TASK VALUE, SELF-EFFICACY AND GOAL ORIENTATIONS:
IMPACT ON SELF-REGULATED LEARNING, CHOICE AND
PERFORMANCE AMONG UNIVERSITY STUDENTS

Sandrine NEUVILLE, Mariane FRENAY, & Etienne BOURGEOIS
Université catholique de Louvain

This study, conducted with 184 first-year Belgian psychology students, examines the relations between motivational variables and achievement behaviours. A multiple-goal perspective with approach and avoidance dimensions was considered. Correlational, stepwise multiple regressions and MANOVA were performed. Results from the regressions indicate: (1) a direct effect of motivational variables on self-regulated learning strategies, and a direct effect of self-regulated learning strategies on performance, but no direct influence of motivational variables on performance; and (2) a direct influence of value and learning-approach goal orientation on choice. Results from the first multivariate analysis of variance (MANOVA) with task value and self-efficacy as independent variables only show a main effect of task value on all learning strategies and behavioural outcomes. Results from the second MANOVA assert the positive effect of the endorsement of multiple goals on deep-learning strategies and choice.

Introduction

Achievement motivation theorists attempt to explain students’ achievement-related behaviours, particularly academic choice and performance. In the expectancy-value tradition, these two behaviours are explained by students’ beliefs about how well they will do on a task (expectancy component) and the extent to which they value the task (value component) (Atkinson, 1957; Eccles, 1983; Eccles & Wigfield, 2002; Wigfield, 1994; Wigfield & Eccles, 1992, 2000, 2002). Goal orientations theories have also been developed with this explanatory aim in view. However, they focus specifically on students’ learning and performance on academic tasks or in school settings, and hardly at all on academic choice (Dweck & Leggett, 1988; Elliot, McGregor, & Gable, 1999; Harackiewicz, Baron, Carter, Lehto, & Elliot, 1997; Harackiewicz, Barron, & Elliot, 1998; Pintrich, 2000).

In these two theoretical perspectives, the link between motivational and behavioural variables does not explicitly integrate the role of self-regulated
learning strategies. However, recent research in the psychology of motivation has seen the accumulation of empirical and theoretical evidence which supports the idea that the use of these strategies is a crucial aspect in understanding student learning and academic performance (Bell & Kozlowski, 2002; Corno & Rohrkemper, 1985; Meece, 1994; Nolen, 1988; Pintrich, 2000; Pintrich & De Groot, 1990; Zimmerman, 2000; Zimmerman & Schunk, 2001). Given the importance of such strategies, many studies have investigated, inter alia, the role of motivational factors in their use. They have shown that efficacy and competence judgments, interest and value beliefs as well as goal orientations can facilitate or impede the use of self-regulated learning strategies. Through these studies, the chain of relations between motivational factors and self-regulated processes, and between self-regulated processes and academic learning or performance has been studied implicitly. However, few studies, except those by Pintrich and his colleagues (Pintrich, 1989; Pintrich & De Groot, 1990; Pintrich & Garcia, 1991; Pintrich & Schrauben, 1992), have taken the three levels of variables into consideration simultaneously.

In this research, we will pursue two main issues. Firstly, in line with Pintrich’s work, we will explicitly examine the links between the three sets of variables. Secondly, we will consider the roles of task value, self-efficacy perceptions and goal orientations as motivational variables simultaneously. Although expectancy-value theories, on the one hand, and goal theories, on the other hand, have both provided much insight, they have rarely been considered jointly. We will begin with a review of the literature on the factors taking a prominent role in explaining, firstly, students’ academic achievement and, secondly, students’ academic choice. Then, we will address different issues which will be developed in this research.

Students’ academic achievement

In order to acquire a deep understanding of a subject matter and to perform well in it, students need to engage in different activities such as setting learning goals, integrating information, controlling motivation, cognition and progress towards their goals. The use of these effortful strategies defines self-regulated learning. More specifically, this construct includes both cognitive and metacognitive strategies (Pintrich & De Groot, 1990; Pintrich & Garcia, 1991; Pintrich & Schrauben, 1992). The cognitive strategies are designed to increase encoding, retention and comprehension of course material. They consist of rehearsal, organisation (e.g., outlining, summarizing, making figures), relating (linking course material to previous knowledge and other situations) and critical thinking (critically evaluating ideas) strategies. The first two could be categorised as surface-level strategies while the other two
involve more deep-processing (Entwistle & Ramsden, 1983). The metacognitive strategies help students to plan (setting goals), monitor (supervising, controlling understanding) and modify (regulating) their learning (Noël, 1997; Parmentier & Romainville, 1998).

