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How achievement emotions impact students' decisions for online learning, and what precedes those emotions

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ABSTRACT

This empirical study investigates students' learning choices for mathematics and statistics in a blended learning environment, composed of both online and face-to-face learning components. The students (N = 730) were university freshmen with a strong diversity in prior schooling and a wide range of proficiency in quantitative subjects. In this context, we investigated the impact that individual differences in achievement emotions (enjoyment, anxiety, boredom, hopelessness) had on students' learning choices, in terms of the intensity of using the online learning mode versus the face-to-face mode. Unlike the general level of learning activities, which is only minimally influenced by achievement emotions, these emotions appear to have a moderately strong effect on a student's preference for online learning. Following this, we explored the antecedents of achievement emotions. Through the use of path-modeling, we conclude that while goal setting behavior only marginally impacts achievement emotions, effort views—a crucial component of the social-cognitive model of implicit theories of intelligence—have a substantial impact on achievement emotions.

1. Introduction

To what extent is it possible to explain students' learning choices, and more specifically their choice to use an online learning environment, through the knowledge of their learning emotions and other individual difference characteristics? Applications of Pekrun's control-value theory of achievement emotions, and their relations to self-regulation of learning and learning performance, are becoming more common in empirical studies (Pekrun, 2006; Pekrun, Frenzel, Goetz, & Perry, 2007; Pekrun & Stephens, 2010). Most of these applications, however, focus on traditional, face-to-face learning settings, in which the self-regulation of a student always interacts with the external regulation by lecturers, and shared regulation within classes (Frenzel, Pekrun, & Goetz, 2007; Pekrun, Elliot, & Maier, 2006; Pekrun, Goetz, Titz, & Perry, 2002). Yet nowhere can the impact of learning emotions on the process of self-regulation of learning be better isolated from external effects on learning regulation than in online learning environments. Artino (2010) is one of the few empirical researchers who does focus on the role of learning emotions and other social-cognitive individual difference factors in a student's preference ('yes' or 'no') to enroll in online courses. In this empirical study, we investigate a strongly related choice problem, but one which is not dichotomous. When offered a blended learning environment composed of both a traditional, face-to-face component and an online component, what choices will students make? By offering a selection of continuous nature, rather than dichotomous, students were able to adjust the intensity of learning in the face-to-face component and in the online component according to their individual preferences. We further considered what learning emotions and other individual difference factors impacted this choice. Like Artino (2010), we made use of Pekrun's control-value theory of achievement emotions to model students' learning choice behavior. This was done in combination with social-cognitive frameworks of learning motivations in order to explore the antecedents of learning emotions.

The students in this study were taking courses in statistics and mathematics. These subjects are viewed as conceptually rich domains, for which there exists a strong research tradition of learning with online environments. Part of this research focuses specifically on the optimal level of blending: see e.g. Azevedo (2008), and Lajoie and Azevedo (2006). It is hypothesized that online learning concerning these conceptually rich domains places a high demand on students' self-regulation of the learning process. Required self-regulation competencies refer to the main processes as planning (e.g., setting goals), monitoring activities (e.g., self-questioning, judgment of learning), strategy use (e.g., drawing, coordinating informational sources, knowledge elaboration), handling task difficulties and demands (e.g., help-seeking behavior), and interest in the task or the content domain of the task (Greene & Azevedo, 2009). Due to this complexity of learning, many students will require outside

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support to learn in the online mode, which has prompted different types of empirical research into the guidance required by students—e.g. by a human tutor—and the investigation into which aspects of self-regulation are necessary for success in online learning (Greene & Azevedo, 2009). We aimed to extend this research by investigating students' learning choices in blended learning environments, when the face-to-face and online components take different positions: it is the type of face-to-face learning, problem-based learning, that constitutes the most demanding component of the blend, while the online learning serves to support students who need additional scaffolds (Tempelaar, Rienties, & Giesbers, 2011). In the aforementioned study, the dependency of learning in the online mode on learning styles and self-regulation of learning was investigated; our research centers on the impact of individual differences with regard to social cognitive aspects of learning emotions and motivations to prefer online learning.

Social cognitive theories of motivation focus on various aspects of achievement motivation that are best regarded as complementary, rather than competing (Anderman & Dawson, 2010). Examples are achievement goal theory, self-determination theory, and expectancy-value theory. The interplay among several components of social cognitive theories can become strong enough as to develop into meaning systems: networks of goals, beliefs and strategies that can be used to classify people into coherent groups with specific profiles. Dweck's implicit theories of intelligence (also called 'self-theories' or 'lay theories') constitute one such meaning system. This system is based on two opposing views of the malleability of intelligence, and associated self-perceptions as goal setting, effort beliefs, and self-regulation strategies (Dweck, 2002; Dweck & Master, 2008; Dweck & Molden, 2005; Molden & Dweck, 2006; Plaks, Levy, & Dweck, 2009). This study focuses specifically on the role of implicit theories as social cognitive antecedents of learning emotions.

2. Theoretical framework

Pekrun's control-value theory of achievement emotions is based on a four-stage feedback loop process of learning, or general performance in achievement settings (Pekrun, 2006; Pekrun & Stephens, 2010; Pekrun et al., 2007). Achievement emotions make up the third stage of the process, directly impacting the fourth stage, learning and learning performance. The direct antecedents of achievement motivations are control and value appraisals: they constitute the second stage. Students' goals and achievement-related control and value beliefs constitute the distal antecedents of achievement emotions. The first stage is shaped by environmental factors. Fig. 1 depicts a schematic overview of the last three stages of the control-value theory of achievement emotions (see Pekrun, 2006; Pekrun et al., 2007; Pekrun & Stephens, 2010; also Artino, 2010), whereby each panel identifies both the general concepts, in the upper part, and the specific operationalization of these concept in this study, in the lower part. With regard to the second stage in Pekrun's theory, appraisals, Fig. 1 explicitly distinguishes the distal antecedents, in the first panel, and direct antecedents, in the second panel. Learning emotions, the third stage, are provided in the third panel. With regard to the fourth stage, learning and achievement, we explicitly distinguish between variables describing the learning process, in the fourth panel, and variables describing learning outcomes, in the fifth and last panel. Samples of constructs used in our study are in italics.

