STUDENTS' ACHIEVEMENTS IN A STATISTICS COURSE IN RELATION TO MOTIVATIONAL ASPECTS AND STUDY BEHAVIOUR

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ABSTRACT

The present study focuses on motivational constructs and their effect on students' academic achievement within an existing statistics course. First-year Health Sciences students completed a questionnaire that measures several motivational constructs: dimensions of causal attributions, outcome expectancy, affect, and study behaviour, all with respect to statistics. The results showed that when the cause of negative events was perceived as uncontrollable, outcome expectancy was negative. When the cause of negative events was perceived as stable, affect toward statistics was negative. Furthermore, negative affect toward statistics and limited study behaviour led to unsatisfactory achievements. Path analysis (Lisrel) largely confirmed the causal relations in a model that was based on attributional and learned helplessness theories. The consequences of these findings for statistics education are discussed.

Keywords: *Statistics education research; Motivation; Conceptual understanding; Study behaviour*

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1. INTRODUCTION

Motivation influences the scope and the quality of study behaviour of students (see e.g., Bruning, Schraw, & Ronning, 1999; Deci & Ryan, 1985; Graham & Weiner, 1987; Pintrich, 2000). High-quality study behaviour involves active knowledge construction. Active knowledge construction is known to enhance understanding of the material in many courses (see e.g., Chi, de Leeuw, Chiu, & LaVancher, 1994; Phye, 1997; Steffe & Gale, 1995), including statistics courses (see e.g., Garfield, 1993; Giraud, 1997; Keeler & Steinhorst, 1995; Magel, 1998). Therefore, in attempts to improve statistics education, it is fundamental to stimulate motivation.

Research on motivation is quite extensive and covers heterogeneous constructs (see e.g., Ames, 1992; Boekaerts, 1997; Volet, 1997; Weiner, 1992). Some of these constructs involve phenomena that are difficult to change, because they are to a large extent determined by traits of the individual that is involved, such as goal orientation, self-determination, and competence. Our aim is not to focus on such phenomena, but rather to focus on constructs that have practical implications for statistics education, that is, constructs that can be manipulated and acted upon while trying to improve statistics education.

For that reason we have focused on two motivational theories that offer opportunities to intervene in motivational processes. Both theories take the starting-point of the explanations people perceive for events they experience. These so called causal explanations have cognitive, affective, and behavioural consequences. Examples of cognitive consequences in a statistics educational context are expected outcomes of attending lectures or studying a course book; examples of affective consequences are enjoyment, pleasure, and interest; and examples of behavioural consequences are effort and persistence. The influence of causal explanations on cognition, affect, and behaviour might be manipulated and driven toward outcomes that are more positive, in terms of motivation. As a consequence, these causal explanations have practical implications for statistics education, because the obtained improvement of motivation might result in study behaviour that enhances understanding. The goal of the study was to investigate these phenomena in the context of statistics education.

2. MOTIVATIONAL MODEL

In statistics education one can sometimes encounter students who think that there is a stable cause for failing an exam (e.g., statistics is a difficult subject). These students may no longer expect to benefit from studying statistics; they may start to dislike it and will not spend much study time on this subject. Other students may think that they have no control over the outcomes of their actions. For example, “no matter how hard I study, I will not be able to understand it.” These students may in advance expect to fail on the exam, will also start to dislike statistics, and will not spend much time studying the material. These examples show the influence of causal attributions (stability of causes, non-controllability of causes) on cognitions such as outcome expectancies (no benefit from studying statistics, expectancy to fail on the exam) and consequently on emotions (affective reactions of starting to dislike statistics) and behaviour (disregarding statistics), which will finally have an effect on achievement. This chain effect, which is consequential for statistics education, is reflected in a model that was developed and tested in this study.

The model as a whole stands for motivation (see Figure 1). Motivation is not a separate entity in our model for two reasons. Firstly, it is difficult to insert it separately into a model, because it is an abstract, complex (Weiner, 1992), and ill-defined (Murphy & Alexander, 2000) construct, which is frequently used in colloquial language and consequently has several connotations. Moreover, motivation is studied in different domains and from different perspectives, which has led to distinct and changing conceptualisations and approaches. Various motivational constructs are studied, such as self-efficacy, goal orientation, metacognitive strategies, value, strategy use, causal perceptions, autonomy, social relatedness, as so forth. (See e.g., Ames, 1992; Boekaerts, 1997; Dweck, 2000; Pintrich & Schunk, 1996; Volet, 1997; Weiner, 1986.) In these studies it is often left implicit whether these constructs are part of motivation or are merely related to motivation (Murphy & Alexander, 2000). Our model as a whole reflects our perspective on motivation.

