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The growth trend in learning strategies during the transition from secondary to higher education in Flanders

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Abstract

As in many OECD countries, the first year in Flemish Higher Education is a major hurdle. Research on the experience of the transition period from secondary to higher education highlights the importance of the change in students' teaching/learning environment. Though this change is hypothesised to affect students' learning strategies, and hereby students' chances of study success, studies examining the change in learning strategies during the transition period are absent. The present research is innovative in the way that it investigates the average and differential growth in learning strategies during the transition from secondary to higher education. All students from thirty-six secondary schools were logged onto the Inventory of Learning Styles-Short Version, and their progress was tracked over five waves from the beginning of the last year at secondary school to the beginning of their second year at a higher education establishment. Six hundred and thirty students were retained for analysis. Results indicate that students on average increased their self-

regulated and deep learning during the transition. The results also showed an increase in students' degree of analysing and lack of regulation. Furthermore, for all the scales except the memorizing scale, the evolution over time varied from student to student.

1. Introduction

In recent years, participation in higher education has increased worldwide. However, this increased participation does not automatically result in increased successful completion of higher education studies. Though there are differences between countries, on average, one third of students entering higher education will not obtain a degree (OECD 2013). It is clear that the first year of higher education is a major hurdle. Student dropout rate as well as non-success rate amongst students is highest during this first year (Hultberg et al. 2008).

In Flanders, the Flemish speaking part of Belgium, only about 40% of first year students succeed in their first year in higher education (Hogeronderwijsadministratie 2008). This high dropout rate is paralleled by a strong influx of students in the first year. Flemish higher education consists of university colleges, which offer professional bachelors, and universities, which offer academic bachelors and masters. Except for a few study domains that have an entrance test (e.g. medical education), students with a secondary education degree from the general, arts and technical track can start higher education, though the first two tracks are viewed more preparatory for higher education. The relatively low study fee per academic year (890 euro in 2015) supports the strong influx as well.

A number of researchers have explicitly devoted their attention to how students cope during the transition from secondary to higher education. One strand has focused on students' emotional experiences during the transition, describing a huge culture change and shock, accompanied by feelings of dislocation and stress (Christie et al. 2008). It

has also been hypothesized that when students enter a new teaching/learning environment (T/LE), friction (i.e., misfit between students' learning and the demands of the context) could incite students to adjust their way of going about learning (Vermunt and Vermetten 2004). It is to be expected, therefore, that the educational transition from secondary to higher education has an impact on students' learning strategies.

Paradoxically, research on the impact of the transition from secondary to higher education on students' learning strategies is currently sparse (Hultberg et al. 2008). The present study will investigate whether and how students' learning strategies change during the transition from secondary to higher education. Given that learning strategies have been found predictive of learning outcomes such as dropout and grade point average (Lindblom-Ylänne and Lonka 1999; Vanthournout et al. 2012), this empirical research is relevant to develop well informed student guidance initiatives.

1.1. Change in learning strategies during the transition

One of the educational theories that aims to develop an understanding of student learning is the Students' Approaches to Learning (SAL) tradition. A frequently used questionnaire associated with SAL theories is the Vermunts' Inventory of Learning Styles Questionnaire (ILS). Using this framework, learning strategies are viewed as consisting of processing strategies (i.e., cognitive activities that a student habitually applies whilst studying) and regulation strategies (i.e., metacognitive activities that students usually undertake, such as planning or testing oneself). An overview of the four processing and three regulation strategies of this model is provided in Table 1.

A number of studies have examined changes in learning strategies during higher education (see Vanthournout et al. 2011). However, what is lacking is research on the change in learning strategies during the transition period from secondary to higher

education, which we consider to range from the last year of secondary education up to the start of the second year of higher education.

With regard to the last year of secondary education, no studies were found to use the ILS framework to map changes in learning strategies. With regard to the start of higher education up to the beginning of the second year, six studies use the ILS framework to map changes in learning strategies (Severiens et al. 2001; Busato et al. 1998; Smith et al. 2007; Marambe 2007; Vermunt and Minnaert 2003; Vanthournout 2011). Regarding deep processing (i.e., relating and structuring and critical processing), most studies found an increasing trend (Severiens et al. 2001; Vermunt and Minnaert 2003; Vanthournout et al. 2011). Stepwise processing (i.e., analyzing and learning by heart) was mostly found to decrease over time (Severiens et al. 2001; Smith et al. 2007; Marambe 2007). Concerning the regulation strategies, self-regulation was generally found to increase, and in most studies, external regulation decreased over time (Severiens et al. 2001; Vanthournout et al. 2011; Vermunt and Minnaert 2003). Lastly, results for the lack of regulation scale were mixed: lack of regulation was found to remain constant (Severiens et al. 2001) or to decrease over time (Vanthournout et al. 2011; Vermunt and Minnaert 2003). In sum, up to the start of the second year of higher education, the change in learning strategies tends to be a move in the direction of self-regulated and deep learning, to the detriment of surface and externally and unregulated learning.