Pekrun's theory supposes a three-dimensional taxonomy of achievement emotions, distinguishing activity versus outcome emotions pertaining to the object focus, positive versus negative emotions with regard to the valence of emotions, and activating versus deactivating emotions with regard to behavioral impact of the emotion. Beyond this taxonomy, the theoretical framework allows for the contextualization of emotional experiences into different types of achievement settings (class-, learning-, and test-related) and different temporal specifications (trait-, course-specific, state-emotions) (Pekrun, Goetz, & Perry, 2005; Pekrun & Stephens, 2010). From this rich structure, we opted to focus on four learning-emotions, which are hypothesized to have a strong impact on students' learning choices and the persistence of these choices: the positive emotion *Enjoyment*, the negative activating emotion *Anxiety*, and the negative deactivating emotions *Hopelessness* and *Boredom*. This selection of emotional concepts is fairly congruent with that of the Artino (2010) study, which investigates the impact of *Enjoyment*, *Boredom*, and *Frustration* on students' preference for online learning. Both ours and the Artino (2010) study focus solely on learning emotions, leaving the class- and test-emotions beyond the scope of study. The motivation for our focus on learning emotions is that the type of process variables investigated by the studies – students' preferences for different types of learning environments – are hypothesized to be impacted directly by students' learning emotions in the specific context.

As a model of distal antecedents of achievement emotions, we applied the framework or 'meaning system' for implicit theories of intelligence that refers to individual theories or beliefs people develop about the nature of their intelligence. These theories are more often implicit than explicit, justifying the labels 'implicit' or 'lay theories'. Implicit theories begin developing as early as preschool age (Dweck, 1999), but only cement into well organized and coherent meaning systems with stable links to effort beliefs and achievement goals at 10–12 years (Molden & Dweck, 2006). Dweck's framework of implicit theories (Dweck, 1999; Dweck & Leggett, 1988) contrasts two opposing beliefs. Learners exhibiting an *Entity Theory*, the so-called 'entity theorists', view intelligence as an unchangeable, fixed, internal characteristic. Learners

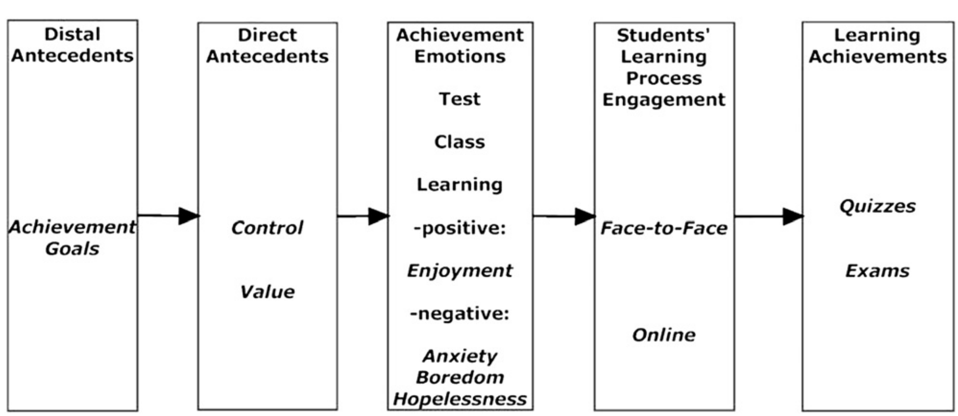

Fig. 1. Control-value theory of achievement emotions.

who have an *Incremental Theory*, the 'incremental theorists', believe that their intelligence is malleable, fluid, and can be cultivated by learning.

Effort beliefs are more or less implied by the definitions of the intelligence views. Students who endorse the view that intelligence is a malleable quality that can be developed with effort will realize that it is through exerting learning efforts that one builds intelligence. The *Effort Positive* belief, therefore, is hypothesized to correspond to the incremental theory framework: effort is viewed as something positive when one believes that exerting effort activates and develops one's own intelligence (Blackwell, 2002; Blackwell, Trzesniewski, & Dweck, 2007; Dweck, 1999). Conversely, when intelligence is seen as something which cannot be cultivated, effort is viewed as something negative. This *Effort Negative* belief is the natural accompaniment to the entity theory framework: exerting effort signals lack of intelligence.

The third component of the meaning system is goal orientations, specifically the distinction between mastery goal-orientation and performance goal-orientation (Dweck and coauthors use the label 'learning goal-orientation' rather than 'mastery goal-orientation', and when focusing on their research, we will follow their terminology). The incremental theory framework is hypothesized to induce a focus on learning goals—the aim to acquire new knowledge or skills—since it corresponds to the view that it is through learning that one develops intelligence (Blackwell et al., 2007; Dweck, 1999; Haydel & Roeser, 2002). In contrast, students endorsing the entity theory framework won't gain from pursuing a learning goal, and are hypothesized to focus on performance goals instead: the best they can do is validating their own intelligence by demonstrating ability, c. q. disguising lack of ability. Grant and Dweck (2003) have extended the learning versus performance goal framework (see also Brophy, 2005; Hulleman, Schrager, Bodmann, & Harackiewicz, 2010; Hulleman & Senko, 2010) by including the dimensions of appearance and normative components in goal operationalization. This refinement produces four forms of performance goals: *Outcome Goals* that focus on obtaining positive outcomes, such as striving for a good grade; *Ability Goals* that focus on the validating of intellectual ability; and two normative versions of these outcome and ability goals that include social comparisons: the *Normative Outcome Goal* and *Normative Ability Goal*. The framework was further extended through the learning-mastery goal, where an operationalization with an explicit challenge-mastery dimension was distinguished from a pure learning operationalization: the *Challenge/Mastery Goal* versus the *Learning Goal*. An overview of the complete meaning system is depicted by Fig. 2, where the included arrows represent the main hypotheses: positive effort beliefs are the main antecedents of all learning and appearance goals, while negative effort beliefs are thought to primarily impact only normative goals.

