Attitudes toward statistics: the Effort of Learning

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Introduction

'Learning' means different things to different people. On the one hand, it could mean an increase of knowledge (acquiring information), memorizing information (such as 'storing') or acquiring facts, skills and methods that can be retained if necessary. On the other hand it could mean 'learning as making sense or abstracting meaning', or 'learning as interpreting and understanding reality' (Atherton, 2010). In order to learn things, people use different strategies. Sometimes it is necessary to obtain 'search information' to be accessed if necessary. Sometimes memorizing things makes sense and sometimes comprehending the 'real world' by interpretation is used as a strategy. In sum, the learning strategy used follows the learning objective.

When students 'encounter' statistics during their first year in college, they choose a learning strategy that best fits their objective. Roughly, the choice lies between two main strategies: put in just enough effort to pass the course, or put in a lot of effort in order to comprehend statistical methods and the way these methods can be applied in the 'real world'. This determines the difference between a 'surface' and a 'deep' learning approach, or, as one could argue, the difference between a negative and a positive approach to learning (Tempelaar, Gijselaers, & Schim van der Loeff, 2006).

Literature shows that there are more approaches to learning than the aforementioned dichotomy (Baeten, Kyndt, Struyven & Dochy, 2010), such as strategic or achieving approaches (Marton, 1997; Biggs, 1987). In this paper the Effort component of the Attitudes toward Statistics scale (Schau, Stevens, Dauphinee, & Del Vecchio, 1995) will be viewed in light of these learning approaches (Tempelaar et al., 2006). It has been suggested that Effort holds a special position among the SATS©-components (Verhoeven, 2009). This special position could be triggered by the way students learn statistics. Previous analyses of the SATS©-scale show a negative change for Effort during the semester, indicating that students (in hindsight) put in less Effort than they anticipated. Secondly, Effort shows negative correlations with other attitude components[1] where this is sometimes not expected (Tempelaar, Schim van der Loeff, & Gijselaers, 2007; Verhoeven, 2009). This hints towards a special position of Effort, but it does not explain how this position can be viewed in light of learning strategies. This paper attempts to take a closer look at Effort in regard to learning strategies and approach the analysis from a different angle. Before doing so, two important aspects need to be discussed: the demarcation of the construct and the way in which Effort can be modeled.

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[1] Both pretest and posttest data show negative within-correlations between Effort and Affect (r_{pre} -.125; r_{post} -.162), Cognitive Competency (r_{pre} -.103; r_{post} -.163) and Difficulty (r_{pre} -.208; r_{post} -.373). The last correlation makes sense, for a more positive attitude on Difficulty corresponds with less Effort (Verhoeven, 2009, 92).

Demarcation, as was mentioned previously, can be done in two directions. Firstly, we can look at Effort as a deep learning approach, with highly motivated students that are willing to deepen their knowledge of statistics (and research) because they like the topic and they feel they will use statistics in their future career. Hence, they are intrinsically motivated to put in Effort, whether they are good in statistics or not. Ideally this is the kind of student every statistics teacher wants in his group. On the other hand, students might take a surface approach to learning statistics. They only learn the topics in order to (just) pass the exam. They are only remotely interested in the topics, they do not like to work with statistical formulas and they expect not to use statistics in their future career. They enrolled in the course only because it is a prerequisite for their degree. This surface learning approach results in less Effort put in, whether students are good in statistics or not (Biggs, 1987).

The second aspect to be discussed is the way in which Effort can be modeled. As was mentioned earlier, it is assumed that Effort has a special position compared to the other SATS©-components (Verhoeven, 2009). Whereas, Affect, Cognitive Competency, Difficulty, Interest, and Value refer to perceptions of attitudes 'outside' the students own approach (output), Effort is an attitude that will actually show 'input' and therefore it is considered that it can be modeled differently. Moreover, it is assumed that the more positive students' attitudes are, the more Effort is put in, thereby resulting in higher (expected) grades. If this holds true, a deep learning approach is taken. That does not only put Effort in a position to directly affect student grades but, moreover, act as a *mediator* in the effect from other attitudes onto (expected) grade.

