QUALITY IN STATISTICS EDUCATION: APPLYING EXPECTANCY VALUE MODELS TO PREDICT STUDENT OUTCOMES IN STATISTICS EDUCATION

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Many freshmen at University sign up for Statistics during their first year. In order to meet the requirements of the institution they attend, students of a broad spectrum of specialties must take this mandatory course. They often find the course difficult and it scares them to work with statistical software or formulas. As a result, teaching statistics requires a special didactical approach. So, teachers benefit from knowledge on how student outcomes can be modeled. The model presented here forms the starting point for a project that took place in the Netherlands and Flanders from 2005 until 2007. The application of the Expectancy Value Model discussed here predicts student achievement as a function of expectancies, motivation to be successful, previous experience, and social and cultural environment. For the aforementioned study the model was applied choosing a special position for Effort and Expectancies.

INTRODUCTION

The study this paper describes focuses on measuring and analyzing attitudes toward statistics by freshmen at universities and colleges throughout the Netherlands and Flanders (Verhoeven, 2009). This doctoral study was centered on the following central question:

"*What is the effect of educational (course) and individual (student) factors on course outcomes with respect to introductory courses in Methods and Statistics at universities and colleges in the Netherlands and Flanders?"*

Theories underpinning this study focus on predicting course outcomes (Verhoeven, 2009; Eccles & Wigfield, 2002; Schau, Stevens, Dauphinee & Del Vecchio, 1995). Course outcomes are demarcated as *individual* student outcomes. Hence, evaluative (more institutional) elements of course outcomes have not been taken into account. For this study student course outcomes are modeled as a function of expectancies, effort (as a result of motivation and attitudes), individual and institutional factors. Furthermore, the emphasis lies on 'changes in attitudes toward statistics' and the extent to which educational factors (such as the course the students take; see Schau, Dauphinee & Del Vecchio, 1992) and individual factors (such as self confidence, prior statistical knowledge, background characteristics, statistics literacy and school careers; see Tempelaar, Gijselaers & Schim van der Loeff, 2006) influence these possible changes and – indirectly – student outcomes.

Let us first look at the original Expectancy Value Theory and then discuss its development in statistics educational research. The development of this theory and the application for this study is discussed in five steps. First the general model will be briefly discussed (1), followed (2) by the application to statistics education by Eccles & Wigfield (2002; see also Wigfield & Eccles, 2000). Then, the model used by Prosser & Trigwell (1999) will be described (3), followed (4) by the application by Schau (2003). Lastly, the model for this study will be explained (5).

EXPECTANCY VALUE THEORY DEVELOPMENTS

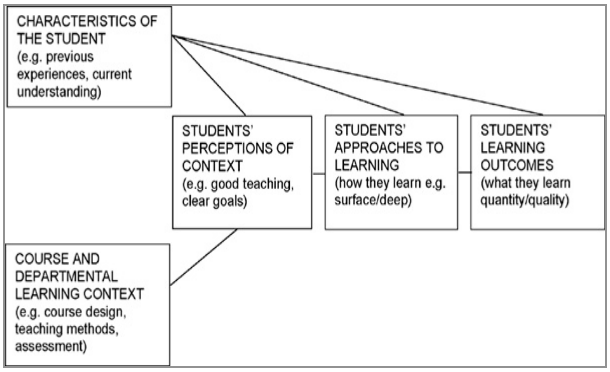
From Lewin to Wigfield & Eccles

The Expectancy Value Theory is a model for explaining achievement related choices (Wigfield, Tonks & Eccles, 2004). The general model development started in the 1930s with Lewin and Tolman, and it was further developed into a general model of achievement motivation by Atkinson (Schunk, Pintrich & Meece, 2008). It has known many applications in achievement related research, among them learning behavior. According to basic theory, achievement behavior can be looked upon as a function of the expectancies for a student, the goals toward which he/she is working and the task value of the student. When the student has more than one choice, he or she will choose the option with the best possible combination of expected success and value.

As a next step, this Expectancy Value Theory is applied to ‘statistics education’. This concept is developed by Wigfield and Eccles (2000; Eccles & Wigfield, 2002; Wigfield et al., 2004). In this model, the expectancies for a student are split into two components: students’ perceived competencies and the students’ perception of the difficulty of a task (Tempelaar, 2007). Furthermore, the model offers a contemporary perspective on the perception of ‘task value’. ‘Task value’ is defined as the value a student attaches to the successful completion of a task. This means that if the student perceives his ability to be successful positively, he has higher expectations and values towards completing the task and he will be better motivated to work hard (Verhoeven, 2009).