Achievement goals constitute the link between Dweck's implicit theories meaning system and Pekrun's control-value theory of achievement emotions. The research questions this study aims to answer, therefore, refer to the investigation of the role that achievement emotions play in the development of students' preferences for learning environments. Specifically, we explore the preference for online learning relative to face-to-face learning within our learning blend, as well as the role of Dweck's meaning systems with the components of implicit theories, effort beliefs, and goal orientations as distal antecedents to the achievement emotions.

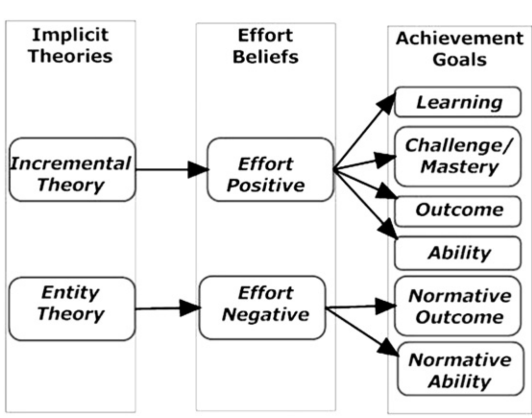

Fig. 2. Meaning system of implicit theories, effort beliefs, and achievement goals.

3. Method

3.1. Participants and educational context

This study is based on the investigation of first-year students of a business and economics school in the south of the Netherlands, who entered the program in 2010/2011. The programs offered by this school deviate from mainstream, European university education in two important ways: the student-centered learning approach known as problem-based learning, and a strong international orientation: the programs are offered in the English language, and mainly attract international students. Among the 730 students on whom this study is based, 72.5% have an international background (mostly European, and somewhat more than 50% from German speaking countries in Europe), while the remaining 27.5% are Dutch students. 37.3% of the students are female, 62.7% male. The average age of students was 20.0 years, over a range of 17.4–30.7 years, though half of the students were in their teens—the median age is also 20.0 years.

The strong diversity in nationalities among freshmen has a strong impact on the education of mathematics and statistics. There exist considerable differences among the national secondary school systems of European countries, even for neighboring countries such as the Netherlands, Belgium, and Germany. For example, high school mathematics education in the Netherlands has closely followed the educational reforms introduced in Anglo-Saxon countries in recent decades, introducing descriptive statistics and data analysis skills using computer technology. The mathematics curriculum in Belgium and Germany, however, has seen fewer changes and is thus characterized by a stronger focus on more traditional mathematical topics. Even within a nation, a second source of diversity is found in the type of mathematics followed in a student's education prior to university. Most national educational systems differentiate at minimum three levels: preparing for arts and humanities programs in tertiary education, preparing for social sciences, and preparing for sciences. The second level is required for admittance to the program followed by the participants in this study, but a large portion of the freshmen, 32.1%, were educated at the highest level.

The principal educational technology applied by the school is one of problem-based learning within small tutorial groups. Because of the large diversity in students' prior schooling and prior mastery of mathematics and statistics, the university added online learning opportunities especially to provide the less-prepared students with a broad range of learning tools. Through this implementation, a blended environment for learning mathematics and statistics was created. The face-to-face component—the problem-based learning setting—focuses on collaborative learning in small groups of students steered by open-ended problems. This is well-documented in the context of business and economics education by e.g. Gijselaers et al. (1995) and Wilkerson and Gijselaers (1996). A report concerning the medical education of the same university by Schmidt, van der Molen, te Winkel, and Wijnen (2009) presents an effect analysis of problem-based learning. The students in this study were enrolled in tutorial groups of a size ranging from 12 to 14 students. The online component of the blend covers several different technologies. First, in the summer between the end of secondary school and the start of the university program in early September, an online bridging course in mathematics using an adaptive e-tutorial was offered to those students whose mathematical background was the weakest. About 175 students participated in this developmental education. Since only a portion of the students participated in this summer course, it has not been incorporated in this study (but see Rienties, Tempelaar, Dijkstra, Rehm, & Gijselaers, 2008; Rienties, Tempelaar, Van den Bossche, Gijselaers, & Segers, 2009, for an account). In the regular curriculum, two distinct online learning components were provided. For learning and practicing statistics a system called MyStatsLab was offered. This is a publisher-based content management system, which contains digital practice and test materials to accompany a traditional textbook. For mathematics practice, students were offered access to an expansive database of mathematics items from which quizzes are generated by random selection of these items.

3.2. Procedures

In the first term of their first academic semester, these students took in parallel two compulsory eight-week courses: an integrated course in organizational theory and marketing, two subjects from the behavioral sciences domain, and an integrated course in mathematics and statistics. In the first three weeks of the term, the students were asked to complete self-report questionnaires concerning implicit theories and goal orientations as part of a data-analysis directed student project for statistics. All students consented that their data, in confidential format, would be used for educational and research purposes. In the third, fifth and seventh weeks of the course, students were offered voluntary participation in quizzes in mathematics and statistics which could bring them a bonus score of at maximum 20%. These quizzes were administered digitally, and randomly generated from large databases of quiz items. In the eighth week of the term the main assessment of student learning took place, which consists of written exams in mathematics and statistics. In the fourth week, half-way the term, the students completed the questionnaire on learning emotions with regard to mathematics and statistics. This timing was chosen so as to ascertain that students were both sufficiently familiarized with the new learning environment and that measurement was not so late in the course as to risk contaminating learning and test emotions.