Many researchers have noted that in order to engage in this kind of strategic behaviour, students need to be motivated to invest the required effort (Paris, Wazik, & Turner, 1991; Pintrich, 1988, 1989; Schunk, 1994; Zimmerman, 1989). Consequently, recent research has tried to identify the personal characteristics that could act as useful predictors of students’ self-regulation. As noted above, they have emphasised the importance of several motivational factors: task value, self-efficacy and goal orientations.


Self-efficacy represents the student's belief that he or she can successfully perform a task (Bandura, 1997; Pajares, 1996; Schunk, 1991). Researchers have found that students with high self-efficacy are more likely to make use of deep cognitive strategies and to engage in self-regulation than students with low self-efficacy (Li & Cheung, 2001; Meece, Blumenfeld, & Hoyle, 1988; Miller, Behrens, & Greene, 1993; Pintrich, 1989, 1999; Pintrich & De Groot, 1990; Pintrich & Garcia, 1991; Pintrich & Schrauben, 1992; Pokay & Blumenfeld, 1990; Schunk & Ertmer, 2000; Silver, Smith, & Greene, 2001; Wolters & Pintrich, 1998; Zimmerman, 2000, 2002; Zimmerman & Martinez-Pons, 1992).

Finally, goal orientation is defined as an integrated pattern of motivational beliefs that is represented by different ways of approaching, engaging in, and responding to achievement activities (Ames, 1992; Dupeyrat & Mariné, 2001). Two major types of goal orientation have been distinguished: learning and performance goals (Dweck & Leggett, 1988; Elliot & Dweck, 1988). Students with the first type of goals are primarily concerned with acquiring new skills or improving competences. In contrast, students who pursue performance goals seek to demonstrate their competence by outperforming others.

The revised goal theory perspective has refined this classification by adding the distinction between an approach and an avoidance dimension (Elliot & Harackiewicz, 1996; Pintrich, 2000). In the performance-approach orientation, the person focuses on doing better than others and on demonstrating abilities; while in the avoidance version, the person focuses on avoiding looking stupid or incompetent in comparison to others. With regard to
learning orientation, the individual using an approach orientation concentrates on mastering tasks, learning and understanding. If, on the other hand, the avoidance orientation is the main concern, the individual concentrates on avoiding misunderstanding, not learning or not mastering the task. This recent perspective has also revised ideas about the mutual exclusivity of learning and performance goals. Several authors now recognise that students can endorse both learning and performance goals with different levels of these two goals (Bouffard, Boisvert, Vezeau, & Larouche, 1995; Dupeyrat & Mariné, 2001; McWhaw & Abrami, 2001; Pintrich, 2000; Riveiro, Cabanach, & Arias, 2001; Shah & Kruglanski, 2000; Wentzel, 2000).

Very little research has been done with reference to these two adjustments of the revised theory. In terms of distinguishing four goal orientations, studies have only taken account of the approach and avoidance dimensions for performance goals. The results are very inconsistent and range from a positive impact of an approach performance goal on the use of deeper cognitive and metacognitive strategies (Wolters, Yu, & Pintrich, 1996) to no relation (Kaplan & Midgley, 1997) or a negative relation (Middleton & Midgley, 1997). In contrast, the results for a learning orientation are consistent: students who endorse this orientation report using more cognitive and metacognitive strategies (Ames & Archer, 1988; Meece & Holt, 1993; Middleton & Midgley, 1997; Pintrich, 1999; Pintrich & Schunk, 2002; Vermetten, Lodewijks, & Vermunt, 2001; Wolters et al., 1996).

With regard to the simultaneous pursuit of learning and performance goals, the sparse results are also divergent. Some findings are more in line with the traditional perspective on goal orientations and show that the high-learning/low-performance profile is the most adaptive in terms of self-regulation (Meece & Holt, 1993; Pintrich & Garcia, 1991). In contrast, Bouffard et al. (1995) and Riveiro et al. (2001) found that the highest levels of cognitive strategy use, self-regulation and achievement were displayed by the high-learning/high-performance group.

Students’ academic choice

In comparison to students’ performance, the choice of academic course or future course enrolment intention has received less attention from researchers. The few studies which have examined this variable have only taken self-efficacy and value beliefs into account as potential predictors. In general, findings are strongly convergent: value beliefs are closely tied to actual and future enrolment decisions, whereas self-efficacy beliefs do not have any influence on choice of course. Once on the course, however, it is students’ self-efficacy belief which influences cognitive engagement (Eccles, 1983; Feather, 1988; Meece, Wigfield, & Eccles, 1990; Wigfield, 1994;
Wigfield & Eccles, 1992). The impact of self-efficacy on choice has nevertheless been shown for males in a study of mathematics with eighth grade students (Ethington, 1991) and for university education students on their midterm intention to enrol in a methodology course (Bong, 2001).