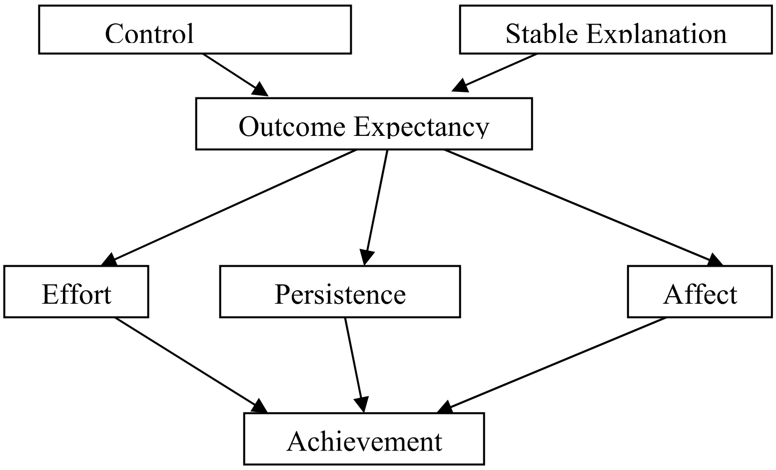

Figure 1. Statistics motivational model based on the attributional and the learned helplessness theory

Secondly, it is in our view not necessary to integrate motivation as a separate construct in the model. Traditionally, motivation was seen as an isolated latent construct that drives behaviour, cognition, and affect. We think that motivation merely is the sum of behaviour, cognition, and affect. Our opinion is in accordance with the remark of Weiner (1992), referring to Kelly (1958), that motivation as a model construct might be redundant; it is sufficient to represent only those variables that make up motivation. This view is also compatible with the fact that most motivational models do not explicitly contain motivation as a construct (see e.g., Bruning, Schraw & Ronning, 1999; Deci & Ryan, 1985; Pintrich, 2000; Pintrich & Schunk, 1996; Weiner, 1992). Therefore, the model that we developed contains only manifest variables that together stand for motivation, and does not contain motivation as a separate latent entity.

Two specific motivational theories were used for our model; namely the attributional and the learned helplessness theory, because they both use the starting-point of perceived causes for aversive events. The attribution-based theory of motivation (Graham & Weiner, 1987; Pintrich & Schunk, 1996; Weiner, 1986, 1992) commences with perceived causes for failure, unexpected outcomes, unusual events, and important situations. Perceived causes are the way people explain to themselves such outcomes, events, and situations. The connotations of the explanations are determined by underlying properties. In attribution-based theory these underlying properties of such explanations are divided into three dimensions: stability, control, and locus. Pintrich and Schunk (1996) propose, however, that the stability dimension is most closely linked to beliefs regarding future success (outcome expectancy) and subsequently to affect and actual achievement behaviour. Therefore, we integrated *stable explanation* in our model in Figure 1. It can be defined as the invariability over time of such perceived causes, namely causal explanations.

Peterson, Maier, and Seligman (1993) present a motivational theory, which originally emanates from the learned helplessness paradigm. In this paradigm, individuals are thought to become passive and to develop affective deficits if they cannot control and avoid the causes of aversive stimuli. They claim therefore, in contrast to Pintrich and Schunk (1996), that controllability is the major factor contributing to a negative outcome expectancy. Uncontrollable events will, according to Peterson et al., lead to a perceived non-contingency between people's actions and the outcomes of their actions. This negative outcome expectancy will lead to pessimistic thoughts, negative emotions (affect), and passivity (behaviour). This is what is called learned helplessness. We integrated *control* influencing outcome expectation as a separate construct in our model. Control is defined as the ability to avoid the causes of aversive stimuli.

Although the two presented theories slightly differ in the emphasis of the causal dimensions control and stability, they both reflect the way these properties of negative causal explanations contribute to a negative *outcome expectancy*, and how this will act upon *affect* and on behaviour, such as *effort* and *persistence,* which will finally result in an effect on *achievement*. The causal relations among these constructs are symbolised by arrows in our model that is presented in Figure 1.

This model was examined within the domain of statistics education. This means that all the constructs were measured with respect to statistical events and phenomena. It is known that perceived causal explanations via expectancy, affect, and behaviour determine future achievements in mathematics (see e.g., Seegers & Boekaerts, 1993; Vålas & Søvik, 1994). Our question was whether this is also true for statistics education and if the results would provide useful information for the reformation of statistics education.

The following research questions were addressed:

1. How do students causally explain statistics related events? Do they think that they have control over, for example, the mastery of the material, the amount of time they can spend on studying statistics, and the result on the tests? We also wanted to know whether or not the causes that the students reported for these events were stable.
2. We further measured the outcome expectancies, that is, whether students experience a contingency between studying statistics and their understanding of the topics and the grades they receive on statistics tests. We also investigated the influence of outcome expectancy on effort, persistence and affect.
3. Finally, we investigated the relations between these motivational constructs and achievement. The potential causal relations among these constructs were tested with structural equation modelling via Lisrel (Jöreskog & Sörbom, 1989).