3.3. Measures

3.3.1. Academic emotions and Academic control

Academic emotions were measured through four scales of the *Achievement Emotions Questionnaire* (AEQ) developed by Pekrun et al. (2005): *Enjoyment*, *Anxiety*, *Boredom* and *Hopelessness*. One assumption underlying Pekrun's (2000) taxonomy of achievement emotions is that these emotions' experience is context-specific. Therefore, the AEQ is subdivided into three sections, each focusing on different contexts of academic settings where students can experience emotions: attending class, when studying, and while taking exams. For the purpose of our study, we have considered the four emotions just mentioned in study situations: the learning-related emotions. The other assumptions underlying Pekrun's taxonomy are that achievement emotions have a valence, which can be either positive or negative, and an activation component, usually referred to as physiologically activating versus deactivating. Considering these dimensions perspectives, enjoyment is a positive activating emotion, anxiety is negative activating, and hopelessness and boredom are negative deactivating emotions. The *Enjoyment* scale (10 items, e.g. 'I enjoy acquiring new knowledge'), *Anxiety* scale (11 items, e.g. 'I get tense and nervous while studying'), *Boredom* scale (11 items, e.g., 'The material bores me to death') and *Hopelessness* scale (11 items, e.g. 'I feel hopeless when I think about studying') used in the present investigation assess the emotions experienced when studying specifically for a course in mathematics and statistics. The items were scored on a 7-point Likert scale (1 = *completely disagree* and 7 = *completely agree*). These four learning emotions are hypothesized as the strongest antecedents of study success. The AEQ is a self-report questionnaire with good psychometric qualities (Pekrun, Goetz, Frenzel, Barchfeld, & Perry, 2011), and it is also useful in assessing the linkages between academic emotions and students' learning and academic achievement (Acee et al., 2010).

Academic control was measured with the perceived *Academic control* scale of Perry, Hladkyj, Pekrun, and Pelletier (2001). The perceived academic control as described by Perry et al. (2001) is a domain-specific measure of college students' beliefs, which has its roots in social cognition literature. In this perspective, *Academic control* is understood as an enduring individual variable. The scale is composed of eight items, each answered on a 7-point scale (1 = *strongly disagree* and 7 = *strongly agree*), e.g. 'I have a great deal of control over my academic performance in my courses'. The perceived control scale has been previously studied and shown to have good reliability and validity (Perry, Hladkyj, Pekrun, Clifton, & Chipperfield, 2005).

3.3.2. Implicit theories of intelligence

Measures of entity and incremental implicit theories of intelligence were adopted from Dweck's (1999) Theories of Intelligence Scale — Self Form for Adults. The scale consists of eight items: four *Entity Theory* statements (e.g., 'You have a certain amount of intelligence, and you can't really do much to change it') and four *Incremental Theory* statements (e.g., 'You can always substantially change how intelligent you are').

3.3.3. Effort beliefs

Measures of effort beliefs have two sources, Dweck (1999) and Blackwell (2002). Dweck (1999) provides several sample statements which portray effort as a negative thing (where exerting effort mirrors the view that one has low ability) and effort as a positive thing (where exerting effort is regarded as a way to activate and increase one's ability). For both of these sets of statements (see Dweck, 1999, p. 40), we used the first ones as the first item of both subscales. For the *Effort Negative* subscale this was 'If you have to work hard on some problems, you're probably not very good at them', and for the *Effort Positive* subscale it was 'When you're good at something, working hard allows you to really understand it'. In addition, the full sets of effort beliefs of Blackwell (2002) were used, containing five positive and five negative items (see also Blackwell et al., 2007). A sample item of viewing *Effort Negative*ly related to ability is 'To tell the truth, when I work hard at my schoolwork, it makes me feel like I'm not very smart'. The item 'The harder you work at something, the better you will be at it' expresses the view that effort leads to positive outcomes (*Effort Positive*). The validity of this instrument in a similar population to this study is demonstrated in Tempelaar, Schim van der Loeff, and Gijselaers (2009).

3.3.4. Goal orientations

In the operationalization of goal setting, the Grant and Dweck (2003) instrument has been applied, which distinguishes two different goal dimensions: the learning versus performance goal dimension, and the dimension of appearance and normative components in goal operationalization. Grant and Dweck's framework contains four forms of performance goals: *Outcome Goal*s which focus on obtaining positive outcomes, such as striving for a good grade (e.g., 'It is very important to me to do well in my courses'); *Ability Goal*s which focus on the validating of intellectual ability (e.g., 'It is important to me to confirm my intelligence through my schoolwork'); and two normative versions of these outcome and ability goals which include social comparisons: the *Normative Outcome Goal* (e.g., 'It is very important to me to do well in my courses compared to others') and the *Normative Ability Goal* (e.g., 'It is very important to me to confirm that I am more intelligent than other students'). A further extension was created in the learning or mastery goal, where an operationalization with an explicit challenge/mastery dimension was distinguished from a pure learning operationalization: the *Challenge/*

Mastery Goal (e.g., 'I really enjoy facing challenges, and I seek out opportunities to do so in my courses') versus the *Learning Goal* (e.g., 'I strive to constantly learn and improve in my courses'). In their empirical studies, Grant and Dweck (2003) opt for using a reduced four-factor model by merging the two normative goals and the two learning goals. In contrast, Donnellan (2008) finds good reason to leave the full six-factor structure intact, an approach we followed as well.

3.3.5. Students' learning behavior

In order to obtain an accurate investigation into how different students allocate their learning time beyond time spent in the online learning mode we would require measures for time spent in tutorial groups and self-study time. Such data is not available, which leaves an important part of student learning behavior unobserved. Nevertheless, all activities of face-to-face student learning, and all self-study, are organized within one general course management system (BlackBoard), allowing for the construction of a proxy of the general level of a student's face-to-face learning activity: the number of *BlackBoard* clicks (although the course management system does not log connection time, it does log total amount of clicks in the system). So in comparing groups, or in estimating relationships, the variable *BlackBoard* serves as the indicator of students' engagement in the face-to-face component of the learning blend. In learning statistics, students had access to the online MyStatsLab learning environment. This tool offers two measures of learning intensity: total coverage (the total number of lessons successfully practiced) and total learning time. These two measures are, however, highly collinear, and for that reason we transformed the learning time measure into an efficiency measure: learning time per lesson. Thus, the two measures related to the engagement of MyStatsLab are: number of lessons successfully learned (*MyStatsLab*) and time spent per lesson learned (inverted into an efficiency measure: *MSLefficiency* as learned lessons per hour). For mathematics, students had access to digital practice quizzes generated from the same item banks as the course quizzes themselves. Measures of students' intensity of practicing with quizzes were the number of different practice quizzes done (*MathQzPract*) and number of times students reviewed their performance in these practice quizzes (*BBMyGrades*).