The role of perceived Difficulty

Perceived Difficulty could also play a role in the learning approach a student takes. The aforementioned correlations show that less Effort is put in if the students like the course better, or they feel more competent; this signals a surface learning approach. However, Difficulty could control over this relation with Effort. If students find the course less difficult, they will need less time to cover the topics. Difficulty is then directly related to Effort, and attitudes will be negatively correlated to Difficulty, i.e. the more Difficult a task is perceived, the less a student will like it. In sum, when a student finds a topic difficult, it overpowers his or her interest, liking, value and perceived competency.

If, however, students take a deep learning approach, more time is dedicated to actually comprehend the bigger picture and applying the learned to (student) research, actually resulting in more Effort. If the controlling effect of Difficulty exists, the correlation between Effort and Affect should be positive and then, despite the degree of perceived Difficulty, Effort is also highly correlated to Expected grade and Grade. Moreover, attitudes toward statistics will be positive, despite the degree of Difficulty.

It is therefore assumed that, when perceived Difficulty is kept constant, the link between Interest, Affect, Value, Cognitive Competency and Effort can show true signs of a deep or strategic learning approach.

Individual background

Besides looking at attitudes, individual background with regard to student achievement in statistics can play an influential role. For this study, three such factors are taken into account: gender, self-confidence and previous mathematics results. Firstly, prior mathematics experience in high school (i.e. mathematics result) is assumed to affect the way in which learning strategies are employed. Although previous results do not always report strong effects (Dempster & McCorry, 2009), having had a better mathematics result in high school puts the students' mind at ease because they know what to anticipate, and therefore they can assess the learning task in a more rational way. In other words, students adopt a mastery orientation that allows them to (again) use an effective learning approach (Ames & Archer, 1988).

Although results on the effect of gender on student achievement are diverse (see for instance Green & DeBacker, 2004; Harris & Schau, 1999), gender differences are assumed to influence the modeling of student achievement in statistics courses. Female students often are more anxious to take statistics than male students. Females start with a more negative attitude toward statistics, but they change more positively over the course of the semester (Verhoeven, 2009). However, they do not perform worse than their male counterparts. On the contrary, female students often put in more Effort and therefore pass the course with slightly better grades (Harris & Schau, 1999).

Lastly, the aforementioned anxiousness is related to self-confidence. Being more self-confident will result in a more positive attitude toward statistics and Effort put in to learn and to comprehend. Having more self-confidence (in other words a higher perceived ability) will result in the use of a more effective learning strategy (Ames & Archer, 1988).

Thus, for this paper the research question is *to what extent can Effort mediate the effect of attitudes toward statistics on student achievement addition to being a direct indicator, and what learning approach could Effort represent?* Additionally, the sub question will be answered *to what extent do background variables such as prior school experience, gender and self confidence play an influential role in predicting the effect of attitudes on student achievement?*

Model specifications

The model used for this study is a simplified application of the Expectancy Value Model (Wigfield & Eccles, 2000), whereby the outcome of a course is modeled by means of attitudes, (individual) background variables and the expectation a student has about the possible outcome. Although the original study (Verhoeven, 2009) also modeled institutional variables, for this paper they have not been taken into account. Attitudes toward statistics are modeled to affect (expected) grade directly and indirectly through Effort. The possible effect of the statistics course taken is constructed by means of 'attitude changes'. Moreover, in order to explore the change from pretest to posttest in one model, instead of analyzing separate pretest and posttest models, pretest to posttest changes will be taken into account, by means of 'change indicators' (see method section for an explanation of the procedure).

Method

Participants

The results presented in this paper form the outcome of a secondary analysis on data collected for a Ph.D. project between 2005 and 2007. Students from 11 universities and colleges took part in this project, all located in the Netherlands and Flanders. In all cases the introductory statistics course was a prerequisite for the bachelor degree in a Social Scientific discipline.

The sample was not randomized; instead we used snowball and convenience sampling methods, based on the willingness of the statistics coordinators to let us collect data during their lectures. Therefore the results suffer low population validity. Approximately 2,555 students who enrolled in the Introductory Statistics classes in these colleges took part in pretest – and / or posttest measurements, at the start and the end of the semester. Complete pretest and posttest data are available from 936 students.

Design and instruments

The data were collected by means of a pretest and post-test questionnaire. The pretest measurement was administered at the start of a semester, during the first statistics class. The lecturer of the participating college administered the post-test questionnaire during the final week of the semester or right after the exams.