3. METHOD

3.1. PARTICIPANTS

Two hundred (*n* = 200) first-year students of the faculty of Health Sciences participated in a pilot study to establish the reliability of a questionnaire that was developed to measure the motivational constructs. In the subsequent year *n* = 94 first-year students of the faculty of Health Sciences participated in the main study; 79 of these participants were female, 15 were male. The ages ranged from 19 to 26 years. Approximately 75 percent of the first-year Health Sciences student body is female. The participants were recruited during educational activities before the start of the introductory statistics course in which this study was executed. During recruitment they were told that they had to answer questions about statistics education and that they would be paid 10 euro. This payment was given to avoid attracting only motivated students who were particularly interested in statistics. All participants took the introductory statistics course.

3.2. MEASUREMENT INSTRUMENTS AND PROCEDURE

A questionnaire to measure the motivational constructs that are relevant for our model was developed. This Motivation toward Statistics Questionnaire (MSQ) consisted of 38 items, divided into six subscales. The items were phrased as statements and participants responded on a 7-point Likert scale. The questionnaire is partly a Dutch translation of the Survey of Attitudes Toward Statistics (SATS) (Gal, Ginsburg, & Schau, 1997). Additional items with regard to causal explanations were formulated using the same principles as the Attributional Style Questionnaire (ASQ) (Peterson et al., 1993), in particular for two attributional dimensions: stability and control. Finally, items were added to measure the two aspects of study behaviour: effort and persistence. All MSQ items concentrated on statistics related events. Because the MSQ was for the greater part based on existing surveys that have been proven to be valid (Peterson et al., 1993; Schau, Stevens, Dauphinee, & Del Vecchio, 1995), it can be considered an adequate measurement instrument regarding the relevant motivational constructs. Example questions are presented in Table 1. Based on content the items were divided into six subscales. To establish the reliability of the MSQ, it was administered to 200 first-year Health Sciences students and Cronbach’s alpha was computed for each subscale. Six questions that did not fit in the subscale were identified. Four questions were removed; two were rephrased. The MSQ was used the subsequent year for collecting data for the main study. It was administered to the students at the beginning of the introductory statistics course. Students received written instructions before they completed the MSQ. The whole procedure took approximately half an hour.

A second instrument was used to assess participants on effort and persistence, because it is well known that self reports and students’ responses to questionnaires may not always adequately reveal mental processes and behaviour (Biggs, 1993; Nisbett & Wilson, 1977; Schwartz, 1999; Watkins, 1996). The goal was to obtain more reliable data on study behaviour. The instrument consisted of two rating scales ranging from zero to ten. It was distributed to the tutors of tutorial group meetings. These are weekly two hour sessions supervised by a tutor, in which the students discuss the subject matter. The sessions are an essential part of the course. The tutors were given instructions on how to infer students’ effort and persistence. They were told what was meant by effort and persistence, examples were given, and they were told how to use the rating scale (grades ranging from zero to ten are customary in our education). This came down to instructing them to ask and register whether students attended the lectures, whether students were prepared for the tutorial group meetings, and whether students were actively involved in the discussion during the obligatory meetings. The tutors had to convert their impression concerning these aspects into a grade called effort. Persistence was analogously a grade based on the tutors’ judgement concerning whether students continued asking questions during the meetings until they really understood the subject matter, whether students at home persisted in trying to solve their assignments by using lecture notes and/or their books, or whether they consulted their teacher when they were not able to solve an assignment. The participants were evaluated by their tutors in the week before the end of the course. Finally, the scores on the exam at the end of the course were used as an indicator for participants' achievements. The exam consisted of 30 multiple choice questions and grades could range from zero to ten. Example questions of the exam are presented in the appendix.

3.3. ANALYSIS

Sum scores of the responses to the questionnaire were computed for each subscale by summing the scores of individual items. Some items were positively phrased, others negatively. Responses on the negatively phrased items were mirrored so that all answers were in the same direction. The sum scores were called: *Stable Explanation, Control, Outcome Expectancy, Affect, Effort*, and *Persistence.* To reflect the facts that people seek causes especially for failure (Graham & Weiner, 1987) and that motivation to study statistics is usually modest, the coding on the variables *Stable Explanation* and *Control* was done in such a way that high scores corresponded with respectively a stable negative explanation and lack of control. Cronbach's α was computed for each subscale. The exam grades (*Achievement*) and the tutor ratings *Effort(T)* and *Persistence(T)* consisted of grades ranging from zero to ten. They were included into the analyses as raw data.