Prosser & Trigwell’s learning approach

As a third step in the development of this model, Prosser and Trigwell added students’ perceptions of the context and students’ learning approaches to the model (Prosser & Trigwell, 1999; Prosser, Trigwell, Hazel & Callagher, 1994). Students’ perceptions of the context affect their learning approach and, in return, their learning outcomes. The effect of contextual perceptions mediates the effect of learning approach on outcomes. Figure 1 shows an example of this model.



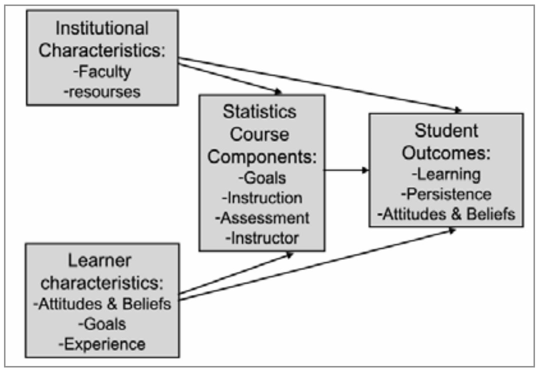


Figure 1. Model by Prosser & Trigwell

Figure 2. Model by Schau (2003)

Schau’s application of the Expectancy Value Model

Schau proposes an application of the Expectancy Value Model using institutional, learner, and course factors (Schau, 2003; Garfield, Hogg, Schau & Wittinghill, 2002), as shown in figure 2. Her model is based on Eccles and Wigfield’s model (2002). For instance she uses the notion of perceived competency and difficulty of the course in the introduction of her attitude components and she applies ‘Task Value’ to the model by means of a straightforward ‘Value’ component. Schau also uses elements from the model by Prosser and Trigwell (1999), by means of combining the contextual perceptions and learning approach into one factor, called ‘Effort’.

Schau’s contribution to the development of the Expectancy Value Theory lies in the fact that she initially developed a *4-factor model* that measures attitudes toward statistics (Schau et al., 1995). These components are:

- *Affect*, i.e., the student’s positive and negative feelings about statistics
- *Cognitive Competency*, i.e., student’s perceptions whether they can master the necessary knowledge and skills
- *Value*, i.e., student’s individual motives and beliefs about the importance of fulfilling a task
- *Difficulty*, i.e., perceived difficulty of a task for a particular student.

Later, she added two factors to the model, turning it into a *6-factor model*:

- *Effort*, i.e., the effort a student plans to put in, in order to achieve a good grade (actually this is ‘planned effort’)
- *Interest*, the student’s level of individual interest in statistics (Schau, 2003; Hilton, Schau & Olsen, 2004).

Model developments for this study

As a final step in the description of the development of the Expectancy Value Theory, the applications for this study are discussed. The two models shown in figures 3 and 4 are based on the previous discussed models. The most basic model for this study used is depicted in figure 3. It follows Schau's original model closely and it holds elements of the model by Prosser and Trigwell. Institutional factors, such as course outline, structure, didactical approach, duration, assessment methods, and class size play a role. Individual factors are self-confidence, previous statistics experience, school career, perceptions of mastery of statistics, and background characteristics. Both groups of indicators are assumed to influence course outcomes through attitudes toward statistics. These attitudes reflect upon certain leaning motivation and, in that sense, influence learning outcomes.

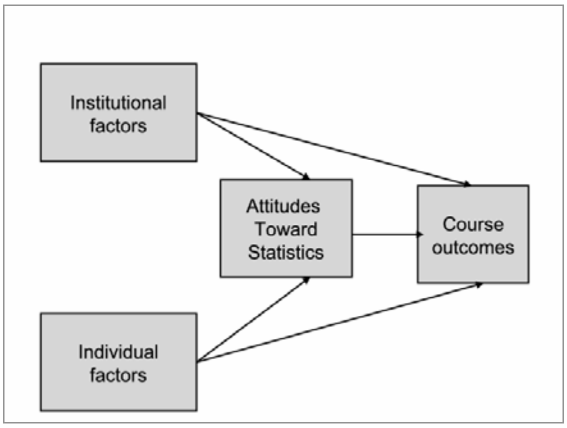


Figure 3. Basic model by Verhoeven (2009)

