The Role of Motivation, Cognition, and Conscientiousness for Academic Achievement

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Abstract

Based on a cognitive motivational process model of learning, the impact of studying behavior on learning outcome is investigated. First-year students (N = 488) participated in the study. Two research questions were addressed: (1) Can cognitive-motivational variables and objective study behavior predict individual learning? (2) Which factors drive studying behavior? Results show low to moderate correlations between cognitive-motivational variables and performance. A cluster analysis yielded three profiles: (1) interested learners with high academic self-concept and effort investment; (2) low interest learners with high academic self-concept and low effort investment; and (3) interested learners with low self-concept and low effort. Groups 2 and 3 are considered at-risk students for developing a surface approach to learning and for drop out.

Keywords: Conscientiousness, Five factor model, university students, Academic performance, Motivation, Study behavior

1. Introduction

Institutions of higher education are faced with the challenge to secure learning environments catering to an increasingly diverse and flexible community of learners. This is due to a variety of reasons: Firstly, given the increase of the proportion of high school graduates who transfer from secondary education to higher education, it is plausible to assume that diversity among students is growing. This entails that it is necessary to provide for adaptive learning environments and to tailor academic programs to a broad range of learning experiences and a variety of learning needs of incoming students in order to avoid dropout and to foster study performance. Second, instructional environments which include blended-learning arrangements and which rely more and more heavily on self-regulated learning on the side of the students, require a set of personal competences, such as self-regulation skills (e.g., Imhof & Vollmeyer, 2009; Masui & De Corte, 2005), which have long been considered to be both prerequisites and results of successful learning (Boekaerts, 1997). A third challenge is related to competence orientation in higher education. As university education goes from teaching to learning, learning environments need to take into account individual differences, needs, and levels of prior knowledge. The objective of this study is to investigate the factors which determine academic success in a lecture class. We will first review the empirical literature on predictors of academic performance and evaluate the findings against the backdrop of the cognitive-motivational model of performance (Vollmeyer & Rheinberg, 1999, 2006); building on this model, we ran our own study over the course of one entire semester to collect data on study behavior, student motivation, and performance levels.

2. Predicting and supporting academic achievement

The cognitive-motivational process model of performance presented by Vollmeyer and Rheinberg (1999, 2006) provides a framework to describe the interaction of various variables and their impact on learning outcome. This model focuses on the process of learning, its prerequisites and mediators (see Figure 1). For predicting academic success, two sets of candidate variables have been identified: On the one hand, research studies suggest that state variables, e.g., invested effort and motivation are most prominent predictors of post-secondary study performance; on the other hand, there are studies which show that dispositional personality variables play a role in academic performance. From the point of view of an educational psychologist, it seems more plausible to assume that current state and actual activities which learners invest into studying for a test should have a larger impact on the outcome than global attitudes and dispositional personality traits. In the following sections, we will briefly review findings from both perspectives.

Cognitive and motivational prerequisites of learning →	Mediators →	Performance / Learning
Current Motivation Dispositional Motivation: Goal Orientation Prior knowledge Academic self-concept	Motivational state Functional state: Flow Self-reported learning strategies Learning behavior	Knowledge test

Figure 1. The cognitive-motivational process model of learning (Vollmeyer & Rheinberg, 1999)

2.1 Motivation and cognition as predictors for academic achievement

One path to explaining academic achievement is to look at the impact of motivation and cognition on academic success. The basic assumption is that variance in learning outcome can best be accounted for by more specific constructs pertaining to the learning process. The cognitive motivational process model of learning presented by Vollmeyer and Rheinberg (1999) provides a framework to investigate the influence of current motivational and cognitive variables on learning outcome. Current motivation is conceptualized as a temporary state defined by four components which include probability of success, anxiety to fail, interest, and challenge. Current motivation is typically measured immediately after learners have had a chance to briefly look at the learning task ahead (Rheinberg, Vollmeyer, & Burns, 2001). There is evidence from a series of laboratory studies that the current motivation carries through to the quality and quantity of learning measured in terms of retention, problem solving, and transfer. In addition to the motivational state at the beginning of a learning episode, the functional and motivational state during the learning episode moderates the learning outcome (Engeser, Rheinberg, Vollmeyer, & Bischoff, 2005; Vollmeyer & Imhof, 2007).

