffenbach (1991), who demonstrated that, if specific attributes of instructional materials related to each of the four principles are manipulated independently, students' motivational reactions vary consistently with the manipulations. Specifically, based on the ARCS model, she enhanced the Attention and Confidence elements of a lesson that was otherwise rather neutral with regard to the other dimensions of motivation. She found significant results demonstrating that the four components of motivation could be varied independently of one another. This is especially important for us, because we also focus on specific interventions targeted at one aspect of learning motivation.

In an integrated approach to motivational enhancement, Margueratt (2007) conducted a single-sample, pre-post-test quasi-experiment in which 204 undergraduate students took part in a two-module course. The second module was redesigned according to the ARCS model. Students completed the IMMS after each module, and results showed significant differences on the Attention, Confidence, and Satisfaction scales. No significant difference was found on the Relevance scale. Also, the second module was perceived as more motivational when the two were compared in terms of overall IMMS scores. Margueratt (2007) concluded that motivational design can be effective in enhancing online students' motivation, and explained the insignificant difference on the Relevance scale based on the insufficient data variability due to the inherent utility of the course to students.

Another integrated intervention was proposed by Huett et al. (2008). They designed a study to test the effectiveness of ARCS-based motivational emails. Results showed significant differences between online treatment and control on all four dimensions except for relevance, with Cohen's d varying from .71 to .94. However, motivation scores did not significantly differ between the treatment group and the face-to-face group.

One final study we would like to mention is Johnson & Sinatra's (2013) research conducted on 166 undergraduates from an Educational Psychology class with the purpose of determining if two different motivational interventions (an utility and an attainment intervention) lead to higher levels of engagement in learning and different degrees of conceptual change on the topic of the causes of the common cold, as compared to a control group. Participants who were in the utility condition rated their engagement as significantly higher than those in the control condition.

Study 3. Enhancing situational interest, task value, and self-efficacy in the context of online learning

Our third study was designed and conducted in order to investigate if specific interventions could be designed for the targeted enhancement of perceived value, self-efficacy, and situational interest.

We suggest that situational interest (SI), value (TV), and self-efficacy (SE) can separately be enhanced by means of instructional design interventions. More specifically, we hypothesized that learners in the SI condition will have a significantly higher level of situational interest, compared to the control group. Learners in the TV condition will perceive significantly higher utility value for the course, compared to learners in the control condition. And finally, learners in the SE condition will experience a significantly higher level of self-efficacy, compared to learners in the control condition.

Moreover and based on previous research showing these three variables to be good predictors of academic achievement, we hypothesize that learners in all three experimental conditions (i.e. SI, TV and SE) will have a significantly higher level of academic performance, compared to learners in the control condition.

Design

For this study, we have used an independent samples, post-test-only design. Participants were randomly assigned to one of the four groups: SI group (n = 31), TV group (n = 38), SE group (n = 31), and control group (n = 34). Each group was exposed to one condition of the independent variable, which was the motivational course design. Although very similar in duration, content and delivery, the course each group took part in differed in very specific ways. For the first group, the course was designed to improve situational interest, for the second group, it was modified to enhance perceived task value, and for the control group, all elements of motivational design were eliminated.

In order to partially control for confounded variables, we decided to use a laboratory setting where all participants took the course under similar conditions, for similar durations of time, and with very similar distractors.

The dependent variables consisted of situational interest, task value, self-efficacy and academic performance measures.

Method

Participants

The study was conducted using a convenience sample of 134 first and second year psychology students. Of these, 112 (83%) were female. All of them enrolled voluntarily and received academic credit for their participation.

Instruments

Self-report measures of situational interest, task value, and self-efficacy were administered once students had the time to familiarize themselves with the course. The questionnaire containing these three scales was developed for the purpose of this study (for more details, see our first study, presented in chapter 3). All three scales showed very good reliability, with Cronbach's alpha of .84 for the situational interest scale, .80 for the utility scale, and .91 for the self-efficacy scale.