Purpose of this study

Several studies mentioned above have provided information about the links between some motivational and cognitive variables and achievement-related behaviours. However, none of them have taken task value, self-efficacy, goal orientations, self-regulation, performance and choice into consideration simultaneously. That’s why we will examine and clarify the relations between all of these variables. More specifically, the first and second goals are to study the relative influence of motivational variables (task value, self-efficacy and goal orientations) on self-regulation, and the relative influence of motivational and cognitive variables on students’ choice and performance.

In addition, to refine our knowledge of the influence of motivational variables on self-regulation and achievement behaviours (choice and performance), two other goals are considered. First, the interaction between value and expectancy, provided that each of them can be shown to be positively related to self-regulation and achievement behaviours. Second, the clarification of the role of goal orientations and the possible pursuit of multiple goals.

In summary, the four research questions are the following:
1. What is the relative influence of task value, self-efficacy and goal orientations on self-regulation?
2. What is the relative influence of motivational and cognitive variables on students’ choice and performance?
3. Do task value and self-efficacy interact as predictors of self-regulated learning and achievement behaviours?
4. Do groups of students with distinct goal orientations differ in self-regulation and achievement behaviours?

Method

Subjects and procedure

The participants were 184 first-year psychology students in a French-speaking university in Belgium. There were 154 females (83.7%) and 30 males (16.3%). The average age was 18.3 (SD = 1.06), ranging from 16 to 23 years old. The data were collected in March 2003, during a first-year course. All stu-
dents were asked to participate and were assured of confidentiality in their responses. They also allowed us to review their final marks for the course.

Measures

The students responded to a self-report questionnaire. All items on the questionnaire were rated on 7-point Likert-type scales (1 = strongly disagree to 7 = strongly agree) and related to a course in clinical psychology.

Task value perception

Task value was operationalized as encompassing intrinsic interest (7 items: $\alpha = .83$), perceived usefulness (4 items: $\alpha = .70$) and perceived importance (6 items: $\alpha = .81$). Even if those subcomponents may be distinguished, Eccles (2006) supports the perception of value as a global concept. The task value score is therefore a sum of these three subcomponents (17 items: $\alpha = .80$). Items included were, inter alia, “I am very interested in the content area of this course”, “I think the course material is useful for me to learn”, “It is important to me to get good grades in this course”. The items were mainly adapted from those used by Eccles and Wigfield (1995) and were validated in a previous study (Neuville, 2004).

Self-efficacy

Self-efficacy was assessed through four items (Dupeyrat, 2000; Galand, 2001) which had previously been validated (Neuville, 2004). The Cronbach alpha is equal to .71. An example of one of these four items is “I think I will succeed in this course”.

Goal orientations

The measures of goal orientations were adapted from Bourgeois, Galand, and Frenay (2003), Dupeyrat (2000), Galand (2001), Pintrich and Schunk (2002). Four scales were distinguished. The first two focused on learning with approach (7 items: $\alpha = .76$) and avoidance (3 items: $\alpha = .65$) orientations (“My main objective in my studies is to improve my knowledge” versus “I worry I may not learn all that I possibly could in this class”). The other two focused on performance, using the competition (3 items: $\alpha = .63$) versus image (3 items: $\alpha = .63$) distinction as demonstrated by Bourgeois et al. (2003) and Galand (2001). In the performance-competition orientation the student tries to outperform others and sees competition as stimulating (e.g., “It is important to me to have better results than other students”). In the performance-image orientation, the individual does not make reference to other students but tries to do well to enhance his or her own image (e.g., “The main reason I study is because I would like my family circle to be proud of me”).
Learning strategies

Learning strategies were assessed by the 20 items used by Bourgeois et al. (2003), which had been adapted from the questionnaire of Vermunt (1994). Factor analysis was used to check the psychometric properties of the scales, resulting in the exclusion of some items because of a lack of correlation. On the basis of this factor analysis, two cognitive scales and one metacognitive scale were constructed. The first cognitive scale includes three organisation-al items ($\alpha = .65$) (e.g., “I summarise the main ideas of the course”) and is therefore considered as a surface-level strategies scale. The second cognitive scale consists of five items ($\alpha = .71$) of relational (e.g., “I try to discover similarities and differences between notions presented separately”) and critical (e.g., “I try to be critical of what I learn”) thinking. This scale is regarded as a deep-processing strategies scale. Finally, the metacognitive scale includes four items ($\alpha = .63$) assessing planning strategies (e.g., “Before starting to study, I set learning goals”) and monitoring (e.g., “After studying, I ask myself if I have achieved my learning goal”).

Choice

One item (“If I could choose the courses I would follow next year, I would like to continue studying this subject”), adapted from Wigfield and Eccles’ research (1992, 2002), was used to enquire about students’ future enrolment intentions.

Academic performance

Students’ marks were collected from university records. These marks constitute the measure of academic performance. Marks ranged from 0 to 20 ($M = 9.99$, $SD = 4.55$).