3.3.6. Students' achievements

Course performance was measured with a performance portfolio, of which four components are used in this study: performance measures in three quizzes of both partial subjects (*MathQuiz* and *StatsQuiz*) and scores in the final written exam (*MathExam* and *StatsExam*). Both quizzes and final exams are multiple-choice tests, quizzes taken in a digital learning environment, final exams not. Questions in the final exam focus on conceptual understanding, whereas those in quizzes emphasize the application of mathematics and statistics. Two categorical variables are used to classify students: gender, allowing for *Female* and *Male*, and level of introductory mathematics education, distinguishing *MathMajor* and *MathMinor* tracks.

3.4. Statistical analyses

Beyond descriptive analyses, this study applies path modeling. To prevent capitalization of chance, rather conservative model building rules were adapted: correlated traits were only allowed for variables measured by the same instrument, and as a cutoff value for significance for the adoption of any regression path, p-values of 1% or less were required. Models were estimated with LISREL (version 8.72) using maximum likelihood estimation. In the path model, the sequence of components was based on both learning theoretic models and on timing of measurements. It was hypothesized that learning emotions predict learning decisions, including intensity to learn in the two different online learning components. Given that the quizzes, and therefore quiz preparation, were distributed over most of the course period, the specification of a bidirectional relationship between learning emotions and learning decisions would have been most adequate; however the estimation of such a model requires repeated measurements of learning emotions.

Our study aims to explain students' learning choices within the blended learning environment in terms of individual difference variables. As the students' engagement in the face-to-face component is unobserved, but well-approximated by the engagement with the course management system, our analysis centers on differences in the relationships between students' engagement with the course management system (*BlackBoard*) and learning emotions and students' beliefs, vis-à-vis relationships between students' engagement with the online component of the blend and the same students' background variables. The two constructs *MyStatsLab* and *MathQzPract* served as main indicators of students' engagement with online learning. All analyses were based on the subset of students for which background characteristics, tool use, and performance data all were available. This subset comprises 730 students, 86% of the total of 849 students enrolled.

The hypothesized path model consists of a concatenation of Dweck's implicit theories meaning system, Pekrun's achievement emotions model, students' observed learning preferences, students' performance in the learning environments, and learning outcomes. Fig. 3 describes the full model; for reasons of readability only direct antecedent relationships have been incorporated, omitting distal antecedent relationships (such as the relationships between effort views and achievement emotions). It should be noted that distal antecedent relationships were, however, included in the model search process.

4. Results

4.1. Descriptive analysis

Table 1 exhibits levels of learning emotions, decomposed for gender. Learning *Anxiety* and learning *Enjoyment* demonstrate about

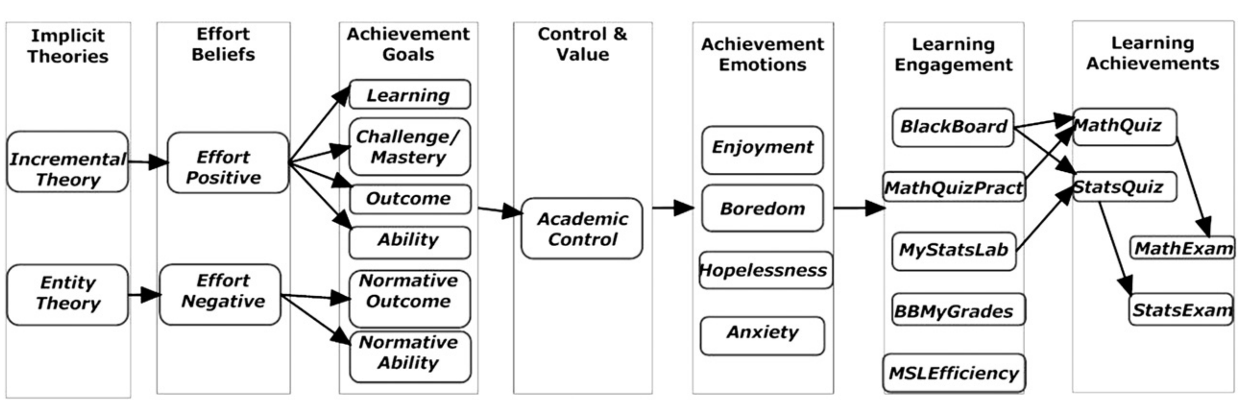

Fig. 3. Structure of hypothesized path model.

Table 1
Means (M), standard deviations (SD), and gender and educational track differences (*t*- and *p*-values) of learning emotions.

	All		Female		Male		Δ Gender		Math Major		Math Minor		Δ Track	
	M	SD	M	SD	M	SD	*t*	*p*	M	SD	M	SD	*t*	*p*
Anxiety	3.79	1.22	4.07	1.21	3.64	1.21	4.57	.000	3.36	1.22	4.00	1.17	−6.68	.000
Boredom	2.94	1.17	2.71	1.10	3.07	1.19	−4.06	.000	2.77	1.07	3.04	1.20	−3.01	.003
Hopelessness	3.00	1.28	3.17	1.27	2.90	1.27	2.70	.007	2.53	1.08	3.21	1.31	−7.35	.000
Enjoyment	4.11	0.97	4.06	0.97	4.13	0.98	−0.90	.370	4.29	0.95	4.01	0.97	3.75	.000

neutral mean levels, though *Anxiety* does contain a strong gender effect, with males scoring significantly less anxious than females. Further gender effects were present in learning *Boredom* and learning *Hopelessness*, both negative deactivating emotions, implying that the below-neutral mean scores indicate favorable emotional states. The gender pattern in negative emotions is not uniform: females scored less favorably on *Anxiety* and *Hopelessness*, but more favorably on *Boredom*, with significance levels below .01. These gender differences are in line with those reported in Frenzel et al. (2007), and Pekrun and Stephens (2010).

