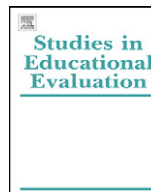




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# Chicken or the egg: Longitudinal analysis of the causal dilemma between goal orientation, self-regulation and cognitive processing strategies in higher education

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### ABSTRACT

The aim of this study was to investigate the direction of the effect between goal orientation, self-regulation and deep processing strategies in order to understand the impact of these three constructs on students' achievement. The participants were 110 freshmen from the engineering faculty at the Université catholique de Louvain in Belgium, who were followed during the first three years of their university studies. Data were analyzed through structural equation modeling. The main finding was that mastery goal orientation increased students' subsequent deep processing which in turn enhanced subsequent self-regulation. Deep processing and self-regulation also appeared to be mutually influential from year 2 to year 3. The implications of our results for the understanding of the interplay between cognitive and motivational processes in higher education are discussed.

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### Introduction

Over the years, a vast body of knowledge has been gathered about how students learn and thrive in an academic context. In this vein, the concepts of self-regulation and cognitive processing strategies have broadened our understanding of students' capacity to learn effectively and steer their own learning. Achievement goal theory has provided some explanation of the processes that lead students to engage in academic tasks. Within these theoretical frameworks, earlier studies in educational psychology have accumulated consistent empirical evidence supporting the position that self-regulation, cognitive processing strategies and goal orientation are important predictors of academic performance (Minnaert & Janssen, 1999; Pintrich & De Groot, 1990; Simons, Dewitte, & Lens, 2004; Vermunt, 2005). In addition, these constructs have also turned out to be linked. Goal orientation has been found to be correlated with self-regulation (Kaplan, Lichtinger, & Gorodetsky, 2009; Zimmerman, 1999) and cognitive

processing strategies (Simons et al., 2004; Galand, Raucourt, & Frenay, 2010). Other studies have also shown a significant link between self-regulation and cognitive processing strategies (Neuville, Frenay, & Bourgeois, 2007; Pintrich, 1999; Pintrich & De Groot, 1990).

Yet, despite the corroboration of links between these variables, only a handful of studies have investigated the direction of causation between these three processes. Therefore, this article aims – through a longitudinal study – to clarify the interplay between goal orientation, self-regulation and cognitive processing strategies.

Last decades, the main goal of higher education has shifted from making students acquainted with a certain domain, to raising reflective and autonomous learners (Dochy, 2001). Therefore, students are now expected to develop autonomous and in depth learning competencies in order to adapt to the lifelong learning and to face unexpected new situations (Poldner, Simons, Wijn-gaards, & van der Schaaf, 2012). In this line, a crucial aspect of educational psychology is to further understand the way students acquire this effective learning process. Several authors insisted on the necessity to more deeply understand the development of effective learning process (Clump, 2005; Johnson & Spicer, 2006; Young, 2005). In this study, the focus will therefore be put on adaptive components of self-regulation, cognitive processing strategies and goal orientations. The core investigation of this study will be centered on the interplay between mastery goal, deep processing and adaptive self-regulation.

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In the following sections, we first present a brief overview of the existing literature about achievement goal theory, cognitive processing strategies and self-regulation. We then describe earlier lines of work dealing with the relationship between these three constructs. Finally, we present the limits of the current literature, the purpose of the study and the hypotheses.

#### *Achievement goal theory*

One of the most prominent theories in the field of motivational research is achievement goal orientation. According to Pintrich (2003, p. 676), goal orientation is defined as “the reasons and purposes for approaching and engaging in achievement tasks”. Despite the complexity of actual students’ goals in a learning context, numerous authors put forward a conceptual model consisting of two orthogonal goals that can be adjusted to the educational context, namely mastery and performance goal orientation (Ames, 1992; Dweck & Leggett, 1988; Nicholls, 1984). Mastery goal orientation refers to a focus on learning and mastering the task, developing new competences toward self-improvement. In contrast, performance goal orientation refers to the student’s concern with demonstrating his or her ability relative to others, obtaining recognition for high performance and attempting to surpass others (Pintrich, 1999; Simons et al., 2004). Theorists have also suggested the necessity to take a third goal into account, namely the work avoidance goal (Ames, 1992). As indicated by Fenollar, Romajn, and Cuestas (2007, p. 877), work avoidance can be defined as the concern “to get work done with a minimum amount of effort”.

The literature on goal orientation has consistently revealed that mastery goal orientation and academic achievement are positively correlated (Bong, 2005; Simons et al., 2004). In contrast, the literature has shown a consistently negative effect of work avoidance on performance (i.e. Fenollar et al., 2007). Theory about work avoidance is underdeveloped making difficult to grasp its complex relations with other achievement goal (Kumar & Jagacinski, 2011). However, while mastery goal is considered as the most adaptive achievement goal, work-avoidance can be considered as the most maladaptive one. Studies on the effect of performance goal orientation on academic achievement have been less consistent (Harackiewicz, Barron, Tauer, & Elliot, 2002). As the purpose of this study is to focus especially on the adaptive pattern of learning that has emerged from existing research evidence, our study will specifically focus on mastery goals, which are consistently depicted as adaptive to the learning contexts. Furthermore previous studies using similar samples (Galand & Frenay, 2005; Galand et al., 2010) have demonstrated that performance goal was not related to effective learning so it was excluded from our scope of analyses.