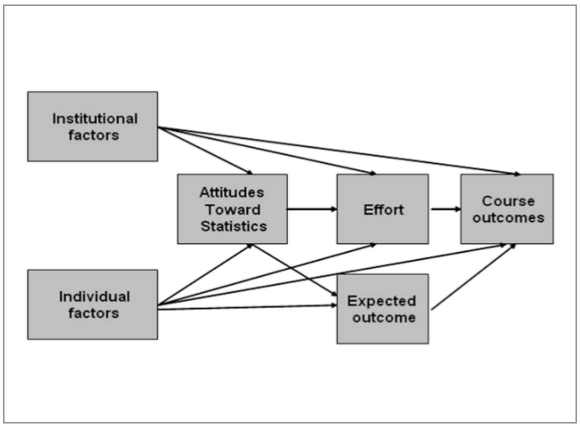


Figure 4. Final model by Verhoeven (2009)

All theoretical models by Verhoeven and Schau show attitudes toward statistics as one single indicator. Nevertheless, attitudes toward statistics already exist before any course starts. As a result of taking this course, these attitudes could change. That means that the indicators shown here are in fact indicators of '*change'*, for attitudes in this study are measured two times: once at the start of the course and once upon completion of that course. The results with regard to attitudes reflect the extent to which a student changes as a result of taking the course.

The model acts as a simplified version of Prosser and Trigwell, because learning approaches are not modeled separately, but added as the component 'Effort'. The latter serves as an indication of the approach to learning. Effort has a special position in the model that is slightly different from the way in which it was modeled by Schau. In Schau's definition (1995), Effort is 'the amount of work a student plans to expend to learn Statistics'. In this study it was assumed that Effort can act both as an indicator as well as a mediator. The special position of Effort is threefold:

- Effort is considered a combination of motivation, interest, energy put in, and time spent and hence, learning approach.
- Effort has a special position regarding the other five components in the 6-factor model by Schau (2003). This is because Effort, apart from acting as an indicator of learning outcomes, it can be seen as the result of certain attitudes, for instance feeling more competent, a student could be motivated to work harder and therefore get a higher grade.
- In accordance with the previous point, Effort could exhibit two processes. Firstly, in a surface learning approach, students only focus on passing the course, on memorization and long time retention is not assumed. Secondly, in a deep learning approach, students are intrinsically motivated to study statistics and take a critical look at the material, linking it to already obtained knowledge (Tempelaar, 2007; Biggs, 2003) and willing to invest time and effort.

Finally, expected outcome is not just considered to be the grade the student expects to get. One can wonder in what way final grade reflects the expectations the student had at the start of the course. And, during the semester, did those expectations change? Therefore, the notion of expected outcome is more than just 'expected grade', but a subjective element of 'academic performance' (Shachar & Neumann, 2003) was added to this construct. For what purpose was this done? The model for this study is meant to establish to what extent the student has realistic expectations of his own performance. Should the course become difficult towards the end, the expectations are supposed to go down. On the other hand if the student is self confident, the expectations are supposed to be higher compared to students with a low self confidence. Hence, this factor is assumed to mediate the effect of individual factors and of attitudes on learning outcomes. These special assumptions on the part of Effort and expectations resulted in the final model that was used for this study, depicted in Figure 4.

MEASURING ATTITUDE CHANGE

The data collection for this study took place between 2006 and 2007 at 11 universities and colleges in the Netherlands and Flanders that offer similar (mandatory) Introductory Statistics courses. Social Science majors in their first year participated (N=2,555) by means of filling a questionnaire at two moments: first at the start of the Introductory Statistics course and again at the end of the course.

The questions of this questionnaire were centered on the SATS©36, measuring 6 components of attitudes toward statistics. Besides background questions, global attitudes were measured by means of questions on mathematics experience, statistics experience, school careers and perceived mastery of these topics.

Institutional factors were measured by means of a teachers' questionnaire, with questions on course organization, didactical approach (delivery methods, such as lectures, project groups, and workgroups) and assessment measures, duration, and size. Prior to administering the questionnaires to the students, an intake interview with Statistics educational experts in the institutions under study was organized.

The data were analyzed with two main objectives. First, it was tested to what extent the model described above would hold, using multivariate and advanced tools such as structural equation modeling. Secondly, a few newly developed statistical tools were put to the test. The latter lies beyond the scope of this paper (for more information, see Verhoeven, 2009).

Some results

The results show that primarily individual factors play a role in predicting statistics attitudes and -changes and, therefore, student outcomes. Main predictors are mathematics experience in high school ($ß$=0.068; p<0.05), self confidence ($ß$=0.487; p<0.000) and age ($ß$=0.155; p<0.000).