Besides measuring individual factors (age, gender, international background), the Survey of Attitudes towards Statistics, the SATS36© was used (Dauphinee, Schau & Stevens, 1997; Hilton, Schau & Olsen, 2004; Schau, Dauphinee, Del Vecchio, & Stevens, 1999; Schau et al., 1995). This inventory consists of 36 items measuring 6 latent constructs: Affect, Cognitive Competency, Difficulty, Value, Interest and Effort. The answers were measured on a 7-point scale. All factors are known to have a good reliability (Schau et al., 1995; Tempelaar et al., 2007; Verhoeven, 2009).

Additionally 'global attitude questions' were posed such as 'mathematics cognitive competency' (among which mathematics results), career value, expected mastery of statistics, the first and the latter indicating self confidence in the study discipline. Lastly, in the posttest a control question was added to measure Effort, by means of asking how many hours the student spent outside class hours.

Analysis procedure

In this paper, the assumed special position of Effort is analyzed and reported. For this purpose two models were tested, using structural equation modeling. Firstly, a hybrid baseline model was fitted as depicted in figure 1. Next, the model was adjusted and two background variables were added, as is shown in figure 2.

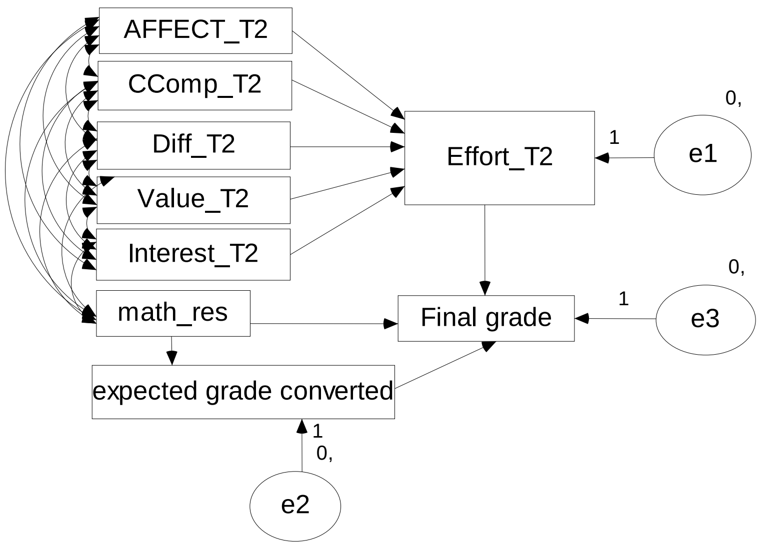

Figure 1 Identified baseline model

In order to incorporate indicators of 'attitude change' into the model, the 6 **T2-components** represent the *change* from pretest to post-test. These 'change indicators' were computed using the outcomes of 6 Latent Change Method Effect Models (LCMEM; Verhoeven, 2009). LCMEM's analyze changes from pretest to posttest, taking into account possible method effects[2] (Pohl, Steyer & Kraus, 2007; for in-depth discussion of this procedure, see Verhoeven, 2009, pp. 100 - 104). The Factor Score Weights from the 6 LCMEM-outcomes were used to calculate the weighted change-value.

The dependent variable is 'final grade'. Effort, for its assumed special position among the attitude components, is placed as mediator between the 5 attitudes changes and the dependent variable. In order to control for previous experience, an individual variable (mathematics experience) was added to the model. Furthermore, the (indirect) effect of 'expected grade' (through math experience) was modeled. As the attitude components are expected to correlate, covariances were added to the model.

The analyses were run using AMOS (17.0) and SPSS (18.0). In AMOS, both unstandardized and standardized estimates were requested, means, total and (in) direct effects. In order to assess model fit X^2 ($p < 0.05$), TLI (> 0.95), CFI (> 0.95) and RMSEA (< 0.06) were evaluated. Relevance of predictors was interpreted by means of b- and ß-coefficients ($p < 0.05$). In SPSS, additional analyses were run, such as descriptive statistics and partial correlation analyses. The program was also used to compute the change indicators.