#### *Cognitive processing strategies*

Decades of studies have focused on understanding which cognitive processes determine students’ effective learning in educational context. Various conceptualizations of cognitive processes have been developed in the literature, and have resulted in a considerable overlap between the different theories (for a review, see Vermunt & Vermetten, 2004). However, a commonly used distinction has emerged between deep and surface approaches to learning (Biggs, 1984; Marton, 1988). Busato, Prins, Elshout, and Hamaker (2000, p. 1058) defined them as “thinking activities students use to process information in order to obtain certain learning results like, for example, knowing the most important points in the study material”. In this vein, a surface approach can be understood as thinking activities leading to the learning of the surface features of a study task, such as rehearsing

or rote processing. Conversely, a deep approach to learning can be conceptualized as thinking activities leading the student to focus on the underlying meaning and complex understanding of a task, such as relating, concretizing and critical processing (Kember & Gow, 1994).

Studies investigating the relationships between surface and deep processing and academic achievement have produced mixed findings (Fenollar et al., 2007). Nevertheless, several authors have argued that deep processing is a particularly important object of learning (Doron, Stephen, Boiche, & Le Scanff, 2009; Vermunt, 2005). A longitudinal study by Zeegers (2001) revealed a consistent positive relation between deep processing and learning outcomes at five consecutive measurement times. Our work will therefore specifically focus on this variable.

#### *Self-regulation*

Through the investigation of self-regulation, several authors have devoted their energy to understanding whether learners regulate their own cognitive resources. According to Elias and MacDonald (2007, p. 2518) “self-regulation refers to the ways in which an individual controls and directs his or her own actions”. When applied to a learning task, self-regulation consists of steering the learning process by using information-seeking, self-evaluation, monitoring, supervising and goal-setting strategies (Dahl, Bals, & Turi, 2005; Nota, Soresi, & Zimmerman, 2004).

Prior work in cognitive psychology has accumulated consistent empirical evidence supporting the view that self-regulation is crucial to understand student learning and academic performance (Nota et al., 2004; Pintrich & De Groot, 1990). For instance, Minnaert and Janssen (1999) have shown that self-regulation explains the same amount of variance in academic performance as intelligence test scores.

#### *The relation between goal orientation, cognitive processing strategies and self-regulation*

A host of studies have highlighted the fact that goal orientation, cognitive processing strategies and self-regulation are correlated. Achievement goals have been widely documented as being correlated with self-regulation (Zimmerman, 1999) and cognitive strategy (Simons et al., 2004). Furthermore, previous studies have also accumulated consistent empirical evidence supporting the view that self-regulation and cognitive strategies are correlated (Pintrich, 2003).

Numerous studies have shown that mastery goal orientation is a strong predictor of deep processing and that the effect of goal orientation on students’ performance is mediated through cognitive processing strategies (i.e. Bouffard, Bouchard, Goulet, Denoncourt, & Couture, 2005; Bruinsma, 2004; Phan, 2009a; Simons et al., 2004). Fenollar et al. (2007) corroborated, through a structural equation model, that mastery goals directly predicted the use of deep processing. Moreover, two longitudinal studies (Phan, 2009b; Young, 1997) have investigated this question through two consecutive years. However, the results of these studies did not provide stable conclusions. The results of Phan (2009b) highlighted that mastery goal orientation implied use of deep processing strategies in the same year but not from one year to another. Conversely, Young (1997) found that mastery goal and deep processing was related from one year to another but only in one of the two samples investigated.

According to several studies, mastery goal orientation is positively correlated with the use of self-regulation strategies (Pintrich, 1999; Shell & Husman, 2008). The study of Patrick, Ryan, and Kaplan (2007) corroborated these results through structural equation modeling highlighting that mastery goal had a strong

impact on self-regulation. Pintrich (1999, p. 467) concluded that “If students set as their goal self-improvement and learning, then they will be much more likely to continue to engage in various cognitive and metacognitive activities in order to improve their learning and comprehension”.

Finally, several authors have argued that self-regulation and cognitive processing strategies are two distinct constructs which are intertwined and mutually influential (i.e. Zimmerman, 1999). For example, a study of Boyle, Duffy, and Dunleavy (2003) showed that self-regulation was positively related to the use of deep processing strategies such as relating, criticizing and concretizing learning process. These results were corroborated by Evans, Kirby, and Fabrigar (2003), who showed that self-regulation enhanced the use of deep processing strategies. Furthermore, these authors found a strong correlation between self-regulation and deep processing, suggesting that deep processing could also have an impact on self-regulation strategies. This assumption was supported by Magno's study (2009), which indicated that deep processing strategies increased self-regulation. Vermunt and Vermetten (2004) went a step further in this issue by taking a person centered perspective and focusing on individual difference in learning. According to these authors, despite a global interrelation between deep processing and self-regulation, two types of students with dissonant learning patterns can be identified (low self-regulation but high deep processing; high self-regulation but low deep processing). Therefore, deep processing and self-regulation would not always be intertwined.

#### *The present study*

Despite the broad corroboration of the link between goal orientations, cognitive processing strategies and self-regulation, as outlined above, two limitations have emerged from the current literature. First, studies that investigate the relationship between these three processes together remain scarce in the literature, the vast majority of studies having focused their analyses on testing relationships among two of these processes at a time. Second, the direction of effects between different variables cannot actually be corroborated without the use of an experimental or a longitudinal design (Cohen, Manion, & Morrison, 2007; Hong, You, Kim, & Kim, 2008). Besides, Phan (2009b, p. 778) argues that “as indicated extensively in educational–psychological research, the use of longitudinal data with latent variables approaches offers a better premise for making developmental inference and the direction of effects”. However, only a handful of studies have used a longitudinal design (Phan, 2009b; Young, 1997). Indeed, the aforementioned studies were essentially correlational or cross-sectional. Moreover, the few longitudinal studies have not lead to strong consistent conclusion. Therefore, in view of the limitations of the current literature, the purpose of the current study is to examine – through three years longitudinal approach – how mastery goal orientations, deep processing strategies and self-regulation are related together. Such an investigation could provide a better understanding of the learning process and could therefore allow for a better promotion of students' effective learning.