Table 1 also contains the same learning emotion data, now decomposed by introductory mathematics education track. All differences are significant, and a consistent pattern arises that students educated at advanced levels of mathematics possess more favorable emotions than students educated at basic levels. Differences are most substantial in the two negative deactivating emotions *Boredom* and *Hopelessness*.

The final step of descriptive analysis concerns the bivariate relationships between learning emotions and learning choices together with learning outcomes. Negative emotions are consistently negatively correlated with all learning intensity measurements, and all learning outcomes, whereas positive emotion is consistently positively correlated with the same variables. To facilitate comparison of the sizes of all correlations, Fig. 4 contains the absolute values of these correlations. Because taking absolute values amounts to mirroring the correlations of negative emotions across the horizontal axis, the legends of the negative emotions are adapted to reverse scoring: '-*Anxiety*', '-*Boredom*', '-*Hopelessness*', with *Enjoyment* being the single positive emotion: see Fig. 4. Due to the large sample size, correlations of .080 and larger are statistically significant at 5% significance level, and correlations of .095 and larger are statistically significant at 1% level.

After reversion of the negative emotions, the correlations exhibited in Fig. 4 were all positive, and all of substantial size. The smallest correlations for all facets of learning emotions are for *BlackBoard*, the proxy for general student activity in the course. Apparently general learning activity, and with it students' activity in the face-to-face component of the learning blend, is only quite weakly related to learning emotions, especially to the negative emotions learning *Anxiety* and *Hopelessness*. Students' activity in the online learning component of the blend, however, is more strongly related to learning emotions, primarily to *Boredom* and *Enjoyment*. For these emotions, correlations with intensity of math-quiz practicing are around .3, implying that about 10% of the variation in online tool use is explained solely by individual differences in these learning emotions. Correlations with *MyStatsLab* use are slightly less, but still substantial. Correlations between course performance measures and learning emotions are more substantial still, especially for mathematics, and strongest for the quiz component in math performance: *MathQuiz*. Moreover, the impact of learning emotions on course performance measures is not limited to the two emotions *Boredom* and *Enjoyment*, but rather spread across all four learning emotions, differing from the relations between learning intensity and learning emotions.

As the main inferential step in the analysis, a path model has been designed with the purpose of deriving a model to explain learning decisions and learning outcomes in terms of learning emotions, and in turn learning emotions in terms of individual learning characteristics which act as antecedents. The resulting model demonstrates satisfactory fit ($\chi^2 = 584.7$, $df = 216$, $p < 0.001$, CFI = .97, RMSEA = .049; recommended cutoff values for satisfactory fit are >.90 for CFI, <.06 for RMSEA; see Hu & Bentler, 1999). Fig. 5 contains a diagram of the path model with standardized estimates (beta's) and latent correlations of several of the factors (in order to preserve readability of the diagram, only part of the latent correlations is depicted). Table 2 provides numerical values of all standardized regression coefficients (estimates of Gamma and Beta parameter matrices).

Fig. 5 and Table 2 demonstrate that the general level of learning activity—approximated by *BlackBoard* clicks—is the best predictor for the intensity of online learning. Learning emotions have only a secondary role, expressed by the negative emotion *Boredom* and the positive emotion *Enjoyment*. As was expected from the correlational patterns, learning emotions had no significant impact on general learning activity against the rigid cutoff values for significance used in the model building process.

In looking at the antecedents of learning emotions we found a remarkable pattern. Learning emotions, and *Academic Control*, have a single dominant predictor: the *Effort Negative* belief. As one might expect, this *Effort Negative* belief positively impacts the three negative

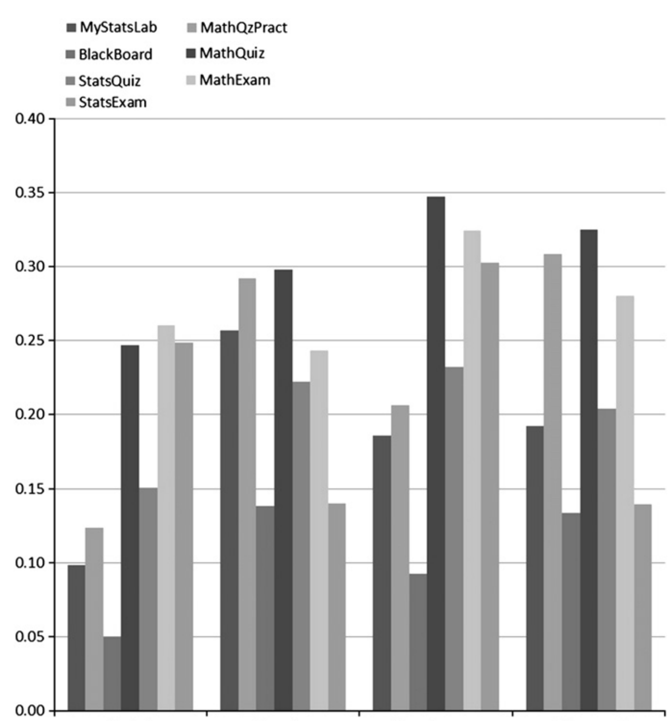

Fig. 4. Correlations (absolute values) between learning emotions, learning intensities, and learning outcomes.