1.2. Differential growth in learning during the transition

We turn our attention now to individual variations in student growth: can students be assumed to follow a comparable growth trajectory over time or not? Of the six studies described above, only one study has examined this differential growth (Vanthournout et al. 2011). For this reason, we broadened our scope to studies outside the transition period, resulting in one extra study (Coertjens et al. 2013) and to other SAL frameworks (SPQ; Phan 2011), which provided a third study.

Using a latent growth model, Phan (2011) concluded upon a comparable differential growth in deep processing: students scoring lower on deep processing at the start of their undergraduate program were found to increase their reliance more rapidly. Vanthournout (2011) detected differential growth for the critical processing, self-regulation, analysing and external regulation scales. For the last two scales, this growth over time was related to student's initial score. Students scoring higher on analysing at the start of higher education tended to decrease their reliance upon it, while those initially scoring lower tended to increase their reliance upon it. For the external regulation scale, the findings suggested that students with a strong preference for external regulation at the start of higher education decreased their reliance on external sources of regulation at a greater rate. Contrary to these findings, Coertjens et al. (2013) did not detect differential growth for any scale during the three years of higher education.

1.3. Research questions

The present research aims to map students' average and differential growth in learning strategies during the transition from secondary to higher education. As mentioned, research describing how students' learning strategies alter when making the change in T/LE is lacking. As such, the first research question is: How do learning strategies change on the short term when students make the transition in learning environment from secondary to higher education?

Taking the entire transition period into account (ranging from the last year of secondary education up to the start of the second year of higher education), we can formulate the following, second research question: How do learning strategies change during the transition period?

Here we can hypothesize that the trends as described in studies on the start of higher education hold.

On average, students' learning strategies change during the transition from secondary to higher education in the direction of

- deep learning (hypothesis 1)
- self-regulated learning (hypothesis 2)

Evidence suggests that for a limited number of scales, students evolve differently over time. Yet, these findings pertain to a limited set of studies, in which the change in T/LE was not taken into account. Thus, the following, third research question is formulated: Is there differential growth in learning strategies during the transition to higher education?

2. Methods

2.1. Design and respondents

The data stems from a project on students' transition from secondary to higher education in Flanders (a Dutch speaking region in Belgium). All students in their final year of secondary education from thirty-six secondary schools offering a mixture of tracks (general, arts, technical and vocational) took part in the research project (N=3,704), which consisted of five waves as shown in Figure 1. During their last year of secondary education, students were questioned twice during school hours (wave 1: N=3,365; 91%, wave 2: N=2,839; 76,6%). At the second wave, students were also asked to fill out a consent form, and 84% complied. During an 18-month period after graduation, students were invited to participate three times (wave 3: N=1,101; 29.7%, wave 4: N=1,705; 46%, wave 5: N=1,029; 27.8%). At each of these waves, the participants received an email invitation to participate in the online questionnaire. As after two reminders via email the response rate was still low, the researchers called the respondents to ask them to complete the questionnaire up to three times.

In total 630 students declared themselves to be studying in higher education at waves three to five. For the analysing, 187 of the 630 students provided complete data, while for the memorizing and lack of regulation scales, 186 did. For the scales self-regulation, critical processing and lack of regulation this was respectively 185, 184 and 180. To give more detail on the amount of missing data, for the memorizing scale, 178 (28.3%) had one missing data point, 174 (27.6%), 84 (13.3%) and 8 (1.3%) had respectively two, three and four missing data points. Regarding which data points were more prone to missingness, data for the memorizing scale suggest that 95.6% provided complete data (i.e., a response at all four memorizing items) at wave one, which descended to 87.8% and 53.8% for respectively wave 2 and 3. The last two waves, respectively 63.5% and 70.8% of the respondents provided complete data for the memorizing scale. Given that only 4.13% of students had item non-response (4.13%), the percentages for the other scales are in line with those of the memorizing scale.

When modelling growth on datasets with missingness, methodological research suggests not using listwise deletion. Especially when data are not missing completely at random (MCAR), as suggested by independent samples *t*-tests on the data, including respondents with incomplete data by relying on a maximum likelihood estimation, for example, has been found to provide better results in terms of unbiased estimates and statistical power (Wothke 2000). For this reason, the analyses were done on a sample of 630 students.

2.2. *Measure*

Students' learning strategies are investigated using the ILS-SV, which has been validated for use on first-year Flemish University College students (Donche and Van Petegem 2008). For all seven scales, the items are scored ranging from (1) 'I never or hardly ever do this,' to (5) 'I (almost) always do this'. For each scale, Table 1 provides the number of items, an example item and the range of scale reliability.

Given that the learning strategy scales each have a small number of items, which strongly affects the Cronbach's alpha (Cortina 1993), a .60 cut-off is considered satisfactory. All scales show adequate reliability at each wave, except for the external regulation scale. Given that its reliability was below .60 at both the second and third wave, we refrain from modelling the evolution in external regulation.

2.3. Data analyses

In order not to confound true growth over time with change in the perception of the learning strategy questionnaire, longitudinal measurement invariance was tested for (Wu et al. 2010). For the memorizing, relating and structuring and lack of regulation scales, one intercept failed to reveal equivalence over measurement moments. For the self-regulation scale, the constraints on two intercepts had to be freed. These small inequivalences were taken into account when modelling growth.