Results

The fit of the baseline model (figure 1) is good, as χ^2 *(12, N = 2,555) = 47.79* ($p < .000$; χ^2/df = 3.983) and *TLI* = .910; *CFI* = .976; *RMSEA* = .034. Looking at table 1 it can be seen that most of the effects are significant, albeit three change factors do not significantly contribute to final grade, at least not through Effort (i.e. Affect, Cognitive Competency and Value). Furthermore, the covariance between math-result and Interest-change is insignificant ($r = .052$; $p = .112$), as the power to reject the null hypothesis is too low. Effect sizes are weak, as the R^2 for expected grade and grade are *.137* and *.180* respectively. The effect size for Effort also is weak ($R^2 = .069$).

	b	S.E.	C.R.	P	ß
ΔInterest → ΔEffort	.229	.043	5.357	***	.199
ΔAffect → ΔEffort	.067	.053	1.261	.207	.055
ΔDifficulty → ΔEffort	-.327	.065	-5.026	***	-.188
ΔCog.Competency → ΔEffort	.070	.058	1.198	.231	.051
ΔValue → ΔEffort	-.015	.063	-.235	.814	-.009
Math.result → Expected grade	.241	.032	7.556	***	.370
Expected grade → Final grade	.800	.181	4.420	***	.317
ΔEffort → Final grade	.365	.100	3.659	***	.144
Math.result → Final grade	.248	.065	3.851	***	.151

Table 1 Regression Weights baseline model (figure 1)

For the adjusted model (depicted in *output*-figure 2), two background variables were added, i.e. self-confidence and gender. Furthermore, the insignificant paths were removed, resulting in a leaner model with regard to attitudes toward statistics. Absent paths indicate a non-significant effect.

[2] Method effects possibly resulted from the circumstances under which the questionnaires were administered.

The results show a better model fit than for the previous model (χ^2 *(23, N=2,555) = 69.95*[3]; *p* < .000; χ^2/df *= 3.041*; *TLI = .938*; *CFI = .978*; *RMSEA = .028*). All paths show a significant effect (*p < 0.000*; see table 2), as well as significant covariances and means.

Looking at the results in table 2, the following is noticed. Among the attitude components, only Difficulty and Interest indirectly affect Grade through Effort (*β=-.135 & .158* resp.). Difficulty has a negative effect on Effort, indicating that a negative change in Difficulty (i.e. students find it *less* difficult) corresponds with less Effort put in. Interest however shows a positive effect on Effort; hence, more Interest results in more Effort. Affect, Cognitive Competency and Value do not significantly predict grade (both directly and indirectly). Furthermore, there's a direct effect of Effort *(β*=.250) on final grade.

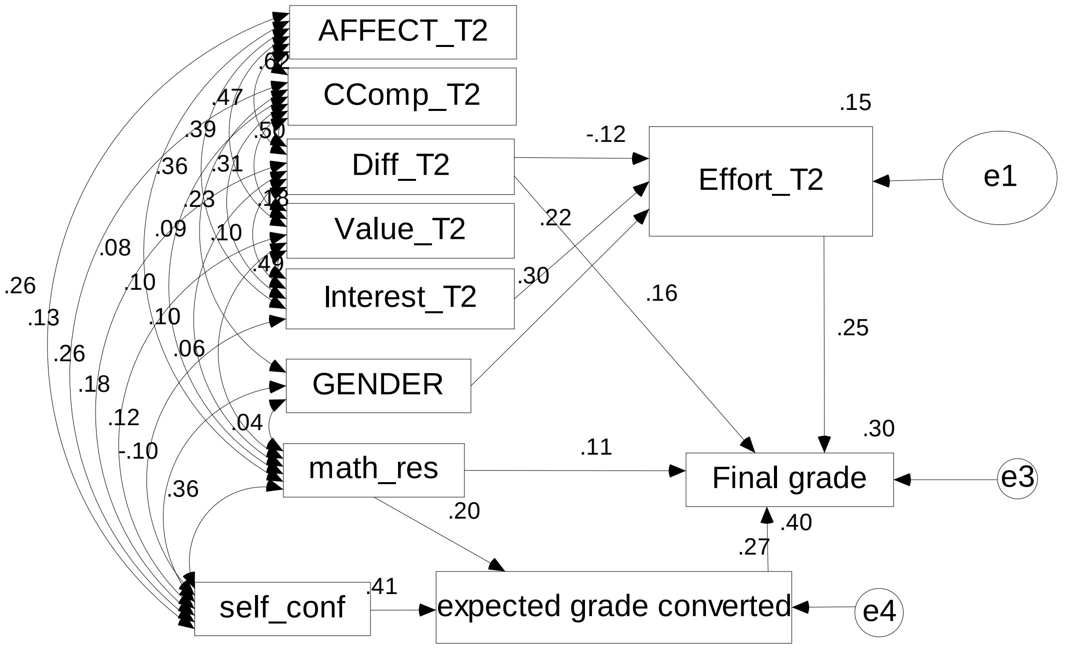

Figure 2 Second model with additional background variables and significant effects