- First, it is necessary to take a holistic view of the process and to put the relation between motivational and cognitive processes into question. It is important to wonder which comes first: motivation or cognition. In this line, mastery goal is mainly considered as an antecedent of deep processing and self-regulation in the educational literature (i.e. Bouffard et al., 2005; Phan, 2009a). However, as the direction of these effects was seldom studied, this assertion could be reconsidered and have to be corroborated. Therefore, the first aim of this article is to confirm that goal orientation is an antecedent of deep

processing and self-regulation. Following Phan (2009a), Phan (2009b), Young (1997) and Fenollar et al. (2007), it is assumed that students' mastery goal orientation will directly entail the use of deep processing.

- Second, the direction of the effects between deep processing and self-regulation is not clear in the current literature. However, following Zimmerman (1999) and Evans et al. (2003), it is expected that self-regulation and deep processing will have a reciprocal influence.

## **Method**

### *Participants and procedure*

The participants were 110 freshmen from the engineering faculty at the Université catholique de Louvain in Belgium (22 females, 88 males). All the students were assured of the confidentiality of their responses and that only members of the research team would have access to the data.

Self-completion questionnaires were group-administered during regular lecture time in three waves. Students were followed up during the first three years of their university studies, with data being collected in November of each year (year 2001, 2002, and 2003). Only students who filled in all three questionnaires were included in the study. In this line the sample is very specific because it is uniquely composed of students who passed their three years without failing any of it.

The initial sample was composed of 373 students but 263 of them have missed at least one questionnaire's completion. Therefore, ANOVA were computed in order to investigate if students of the sample significantly differed on goal orientation, cognitive processing strategies and self-regulation scales on year 1. Sample with completion for the three years was compared ( $N = 110$ ) with sample with missing completion ( $N = 263$ ). The analyses revealed that students' score on mastery goal ( $F(1, 362) = 0.217$ ,  $p = .642$ ), deep processing strategies ( $F(1, 362) = 0.025$ ,  $p = .874$ ) and self-regulation ( $F(1, 362) = 0.327$ ,  $p = .568$ ) did not differ from one group to another.

### *Measures*

The questionnaire was constructed on the basis of an extensive review of the literature selecting various scales (i.e. Learning and Study Strategies Inventory, Inventory of Learning Styles...) that were submitted to a broad panel of educational experts and members of the engineering faculty. More detailed description of the validation of the scales is given in Galand and Frenay (2005) and Galand et al. (2010). All items of the questionnaire were rated on five-point Likert-type-scales (achievement goal orientation: 1 = strongly disagree, 5 = strongly agree; self-regulation and cognitive processing strategies: 1 = never, 5 = very often). Exploratory factor analysis using oblimin rotation method was conducted on each year and factor solutions were extracted based on eigenvalue greater than 1. Table 1 provides an overview of each extracted scale with internal consistency, number of items and an example of the items. Given the limited internal consistency of several scales and the necessity to build stronger and more synthetic indicators, exploratory second-order factor analyses were conducted on the scales (second-order factorial analysis outcomes are detailed in Table 2).

*Mastery goal orientation* was investigated through eight items adapted from previous studies (Bouffard, Boisvet, Vezeau, & Larouche, 1995; Dupeyrat, 2000; Midgley et al., 1998; Nicholls, 1989). The three first-order factor analysis consistently produced a two factor solution. In line with these outcomes, mastery goal orientation was divided into two factors: mastery-approach and

**Table 1**

Goal orientation, self-regulation and cognitive processing strategies subscales.

| Subscales                       | Alpha wave 1 | Alpha wave 2 | Alpha wave 3 | N | Example items                                                                                                                   |
|---------------------------------|--------------|--------------|--------------|---|---------------------------------------------------------------------------------------------------------------------------------|
| Mastery goal orientation        |              |              |              |   |                                                                                                                                 |
| 1. Mastery-approach             | .74          | .74          | .72          | 5 | Understanding the subject-matter is more important to me than grades I get                                                      |
| 2. Work-avoidance               | .60          | .54          | .62          | 3 | Understanding the subject-matter is not important for me, as long as I get the right answers                                    |
| Self-regulation                 |              |              |              |   |                                                                                                                                 |
| 1. Information-seeking          | .71          | .65          | .68          | 4 | If I don't understand part of the subject-matter, I try to find relevant information from other sources                         |
| 2. Supervising                  | .66          | .67          | .67          | 6 | When I am facing a difficulty in understanding part of the content, I try to analyze finely the nature of the problem in detail |
| 3. Monitoring                   | .69          | .69          | .70          | 3 | To test my progress in my studies, I try to answer questions I ask myself about the subject-matter                              |
| Cognitive processing strategies |              |              |              |   |                                                                                                                                 |
| 1. Relating                     | .81          | .82          | .82          | 6 | I try to see the connections between the content of several courses                                                             |
| 2. Criticizing                  | .67          | .70          | .69          | 4 | I draw my own conclusion from the data presented by the teachers                                                                |
| 3. Contextualizing              | .79          | .77          | .84          | 4 | I use what I learn at university in my activities outside university                                                            |