Procedure

Participants were scheduled to attend an online course on academic writing in the Department of Psychology laboratory, in groups of 9 to 12 people. The course consisted in several video lectures on different aspects and stages of preparing an academic paper, with a total duration of 30 minutes. The content included aspects of planning the project, activating previous knowledge, identification of bibliographic resources, outlining, actual writing, revising and some special considerations on writing reaction papers. The same information was delivered to all four groups, with the same duration and in the same format. The only differences were in terms of motivational design, which are presented in detail below.

Students were instructed to log on to a computer in the laboratory and go through the entire course. After that, they could take the motivation to learn survey, which measured situational interest, task value and self-efficacy. Then they could immediately take the academic performance test, or they could take more time to learn. They were told they could only take the test once and that they can take up to another hour and a half to learn.

The questionnaire and the test were delivered online, as part of the course. Data was recorded using a Learning Management System (LMS), and then exported to Excel and SPSS for further processing.

Intervention

Keller (2010) describes in detail the elements of motivational design that are supposed to spark situational interest, to raise self-efficacy, or improve perceived task value. These suggestions are based on previous research, especially classroom-based research, and on theories of motivation for learning.

The academic writing course for the SI group included a more dynamic presentation style, more images and graphics on screen, more visual aids, and more color. The script was tweaked to create cognitive dissonance and to present new information based on problematic situations.

Moreover, Keller (2010) suggested making the content as personal as possible. One way of making content personal that we included in the design of the SI version of the course was to replace generic examples with the example of Vlad, who is described as a first year psychology student, very similar to our participants.

On the other hand, we tried to improve perceived task value by creating a link between the content and learner's objectives, and therefore making the information more relevant. The same examples were worded so as to illustrate the utility of the principles and techniques presented. We emphasized what a student stood to gain if she used our advice on how to prepare, write and revise her academic project. Also, Keller (2010) suggested using a direct and personal voice in presenting the content. Therefore, in this version of the course, the trainer addressed the learner directly, like engaging him or her in a conversation.

The third version of the course was designed to raise learners' self-efficacy. For this, the first thing we have done was to clearly state what was expected from the learner after taking this course. Secondly, we designed course tasks in gradually increasing difficulty, with immediate feedback, including reinforcing feedback and encouragement designed to build up confidence.

Finally, the control group received a different version of the course, one that excluded all of the motivational design components mentioned above.

Results

Normality and homogeneity of variance

Before testing the hypotheses, we verified if normality and homogeneity of variance assumptions were upheld. Only two of the cases proved to be statistically non-significant, suggesting that for most groups and variables, the distribution was significantly different from normal.

Regarding the homogeneity of variance, the Levene test was not significant for situational interest, and value, but proved to be significant for self-efficacy. Hence, data variance for the four groups were not homogeneous for the self-efficacy variable.

Based on these results and our failure at normalizing the distribution, we decided to use non-parametric methods of analysis. Specifically, we calculated the Mann-Whitney test for each dependent variable.

Hypothesis testing

Our results show that task value was significantly higher in the TV group, compared to the control (U = 514; z = 1.63; p< .05; r = .20). Perceived self-efficacy was significantly higher in the SE group, compared to the control group (U = 395.5; z = 1.727, p< .05; r = .22). Finally, situational interest was also higher for the SI group, compared to the control group (U = 411.5; z = 1.67; p< .05; r = .21). These results support our first three hypotheses, suggesting that our interventions designed to increase situational interest, task value, and self-efficacy, respectively, had a significant effect. All three experimental groups differed from the control group on the targeted variable, and effect sizes were all in the small to average range.

Regarding academic performance, no significant difference was found between learners in the control group and those in the TV group (U = 423; z = -1.179; p > .05; r = 0,15), the SI group (U = 451; z = -.196; p > 0,05; r = .025), and the self-efficacy (U = 411; z = -.787; p > .05; r = .10). Although results are not statistically significant, the effect sizes are sizable at least in the case of the task value and self-efficacy.