In a similar vein, a field study by Heikkilä, Niemivirta, Nieminen, and Lonka (2011) looked at student approaches to learning, regulation of behavior, and cognitive and attributional strategies among university students. The authors identified three clusters of students which differed in their cognitive-motivational profiles as reflected in approaches to learning, self-regulation and lack thereof, success expectations, and task irrelevant behavior. Students from the self-directed cluster who had a preference for critical evaluation and deep approach, who were above average in self-regulation and success expectations had a significantly higher GPA compared to helpless students who showed equal preference for deep understanding and surface approach, above average lack of self-regulation, and low success expectations, with an extremely high relative score in task-irrelevant behavior; yet at the same time, helpless students felt most exhausted and stressed. Interestingly, students in the so-called non-academic cluster who were inclined towards surface approach, low self-regulation, and average success expectation did not differ from self-directed students on their academic achievement as measured by their GPA and the accumulation of credits.

Steinmayr and Spinath (2007) proposed that both situational aspects of motivation and dispositional personality traits play an equally important role for academic performance. They also found that measures of domain specific performance were more closely associated with specific motivational variables than with generalized personality traits. Beaujean, Firmin, Attai, Johnson, Firmin and Mena (2011) conducted a study to disentangle the impact of personality variables and cognitive ability when predicting academic performance of post-secondary students. Their results suggested that cognitive ability and personality play a different role for academic performance depending on the domain. In any case, conscientiousness is closely correlated with achievement, while general cognitive ability and other aspects of personality had more complex relationships with the outcome in math and reading respectively. It seems that a higher level conscientiousness may have a compensatory effect on performance in particular for students with low or average cognitive ability. The assumption that personality traits affect distinct academic domains in different ways was also supported by a study on high school graduates and beginning students (Marsh, Trautwein, Lüdtke, Köller, & Baumert, 2006). In several analyses using different criteria, an average of 8.8% of the variance in academic outcome could be explained by the personality variables. Their results supported the conclusions that firstly, personality has an impact on performance and that, secondly, this impact depends on the academic domain, and finally, other constructs need to be considered to explain the picture more fully.

2.2 Personality as predictor for academic achievement

For the discussion of the relationship between personality traits and academic performance, we refer to a series of meta-analytical studies in the area (O'Connor & Paunonen, 2007; Poropat, 2009; Trapmann, Hell, Hirn, & Schuler, 2007). The common denominator of these studies is that personality traits have been used to predict performance parameters. Overall, there is evidence to support the notion that the Big Five Model of Personality (cf. Costa & McCrae, 1992) has been quite successfully employed to return valid and reliable results in both longitudinal and quasi-experimental field studies.

Trapmann et al. (2007) reviewed a total of 73 studies published in journals and in conference proceedings from 1980 to 2004 which had dealt with the relationship between personality measures and academic performance at university level. The authors selected studies which had used the Big Five Model of personality as a theoretical framework and which had considered grades, self-reported satisfaction, and retention as criteria for success. As a result, the authors presented a comprehensive list of correlations between personality factors and the criteria for success, mostly grade point average (GPA), individual scores, retention, and satisfaction. Across the board, the mean observed correlation was reported as $r = .22$ for *Conscientiousness* (*C); also*, when the full set of personality factors was considered, coefficients were always largest for *C*, irrespective of the study major, of study level, and success criterion.

Poropat (2009) presented a meta-analysis which covered about the same time period as the one published by Trapmann et al. (2007). In the analysis of 80 research reports they took into account the academic levels, i.e., primary, secondary, and tertiary education. As it turned out, the correlation of personality factors and academic performance varied across the educational levels. While *C* was returned as a predictor for academic success in all groups (mean observed correlation $r = .24$), the author found *Agreeableness (A)* and *Openness to Experience (O)* relevant for academic achievement in primary education. While *C* maintained its predictive power throughout the academic career, the (moderate) correlations between academic performance and both *A* and *O* declined considerably over time.

Van Bragt, Bakx, Bergen and Croon (2011) proposed a conceptual framework for academic success which assumes personality features to be at the basis from which individuals build their personal orientations on learning, e.g., the willingness and competence for self-regulation, which eventually result in either a deep or a surface approach to learning with the pertaining study behavior and outcome. Using a large sample from a Dutch university, the authors found in a logistic regression analysis that *C* and self-regulation competence predict credits ($B = .69$) and study continuance ($B = .45$).