Four analyses were done. First, several t tests were done to test for possible selection biases. A comparison was done between the male and female participants on *Achievement, Stable Explanation, Control, Outcome Expectancy, Affect, Effort(T),* and *Persistence(T)*. Moreover, achievement was compared between the participants in our study and the rest of the cohort that took the introductory course. Second, bivariate correlations between all variables were calculated to inspect the correlation patterns. The covariance structure modelling was, because of the rather small sample size, done in two separate steps (Scott Long, 1983), resulting in the third and fourth analysis. The third analysis was a robust maximum likelihood confirmative factor analysis (the simultaneous analysis of the covariance and the asymptotic covariance matrix; Jöreskog & Sörbom, 1989), which was done to confirm the measurement structure. Fourth, a path analysis (a robust maximum likelihood structural equation modelling) was done with Lisrel. Due to the sample size it was necessary to disregard the measurement structure in this analysis. Hence, the analysis was done without latent variables and the sum scores of the separate items of the MSQ served as manifest variables. With this path analysis the model presented in Figure 1 was tested.

4. RESULTS

From the pilot study, Cronbach's α for each subscale (after the removal of the four items) and some example questions are presented in Table 1.

A robust maximum likelihood confirmatory factor analysis was executed on those data of the MSQ that were also used in the path analysis of the main study (n = 94). The content based classification of the items on the subscales *Control, Stable Explanation*, *Outcome Expectancy,* and *Affect* was supported by the results of this confirmatory factor analysis; indices showed a proper fit. The Satorra-Bentler chi-square was used. It is considered to be more robust against a small sample size and violations of distributional assumptions (Hu, Bentler, & Kano, 1992; Satorra & Bentler, 1994).

Table 1. Subscales of the MSQ (n = 200)

Subscales and example questions	*Number of items*	*Cronbachs's α*
Stable explanation: Statistics is just a difficult subject. I have always had difficulties with statistics.	4 items	.8427
Control: The result on the statistics exam is determined by my own endeavour. Whenever I don't understand a statistical topic, I know what to do.	5 items	.7797
Outcome Expectancy: It pays off to study statistics. The time I spend on statistics is wasted.	6 items	.6048
Affect: To study statistics is enjoyable. I think statistics is interesting.	8 items	.7813
Effort: I spend a lot of time on statistics. I never prepare myself for the statistics tutorial group meeting.	8 items	.8058
Persistence: Whenever I don't understand something from statistics, I quit. When I cannot complete a statistics assignment, I go through the book once again.	7 items	.7405

The Lisrel program provides several additional indices for how well the model fits the data (Jöreskog & Sörbom, 1988). A goodness of fit index (GFI) is given for the whole model. It compares the tested model with a so called null-model, that is, all parameters are fixed on zero. A second index is the normed fit index (NFI), which compares the tested model with an independence model (variances are set free, covariances are fixed on zero). This index, however, continues to improve when paths are added and therefore does not appraise parsimonious models adequately. The most meaningful index is the non-normed fit index (NNFI). In this index the degrees of freedom are taken into account and consequently it appraises not only the best fitting, but also the most parsimonious model. All three fit indices should be close to one. Finally the root mean square residual (RMR) is given. This index, as the residuals, is ideally close to zero. The indices presented in Table 2 show a proper fit for this model; that is, the items adequately fit into their subscales.

Table 2. Fit indices for the confirmatory factor analysis on Control, Stable Explanation, Outcome Expectancy, and Affect

Satorra-Bentler chi-square ($df = 224$, $n = 94$)	277.18; $p = .04$*	GFI	.86	Standardised RMR	.22
		NFI	.89		
		NNFI	.93		
		CFI	.94		

* $p < 0.05$

In Table 3 descriptive statistics of all the variables as measured by the MSQ, as well as the tutor ratings and the exam grades are given.

Table 3. Descriptives of the motivational variables and achievement

	Mean	*SD*	*Items*	*Scale min*	*Scale max*	*Min score*	*Max score*	*Skewness*	*Kurtosis*
Stable Explanation	16.39	5.61	4	4.00	28.00	4.00	28.00	.100	-.459
Control	16.22	4.84	5	5.00	35.00	5.00	31.00	.697	.637
Outcome Expect	29.13	5.13	6	6.00	42.00	14.00	40.00	-.562	.826
Affect	26.66	7.60	8	8.00	56.00	12.00	51.00	.196	.174
Effort	37.88	7.62	8	8.00	56.00	16.00	54.00	-.477	.347
Persistence	31.93	6.48	7	7.00	49.00	11.00	46.00	-.207	.293
Effort(T)	7.11	1.55	4	0.00	10.00	2.00	10.00	-.803	1.212
Persistence(T)	6.64	1.73	4	0.00	10.00	1.00	10.00	-1.028	1.862
Achievement	7.05	1.90	30	0.00	10.00	1.60	9.40	-.780	-.133

The results of the *t* tests showed no significant differences between female and male participants. This might partly be because of the restricted power of the tests, so additionally the effect sizes (Cohen's *d*) were computed. The results are respectively for *Achievement* (d = .13; p = .65)*, Control* (d = .17; p = .51)*, Stable Explanation* (d = .53; p = .08)*, Outcome Expectancy* (d = .22; p = .49)*, Affect* (d = .008; p = .97)*, Effort(T)* (d = .02; p = .94)*,* and *Persistence(T)* (d = .20; p = .52). Combined, these results indicate no substantial differences between male and female participants. An additional *t* test was done to test for another possible selection bias. In this *t* test the achievement of the students who participated in our study was compared to the rest of the cohort (n = 122). No significant difference was found, nor a consequential effect size (p = .82; d = .06).