Discussion

Our results show that each of the three design interventions was effective in enhancing its targeted motivational factor. When compared to the control condition, each of the three experimental groups experienced significantly higher levels on their targeted motivational dimension.

Previous research in online learning motivation presented evidence that all three dimensions could be enhanced by means of instructional design or motivational messages. However, we did not know which aspects of the intervention affected which motivational dimension. Our study brings further evidence that Keller's (2010) motivational design ideas are not only effective overall, but that they each lead to their intended purpose. More specifically, strategies intended to catch and maintain interest or attention, actually arise students' situational interest. Strategies targeted at establishing relevance do lead to students perceiving the content as useful and important for their goals and needs. And strategies meant to build confidence are effective in enhancing students' self-efficacy.

On the other hand, previous research, including our second study, supported the assertion that interest, value and self-efficacy all lead directly or indirectly to higher levels of learning and academic achievement. Although our results showed that higher levels of these three motivational variables predicted higher grades in the multiple choice test at the end of the learning period, none of them reached statistical significance. This is most probably due either to low sample size (and therefore statistical power), or to insufficient variation in data on the end-of-the experiment knowledge test.

Further research is needed see if certain specific modifications in instructional design lead to similarly specific enhancements in different motivational aspects of learning online. Our study was conducted in a laboratory environment in order to control for some of the confounded variables, but similar interventions should be tested in more ecological environments, where the stakes for the students are higher, and both courses and the respective design interventions would have longer durations.

Despite its limitations, this third study does bring important contributions to the theory and practice of online learning. From a theoretical point of view, it is, to our knowledge, the first study to ever test specific interventions for all three motivational aspects of the ARCS model. Naime-Diffenbach's (1991) experiment was the only other study we could find that tested the effects of specific interventions based on Keller's model. However, her design was limited to interventions on the Attention and Confidence dimensions of the model, excluding Relevance. We went forward to delineate specific interventions for all three of the motivational dimensions of the ARCS model. Moreover, we used measures of student motivation and not motivational content, as in the case of Naime-Diffenbach (1991). As we have mentioned in chapter 3, the IMMS measures how motivational the student considers the content he or she was exposed to. By contrast, we have used scales that actually measure their level of perceived value, self-efficacy, and situational interest.

On the other hand, our study can be extremely valuable to instructional designers and online trainers. As we have shown in our second study, it is possible that each motivational aspect has different means of influencing student performance in online learning. If the results of our second study can help instructors delineate which aspect of motivation to target, the results from this study offer the specific means of intervention to enhance perceived value, self-efficacy, or situational interest, depending on their needs. We have further empirical support to Keller's (2010) suggestions, making them even likelier to become best practice guidelines for motivational design of online learning.

Chapter 6. General discussion and conclusions

In the current paper we have presented the premises, processes and results of a research program designed to investigate aspects of measurement, prediction and intervention in the area of motivation for online learning. We tackled many of the issues we have just mentioned. This program took the form of three separate studies conducted on both undergraduate students, and working adults, in the lab and in an ecological environment, using a diverse set of methodologies and statistical analysis.

The result of our first study was the Motivational Aspects of Online Learning Scales (MAOLS), comprising an utility value scale, a situational interest scale, and a self-efficacy scale. There are two aspects that set this instrument apart from all others. First, it does not measure self-efficacy level, but self-efficacy strength, which is the product of difficulty level and confidence. And second, we chose to measure value more as utility value than attainment or intrinsic value. This was because previous attempts to differentiate attainment from utility value have failed to do so, and second because, in analyzing the items for both intrinsic value and situational interest, we found they overlap considerably.

The results from our first study confirmed the internal consistency and factorial structure for the MAOLS. That is why we have used it further in the second and third studies.

Based on our review of theory and previous research in both classroom and online learning, we proposed that all three motivational aspects have direct effects on performance, but also indirect effects through level of effort and use of effective learning strategies. This model and the hypotheses derived from it constituted the basis for our second study. The results confirmed most of our hypothesis. We found significant effects of all three motivational aspects on performance. We also found indirect effects from all of them to performance.