2.3 Research Questions for the current study

In summarizing the findings from the previous studies and meta-analyses, some validity concerns need to be addressed. Reliance on self-report data may cause a bias because participants might not have access to the relevant information or they are susceptible to a self-serving bias induced by social desirability and impression management strategies (Trapmann et al., 2007). Also, as Heikkilä et al. (2011) pointed out, self-report instruments require that participants "generalize their actions across multiple situations rather than referencing singular and specific learning situations" (p. 526), so self-reports may not reflect a valid representation of actual study behavior.

Results of the previous studies may also have been influenced by the fact that personality measurements and performance measurements were taken with a considerable time lag. The personality questionnaires had, in many cases, been administered in the context of student admission and data on success criteria had been collected later. As a consequence, the relationship between personality traits and success could have been affected by changes and adjustments which might have taken place in the personal developments of the young adults. Conversely, other studies relied on one-time measurements, when both personality factors and studying and learning data were collected at the same time. This type of measurement obviously failed to allow for possible changes which may have taken place in the process of studying. The research questions and hypotheses of the current study are stated as follows:

RQ 1: Can individual learning scores be predicted from cognitive-motivational variables and objective study behavior in an ecologically valid setting?

Specifically, we plan to investigate the relationship between students' initial characteristics and performance, and between the mediators, e.g., motivational and functional state, learning strategies, and study behavior, and performance. Ecological validity of the investigation should be secured since it is placed in the context of a one-semester mandatory course which requires a final exam for all participants. Secondly, in order to control for a self-serving bias inherent in questionnaires, the effort which the participants invest in learning is also measured in terms of objective behavior indicators.

RQ 2: What are the factors which drive studying behavior and what is their impact on learning outcome? In particular, it will be of interest to generate a model which reflects the interaction of the different variables and to identify different types of learners with distinctive profiles in specific sets of motivational and cognitive variables and objective study behavior.

3. Method

3.1 Sample

A total of $N = 488$ students, among them $n = 215$ males, enrolled in the teacher training program Bachelor of Education initially participated in this study. All students were in their first year of studies and had registered for a mandatory course "Introduction to Educational Psychology". A subsample of $n = 107$ participants completed all or most of the questionnaires as required by the course of the study.

3.2 The instruction scenario

The introductory course was presented as a large lecture class in a blended learning environment which comprehended three components: Face-to-face lecture, self-study on books, and a web-based learning platform. The students could attend weekly meetings in a traditional lecture using presentation slides, and, in addition, exercises, discussions, case studies, and experiments to present the content and to stimulate transfer. Attendance was neither required nor taken. The lecture was complemented by a recommended textbook and optional reading material. The web-based learning platform offered the lecture slides, video-clips pertaining to the lecture topics, additional case study material for transfer exercises, self-tests, transfer tasks, and links to relevant websites. Students were required to take a final test for course credit. This composition of the course challenged student self-regulation, as students needed to organize their own study time, to select the material according to their needs, and to control and monitor their learning progress. It is plausible to assume that there were considerable individual differences in the tendency to regularly study for the course as opposed to delaying learning efforts.

3.3 Material

All data, including the final test, were collected electronically, either by online questionnaires or by analyzing log data. To encourage participation, access to study materials (all definitely optional, since the textbook contained all of the relevant information for the final exam) was granted immediately after the questionnaire had been completed. During the course of a semester, the following constructs were measured:

Prior knowledge and final test. In order to have an estimate for knowledge acquisition, prior knowledge was assessed by a 12-item version of the final test. The final exam consisted of a 40 multiple choice items which covered the entire course content. Test duration in the final test was 45 minutes.

Habitual and specific learning strategies. Since habitual study habits were considered relevant mediators for academic performance, the inventory proposed by Gold and Souvignier (2004) on study habits was administered early in the semester (T1). The questionnaire survey is based on a factor analytical construct of learning behavior which comprehends memorizing material, knowledge transformation, visualization of information, elaboration, time-management, and effort investment. The 35 items appear as general statements on study behavior, for example, "When I want to learn something, I memorize the material word by word". Participants had a five-point scale from 1 (= very seldom) to 5 (= very often) to express their agreement. After re-writing the items to represent actual – as opposed to habitual – study behavior, e.g., "To prepare for the final exam, I memorized the material word by word", the questionnaire was administered a second time (T2) a week before the final test. For the second measurement the instruction was adjusted to refer to the actual study behavior related to the upcoming final test.