A correlation matrix of all variables was computed and is presented in Table 4. The significance level was adjusted with a Bonferroni correction. Both dimensions of attribution (*Stable Explanation* and *Control*) were significantly correlated to *Outcome Expectation*. The notion of having no control was most strongly correlated to *Outcome Expectation*. *Outcome Expectation* was significantly correlated with *Affect* toward statistics.

Affect was significantly correlated to *Achievement*, but as expected not to the self-reported behavioural constructs (*Effort* and *Persistence*), which were also not correlated to *Achievement*. The tutor ratings *Effort(T)* and *Persistence(T)* on the other hand were much better predictors for *Achievement* and were more highly correlated to *Affect*. This is consistent with research that established the inaccuracy of self-reports and research that showed that students' responses to questionnaires may not always adequately reveal their own learning (Biggs, 1993; Glenberg, Sanocki, Epstein, & Morris, 1987; Nisbett & Wilson, 1977; Schwartz, 1999; Watkins, 1996).

A path analysis with Lisrel was conducted, because of this above-mentioned inaccuracy of self-reports, on a model where the tutor ratings *Effort(T)* and *Persistence(T)* were inserted instead of the self-reported study behaviour (*Effort* and *Persistence*). We started with our model that was presented in Figure 1. The relation between *Stable Explanation* and *Outcome Expectancy* based on attributional theories was not significant (Standardised Path coefficient β = .06; p = .31). We did find a strong negative relation between the notion of having no control (*Control*) and *Outcome Expectancy* (β = -.68; p < .001). Apparently, if a student thinks that there is no contingency between, for example, his study activities and the result on an exam, he will not expect a positive outcome of his actions.

Table 4. Correlations between the motivational variables and achievement.

	Stable Explanation	*Control*	*Outcome Expectancy*	*Affect*	*Effort*	*Persistence*	*Effort(T)*	*Persistence(T)*	*Achievement*
Stable Explanation	1	.584* $p < .001$	-.336* $p = .001$	-.550* $p < .001$	.156 $p = .067$	-.052 $p = .310$	-.116 $p = .132$	-.138 $p = .093$	-.392* $p < .001$
Control		1	-.647* $p < .001$	-.306 $p = .003$	.152 $p = .072$	-.099 $p = .172$	-.020 $p = .423$	.016 $p = .439$	-.121 $p = .123$
Outcome Expectancy			1	.312* $p = .001$	.020 $p = .424$	.157 $p = .065$	.127 $p = .112$	-.006 $p = .479$	.226 $p = .015$
Affect				1	.125 $p = .115$	.239 $p = .010$	.266 $p = .005$	.216 $p = .018$	.429* $p < .001$
Effort					1	.746* $p < .001$	.273 $p = .004$	.263 $p = .005$	.261 $p = .006$
Persistence						1	.368* $p < .001$	.337* $p = .001$	.294 $p = .002$
Effort(T)							1	.843* $p < .001$	.455* $p < .001$
Persistence(T)								1	.478* $p < .001$
Achievement									1

* $p \leq 0.001$ (Bonferroni corrected)