Contrary to many expectations (and certainly those of the students themselves), attitude scores are not negative at all, as on average they are located in the upper half of the attitude scale. For the pretest mean attitudes range from 3.30 (Difficulty) to 6.10 (Effort) on a 7-point scale; for the posttest, they range from 3.32 (Difficulty) to 5.41 (Effort). Attitudes do change as a result of taking the course, but not always in the direction we anticipated. Attitude-changes $\Delta_{\text{pre-post}}$ range from -0.69 (Effort; p<0.000; Cohen's d 0.70) to +0.029 (Cognitive Competency; p<0.000; Cohen's d 0.31). In sum, students still find Statistics equally difficult after taking the course ($\Delta_{\text{pre-post}}$ =0.02; p=0.358), and they do not grow to like statistics better ($\Delta_{\text{pre-post}}$ =0.04; p=0.202). However, they do think they became more competent and skilled, as the aforementioned Cognitive Competency scores show.

Effort plays a minor role when it comes to predicting course outcomes, but students report to have put in less effort than they anticipated. Expected grade is a positive predictor of course outcome ($ß$=0.184; p<0.000). In the complete model with course outcome, 20.6% of the variance is explained by all factors. Gender differences are more diverse, as they partly run through other factors, such as self-confidence, expectancies and effort.

Institutional factors show a diffuse result in this study, as the diversity of institutions and settings did not sketch a clear picture. Partly, this is caused by the fact that institutional factors were measured at a different level compared to individual factors. There is some evidence that course duration, the existence of project groups doing 'real life projects', and class size play an influential role. In order to confirm this claim *multilevel analysis* is needed, where students and institutions are analyzed at multiple hierarchical levels. Unfortunately the small institutional sample size (n=11) compared to the student-sample size (n=2,555) did not warrant the use of these tools. Moreover, the nested nature of these data could not be acknowledged with such a small institutional sample.

CONCLUSION

In hindsight the Expectancy Value model developed for this study can explain achievement related choices by means of individual factors, expectancies, and effort. For the most part it holds for Dutch and Flemish data. In general attitudes toward statistics (and their change) contribute to student achievement, but the effects found were not very big. Most importantly, institutional factors did not prove to be good predictors of achievement. This was mainly caused by the nature of those factors. Being measured at different hierarchical levels, individual and institutional factors are not easily combined without the use of multilevel tools.

The special position of effort has been made visible in several ways. First of all, effort mediates the effect of the other attitudes on student outcomes and it therefore maintains its special position. Furthermore, it turned out that effort refers to 'more active learning behavior' rather than the other five attitude components that refer to 'beliefs'.

Discussion

As most of the results found concentrated on individual factors, a number of recommendations for teachers were formulated in this study. We saw that attitudes in general are not as bad as most people would expect, however they sometimes change for the worse and they are affected by self-confidence, mathematics experience and age.

Attitudes toward statistics play an important role in predicting course outcomes (Omwuegbuzi, 2003), and teachers can do a lot to create an emotionally and cognitively supportive environment in statistics training (Estrada & Batanero, 2008) and to improve student motivation. Thus, for teachers it is important to know what the students' attitudes are at the start of a course and how the course can contribute to a positive attitude change. It puts pressure on the teachers, for they have to teach these so-called complex skills, encourage students to learn statistical concepts and, moreover, teach them how to apply statistics in everyday life. A few of the recommendations for this study were:

- The use of '*well informed expectations'* of course outcomes. Informing students of what they can expect will take away some of the uncertainty. In return students are expected to obtain as much information about the course as they can get, simply by reading the course manual before the course starts and asking the right questions (Svanum & Bigatti, 2006).
- The use of *continuous assessment tools* makes students realize that it is not only the final exam that counts, and that there are many more assessment moments to concentrate on besides that one exam.
- The use of *'real life projects'* makes students experience actual applied research projects. This helps them understand the process of doing research with all its opportunities and restrictions. Experience in Dutch universities learned that it motivates students to take on a deeper learning approach. It brings the theoretical formulas to life and they learn how these concepts are put to use.

The learning and teaching of complex skills such as statistics has become an important research topic over the years. Besides, the research focus has shifted from 'teaching' to 'learning' statistics, and from 'receiving lecture material' to 'experiencing the material by students' (Steinhorst & Keeler, 1995). In this constructivist approach students do not learn individually anymore, but their learning is embedded in the social environment. It has shifted more and more toward statistical reasoning (Garfield & Gal, 1999; see also Tempelaar et al., 2006).

In order to be able to encourage students to learn statistical concepts, teachers need to be able to analyze student attitudes and their effect on student outcomes. The models presented here can help in obtaining a clear picture on student learning behavior. Despite analyses, models and conclusions, the main aspect of teaching statistics irrespective of time and place is, that teachers need to be highly motivated and that they can motivate students. If we can accomplish that, then student achievement will be high, even (or *especially*) in statistics!

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