Dispositional aspects of motivation: Goal orientation. As derived from the cognitive-motivational process model of performance, dispositional motivation was conceptualized as goal orientation. Köller and Baumert (1998) had proposed an instrument based on the goal orientation theory (Dweck, 1986) which differentiates between three directions inherent in goal orientation, i.e., *task orientation*, *ego orientation*, and *avoidance of work*. General findings are that individuals who range high in task orientation develop more persistent and learning focused patterns of study behavior than individuals who are high in ego orientation who strive to excel with their performance. The questionnaire consists of 21 items on a four-point scale.

Academic self-concept. The questionnaire on academic self-concept devised by Dickhäuser, Schöne, Spinath, and Stiensmeier-Pelster (2002) was used to assess academic self-concept. This instrument returns a measure for the academic self-concept in relation to social, individual, criterion-oriented, and an absolute norm. The academic self-concept has been shown to have an impact on academic performance (Marsh et al., 2006) because it influences choice of learning strategies, persistence, and investment of effort. The constructs are captured by 22 items on a seven-point scale.

Current motivation. The current motivation was measured one week prior to the final exam. The students had been informed about the item format of the test and then filled in the *Questionnaire on Current Motivation (QCM,* Rheinberg et al., 2001). Current motivation is composed of situational interest, anxiety, challenge, and probability of success. The instrument contains a total of 18 items which are assessed on a seven-point scale.

Flow. To measure functional state, the *Flow Short Scale* (*FSS*, Rheinberg et al., 2003) was used. Students were asked to report their flow experience the day after the test. This deviates from the regular instructions for the test, but it was the next best option considering the circumstances of the test situation. The *FSS* consists of 10 items which are rated on a seven-point scale and which fall into two subscales (absorption, balance between ability and challenge).

Knowledge self-tests. To familiarize the students with the item format for the final exam and to support self-monitoring during the course of a semester, twelve weekly self-tests which comprised eight to ten items were provided for the students to use at their own discretion. Self-tests contained multiple-choice questions which covered the material of one lecture class. The students received immediate feedback if they had answered the items correctly, and in case not, they received an explanation why the answer was wrong. Every student had the permission to run the self-test two times. The log-file of the electronic learning platform was evaluated for the number of different tests (*n*ST) run by each student and for the mean scores of correct items per test (*s*ST).

3.4 Procedure

The questionnaires were administered online in a web-based learning environment and all students were invited to participate by an email blast. They were assured that participation was both voluntary and irrelevant for their final degree and that all data were processed anonymously. The order in which the instruments were presented is visualized in Table 1.

Table 1. Order in which the instruments had been administered across the course of the semester

Administration Period	Instrument
Week 1 (beginning of semester)	Prior knowledge
Week 2	Habitual learning strategies questionnaire
	Self-test 1
Week 3	Goal orientation questionnaire
	Self-test 2
Weeks 4-12	Self-tests 3-11 (one test per week)
Week 13	Actual learning strategies questionnaire
	Current motivation questionnaire
	Self-test 12
Week 14[a] (end of semester)	Final test
One day after the final test	Flow questionnaire

Note. [a]All students had to take the final test at the same time.

4. Results

4.1 Data inspection

Data files were inspected for missing data and data plausibility. Individual sets of data were removed from the file when a monotonous pattern of responses was detected and when responses to more than one third of the items on a questionnaire were missing. As a consequence, 488 out of 518 sets of data could be included in the analyses. However, only 106 sets of data met the criterion for a comprehensive compliance which was defined as responding to five out of six questionnaires which had been administered throughout the semester. This means, in turn, that 382 students had an inconsistent record of completed questionnaires.

4.2 Scale characteristics

Prior to data processing, scale characteristics were tested for the prefabricated instruments. As shown in Table 2, the reliability values which were returned as Cronbach's alpha were in most cases acceptable and consistent with the values reported by the original authors except for subscale *probability of success* from the *QCM* and the *FFS* subscale of *absorption,* which were excluded from further analyses.