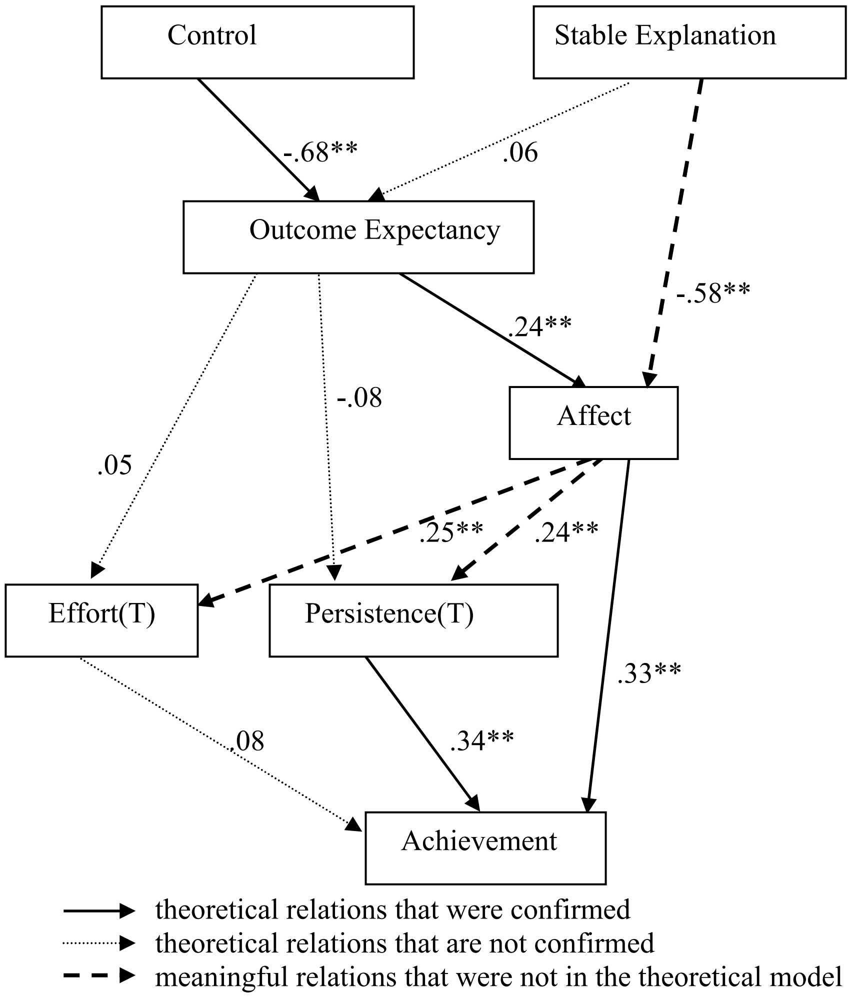

Figure 2. Statistics motivational model, as confirmed by path analysis (Lisrel)
Notes: Coefficients are standardised; *p < 0.05; **p < 0.01.

The relations among the motivational constructs as well as the coefficients are displayed in Figure 2. The solid arrows in Figure 2 stand for the theoretical relations that were confirmed, the dotted arrows stand for the theoretical relations that were not confirmed, and the dashed arrows indicate meaningful relations that were not in the hypothesised theoretical model, as shown in Figure 1.

Figure 2 shows a strong direct relation between *Stable Explanation* and *Affect*, that is, if students think that there are stable causes for negative statistics related events, failing their exams for example, they will develop negative feelings toward statistics. In the model, as displayed in Figure 1, this relation was mediated by *Outcome Expectancy*.

A negative *Outcome Expectancy* also had an adverse effect on *Affect*. *Affect* is related to all other constructs except to the notion of no control (*Control*) (β = .19; p = .08). To emphasise the importance of *Affect*, it has been placed in a more central position in Figure 2. It is strongly related to *Achievement* directly, as well as via *Persistence(T)*. Also important is that *Achievement* is determined by *Persistence(T)* (β = .34; p < .001) but not by *Effort(T)* (β = .08; p = .36).

To enhance the fit of the model, the residuals of the behavioural constructs *Effort(T)* and *Persistence(T)* had been set free to correlate (error covariance = 2.12; t = 5.34) in

Lisrel. With this relaxation of the model (as presented in Figure 2), all fit indices showed a good fit. The values of these indices for our model are provided in Table 5. Again the Satorra-Bentler chi-square is presented because of its robustness against a small sample size and violations of distributional assumptions (Hu et al., 1992; Satorra & Bentler, 1994).

Table 5. Fit indices for the model in Figure 2

Satorra-Bentler chi-square (df = 7, n = 94)	13.40; p = .063	GFI	.96	Standardised RMR	.042
		NFI	.95		
		NNFI	.93		
		CFI	.98		

5. DISCUSSION

This study was done in an introductory statistics course. It focussed on causal explanations of statistics related events, perceived outcome expectancy of students' activities within this statistics course, affect and study behaviour toward statistics, and the relation of these constructs to the results on the exam at the end of the course. These constructs were chosen because of their practical implications for the teaching of statistics.

Our first findings concern causal explanations. In the two presented motivational theories, perceived causes for events have underlying properties that have affective, behavioural, and cognitive consequences (Peterson et al., 1993; Pintrich & Schunk, 1996). In our study we focused on the dimensions of control and stability of causal explanations.

The first result concerns control. The model in Figure 2 indicates that the perception of having no control over causes of statistics related events may lead to decreased outcome expectancy. For example, a student who thinks that there is nothing he can do about the causes for failing the statistics exams, or thinks that he is not able to understand statistics anyway, may not expect a positive outcome from attending the lectures or studying the material. This mechanism is intuitively appealing.

The second result indicates that the stability of causal explanations may be more directly related to affect. As is seen in Figure 2 we found a significant path from *Stable Explanation* of such causes to *Affect*. The path that we found may be interpreted as follows. The perception of stable causes for aversive events related to statistics may lead to displeasure and frustration. If students perceive that failing statistics exams is not easily changeable, students may start to dislike statistics. This was reflected in responses like: *I dislike statistics; I do not have a positive perception of statistics*; and so forth.

In sum, these two findings indicate that students who think that they lack control may not expect to profit from studying statistics, and students who do invest time but think that there are stable causes for failing in spite of that, may start to dislike statistics.