Results

Two sets of analyses were performed in order to study our research questions. The first set used multiple stepwise regressions to examine, first, the relative influence of motivational variables on self-regulation (Research question 1) and, second, the relative influence of motivational and cognitive variables on students’ choice and performance (Research question 2). The second set used multivariate analysis of variance (MANOVA) to examine the effect of potential interactions between value and expectancy on self-regulation and achievement behaviours (Research question 3) and to clarify the possible role of the pursuit of multiple goals in self-regulation and achievement behaviours (Research question 4). However, as a first step, correlational analyses were conducted to examine the pattern of relationships between
the three motivational variables (task value, self-efficacy and goal orientations), the three components of self-regulation (surface-level and deep-processing cognitive strategies, and metacognitive strategies), choice and academic performance

Correlational analysis

Table 1 displays the descriptive statistics and the zero-order correlations between task value, self-efficacy, goal orientations, surface-level cognitive strategies, deep-processing cognitive strategies, metacognitive strategies, choice and academic performance. Inspection of this table reveals significant relations among many variables. The most interesting ones for the purposes of this study are discussed below.

First, task value is correlated with deep-processing cognitive strategies and with metacognitive strategies. This result confirms previous findings in the literature (McWhaw & Abrami, 2001; Pintrich, 1989; Pintrich & De Groot, 1990; Pokay & Blumenfeld, 1990; Schiefele, 1992; Wolters et al., 1996). Task value is also strongly related to choice, as found by Bong (2001) and Ethington (1991).

Second, self-efficacy is related to the use of deep-processing strategies. This result diverges from that of Dupeyrat and Mariné (2001) but is consistent with several other studies (Meece et al., 1988; Miller et al., 1993; Pintrich & De Groot, 1990).

Third, the approach and avoidance dimensions of learning goal orientation are both correlated with choice and metacognitive strategies. There is also a correlation between the approach-learning orientation and deep-processing strategies. The finding that learning goals are related to components of self-regulation is consistent with the findings of several earlier studies, where the approach-avoidance distinction was not made (see, *inter alia*, Anderman, Griesinger, & Westerfield, 1998; Bouffard et al., 1995; Dupeyrat & Mariné, 2001; Elliot et al., 1999).

Fourth, the image-performance goals are related to surface-level cognitive strategies. This differs from Dupeyrat and Mariné’s (2001) results.

Fifth, all the learning strategies are inter-correlated but this is particularly true for deep-processing and metacognitive strategies. This is consistent with the work of Wolters and Pintrich (1998). Deep-processing and metacognitive strategies demonstrate links with academic performance, as found by Bouffard et al. (1995) and Pintrich and De Groot (1990). Deep-processing strategies are also related to choice.

Finally, choice is related to academic performance. This is in line with Bong’s (2001) results for midterm marks.
Table 1.
Descriptive Statistics and Zero-Order Correlations Coefficients Among Variables.

<table>
<thead>
<tr>
<th>Variables</th>
<th>M</th>
<th>SD</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Task value</td>
<td>4.82</td>
<td>2.33</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Self-efficacy</td>
<td>4.35</td>
<td>.88</td>
<td>.19**</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Lapp-GO</td>
<td>4.78</td>
<td>.85</td>
<td>.22**</td>
<td>.13</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Lavo-GO</td>
<td>4.46</td>
<td>1.25</td>
<td>.31**</td>
<td>-.16*</td>
<td>.05</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Pcom-GO</td>
<td>3.04</td>
<td>1.17</td>
<td>.07</td>
<td>-.05</td>
<td>.24**</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Pima-GO</td>
<td>4.77</td>
<td>1.25</td>
<td>.29**</td>
<td>.03</td>
<td>.12</td>
<td>.33**</td>
<td>.32**</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. Surf. Cog. Stra.</td>
<td>3.32</td>
<td>1.32</td>
<td>.01</td>
<td>.10</td>
<td>.07</td>
<td>.11</td>
<td>.06</td>
<td>.16*</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8. Deep Cog. Stra.</td>
<td>4.79</td>
<td>1.05</td>
<td>.20**</td>
<td>.21**</td>
<td>.47**</td>
<td>.07</td>
<td>-.03</td>
<td>.14</td>
<td>.25**</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9. Metacog. Stra.</td>
<td>4.37</td>
<td>1.25</td>
<td>.15*</td>
<td>.06</td>
<td>.21**</td>
<td>.19*</td>
<td>-.03</td>
<td>.14</td>
<td>.26**</td>
<td>.40**</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10. Choice</td>
<td>6.05</td>
<td>1.28</td>
<td>.64**</td>
<td>.03</td>
<td>.24**</td>
<td>.17*</td>
<td>.01</td>
<td>.12</td>
<td>.07</td>
<td>.24**</td>
<td>.14</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>11. Acad. Perfor.</td>
<td>9.99</td>
<td>4.55</td>
<td>.11</td>
<td>.09</td>
<td>.14</td>
<td>-.06</td>
<td>.04</td>
<td>.08</td>
<td>.22**</td>
<td>.18*</td>
<td>.17*</td>
<td>1.00</td>
<td></td>
</tr>
</tbody>
</table>