Table 2. Descriptive data (M, SD, n) and scale reliabilities (Cronbach's alpha) for the measurements of the cognitive and motivational prerequisites, the mediators of learning, and performance measures

Cognitive and motivational prerequisites of learning				
	n	*M*	*SD*	*α*
Current Motivation (Rheinberg et al., 2001), 7-point scale				
Interest	300	4.95	.51	.73
Challenge	300	5.32	.83	.68
Probability of Success	300	4.21	1.22	.40
Anxiety	300	3.88	.64	.74
Dispositional Motivation (Köller & Baumert, 1998), 4-point scale				
Task Orientation	260	3.07	.44	.81
Ego-Orientiation	260	2.35	.17	.87
Avoidance of Work	260	2.55	.14	.90
Academic self-concept (Dickhäuser et al., 2002), 7-point scale				
Criterion-Referenced	235	4.64	.11	.80
Individual Reference	235	4.60	.10	.86
Social Reference	235	4.21	.04	.89
No Reference	235	4.56	.14	.89
Mediators				
Motivational State (Rheinberg et al., 2003), 7-point scale				
Flow: Absorption	187	4.69	.49	.38
Flow: Balance between ability and challenge	187	4.71	.24	.91
Self-reported learning strategies (Gold & Souvignier, 2004), 5-point scale				
Habitual Learning Strategies (self-report T1)				
Memorizing	369	2.88	.35	.80
Knowledge Transformation	369	3.69	.10	.88
Visualization of Information	369	2.81	.01	.89
Elaboration	369	3.48	.19	.86
Time Management	369	2.74	.44	.78
Effort Investment	369	3.18	.42	.74
Actual Learning Strategies (self-report T2)				
Memorizing	264	2.92	.29	.84
Knowledge Transformation	264	3.69	.09	.92
Visualization of Information	264	2.79	.08	.92
Elaboration	264	3.49	.18	.88
Time Management	264	2.80	.33	.81
Effort Investment	264	3.25	.35	.77
Performance				
Prior Knowledge Test (12 items total)	232	4.54	1.60	.68
Final Test (40 items total)	488	30.8	4.18	.72

4.3 Descriptive results

Inspection of the descriptive results reveals that the prior knowledge test was rather difficult with an average of M = 4.54 (SD = 1.60) items correct out of 12. This means that prior knowledge is rather low, which is reasonable to expect at the beginning of the term. The final test at the end of the term returns an average of M = 30.8 (SD = 4.18) items correct out of 40. Neither a ceiling effect nor a floor effect is observed with a minimum at 14 and a maximum at 39 items correct. The values for current motivation show that interest and challenge are rather high prior to the final test. In terms of dispositional motivation, participants seem to lean towards a task orientation. For the academic self-concept, there appears to be no clear preference for a certain frame of reference. The self-reported habitual learning strategies and the actual learning strategies yield values which are located under the scale mean. The use of learning strategies in this group has room for growth. The average values which were returned for habitual (T1) and actual (T2) learning activities are rather consistent and appear in a comparable range.

To address the first research question which is concerned with the relationship between students' initial variables and their final performance, we calculated a set of correlations. Table 3 shows that prior knowledge, situative interest, and self-concept return positive and significant correlations with final performance, whereas dispositional motivation in terms of general goal orientation fails to yield a significant correlation with final test performance. In addition, most of the mediators which are included in the model are correlated with performance. In particular, the investment of complex learning strategies, such as elaboration and effort, is positively related to performance, while the preference for rote learning (memorizing) shows a negative correlation with performance. The strongest correlation appears between the mean score from the self-tests and the final test score. Also, flow during the task is positively related to performance.

Table 3. Correlations of the cognitive and motivational variables and mediator variables with final test scores

Cognitive and motivational prerequisites of learning		n*
Current Motivation: Interest	$r = .12, p < .05$	298
Prior Knowledge	$r = .13, p < .05$	235
Academic Self-Concept	$r = .21, p < .001$	230
Mediators		
Functional State: Flow		
Balance between ability and challenge	$r = .37, p < .001$	187
Absorption	$r = .17, p < .05$	187
Self-reported learning strategies		
Habitual: Memorizing	$r = -.14, p < .01$	344
Test-related: Elaboration	$r = .13, p < .05$	262
Test-related: Effort	$r = .18, p < .05$	262
Learning Behavior: Number of Self-Tests	$r = .42, p < .001$	488

Note. Only statistically significant correlations are reported. All other variables did not correlate significantly with learning outcome.

* sizes of subsamples vary due to student participation.

The current pattern of results confirms the assumption that prior knowledge is a reliable predictor for future performance. We also see that situational interest drives learning and that a positive self-concept is correlated to learning. We see a trend that learners with simple strategies, such as memorizing, do not achieve high scores, while more complex strategies seem to be beneficial for performance. The number of self-tests run during the semester carries the highest correlation with final performance.