work avoidance goal orientation. Similar components of goal orientation have been identified by various authors (i.e. Serra de Lemos and Gonçalves, 2004; Young, 1997). Second-order factorial analysis was conducted on the two goal orientation subscales and one factor emerged from the analyses. These analyses were replicated on the three waves and the same factorial structure emerged. The explained variance of the factor ranged from 64 to 70%. The results revealed that mastery approach and work avoidance goal orientation subscales loaded on the same factor: positively in the case of mastery approach and negatively in the case of work avoidance. These results tally with a previous study that highlighted that mastery approach and work avoidance goal are negatively correlated (Kumar & Jagacinski, 2011; Shell & Husman, 2008). Moreover, previous study of Galand and Philippot (2002) on the factorial structure of goal orientation highlighted – through confirmatory factor analyses – that mastery-approach and work-avoidance were closely interrelated and can be considered the two sides of a same construct. We therefore postulated that these two subscales could be considered as the two extremities of the mastery goal construct: a mastery-approach goal orientation would then represent a major orientation on the understanding of the task. Conversely, a work avoidance goal orientation would refer to a minor orientation on the understanding of the task. In this study, factor scores were therefore extracted to create an overall mastery orientation scale. For instance, a student with a high score on the mastery orientation scale will aim to maximize his understanding of a course, whereas a student with a low score will try to do the minimum necessary to succeed in the course. It should be recalled that theory about work avoidance is underdeveloped making difficult to grasp its complex relations with other achievement goals (Kumar & Jagacinski, 2011).

**Self-regulation.** Items related to adaptive self-regulation were adapted from previous work as the Learning and Study Strategies

Inventory (LASSI, Entwistle & Ramsden, 1983; Weinstein, Goetz, & Alexander, 1988) and the Inventory of Learning Styles (ILS, Vermunt, 1994). Students' self-regulation was measured through three subscales: information-seeking, supervising and monitoring. Second-order factorial analysis was conducted on the three self-regulation subscales. One factor accounting for the majority of the variance was extracted, and an overall adaptive self-regulation scale was created, including information-seeking, supervising and monitoring subscales. An identical factorial structure emerged for all three waves, and the explained variance ranged from 56 to 60%.

**Cognitive processing strategies.** As for self-regulation, items associated with cognitive processing strategies were adapted from previous studies on LASSI and ILS (Entwistle & Ramsden, 1983; Vermunt, 1994; Weinstein et al., 1988). Three subscales emerged from exploratory factorial analysis. Second-order factorial analysis was conducted on the three learning strategy subscales. One factor that accounted for the majority of the variance emerged from the analyses. Factor scores were extracted to create an overall deep processing scale, including relating, criticizing and contextualizing subscales. The same factorial structure emerged for the three waves, and the explained variance ranged from 69 to 74%.

### Analytical procedure

The relationship between mastery goal orientation, self-regulation and deep processing strategies was explored in a two-stage process using path analysis.

In the first stage, path analysis was applied to test relationships among two of these processes at a time. To do so, the direction of the effects between mastery goal orientation and deep processing strategies was first investigated. Then the direction of the effects between mastery goal and self-regulation was tested. Finally, the direction of the effects between deep processing strategies and self-regulation was investigated. Moreover, in each side-by-side comparison a model solely composed with stability coefficient was compared with a model including cross-lagged effects (for more information see Creed, Patton, & Prideaux, 2006; Delsing, Oud, & De Bruyn, 2005; Oud & Delsing, 2010; Skaalvik & Valas, 1999).

In a second stage, an overall model was elaborated to ascertain the complete dynamic that governs the development of goal orientation, self-regulation and cognitive processing strategies. This model was built on the best fitting models that have emerged from the first stage and was compared with an alternative model solely composed with stability coefficients.

The analyses were conducted with AMOS16 on the three waves. The parameters of the models were estimated using the maximum likelihood. It is worth noting that in structural equation modeling,

**Table 2**

Second-order factorial analysis outcomes.

|                                 | Wave 1 | Wave 2 | Wave 3 |
|---------------------------------|--------|--------|--------|
| Mastery goal orientation        |        |        |        |
| 1. Mastery-approach goal        | .83    | .77    | .82    |
| 2. Work-avoidance goal          | –.84   | –.82   | –.83   |
| Self-regulation                 |        |        |        |
| 1. Monitoring                   | .85    | .84    | .84    |
| 2. Supervising                  | .72    | .71    | .76    |
| 3. Information-seeking          | .75    | .70    | .61    |
| Cognitive processing strategies |        |        |        |
| 1. Relating                     | .89    | .89    | .88    |
| 2. Criticizing                  | .84    | .87    | .89    |
| 3. Contextualizing              | .75    | .81    | .77    |

**Table 3**

Skewness, kurtosis and correlation matrix of the dependent and independent variables.

|     | Skew. | Kurt. | 1     | 2     | 3     | 4     | 5     | 6     | 7     | 8     | 9    |
|-----|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|------|
| SR1 | .01   | −.42  | 1.00  |       |       |       |       |       |       |       |      |
| SR2 | −.11  | −.14  | .64** | 1.00  |       |       |       |       |       |       |      |
| SR3 | .02   | −.13  | .62** | .66** | 1.00  |       |       |       |       |       |      |
| DP1 | −.14  | −.21  | .67** | .58** | .47** | 1.00  |       |       |       |       |      |
| DP2 | −.18  | −.57  | .55** | .70** | .58** | .72** | 1.00  |       |       |       |      |
| DP3 | .03   | −.46  | .56** | .64** | .67** | .64** | .73** | 1.00  |       |       |      |
| MG1 | −.21  | −.48  | .48** | .38** | .41** | .40** | .46** | .49** | 1.00  |       |      |
| MG2 | −.22  | −.49  | .31** | .49** | .29** | .29** | .44** | .46** | .61** | 1.00  |      |
| MG3 | .21   | −.64  | .28** | .39** | .32** | .25** | .41** | .49** | .67** | .70** | 1.00 |