Note. * <.05    ** <.01
Lapp-GO = learning-approach goal orientation; Lavo-GO = learning-avoidance goal orientation; Pcom-GO = performance-competition goal orientation; Pima-GO = performance-image goal orientation; Surf. Cog. Stra. = surface-level cognitive strategies; Deep Cog. Stra. = deep-processing cognitive strategies; Metacog. Stra. = metacognitive strategies; Acad. Perfor. = academic performance
For the academic performance, the marks ranged from 0 to 20.
Regression analyses

Relative influence of task value, self-efficacy and goal orientations on self-regulation

Stepwise multiple regressions were conducted to identify the best predictors of the various learning strategies among the motivational variables included in this study. To this end, the three measures of learning strategies were regressed on task value, self-efficacy and the four goal orientations. Table 2 shows the results of these regression analyses.

The performance-image orientation is the only predictor of surface-level strategies. This result is similar to those of Ames (1992), Dweck and Leggett (1988) and Kaplan and Midgley (1997). Approach-learning goal orientation is the best predictor of both deep-processing cognitive and metacognitive strategies. This is consistent with the findings of Dupeyrat and Mariné (2001). For deep-processing cognitive strategies, self-efficacy appears to also have a predictive effect. This result is consistent with that of Wolters and Pintrich (1998). We also found that avoidance-learning orientation made a small contribution to the prediction of metacognitive strategies.

Relative influence of motivational and cognitive variables on students’ choice and performance

Stepwise multiple regressions were also used to identify the best predictors of choice and academic performance among the motivational and cognitive variables. To this end, the two outcome variables were regressed on task value, self-efficacy, the four goal orientations and the three components of self-regulation. Table 3 shows the results of these regression analyses.

The significant predictors of choice are task value and learning-approach goal orientation. This result matches the prediction of the expectancy-value model that task value would influence choice (Eccles, 1983; Eccles & Wigfield, 2002; Wigfield, 1994; Wigfield & Eccles, 1992; 2000, 2002). Academic performance has a single significant predictor, namely the use of deep-processing strategies, as found by Bouffard et al. (1995).

Multivariate analyses of variance

Effects of task value and self-efficacy on self-regulation, choice and academic performance

To consider the main effects and interactions of task value and self-efficacy on the three components of self-regulation, choice and academic performance, scores on task value and self-efficacy were dichotomized by median split (median of task value = 5.87; median of self-efficacy = 4.36). This allowed the formation of low/high categorical measures to be used as inde-
### Table 2.
Summary of Stepwise Multiple Regression Analyses for Variables predicting Learning Strategies.

<table>
<thead>
<tr>
<th>Dependent variables</th>
<th>Independent variables</th>
<th>β</th>
<th>At Step</th>
<th>Final</th>
<th>R²</th>
<th>R² change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surface level cognitive strategies</td>
<td>Performance-image goal orientation</td>
<td>.17*</td>
<td>.17*</td>
<td></td>
<td>.027*</td>
<td></td>
</tr>
<tr>
<td>Deep-processing cognitive strategies</td>
<td>Learning-approach goal orientation</td>
<td>.47***</td>
<td>.45***</td>
<td>.218***</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Self-efficacy</td>
<td>.16*</td>
<td>.16*</td>
<td></td>
<td>.243***</td>
<td>.025*</td>
</tr>
<tr>
<td>Metacognitive strategies</td>
<td>Learning-approach goal orientation</td>
<td>.21**</td>
<td>.20**</td>
<td>.043**</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Learning-avoidance goal orientation</td>
<td>.18*</td>
<td>.18*</td>
<td>.074**</td>
<td>.031*</td>
<td></td>
</tr>
</tbody>
</table>

*Note. * < .05    ** < .01      *** < .001

### Table 3.
Summary of Stepwise Multiple Regression Analyses for Variables predicting Academic Behaviours.

<table>
<thead>
<tr>
<th>Dependent variables</th>
<th>Independent variables</th>
<th>β</th>
<th>At Step</th>
<th>Final</th>
<th>R²</th>
<th>R² change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Choice</td>
<td>Value</td>
<td>.64***</td>
<td>.62***</td>
<td>.407***</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Learning-approach goal orientation</td>
<td>.13*</td>
<td>.13*</td>
<td>.422***</td>
<td>.015*</td>
<td></td>
</tr>
<tr>
<td>Academic Performance</td>
<td>Deep-processing cognitive strategies</td>
<td>.22**</td>
<td>.22**</td>
<td>.049**</td>
<td>-</td>
<td></td>
</tr>
</tbody>
</table>

*Note. * < .05    ** < .01      *** < .001
ependent variables in MANOVA. This analysis therefore consisted of a 2 (task value: low/high) by 2 (self-efficacy: low/high) MANOVA with the three components of self-regulation, choice and academic performance as dependent variables.