Considering the second research question and in order to gain a better understanding of the factors which drive studying behavior, the next feasible step would be to test a path model for the interrelations between these variables. Since the quality of the data, in particular the low number of complete data sets in relation to the number of variables in a potential model, was not appropriate for this kind of statistical operation, we can only address the aspect of exploring different profiles of learners.

The challenge remains to define a criterion to select those subjects which should be included in this analysis accounting for missing scales in a rational way. So, the first step was to find out if the compliant pattern of behavior of completing the various questionnaires and of going through the self-tests (*n*ST) made a difference for the learning outcome. The results of a regression analysis suggest that both indicators have high correlations with the final test score and that both explain a substantial proportion of the variation in the final performance (16% for questionnaires and, in addition, 34% for self-tests; see Table 4). This pattern of results leads us to the conclusion that the behavior of regularly working on the course tasks has a distinct effect on performance and that it would be justified to consider this selected group for further analyses. Therefore, to identify different types of learners, a cluster analysis was performed on the subset of n = 107 complete data sets.

Table 4. Regression Analysis for the Impact of Behavior Variables Indicating High Conscientiousness on Learning Outcome

Variable	*B*	*SE B*	β	*p*
Number of completed questionaires	.26	.09	.16	< .01
Number of self-tests	.31	.05	.34	< .001

In preparation for the cluster analysis, the scores of all scales were z-standardized. Figure 2 depicts the three-cluster solution (Ward-method) which represents three distinct types of conscientious students.

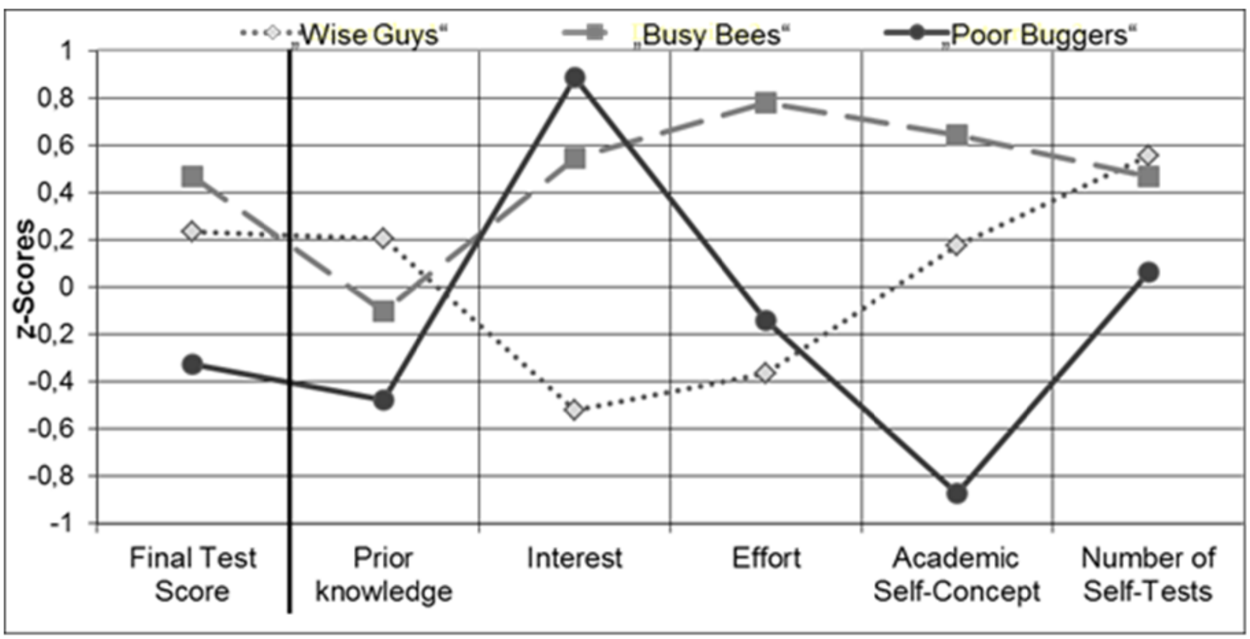

Figure 2. Three clusters of students with a conscientious pattern of study behavior (subsample of n = 107).

The final test scores were not considered for the cluster analysis.