Significance level:

\*  $p < .05$ .\*\*  $p < .01$ .\*\*\*  $p < .001$ .

the chi-square compares the sample covariance matrix with the theoretical model covariance matrix. Therefore, a non-significant chi-square attests of a good fit of the sample to the theoretical model. Beyond the chi-square, numerous goodness-of-fit indicators are used in educational literature and there is no consensus on whose are the best indicators. In line with several authors, we decided to use three frequently used indicators (i.e. Schreiber, Stage, King, Nora, & Barlow, 2006). The goodness of fit was evaluated using the comparative fit index (CFI), the root mean square error of approximation (RMSEA), P for the test of close fit (PCLOSE) and standardized root mean square residual (SRMR). A good fit is generally indicated by a CFI close to 0.95, an RMSEA less than 0.08, a PCLOSE higher than 0.05 and a SRMR lower than 0.05 (Schreiber et al., 2006). Finally two additional indices were used to compare the model tested namely AIC (Akaike Information criterion) and chi-square difference. The chi-square difference statistic is used in nested models comparison to test the statistical significance of the improvement in fit when parameters are added (Kline, 2011). AIC is used with non-nested models and is expected to be as low as possible.

In this study, standardized path coefficients are reported and  $p < .05$  was used as a criterion of statistical significance. Yet, considering for the low power of the sample, marginally significant paths ( $p < .10$ ) were also reported if they significantly improve the fit of the model (for a discussion see Fan, 2001).

## Results

Table 3 shows skewness, kurtosis and the correlation matrix between scales tapping mastery goal, deep processing and self-regulation on the three years.

Correlations highlight that self-regulation, deep processing and mastery goal are highly related but they are not informative concerning the dynamic between these factors. Therefore path analyses were conducted to investigate the relationship between these three variables from one year to another.

Skewness and kurtosis indicators found to be within normal limits. However, as maximum likelihood method makes the assumption of multivariate normality, Mardia's test of multivariate kurtosis was also conducted (Kline, 2011). This test shows a multivariate kurtosis indicator of 7.71. It did not exceed 10 and can therefore be considered to be normally distributed.

### Exploring the direction of the effects through path analysis

In order to test the direction of the effect between self-regulation, deep processing and mastery goal orientation, three path analyses were conducted separately. The direction of effects of each variable was tested through relationships among two of these processes at a time, in three cross-lag model comparisons. These models compared causal effects between deep processing strategies and mastery goal orientation, deep processing strategies and self-regulation, and between mastery goal orientation and self-regulation. First, a model solely composed with stability coefficient was tested. Errors were allowed to correlate within each wave. Second, a model with stability coefficient and cross-lagged effects was tested. Third, a more parsimonious model composed with only significant path was investigated. The model fits were compared through AIC and  $\chi^2$  difference test. Table 4 detailed the fit results from the three cross-lagged model comparisons. In this line, the results described below only focused on the best fitting models.

**Table 4**

Path analysis results: cross-lagged comparison.

| Model                             | $\chi^2$ | df | CFI | RMSEA | Pclose | SRMR | AIC  | $\chi^2_B$ |
|-----------------------------------|----------|----|-----|-------|--------|------|------|------------|
| Mastery goal – deep processing    |          |    |     |       |        |      |      |            |
| Stability                         | 19.8**   | 6  | .96 | .15   | .01    | .10  | 49.8 |            |
| Cross-lagged                      | 4.1ns    | 2  | .99 | .10   | .20    | .02  | 42.1 | 15.74**    |
| Parsimonious                      | 4.8ns    | 4  | .99 | .04   | .44    | .02  | 38.8 | 0.72ns     |
| 2. Mastery goal – self regulation |          |    |     |       |        |      |      |            |
| Stability                         | 7.2      | 6  | .99 | .04   | .46    | .04  | 37.3 |            |
| Cross-lagged                      | 5.5      | 2  | .98 | .13   | .11    | .02  | 43.5 | 1.84ns     |
| Deep processing – self regulation |          |    |     |       |        |      |      |            |
| Stability                         | 28.4***  | 6  | .95 | .19   | .01    | .11  | 58.4 |            |
| Cross-lagged                      | 2.8ns    | 2  | .99 | .06   | .33    | .02  | 40.8 | 25.64***   |
| Parsimonious                      | 4.7ns    | 3  | .99 | .07   | .30    | .03  | 40.7 | 2.11ns     |

\*  $p < .05$ .\*\*  $p < .01$ .\*\*\*  $p < .001$ .