	b	S.E.	C.R.	P	ß
Gender → ΔEffort	.597	.059	10.062	***	.297
ΔInterest → ΔEffort	.254	.036	7.128	***	.216
ΔDifficulty → ΔEffort	-.216	.053	-4.065	***	-.123
self_confidence → Expected grade	.300	.032	9.293	***	.411
Math.result → Expected grade	.135	.031	4.295	***	.203
Expected grade → Final grade	.989	.131	7.551	***	.400
ΔDifficulty → Final grade	.694	.164	4.224	***	.159
Math.result → Final grade	.178	.056	3.166	.002	.109
ΔEffort → Final grade	.623	.087	7.201	***	.250

Table 2 Regression Weights: (Model figure 2)

[3] *Δ χ² (Δdf 11) = 22.16; p = 0.023.*

Splitting up the analysis

In order to test the controlling influence of 'change in perception of Difficulty' with regard to the correlations between Effort and the other attitude components, (partial) correlation analyses were run (in SPSS) for all components, (expected) grade and individual background variables. Table 3 shows that after controlling for Difficulty, the correlations between Effort and the other attitude components become a little stronger or they turn significant (as with Cognitive Competency). Controlling for Difficulty in regard to correlations between Effort and background variables remains equally high. This suggests that, when Difficulty is kept constant, a deep learning approach is visible through the positive but weak correlations between Effort and the other attitude components; however, effect sizes are small.

If you control for Difficulty the positive relation between Effort and Grade only becomes a bit stronger, so it is not affected by the perceived Difficulty. This, again, points towards a deep learning approach, albeit the signs are weak. At least it indicates that despite the difficulty of the topic, putting in more Effort pays off.

	ΔEffort	**ΔEffort Controlling for ΔDifficulty**
ΔDifficulty	-.120*** (936)	.
ΔAffect	.066* (936)	.139*** (933)
ΔCog.Competency	.036 (936)	.110** (933)
ΔValue	.092** (936)	.116*** (933)
ΔEffort	1.000	1.000
ΔInterest	.208*** (936)	.222*** (933)
Final grade	.146** (562)	.171*** (559)
Expected grade	-.048 (220)	-.048 (217)
Number of hours	.271*** (917)	.268*** (914)
Self Confidence	-.047 (936)	-.020 (933)
Math. result	.040 (935)	.053 (932)

Table 3 (partial) correlation analyses [4]

Self-confidence is significantly correlated with all attitude components except Effort. After controlling for Difficulty, correlations become weaker, and the correlation between self-confidence and Cognitive Competency ($r_{sc,cc}$=.114; p<0.000) becomes insignificant ($r_{sc,cc}$=-.003; p=0.920), indicating the influential effect of Difficulty on this relation. Higher math-result in high school is related to more positive attitudes for Value (r=.083; p=0.011), Difficulty (r=.107; p=0.001), Cognitive Competency (r=.109; p=0.001) and Affect (r=.100; p=0.002), but after controlling for Difficulty, the correlations become weaker and for Affect and Interest even insignificant (r=.058; p=0.077, r=.039; p=0.233 resp.).

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[4] Note that only paired data (N=936) have been taken into account in SPSS, because pretest - post-test data are involved. Sample size is available in parentheses. Furthermore, (expected) grade was only available for a small subsample of the respondents. Significance levels are indicated as follows: ***, p<0.000, **, p<0.001, *, p<0.050.