The three groups show significantly different final test scores (F (2,104) = 5.45, p < .01, eta² = .095). The best test scores are returned by Cluster 1. Students in this cluster start with relatively low prior knowledge, they report high interest and high investment of effort; they hava a sound academic self-concept and use the self-assessment tests quite frequently. We can call them the diligent students or the “Busy Bees” (n = 39). Students in Cluster 2, the group with the second highest average scores in the final exam, start with high prior knowledge, but low interest and a low investment of effort; however, they have a high academic self-concept and use the self-assessment tests to prepare for the final exam. We can call them the “Wise Guys” (n = 46). Students in Cluster 3 come home with the lowest final test scores. On the one hand, they start with low prior knowledge, but they are very interested in the course content. On the other hand, and somewhat inconsistent with their reported interest, they show both little effort and an extremely low academic self-concept. They use the self-assessment tests less frequently than the other two groups. This group of students has, obviously, an interest but lack the confidence and the tools to study efficiently. We call them "Poor Buggers" (*n* = 22).

5. Discussion and conclusions

5.1 Interpretation and Conclusions

Based on a cognitive motivational process model of learning, the current study investigated the impact of studying behavior on learning outcome in an ecologically valid context across the period of one semester. The empirical literature has been reviewed for evidence as to which factors influence academic performance. We found studies which supported the notion that personality traits, such as conscientiousness, play an important role, while others have shown the impact of behavioral variables on learning and achievement. In general, the results from the pertaining studies have one of the two problems: Either, they relied on self-report data about both personality traits, and learning and studying or they used objective data of studying behavior in highly controlled, time-limited, laboratory studies with clear cut tasks. Since both scenarios are somewhat removed from ecologically valid learning situations, the current study used a sample of students over the course of an entire semester to collect questionnaire data on relevant prerequisites of learning and, what is more, objective indicators of studying behavior and learning outcome. Whereas the participants were interested in and challenged by the course, the (self-reported) engagement in learning activities leaves room for growth.

It was found that correlations of learning outcome with all cognitive and motivational variables were low to moderate. In particular, the expected positive effects of learning strategies and of motivational orientation could not be detected. However, results cannot be considered conclusive for two reasons: First, the data were lob-sided by a substantial amount of missing scales, and second, the subsample of *n* = 107 students who had dutifully filled in all the questionnaires, are also the top quartile of students in terms of grades. Therefore, caution is advised to generalize the findings beyond this group of good and complying students.

When looking at the subset of participants who had completed all the online-questionnaires and who had run almost all of the optional self-tests, we may be dealing with students who are high in "conscientiousness" (*C*). In analyzing the data of this subgroup, we found three distinct profiles which call for special attention by university teachers. Results suggest that there are different profiles in the group of those students who achieve good results by regularly and dutifully returning the assignments. The group of the "Busy Bees" is probably easiest to handle: They come with high interest in the content, they are ready to invest effort and have a positive self-concept. They are – globally speaking – a teacher's best clients. The group of the "Wise Guys" is somewhat harder to reach. They come with some prior knowledge but they have or develop only a low level of interest, they avoid investment of effort and prefer surface learning strategies instead. However, they are likely to do well on tests, because they have a high academic self-concept and – this would be our inference – a clear idea of what they need to do to achieve a good grade in a test. However, it is doubtful if the students with this profile develop a reflected expertise and a deep learning approach (Janssen, 1996). Alternatively, it might very well be the case that for this group, which comes with rather high prior knowledge, the course does not offer enough of a challenge to engage in deeper learning activities (Kyndt, Dochy, Struyven, & Cascallar, 2011).

The third group offers again a different perspective. The "Poor Buggers" are interested in the course content, but they have a very low academic self-concept and do not invest effort into studying. They somehow keep going continuously, but with low effort intensity and comparatively low efficiency. It might very well be that their poor academic self-concept is rather conducive to using a surface approach to learning; another explanation for their profile might be that they lack both the competence and the confidence to pursue a deep approach to learning which would imply the use of complex and sustainable learning strategies. This group poses a challenge for teachers, because they might go undetected. They typically comply with course requirements and achieve good grades, while they fail to develop a positive concept of themselves as academic learners and while they invest restricted effort into studying, due to either a knowledge deficit or a production deficit in adequate learning strategies. It is plausible to assume that these students are at risk for drop out, because they might not have and not develop the learning strategies which are required for more advanced challenges in their university career. The overall pattern of results suggest that there is considerable heterogeneity in the group of the willing and the dutiful and that teachers need to look beyond the surface of test results to figure out what kind of learning their students have accomplished.