More specifically, we found that student effort partially mediated the effects of value on performance, and that self-evaluation only mediated the effects of self-efficacy and situational interest on performance.

Encouraged by the results of our second study, we set out to test if and how value, interest and self-efficacy can be enhanced in an actual online course. Results showed each intervention was effective in enhancing its targeted aspect of motivation. Participants in the self-efficacy group reported higher levels of self-efficacy, compared to the control group. Those in the value condition reported higher task value, and students in the situational interest reported higher situational interest, compared to the control group. However, the differences in performance between the three experimental groups and the control group were not statistically significant. Nevertheless, the effect size ranged from .10 to .25, which suggests there was an effect of each of the motivational aspects on performance, but we cannot generalize this result to the population.

Limitations

Most of our results and conclusions should be qualified by methodological limitations, especially those related to measurement and sample size. If for our first study our sample was large enough and bootstrapping techniques ensured significantly increased statistical power to be able to draw conclusions that would generalize to the entire population, for the third study, our sample was insufficient for a powerful analysis of the data. On the other hand, this study was conducted in the laboratory, for confounded control purposes. However, it is possible that students do not act the same in naturalistic contexts as in the laboratory. Therefore, our results might have been influenced by the context. That is why, replication in actual and meaningful contexts is warranted.

Moreover, the MAOLS, which was developed specifically for the purposes of this research program still needs further development and assessment of psychometric qualities and factor structure. Also, the self-evaluation scale did have a marginally adequate internal consistency which could partially explain some of the non-significant results we obtained with it.

Future directions

Based on our results and our limitations we suggest future research directions. First, more research is warranted to test MAOLS psychometric qualities and factor structure. Although our results support the current item structure, we believe this measure requires further validation, especially in blended learning contexts. Moreover, new scales to measure different motivational aspects could be added to this measure.

Regarding the prediction of learning performance, further research is needed on the specific paths each motivational aspect takes to influence this very important outcome variable. Our initial results suggest that indirect effects of perceived value, situational interest and self-efficacy are mediated differently by effort and self-evaluation. However, we found no other study showing exactly this pattern. Therefore, future studies might further investigate if the mechanisms suggested by our results stand in different online learning contexts.

Last but not least, we suggest a finer grained investigation of instructional and design strategies that could be effective in enhancing student motivation for online learning. We proposed and tested specific sets of techniques for each of the three motivational aspects under investigation. However, future research can analyze even more specifically each strategy on its own and its effects on the targeted motivational aspect and student performance. On the other hand, our results, especially those regarding impact on performance need replication on larger sample size if we are to conclude that enhancing student motivation in online learning does lead to higher levels of student performance.

Theoretical, methodological and practical contributions

Finally, we wish to emphasize the contributions our work has made to online learning theory, research and practice.

First, from a methodological stand point, we have developed a new measure of motivational aspects in online learning (MAOLS), which is both psychometrically sound and easy to use for diagnosis and assessment of student motivation in online contexts. It was developed specifically for these purposes, and data from the laboratory and the industry support its factorial structure and internal consistency.

Second, we have contributed to the theory of motivation for learning by furthering the understanding of the impact motivation can have on performance. We have identified both direct and indirect effects of value, interest and self-efficacy on student learning performance. Moreover, we have showed that these motivational aspects are malleable, state-like dimensions that can be rather easily changed or enhanced. In doing so, we provided valuable support to Keller's ARCS model of motivational design, and his suggestions for motivational enhancement.

Third, we believe our results are most valuable to practitioners. We provided them with an instrument they can use to assess their students' motivation quickly and accurately. Based on their results, they can use interventions we tested for targeted enhancement of relevant motivational aspects. Also, they can guide their interventions with more specific outcomes in mind, knowing that different aspects of motivation influence students' effort and learning strategies use differently.

We believe motivational aspects of online learning is a worthy research topic that will bring valuable benefits for both motivational theorists and e-learning professionals on the long run.

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