Conclusion and discussion

The secondary analysis on Dutch and Flemish data collected between 2005 and 2007 shows some signs of a mediating effect of Effort, although these signs vary in strength and nature. Firstly, only Difficulty and Interest affect final grade through Effort. Furthermore, ruling out the influence of perceived Difficulty, there are signs of a deep learning approach, for more positive attitudes toward statistics result in a higher Effort and therefore in a higher grade. Students who really like the topic of statistics will go ‘the extra mile’ to comprehend the way statistics works and apply it to new fields. They will overcome difficult formulas and software techniques and link statistics techniques to models and formulate recommendations. They will take initiative to uncover new statistical theories and applications.

However, in this secondary analysis the signs are not very strong, albeit in accordance with previous findings (Tempelaar et al., 2007; Verhoeven, 2009). One of the reasons could be the way Effort is measured, simply by asking whether students intend to work hard, study for their test, complete their assignments and attend all class meetings. There’s more to a learning strategy than just studying hard and going ‘by the rules’. Stronger and more consistent proof needs to be established. This can be done by developing and validating an instrument to measure surface - and deep learning with students in colleges and universities. For instance items on taking initiative, or broadening ones view could be added to measure Effort.

Individual characteristics play a role in the way in which attitudes toward statistics are modeled. This leads to the conclusion that (parts of) the Expectancy Value model successfully predicts student achievement. Firstly, there’s a difference in males’ and females’ approaches through self-confidence and Effort. As females start of more negative than males, their attitudes improve more compared to males’ attitudes; they put in more Effort and hence obtain a higher grade. The latter conclusion confirms earlier findings (Schau & Harris, 1999). Both self-confidence and previous math-result predict final grade, directly and through expectations. Moreover, the relation between background characteristics and attitudes has been confirmed. Mathematics results are related to the way in which attitude changes affect achievement, as higher math-results cause the students to become more self-confident, it improves his interest in and liking of the topic, he realizes the added value of statistics, and (almost obviously) perceives his cognitive competence more positively.

No research project is flawless. Non-probability sampling, missing data and possible method effects affect the validity of this study and, to a certain extent, also its reliability. Therefore this conclusion has to be treated with much care and can only apply to the students under study. Random sampling techniques, valid experimental setups and complete datasets necessarily overcome these problems.

For years, statistics teachers have asked themselves how they can trigger a deep learning approach and teach students to take a closer look at statistics, thinking outside the box. Besides the usual recommendations such as clear examples, interactive teaching and continuous assessment, we have great experience with group projects where students conduct small, ‘real life’ research projects for real clients in the region the university resides. The first assessment results show the positive impact on attitudes toward statistics (Verhoeven, 2009). This approach has many advantages. Firstly, students practice with real research questions. Second, it makes them feel professional, thereby enabling students to obtain research experience and client contact. Lastly it shows them what implications recommendations might have on organizational policy and – structure.

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ABSTRACT

In order to meet the requirements of the college they attend, students from a broad spectrum of specialties take Introductory Statistics. However, they often find Statistics difficult, it scares them to work with statistical software or formulas and they do not always see the added value of statistics for their future job. As a result, teaching statistics requires a special didactical approach. Therefore it is helpful for teachers to have insight in students' attitudes toward statistics, especially the learning strategies they use and in changes therein as a result of taking their course.

The paper presented here describes the results of a secondary analysis, following up on a PhD-project that took place in the Netherlands and Flanders from 2005 until 2007. During this project, 2,550 students took part in a pretest-posttest attitude-measurement using the SATS36 questionnaire developed by Schau in 1995; then, student outcomes were analyzed as a function of expectancies, attitudes (Affect, Cognitive Competency, Value, Difficulty, Interest & Effort), individual and institutional factors.

In this paper the focus lies on the special position of Effort in the aforementioned model. Previous results indicate that Effort could possibly function as a mediator between the other 5 attitudes and the prediction of student outcomes, instead of acting as a direct indicator. Furthermore, Effort is assumed to fulfill a twofold function in student achievement models, dependent on the learning approach (deep or surface learning) that students adopt when taking Introductory Statistics.

The first results of this secondary analysis imply that Effort indeed holds this special position. Not only does Effort act as a mediator for the effect of some attitude change on student outcomes, but controlling for perceived Difficulty also results in consistent positive correlations between Effort and attitude change on the four remaining components.

Keyword 1*: attitudes toward statistics* ***Keyword 2****: student outcomes* ***Keyword 3****: effort as a mediator*
Keyword 4*: deep vs. surface learning approach*