The results only revealed significant main effects for task value ($F(5, 176) = 12.45, p < .001$). The interaction between the variables was also not significant. Univariate F-tests were then performed to identify group differences on the dependent variables. There were significant differences on all dependent variables but on academic performance they were only marginal.1 Students with high task value scores reported more learning strategies of all three types, showed more future course enrolment intentions, and performed better academically (marginal effect) than students with low task value scores.

Differences between groups of students with distinct goal orientations on the three components of self-regulation, choice and academic performance

In order to explore the existence of group differences between students with distinct goal orientations, two sets of MANOVAs were performed. Prior to this, groups of students with distinct goal orientations had to be formed. Two methods, which will be detailed below, were used to construct these groups of students: 1) a cluster analysis, 2) a median split procedure.

Cluster analysis and MANOVA. A cluster analysis with the four goal orientations (learning-approach, learning-avoidance, performance-competition, performance-image) was conducted to identify the combinations of goal orientations present among the students in this study. To conduct this analysis, the scores on the four goal orientations were computed for each of the 184 students. The four goal orientations were then used as variables to generate the clusters. The k-means method was selected for several reasons. First, this iterative method works directly upon the raw data (original $N*P$ matrix with $N =$ cases and $P =$ variables), unlike hierarchical agglomerative methods which require the calculation and the storage of the $N*N$ matrix of similarities between cases. The k-means method is thus suitable for handling large data sets (> 150 subjects). Second, iterative methods, as their name suggests, make more than one pass through the data and can compensate for a poor initial partition of the data. This is not the case with hierarchical agglomerative methods which make only one pass through the data: once a subject has been classified in a cluster, it cannot subsequently move to another. Finally, the k-means method, through this iterative process of classification, minimises

---

1 surface-level cognitive strategies: $F(1, 180) = 4.43, p < .05$; deep-processing cognitive strategies: $F(1, 180) = 9.38, p < .01$; metacognitive strategies: $F(1, 180) = 12.19, p < .01$; choice: $F(1, 180) = 50.47, p < .001$; academic performance: $F(1, 180) = 2.78, p = .097$. 

---
variance within each cluster, so ensuring a maximum of intra-cluster homogeneity. Despite these advantages, a problem with the k-means method is that it requires the researcher to specify the number of clusters to be distinguished. This means that several analyses sometimes need to be conducted, and that the solution retained involves some subjectivity: the researcher chooses the solution which provides the most interesting results for interpretation (Aldenderfer & Blashfield, 1984).

In this study, a five-cluster-solution was adopted because it provided the set of clusters that were most distinct from one another. Consequently, five groups of students with different profiles of goal orientations could be clearly distinguished. To give meaning to the five clusters as objectively as possible, the median of the four variables was used to distinguish between two levels: low and high. When a cluster has a higher value than the median on a variable (which corresponds to a type of goal orientation), we can say that the students in this cluster are characterised by a high level on this specific goal orientation. Table 4 reports the medians of the four variables as well as the final cluster centres of the five clusters, including the low/high coding based on the median.

Based on the low/high coding, the five clusters can be described as follows. Cluster 1 is constituted by students high on learning-avoidance orientation only \((n = 34)\). Cluster 2 is made up of students high on all orientations except learning-approach \((n = 34)\), while Cluster 3 brings together students high on performance-image orientation only \((n = 56)\). Cluster 4 merges students high on all orientations \((n = 35)\), and, finally, cluster 5 consists of students low on all four orientations \((n = 25)\).

After the identification of the different combinations of goal orientations, the MANOVA was conducted with the three components of self-regulation, choice and academic performance as dependent variables. The results confirm the existence of differences between the five clusters of students \((F(5, \ldots)\).
Motivation and Performance Among University Students

178) = 6.30, \( p < .001 \). Univariate F-tests were then examined to identify group differences on the dependent variables. There were significant differences on metacognitive strategies, choice and, marginally, on deep-processing cognitive strategies.\(^2\) Students from the fourth cluster (high on all orientations) had significantly higher scores than students from the four other clusters on all three dependent variables, with the exception of deep-processing strategies where the difference between Cluster 4 and Cluster 3 (high on performance-image only) was not significant. Figure 1 presents the scores on the three significant dependent variables for the five clusters of students.