The last path from *Stable Explanation* to *Affect*, though intuitively appealing, was not anticipated. The model in Figure 1 contained a relation between *Stable Explanations* and *Outcome Expectancy*. This relation was based on the general attributional position that the stability of a cause has the most influence on shifts in expectancy (Pintrich, 2000; Pintrich & Schunk, 1996; Weiner, 1986, 1992). Our findings are more consistent with the basic assumption from Peterson et al. (1993) that controllability is the major factor influencing outcome expectancy. Yet, the direct influence of *Stable Explanation* on *Affect* may also have important practical implications for statistics education.

The implication for education from our findings may be that when students discover the material is comprehensible to them and they experience success, they will be stimulated to study the material. This means that in constructing a learning environment, there should be tasks built in that are feasible for students. In that way the sequence of events that may lead to diminished motivation (Weiner, 1986) may be interrupted. Students will gradually sense that they can master the topics, they will discover they can control their learning outcomes, they will experience success, and they will abandon the idea that there are stable causes for failure. Control over learning outcomes may foster the positive expectation of future study activities. This positive expectation, together with the reduction of the perception of stable negative causes for failure, may even promote students to enjoy studying statistics. Only then should more difficult tasks be administered.

A second finding of interest in our study seems to be the central position of *Affect* in our model in Figure 2. Students who appreciate the value and relevance of statistics, who think it is interesting, challenging, and who like statistics, appear to study statistics more and qualitatively better, and perform better on the exams. In attributional theories (Pintrich, 2000; Pintrich & Schunk, 1996; Weiner, 1986, 1992) as well as in the learned helplessness theory of Peterson et al. (1993), affect is on the same level as behaviour and cognition. In the model in Figure 1 *Affect* was therefore put on par with behavioural consequences of *Outcome Expectancy*. However, affect seems to have a more prominent role in motivational processes in the present statistics education context. In our study we found that *Affect* directly and positively influenced *Achievement*. It also influenced study behaviour, namely *Effort(T)* and *Persistence(T)*. *Persistence(T)* in turn also influenced *Achievement*. Thus, *Affect* seems to determine achievement directly, as well as indirectly. Moreover, we found that *Affect* functioned as a mediator between *Control*, *Stable Explanations,* and *Outcome Expectancy* on the one hand, and the rest of the motivational constructs on the other. For this reason *Affect* holds a more central position in our model in Figure 2 than in the model presented in Figure 1.

The central role of *Affect* suggests that the students' feelings toward statistics appear to be an important theme for innovating and improving statistics education. Our results with respect to *Affect* are in line with Malone and Lepper (1987), who state that implementing features that make learning more appealing, enjoyable, and challenging makes learning more intrinsically motivating. Our finding that the feelings toward statistics are crucial in reaching satisfactory achievements corroborates the results of Isen, Daubman, and Gorgoglione (1987). In their study they found that positive affect may foster student's tendencies to see relations among stimuli, because positive affect leads to different ways of information processing, for example using different strategies. More relations between concepts are characteristic for richer knowledge networks, which indicate better integrated knowledge and deeper understanding (Kintsch, 1988, 1998).

It seems to be of relevance in the improvement of statistics education to make statistics courses more attractive, interesting, and enjoyable. One of the ways this might be achieved is by making the courses less theoretical. We think that a small experiment may engage students in a more active way, it may be fun to analyse data that are collected by the students themselves, and it may foster the notion of relevance of statistics.

A final result in our study was that *Effort(T)* had no significant relation with *Achievement*. Both *Effort(T)* and *Persistence(T)* were determined by the tutors. *Effort(T)* reflected the amount of time students studied, and whether students prepared themselves, attended lectures, or were actively involved in the discussion during group meetings.

Effort per se seemed to have a minor effect on achievement. What counts seems to be the way students study. In our study, *Persistence(T)* contributes significantly to exam performance. Students who did not quit that easily, who persisted, who turned to their lecture notes or their books, or consulted a teacher when they were not able to solve a statistical problem, those students did better on the exam. This result suggests that persisting is the best way to study statistics. It is in line with research in other subjects that established the importance of learning strategies and mastery goals for achievement in educational settings. (see e.g., Ames, 1992; Boekaerts; 1997; Pintrich, 2000; Dweck, 2000).

This finding may also be important for educational purposes. In the teaching of statistics, students should be stimulated to try to solve their problems. They should try to persist instead of quitting all too easily. This can be done by guiding them through the topics and by pointing them in the correct direction, instead of giving the solution to a problem promptly. Persisting and learning from mastering their own difficulties may be the most valuable way of learning.

The student population from which we recruited our participants consists largely of female students. Consequently, most of our participants were female (79 female versus 15 male). This could have affected our results. However, t tests on all the core variables (*Control, Stable Explanation, Outcome Expectancy*, *Affect, Effort(T)*, *Persistence(T),* and *Achievement*) in our models showed no significant differences between the female and male students. Therefore, the fact that the majority of our participants was female seems not to affect the motivational processes that were studied.