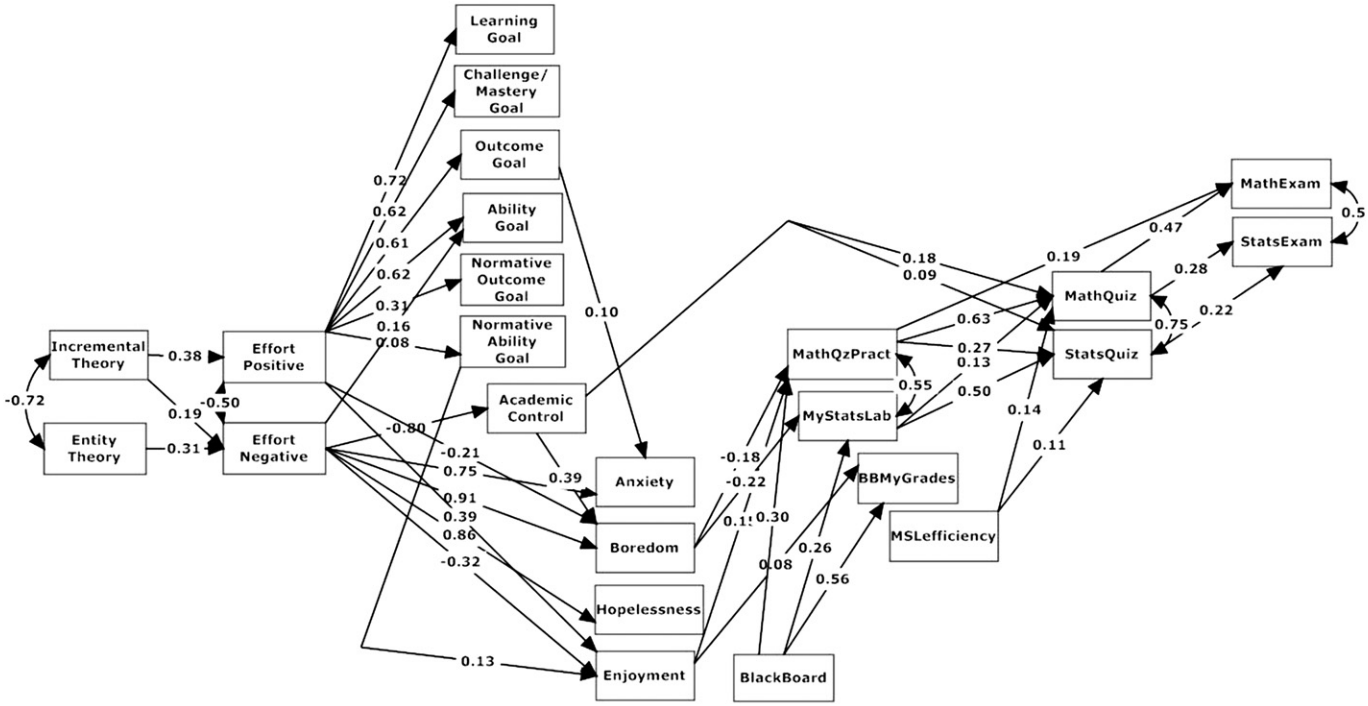

Fig. 5. Path diagram with standardized estimates.

learning emotions, and negatively impacts *Academic Control* and the positive emotion *Enjoyment*. The *Effort Positive* belief plays a more modest role, explaining *Boredom* and *Enjoyment*; for *Enjoyment* it is the stronger predictor. *Academic Control* has no impact on learning emotions beyond that of *Effort Negative* belief, with the exception of *Boredom*. Nevertheless, the sign of that path is opposite to that of the bivariate correlation, suggesting that *Academic Control* is primarily mediating the relationship between the *Effort Negative* belief and *Boredom*.

Where the *Effort Negative* belief plays a crucial role in the explanation of learning emotions, it is the *Effort Positive* belief that acts as dominant explanatory factor of the goal setting behavior of students. Both learning goals (*Learning Goal* and *Challenge/Mastery Goal*) and both nonnormative performance goals (*Outcome Goal* and *Ability Goal*) are strongly related to the *Effort Positive* belief, with a parallel role for the *Effort Negative* belief in explaining the *Ability Goal*. Another remarkable result is that goal setting behavior and learning emotions were essentially two uncoupled systems: only two paths connect them, with restricted beta's.

The relationships between learning decisions and learning outcomes are unsurprising. The intensities of learning in both online learning systems are by far the prime and strongest predictors of performance in both types of quizzes. Secondary effects are present for *Academic Control* and *MSLefficiency*—the efficiency of students in using the MyStatsLab online learning tool. In turn, quiz performance predicts exam performance, but lacks very high predictive power. Squared multiple correlations for all structural equations, expressed as percentages, are provided in the last column of Table 2. They indicate that the model explains a substantial part of variation in learning emotions, specifically the emotions with a negative valence, up to an R^2 of .74 for *Hopelessness*. Learning choices however depend much weaker on learning emotions, with squared multiple correlations ranging from .12 for the intensity of using the MyStatsLab online learning tool, to .38 for the intensity of using feedback available in BlackBoard. Explained variation of learning performance is again at a higher level, specifically for performance in quizzes. Correlations over .5 indicate that due to strong correspondence between quizzes and test materials in the digital learning tools, learning behavior in the tools is a powerful predictor of learning outcomes.