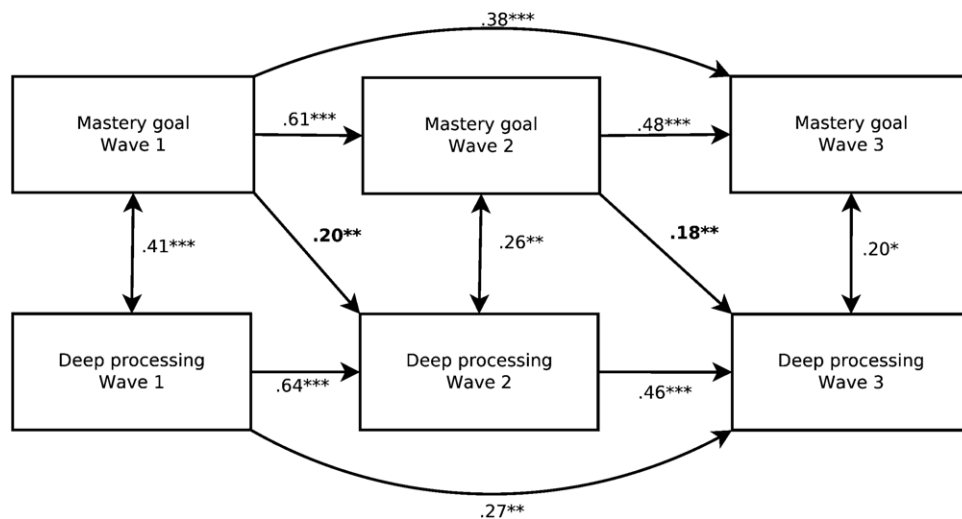


Fig. 1. Path analysis on direction of the effect between mastery goal and deep processing. Note. \* $p < .05$ ; \*\* $p < .01$ ; \*\*\* $p < .001$ .

**Mastery goal orientation and deep processing strategies.** The results revealed a good overall fit of the data to the parsimonious model ( $CFI = 0.99$ ;  $RMSEA = .044$ ;  $PCLOSE = .439$ ;  $SRMR = .019$ ). The chi-square was also non-significant ( $\chi^2 = 4.83$ ,  $df = 4$ ,  $p = .305$ ). The parsimonious model is presented in Fig. 1. The model comparison has highlighted that the parsimonious model was the best fitting model. The AIC was lower than the stability and the cross-lagged model.

This model showed that mastery orientation and deep processing strategies remained highly stable across the years. Mastery goal orientation consistently predicted the use of deep processing strategies from one year to another. Eventually, the two variables were also found to be correlated in the same year. These results support our assumption that mastery goals have a direct impact on the use of deep processing strategies.

**Mastery goal orientation and adaptive self-regulation.** The results revealed that the stability model was the best fitting model compared with cross-lagged model. This model has a good overall fit of the data to the model ( $CFI = 0.99$ ;  $RMSEA = .044$ ;  $PCLOSE = .459$ ;  $SRMR = .037$ ). The chi-square was also non-significant ( $\chi^2 = 7.21$ ,  $df = 6$ ,  $p = .295$ ). The results of the path analysis are presented in Fig. 2.

As for mastery goal orientation and deep processing strategies, stability model showed that adaptive self-regulation scores remained highly stable across the years. Mastery orientation and adaptive self-regulation were not associated from one year to another. However, the two scales were correlated in year 1 and year 2.

**Deep processing and adaptive self-regulation.** The results revealed a good overall fit of the data to the parsimonious model ( $CFI = 0.99$ ;  $RMSEA = .073$ ;  $PCLOSE = .297$ ;  $SRMR = .027$ ). The chi-square was also non-significant ( $\chi^2 = 4.72$ ,  $df = 3$ ,  $p = .193$ ). The results of the path analysis are presented in Fig. 3. The model comparison has highlighted that the parsimonious model was the best fitting model. The AIC was lower than the stability and the cross-lagged model. A marginally significant path was kept in the parsimonious model because it significantly improved the model fit.

Although the path between deep processing and self-regulation from wave 2 to wave 3 is only marginally significant ( $p < .075$ ), the results highlighted that deep processing consistently predicted adaptive self-regulation from one year to another. Moreover, adaptive self-regulation in wave 2 predicted deep processing strategies in wave 3. As for mastery goal, deep processing also proved to be in concurrent association with self-regulation. The results support the hypothesis that deep processing and adaptive self-regulation are two intertwined constructs.

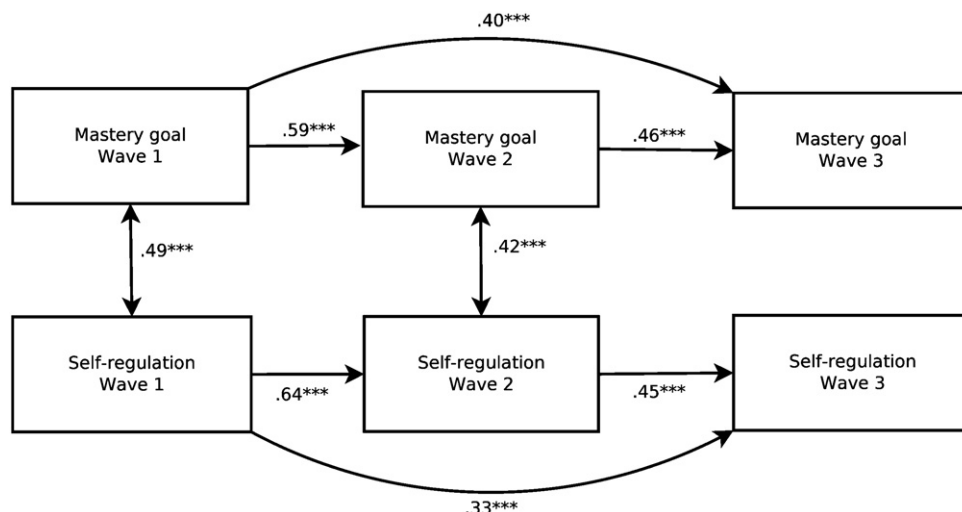


Fig. 2. Path analysis on direction of the effect between self-regulation and mastery goal. Note. \* $p < .05$ ; \*\* $p < .01$ ; \*\*\* $p < .001$ .