---

**Median split procedure and MANOVA.** For this second set of analyses, two global scores for learning and performance orientations were computed by summing 2 subscales for each. Dichotomous variables were then created from the continuous data by median split. This allowed the formation of four groups of students: low learning/low performance (LLLP: \( n = 54 \)), low learning/high performance (LLHP: \( n = 38 \)), high learning/low performance (H LLP: \( n = 37 \)) and high learning/high performance (HLHP: \( n = 55 \)). MANOVA was then conducted with self-regulation, choice and academic performance as dependent variables.

---

\(^2\) metacognitive strategies: \( F(4, 179) = 4.11, \ p < .01 \); choice: \( F(4, 179) = 4.2, \ p < .01 \); deep-processing cognitive strategies: \( F(4, 179) = 2.28, \ p = .063 \).
The results confirmed the existence of differences between the four groups of students \( F(5, 178) = 5.14, p < .001 \). Univariate F-tests were examined to identify group differences on the dependent variables. There were significant differences on deep-processing cognitive strategies, metacognitive strategies and choice.\(^3\) Pairwise comparisons between groups revealed the following significant differences \( p < .05 \). HLLP and HLHP students reported more use of deep-processing cognitive strategies than LLLP students. Students in the LLLP group reported fewer metacognitive strategies than the three others groups. Finally, students in the HLHP group showed more future course enrolment intentions than LLLP and LLHP groups. Figure 2 presents the scores on the three dependent variables for the four groups of students.

**Discussion**

The purpose of this research, conducted with university students, was to investigate the relationships between motivational variables, learning strategies and achievement behaviours.

Correlation and regression analyses showed that motivational variables and students’ learning engagement were linked in various ways. Task value,

\(^3\) deep-processing cognitive strategies: \( F(3, 183) = 3.87, p < .05 \); metacognitive strategies: \( F(3, 183) = 4.95, p < .01 \); choice: \( F(3, 183) = 3.49, p < .05 \).
self-efficacy and goal orientations, especially learning goals, were all positively related to deep cognitive and metacognitive strategies. Students who found the course worthwhile, who believed that they were capable or were focused on knowledge and skills development were more likely than other students to report the use of deep cognitive and metacognitive strategies.

The same analyses revealed that learning strategies were strongly related to one achievement behaviour: academic performance. Students who reported greater use of deep strategies achieved better academically. This link was also found by Bouffard et al. (1995) and by Dupeyrat and Mariné (2001) who showed that self-regulation was the best predictor of academic achievement. This pattern of relations between motivational factors, cognitive variables and performance is absolutely consistent with the model of self-regulated learning developed by Pintrich and his colleagues (Pintrich, 1989; Pintrich & De Groot, 1990; Pintrich & Garcia, 1991; Pintrich & Schrauben, 1992). They argue that learning strategies have a direct effect on student achievement, while motivational variables support the use of these strategies but do not influence student performance directly. These results are contrary to the assumptions of classical expectancy-value models: we found no predictive effect of self-efficacy on performance. Self-efficacy is only a significant predictor of deep-processing strategies, which are in turn predictors of performance.

The assertions of expectancy-value models are, however, congruent with our results with regard to choice: task value was a direct and very significant predictor of students’ future course enrolment intention.

In a second step, multivariate analyses of variance allowed us to delve further into the influence of, first, value and self-efficacy, and, second, goal orientations on outcomes. These analyses demonstrated two important results.

First, they indicated the crucial role of task value perceptions in self-regulation. Students with high task value reported significantly more use of all learning strategies than students with low task value. Given the well-known influence of these strategies on academic performance, our results indicate the need for teachers to enhance students’ perceptions of the value of the course material.

The second main result concerned the effect of the endorsement of multiple goals. Two sets of analyses were conducted: the first, with clusters of students, to consider simultaneously four dimensions of goals; the second, with groups of students after median splits, to allow comparison with the results of the scarce existing literature on differences between learning and performance goals. The results of these two analyses lead to the same conclusion. Both are consistent with the revised goal theory perspective which argues that having high levels of multiple goals is the most adaptive profile (Archer, 1994; Bouffard et al., 1995; Dupeyrat & Mariné, 2001; Dweck & Leggett,
The results of the first set of analyses were more significant, which is explained by the fact that the clustering method separates groups of students more accurately than the median split technique. In other words, the grouping of students with same goal orientations is purer in the clusters than in the groups created with median splits.

This research has both theoretical and practical implications. In addition to the simultaneous consideration of multiple variables and the clarification of their relationships, the main theoretical gain concerns the influence of the pursuit of multiple goals. Research focusing on multiple goals need to be pursued as it gives a more complex picture to understand their relationships with various achievement behaviours. This study has also provided some information on the importance of the value aspect of learning, which has been less studied than, for example, the self-efficacy aspect.