5. Discussion and limitations

The principal finding of this study is that the positive learning emotion (*Enjoyment*) contributes positively, and negative learning emotions (specifically *Boredom*) contribute negatively, to a student becoming an intensive online learner in a blended learning environment. This exists beyond the important role that general levels of student activity play in understanding students' behavior within blended learning environments. This is itself in line with the function one would expect learning emotions to have in situations of relative user preferences—when choosing from a blend of options, or even from mutually exclusive learning choices as was the case in the study by Artino (2010). In previous research focusing on the role of students' learning styles on their preferred mix of a variety of learning tools, we concluded that it is weaker, less academically-adapted students who profit most from the availability of online learning tools (Tempelaar et al., 2011). One might have hoped for similar findings in this empirical study on the role of learning emotions. This would entail students who are low in positive learning emotion and high in negative learning emotion—and therefore less academically-adapted than students with the reverse profile—profiting most from the support by online learning tools. For such a compensation mechanism to be relevant, the signs of the relationships would need to be opposite. Apparently, a student should already possess favorable learning emotions beyond the general willingness to be an active student in order to become an intensive online learner. But in the present study, the timing of the measurement of learning emotions did not completely exclude the possibility of a bidirectional relationship, where students who actively employ online learning tools in the start of the course develop a positive learning emotion as measured in the middle of the course, and then continue to be active online learners in the second half of the course. Further research containing multiple

Table 2
Standardized structural equation coefficients: standardized estimates of Gamma matrix in columns 1, 2; of Beta matrix in columns 3–17, and squared multiple correlations for structural equations, in column 18.

Variable	Entity Theory	Incremental Theory	Effort Negative	Effort Positive	Outcome Goal	Norm Ability Goal	Academic Control	Anxiety	Boredom	Hopeless ness	Enjoyment	Black Board	MathQz Pract	My Stats Lab	MSL efficiency	Math Quiz	Stats Quiz	R^2
EffortNegative	.31	.19																5%
EffortPositive		.38																15%
OutcomeGoal				.61														37%
AbilityGoal			.16	.62														31%
NormOutcomeGoal				.31														10%
NormAbilityGoal				.08														1%
LearningGoal				.72														52%
ChallengeMasteryGoal				.62														38%
AcademicControl			−.80															64%
Anxiety			.75		.10													52%
Boredom			.91	−.21			.39											57%
Hopelessness			.86															74%
Enjoyment			−.32	.39		.13												41%
BlackBoard																		
MathQzPract									−.18		.15	.30						18%
MyStatsLab									−.22			.26						12%
BBMyGrades											.08	.56						38%
MSLefficiency																		
MathQuiz							.18						.63	.13	.14			58%
StatsQuiz							.09						.27	.50	.11			52%
MathExam													.19			.47		38%
StatsExam																.28	.22	23%

Note: all coefficients are significant at .01 level.

measurements of learning emotions would be necessary to resolve these issues of potential dynamic, bidirectional relationships.

In contrast to the intensity of tool use, students' engagement in the face-to-face component of the learning blend (approximated by *BlackBoard*) appears to be independent of learning emotions and their antecedents, as visible from the absence of any path explaining general student activity. This may be partially explained by our specific composition of the learning blend, consisting of an unmoderated online tool and collaborative, face-to-face learning within the problem-based learning system. Apparently, favorable learning emotions are a required condition for becoming an online learner, but are not necessary for collaborative, face-to-face learning. To the extent that it can be generalized to other contexts, this finding has major educational implications. Our research discovered that even more than a traditional teacher, or at least a tutor in problem-based learning, an online teacher is faced with a dual task: providing adequate instruction and creating favorable learning conditions. Other studies also demonstrate how crucial learning conditions are in online learning; see e.g. Arbaugh et al. (2009) regarding general aspects; Artino (2010) regarding learning emotions specifically. What the present study adds is the inherently complex nature of this dual task. As will be elaborated in the following paragraph, crucial antecedents of learning emotions belong to the category of relatively stable, not highly malleable individual difference characteristics as implicit theories and effort beliefs. For any teacher to shape these, in optimal form, would be no easy task.

Control-value theory of achievement emotions hypothesizes that appraisals of control and value are the proximal determinants of achievement emotions, and achievement-related beliefs are distal individual antecedents (Pekrun, 2006; Pekrun & Stephens, 2010). In our study, these proximal determinants were operationalized by *Academic Control*. Unlike the process hypothesized by control-value theory, however, relationships between control appraisals and learning emotions were weak and of mediating nature. Instead, powerful and direct relationships were identified between the *Effort Negative* belief and all learning emotions. Effort beliefs have not been incorporated into empirical studies of control-value theory of achievement emotions before, and are classified as belonging to a set of achievement-related beliefs, hypothesized to be part of the distal antecedents of emotions. The pivotal role of Effort beliefs, both in the determination of learning emotions (mainly through the *Effort Negative* belief), and in the determination of goal setting behavior (mainly through the *Effort Positive* belief), suggests a crucial finding of this study. These results warrant supplementary empirical investigations, from both inside and outside the context of the impact learning emotions have on students' preferences for online learning compared with traditional face-to-face formats of learning.

5.1. Limitations

The present research underscores the importance to examine learning behavior and to understand learning behavior as a dynamic process which continuously adapts to requirements set in the course environment. Our research suggests that learning emotions, behavior and outcomes cannot be treated as stable antecedents. Examining learning behaviors over time requires repeated measurements over time. However, this puts heavy demands on the research itself, and on students to participate in these measurements. We recognize the importance of those issues, but we couldn't resolve them in the present research because it took place in a real course setting with limited possibilities to collect data. Next, the results of the present research emphasize the importance of collecting data on both learning behaviors in the online learning environments and face-to-face settings. However, the latter remained unobserved and could only be approximated by collecting data about the learning activities in general about the course management system. Future research should develop methodologies which included data collection in both parts of the course environment.

6. Conclusions

Positive learning emotions contribute to becoming an intensive online learner, as do positive effort beliefs, as distal antecedents. Negative learning emotions and negative effort beliefs appear to form significant obstacles for online learning. These outcomes are in line with the findings reported in Artino (2010), where students opting for an online course and students opting for a face-to-face course are compared with regard to learning characteristics, with the conclusion that online learning demands learners to be highly motivated, self-regulated learners. In itself this is no more than an intuitive conclusion: any format of learning tends to be more successful when learners are skillful, properly motivated, and possess favorable learning emotions. However, the dual task facing the online instructor is even more stringent than that of the traditional instructor, given the additional alternative for learning behavior: that of opting out of online learning.

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