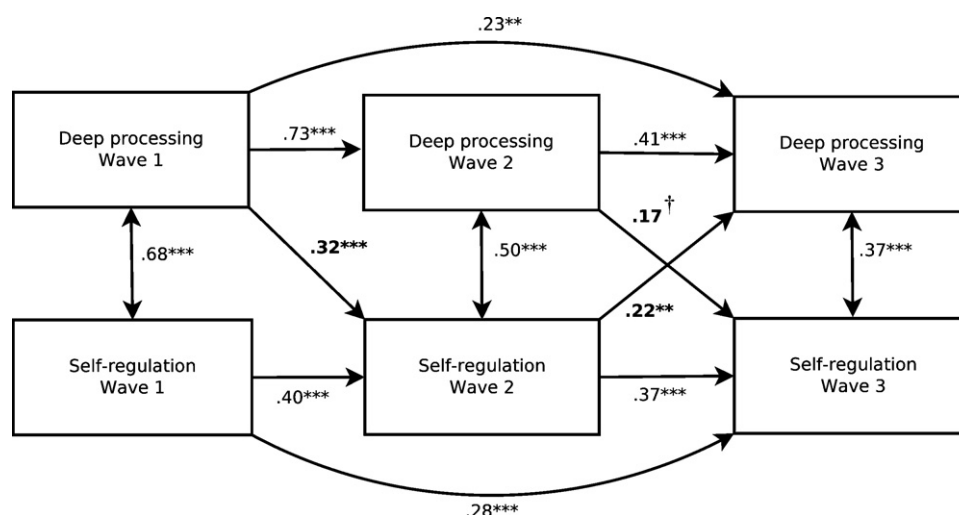


Fig. 3. Path analysis on direction of the effect between self-regulation and deep processing. Note.  $^{\dagger}p < .10$ ;  $^*p < .05$ ;  $^{**}p < .01$ ;  $^{***}p < .001$ .

### Toward an overall model

In order to investigate the direction of the effects together and to obtain a more comprehensive picture of the dynamic of the three variables, an overall model based on the three best fitting cross-lag models was tested. This model was also compared with an alternative model composed only with stability coefficients. Table 5 describes the fit results for the overall model and the alternative stability model.

The overall path model yielded an excellent model fit ( $CFI = 1$ ;  $RMSEA = .000$ ;  $PCLOSE = .761$ ;  $SRMR = .033$ ). The chi-square was also non-significant ( $\chi^2 = 12.86$ ,  $df = 14$ ,  $p = .537$ ). The path diagram is presented in Fig. 4. This model was much better than the alternative model with a lower AIC and significant  $\chi^2$  difference.

This model revealed that mastery goal orientation predicts deep processing, which in turn predicts adaptive self-regulation. It also displayed a marginal mutually supportive relationship between self-regulation and deep processing from wave 2 to wave 3 ( $p < .075$  and  $.056$ ). These two paths were kept because they significantly improve the model fit.

### Discussion

The current study aimed to broaden our understanding of goal orientation, cognitive processing strategies and self-regulation dynamics in higher education. The main concern was to determine how these three constructs relate with one other. Our two precise assumptions here were that mastery goal orientation will predict the use of deep processing and that deep processing and self-regulation will be interrelated. The results provided some evidence on these points.

Table 5  
Path analysis results: overall model comparison.

| Model       | $\chi^2$ | df | CFI | RMSEA | Pclose | SRMR | AIC   | $\chi^2_D$            |
|-------------|----------|----|-----|-------|--------|------|-------|-----------------------|
| Overall     | 12.8ns   | 14 | 1.0 | .00   | .76    | .03  | 74.8  | 36.4 <sub>5</sub> *** |
| Alternative | 49.2***  | 19 | .95 | .12   | .01    | .11  | 101.2 |                       |

\*  $p < .05$ .

\*\*  $p < .01$ .

\*\*\*  $p < .001$ .

### Getting to the bottom of an intricate intertwining

The analyses carried out have provided part of the answer to the questions outlined above. Stable paths were identified in this three-year longitudinal survey.

First, our findings indicate significant stability of motivational and cognitive variables from one year to another. This means that, for instance, an initial mastery goal orientation in the first academic year will tend to be maintained year after year. Such strong stability over the course of time has already been reported in previous work (Phan, 2009b; Young, 1997; Zeegers, 2001).

Second, confirming our assumption and the results of previous studies (Fenollar et al., 2007; Phan, 2009a; Young, 1997), mastery goal orientation proved to be a consistent predictor of deep processing strategies. Accordingly, we can conclude that a student who is interested in improving his competence in a given task will therefore enhance his thinking activities in order to achieve a deeper understanding of the task.

Third, our results also highlighted that the use of deep processing increased self-regulation from the first to the second year and that these two constructs were mutually influential from the second to the third year. These findings tend to support our second assumption and Magno's (2009) conclusions that deep processing is the predictor of self-regulation, and contradict the assumption that the use of deep processing strategies cannot be achieved without prior development of self-regulation strategies (Evans et al., 2003). The current study could indicate that in a new learning context, such as an university context, students will initially make use of deep processing strategies (relating, criticizing and contextualizing), which will then increase the use of self-regulation strategies, such as information-seeking, supervising and monitoring. Afterwards, when students have adapted to the academic context, results show that deep processing and self-regulation could reinforce each other in a virtuous circle.