The practical contributions of this research are, of course, linked to the theoretical ones. First, our results indicate that teachers should stress not only the goals of acquiring skills, knowledge and competences, but also the goals of demonstrating abilities. To stimulate the acquisition of these learning goals, teachers could use many strategies. Ames (1992) and Maehr and Midgley (1991) have suggested a number of such strategies but not all of them are appropriate in higher education. In this context, teachers could, for instance, stress how learning activities and academic task are “relevant and authentic” tasks that have meaning in the “real world” or in future jobs (Frenay & Bédard, 2004). They can also design academic tasks which involve cooperation between students and thus encourage them to participate actively. It is also important that teachers, through their feedback during the course, support the view that mistakes happen to everyone regardless of their ability and in fact represent an opportunity to learn. Teachers should not let mistakes go by without comment, but should treat them in a way that encourages students to see them as positive and fruitful for learning. With regard to the stimulation of performance goals, strategies such as public evaluation, incentive to social comparison, stress on competition between students (strategies which often characterise higher education environments (Eccles & Midgley, 1989; Harackiewicz et al., 1997)), may be effective, but with caution.

Second, as previously indicated, our results also highlight the importance for teachers not only to support, but also to intensify, students’ conscious perception of the value of their course material. With this aim in view, teachers can activate students’ personal interest through opportunities for choice and control over some academic activities. For example, teachers could constrain the general framework of an oral or written exercise (e.g., to have recourse to the theories developed in the course) while giving students the freedom to choose their own specific subject.

Three strategies to stimulate the acquisition of new values or interests in
domain-specific activities have been proposed by Brophy (1999). He referred to processes usually defined and exemplified in ways that focus on the cognitive aspects of learning, using them to address value/interest/appreciation aspects. The three strategies are those of modeling, coaching and scaffolding. Without going into detail, teachers could arouse what he called a “scaffolded appreciation” if they convey their own enthusiasm and positive feeling for the activity.

It is also important that teachers clarify the utility of the course to enhance its perceived value. This is possible through explicit verbalisation of course goals and usefulness but also through less direct means. For example, teachers can utilise professionals’ stories to explain how to use different theories in practice and why these are important.

In further research, it would be very interesting to analyse the role of other variables, namely contextual variables, in the relationships between motivational beliefs and the use of learning strategies. It is becoming evident that the effective use of such strategies is not necessarily given. It needs to be learned and fostered by adequate learning settings. Many studies highlight the significant impact of learning environments on self-regulated learning (Hadwin, 2001; Randi & Corno, 2000; Schunk & Ertmer, 2000; Schunk & Zimmerman, 1998; Turner, Midgley, Meyer, Gheen, Anderman, Kang, & Patrick, 2002).

More research is also needed to analyse in greater depth and increase our understanding of the multiple relations and dynamics of interactions between all these variables. This could be achieved by means of structural equation modeling, which allows the development of complex models. Another way is to adopt an in-depth qualitative approach which gives access to richer, contextualised, holistic descriptions and is more oriented to revealing complexity (Brewer & Hunter, 1989; Miles & Huberman, 1994).

Finally, we would like to see this type of research extended to other populations from different subject-matter areas and institutional settings.

References


educational applications (pp. 25-44). Hillsdale, NJ: Lawrence Erlbaum Associates.
Meece, J.L., Blumenfeld, P.C., & Hoyle, R.H. (1988). Students’ goal orientation and
cognitive engagement in classroom activities. *Journal of Educational Psychology, 80*, 514-523.
influence on young adolescents’ course enrolment intentions and performance
in mathematics. *Journal of Educational Psychology, 82*, 60-70.
Middleton, M., & Midgley, C. (1997). Avoiding the demonstration of lack of ability:
An underexplored aspect of goal theory. *Journal of Educational Psychology, 89*,
710-718.
CA: Sage.
Miller, R.B., Behrens, J.T., & Greene, B.A. (1993). Goals and perceived ability:
Impact on student valuing, self-regulation and persistence. *Contemporary
Educational psychology, 18*, 2-14.
des déterminants et effets. [The subjective task value: Study of its determinants
and effects.]*. Doctoral dissertation, Université Catholique de Louvain, Louvain-
la-Neuve, Belgium.
Nolen, S.B. (1988). Reasons for studying: Motivational orientations and study strate-
gies. *Cognition and Instruction, 5*, 269-287.
York: Longman.
ways to learn at university. In M. Frenay, B. Noël, P. Parmentier, & M. Romainville (Eds.), *The student-learner: Reading grids for university teachers*]. Brussels: De Boeck Université.
Parsons, J.E., & Goff, S.B. (1980). Achievement motivation and values: An alternative
perspective. In L.J. Fyans (Ed.), *Achievement motivation* (pp. 349-373). New
York: Plenum.
Pintrich, P.R. (1989). The dynamic interplay of student motivation and cognition in the
college classroom. In C. Ames & M. Maehr (Eds.), *Advances in motivation
Pintrich, P.R. (1999). The role of motivation in promoting and sustaining self-regu-