With reference to the research questions and based on our results, we suggest that a model of academic performance take into account both personality and situative factors simultaneously. This would be an extension in line with earlier findings from self-report studies by Marsh et al. (2006), and Steinmayr and Spinath (2007). From what we see in the current study, conscientiousness, which had quite frequently turned out to be a predictor for academic success in previous studies, seems to play an important role for academic success, but attributing academic outcome to this global trait does not tell the whole story. Research which looks at study behavior may reveal only part of the story since, in an ecologically valid context, persistence and consistency over time are closely associated with successful learning. We consider it a valid research approach to use objective indicators of both studying behavior and personality traits in order to come closer to the complex picture of factors which impact academic performance. This would be the necessary basis which is a prerequisite for teachers to create a learning environment which stimulates efficient learning activities and caters to the learning needs of a specific learner profiles.

5.2 Instructional implications

The objective of this study was to identify factors which determine academic success to guide institutions of higher education in their decisions on how to invest into providing adequate support for learners. Despite the limitations of this study, some guidelines can be derived from our results and literature review.

The “Busy Bees” seem to be ideal students who are easy and a pleasure to teach. Although they start with limited prior knowledge, they are ready to invest effort and do so with some confidence in themselves. As teachers in higher education, it is important to reinforce their attitude and behavior, and encourage them to be a model for their fellow-students. Instructors should not emphasize or praise prior knowledge but let their students know that they believe that a sound knowledge base can be built and that there is a learnable and teachable way how this can be done.

When instructors teach students who show high interest, they would be well-advised to fill in prior knowledge and to teach learning strategies, since there is a high probability that high interest may also be associated with both low prior knowledge and low effort investment. Those “Poor Buggers” who have an interest to learn, but who have a low academic self-concept and who have not yet acquired appropriate learning skills might be good candidates to benefit from tutoring systems, mentoring programs, and study skills programs.

In teaching a class over an extended period of time, the instructor should arrange for multiple and challenging learning tasks which foster both knowledge base and learning skills. When meaningful mandatory tasks are implemented in university courses throughout the semester, both “Poor Buggers” and “Wise Guys” are encouraged to go through the material and to practice and extend their skills. This might be a way to help them adjust their academic self-concept to a more realistic estimation of their strengths and challenges.

The biggest question is how those students who had obviously low attendance and who did not continually invest time and effort on this lecture class could be attracted in the first place. Further research is needed to find out what the causes are. For now, the characteristics of the “Wise Guys” may serve as a substitute. Optional additional material and exercises should be provided for students with more prior knowledge (i.e., for “Wise Guys”) to stimulate interest. Setting high goals which help the students understand what kinds of challenging problems they are able to solve when they use their expertise may increase their interest as they will experience themselves as competent problem solvers.

By no means should instructors be satisfied with explaining learning outcome monocausally as a result of students’ personality – meta analyses show a high impact of teaching strategies on learning outcome (Hattie, 2009). Thus, as instructors, we should always be challenged with the task to help all our students achieving better results.

5.3 Limitations

This study has certainly its limitations which need to be considered. First of all, the amount of missing data is a substantial problem. Conclusions from the current study are certainly limited to the selective subgroup of those students with presumably high values of conscientiousness. There is no doubt that further studies are needed to gain a clearer picture about the different types of students and about the factors which determine learning.

The cognitive-motivational process model of learning which was used to define the relevant variables for the prediction of learning has been developed for laboratory studies, but it had not been tested for the use in a real life setting previously. So, we can only assume but not provide empirical evidence that the model works for such a complex situation. It is a challenge for further studies to propose and test a model of learning which is adjusted to the learning environment.

Also, the current study clearly takes a person oriented approach to explaining academic performances while other avenues which consider social-economic background and school context have been neglected (Shulruf, Hattie, & Tumen, 2008). It is plausible to assume that academic achievement is the result of complex processes which are a function of more than the person-oriented variables of the cognitive-motivational model which we used for the investigation.

5.4 Final conclusions

Instructional strategies to stimulate effective learning behavior need to take into account a variety of motivational and cognitive aspects which determine the presage, the process, and the product of learning. As institutions of higher education take action to meet the challenge of tailoring their programs to an increasingly diverse community of learners, it is important to understand how these factors interact and contribute to academic success. Based on the results of the current study, we suggest that instructors in higher education learn more about the nature of their students, how their learning needs and attitudes are different and how they can challenge and guide their students to develop into more mature and effective learners. As the one-size-fits-all idea of teaching has been overthrown for a while now, further research is needed to obtain a clearer picture of individual differences and how they can be addressed.

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