These results substantiate the assertion of several authors (Bouffard et al., 2005; Bruinsma, 2004; Fenollar et al., 2007; Zimmerman, 1999) that goal orientation is an antecedent of cognitive processing strategies and self-regulation. Moreover, the results also highlight subtler processes. According to our assumption, student's mastery goal orientation will entail the use of deep processing strategies which will in turn imply the development of self-regulation. This process resonates with Zimmerman's (2005, p. 17) assumption that "self-regulatory skills are of little value if a person cannot motivate themselves [sic] to use them".

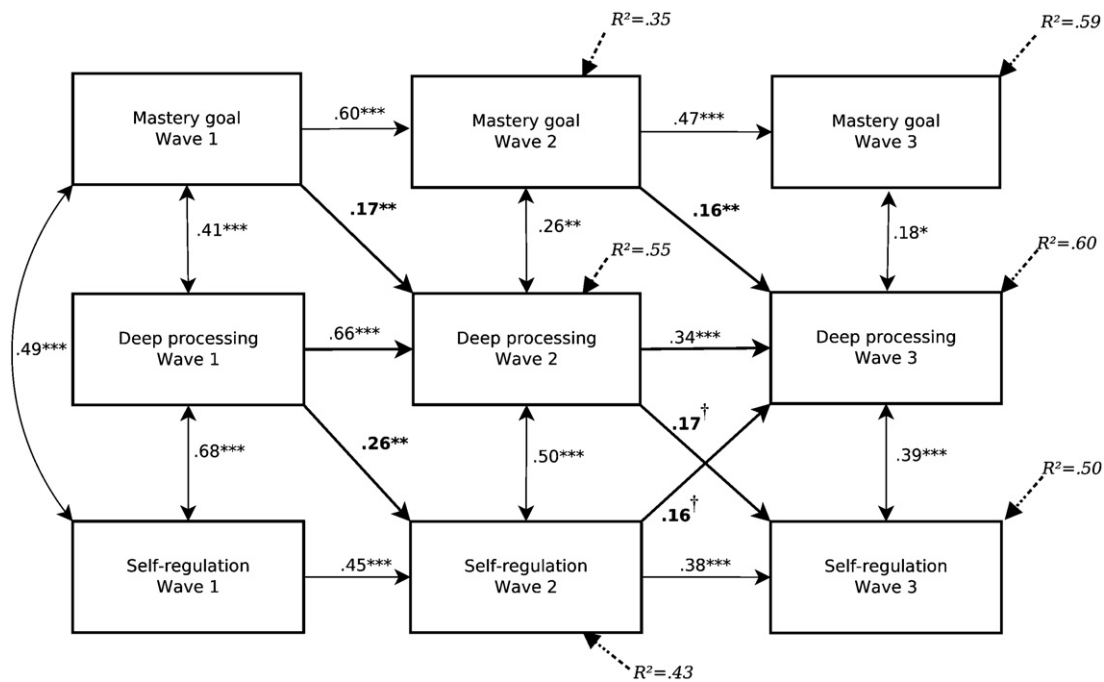


Fig. 4. Path analysis on direction of the effect between self-regulation, deep processing and mastery goal. Note. † $p < .10$ ; \* $p < .05$ ; \*\* $p < .01$ ; \*\*\* $p < .001$ .

However, beyond the global dynamic depicted in this study, mastery goal, deep processing and self-regulation also found to be correlated in the same year. In this vein, concurrent synergy could operate between these three variables when taken short term view into consideration. In other words, despite consistent results depicting stable direction of the effects between mastery goal, deep processing and self-regulation, it cannot be excluded that these three factors interact with one other within the same year. For instance, although mastery goal orientation globally predict deep processing strategies from a long term view, deep processing strategies could also have some influence on goal orientation from a short term view.

#### Limitations and perspectives

Among the limitations of this study, three are especially noteworthy. First, the sample size was quite small for the use of structural equation modeling. Moreover, two paths of the final model are marginally significant. The results of the study therefore need to be considered carefully. Second, our sample was only composed of engineering students who successfully completed their first three years at university. Although, students that completed the questionnaire across the three years do not differ from students with a missing completion, the sample reflected a very specific profile that questions the suitability of our findings for generalization to higher education as a whole. The findings should therefore be treated with caution, and replicated results from a broader sample are needed to corroborate them. Third, it would be interesting to investigate the global dynamic emerging from our analyses, while controlling for factors that could impact on it. Indeed, to really confirm the causal relationship between two variables, the effect of other variables needs to be excluded (Cohen et al., 2007). For example, we can postulate that variables such as behavioral engagement (Dupeyrat & Mariné, 2005) or background variables (De Clercq, Galand, Dupont, & Frenay, 2012) could mediate the impact of mastery goal on deep processing.

Another fruitful future perspective would be the adoption of a person-centered approach to explore whether this global process is the same for all students. For instance, the model could be compare between low and high-achieving students or across different learning patterns (Vermunt, 1998). In line with this author, several groups of students characterized by different learning patterns can be identified in higher education (Vermunt & Vermetten, 2004). It could therefore be postulated that the relations between mastery goal, deep processing and self-regulation change from one learning pattern to another.

Ultimately, although several limitations have to be taken into account, the current study does provide some hints about ways of promoting adaptive learning processes, about the relation between motivational and cognitive processes in an academic context, and about students' achievement in higher education. The results suggest that the use of deep processing strategies could be very important during the first year at university because it induces further development of self-regulation. Moreover, they also suggest that deep processing is consistently increased by mastery goal orientation. Therefore, cognitive processes could be enhanced through the initial encouragement of mastery goal orientation. These points could lead to a better understanding of students' learning processes and to the development of precise interventions to promote effective rising of more self-regulated and deep learners.

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