The tutor ratings that we used to measure effort and persistence are another limitation of our study. We instructed the tutors in great detail and asked them to record students' activities that we hold indicative for effort and persistence. We are confident that the ratings of the tutors are a quite valid and reliable measurement of the relevant behaviour. Still these ratings only reflect observable, external behaviour. Consequently we cannot discuss internal processes of reflection and mental activity. Our results only pertain to self-reported cognitions, affect, and observed behaviour.

In the present study only first-year students were studied. In future research second- and third-year students could be studied. Secondly, our results could be corroborated in studies with a larger sample. In our study a rather small sample was used (n = 94). It could also be investigated how in a practical educational context we can determine whether students persist during studying statistics. How can students optimally be guided to the correct solution of the problems? Will this reduce the perception of stable negative causes for failure and enhance the notion of control? Will such a reduction lead to a positive expectation of future study activities and to more enjoyment? Will all this eventually lead to more persistence and better results on the exam? Finally, further research is needed to investigate additional ways statistics education can be made more enjoyable. In the past, our department spent most attention on how to make lectures more informative, to select the best instruction books, and to develop assignments that are mainly educational. Now our attention has somewhat shifted toward making the courses more attractive, interesting, and enjoyable. We have tried to make the courses less theoretical by introducing a small experiment. Even so, future research may include investigating the most effective ways of making statistics education more enjoyable.

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APPENDIX

Example questions from the exam at the end of course (used for the measurement of achievement).

1. In a sample of 101 newborn babies, the mean birth weight is 3.8 kg and the standard deviation is 0.85. The null hypothesis is H_0: $\mu = 4$ kg.
   If this null hypothesis holds, then:

a. The probability that we will find a sample mean smaller than or equal to 3.8 kg is 50%
b. The probability that we will find a sample mean smaller than or equal to 3.8 kg is 80%
c. The probability that we will find a sample mean smaller than or equal to 3.8 kg is less than 50%
d. The probability that we will find a sample mean smaller than or equal to 3.8 kg is greater than 50%

2. Given the same sample as in question 1, we are testing H_0: $\mu = 4$ kg against H_1: $\mu \neq 4$ kg. The *p*-value of the sample mean of 3.8 kg is:

a. $p \leq .01$
b. $.01 < p \leq .02$
c. $.02 < p \leq .05$
d. $p > .05$

3. Given the same sample as in question 1, we are again testing H_0: $\mu = 4$ kg against H_1: $\mu \neq 4$ kg. Suppose the null hypothesis is rejected at $\alpha = .10$. What is the implication of this $\alpha = .10$?

a. In 10 % we will wrongfully conclude that H_0: $\mu = 4$ kg holds.
b. In 10 % we will wrongfully conclude that H_1: $\mu \neq 4$ kg holds.
c. In 5 % we will wrongfully conclude that H_0: $\mu = 4$ kg holds.
d. In 5 % we will wrongfully conclude that H_1: $\mu \neq 4$ kg holds.

4. The effects of 3 instructional methods on comprehensibility of the information (SCORE) were investigated. The 3 methods were: a standard method and 2 experimental methods (experimental method 1 and experimental method 2). The coding of the dummy variables was as follows:

	D_EXP1	D_EXP2
Standard method	0	0
Experimental method 1	1	0
Experimental method 2	0	1

It is tested whether the comprehensibility of the information (SCORE) for all methods is equal (H_0), or if at least one of the three methods is different (H_1).
Part of the output of the SPSS analysis is presented below:

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3341.722	2	1670.861	6.317	.005
	Residual	8727.917	33	264.482		
	Total	12069.639	35			

Predictors: (Constant), D_EXP2, D_EXP1
Dependent Variable: SCORE

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	37.750	4.695		8.041	.000
	D_EXP1	14.250	6.639	.367	2.146	.039
	D_EXP2	23.417	6.639	.603	3.527	.001

Dependent Variable: SCORE

Question: What conclusion can be drawn? Assume $\alpha = 0.05$.

a. There is a difference between the instructional methods because the *p*-value of *F* is smaller than 0.05.
b. There is a difference between the instructional methods because the *p*-value of *F* is smaller than 0.05/2 =0.025.
c. There is no difference between the instructional methods because the *p*-value of *F* is smaller than 0.05/2 =0.025.
d. There is no difference between the instructional methods because the *p*-value of *F* is smaller than 0.05.

Given the same research and the same results as in question 4, suppose that the F-test indicates a difference between the three methods. Which groups differ significantly? Assume $\alpha = 0.01$.

a. Each method differs significantly from the others.
b. The standard method differs significantly from experimental method 1.
c. The standard method differs significantly from experimental method 2.
d. The experimental method 1 differs significantly from experimental method 2.

5. Given the same research and the same results as in question 4, what is the proportion of explained variance in the SCORE variable?

a. 0.28
b. 0.72
c. 0.38
d. 0.86