As suggested by Wang and Wang (2012) and Muthén and Muthén (2010), six latent growth models were estimated to adequately describe the growth trajectory for each scale. First, a *linear* growth trajectory was estimated¹. Examples of such increasing, decreasing or constant linear trends are given in Figure 2(a). Second, a *quadratic* growth trend is modelled. Next to the intercept and slope, a quadratic parameter is estimated, suggesting one bending point in the growth of a learning strategy over time (for examples of quadratic growth, see Figure 2(b)).

Third, a *cubic* growth trend is assessed for how well it captures the growth in a learning strategy scale. With such a model, it is assumed that the growth in a learning strategy scale follows a trajectory with two bending points. For example, reliance on a learning strategy could initially decrease, then increase and by the end, decrease again (see Figure 2(c)).

¹ Due to data gathering at unequal time intervals (see Figure 1, respectively 6, 7, 5 and 7 months between the waves), the values of the factor loadings for the slope are adjusted to 0, 0.5, 1.08, 1.5 and 2.08 respectively (Byrne 2010; Muthén and Muthén 2010).

Fourth, a *piecewise growth model* is run. As shown in Figure 2(d), it approximates the nonlinear growth “through the use of two or more linear piecewise splines” (Bollen and Curran 2006). This is particularly useful for making comparisons in growth rates based on different developmental periods (Kim and Kim 2012). In our study, two slopes are estimated (two-piece growth model), one for the two waves of secondary education and a second for the three waves of higher education.

Fifth, a *discontinuous piecewise growth model* estimates two different growth trajectories (Muthén and Muthén 2010). As depicted in Figure 2(e), a separate intercept and slope are estimated for both secondary and higher education. As with the piecewise growth model, the slopes can be compared between the two educational periods. Next, it is possible to assess whether the leap due to the transition (i.e., the difference between the last score in secondary education and the first score in higher education) is significant (Kim and Kim 2012).

The prior five models all assume that there is a certain predetermined trend that best captures growth in a learning strategy scale. When a predetermined trend is inadequate in capturing the change, the growth model with *free time scores* will likely provide more information, by explicitly modeling the capricious trend in the latent scale scores. This is done by freely estimating a number of time scores (Wu et al. 2010; Bollen and Curran 2006). As shown in Figure 2(f), conceptually, this growth model discerns the time intervals in which the change in a learning strategy accelerates or decelerates (Muthén and Muthén 2010; Wu et al. 2010; Wang and Wang 2012). Next, it also allows the total change in a learning strategy to be partitioned over the time intervals. As such, the results suggest which time intervals are most important with regards to the total change over time.

The six models for each learning strategy scale were estimated using Mplus 6.1, using maximum likelihood estimation procedure. The model showing the lowest AIC and

BIC was judged to best represent the observed trend (Grimm and Ram 2009). Given that each learning strategy scale was modelled separately, it is important to verify the factor structure for the specific sample. Confirmatory factor analysis for the sample at the first wave (N=606) reveals that, when two error covariances are allowed for within the factor analysing and one within the factor self-regulation, the model fit is adequate to good (RMSEA=.046; SRMR=.057; CFI=.90; Byrne 2010; Bollen 1989). The factor structure was verified anew at the start of higher education (N=342). Anew, fit indices point to adequate to good model fit (RMSEA=.048; SRMR=.059; CFI=.90). These results suggest that the ILS items are specific for each scale.

3. Results

The fit of the latent growth models is described in Table 2 for each learning strategy scale. This table displays the final accepted model for each scale, each of which provided good fit (CFI>.95; NNFI/TLI>.95; RMSEA≤.05; Byrne 2010). Tables 3, 4 and 5 present the parameter estimates for the discontinuous piecewise growth model, the models with free time scores and the model with a cubic growth trend, respectively. Figure 3 visualises, for each scale, the growth trend as predicted by the latent growth model (white line). Next to this, to illustrate the variation in this growth trend, for a random subset of 150 students, the estimated growth over time is plotted as well.

3.1. Processing strategies

The change in memorizing scale is best captured by a discontinuous piecewise growth trend (Table 2). Prior to the transition from secondary to higher education, the average rate of change in the slope was -.313 ($se=.060$, $p<.001$), meaning that, on average, memorizing decreased .313 points over a 12 month period (Table 3). During the

transition period, there was a significant leap in memorizing². After the transition, the rate of change in the slope was $-.104$ ($se=.032$, $p<.001$), implying another, albeit less outspoken than during secondary education, decrease in memorizing (see Figure 3).

Regarding differential growth, the slope variance during higher education results non-significant ($est=.063$, $se=.077$, $p>.05$). This suggests that the general decreasing trend in memorizing during higher education can be assumed to hold for all students. We also note a positive association between the intercepts at secondary and at higher education ($est=.267$, $se=.030$, $p<.001$). This implies that students scoring higher on memorizing at the start of their last year of secondary education also score higher at the start of higher education. The covariances between the intercepts for secondary education and higher education on the one hand and the slope during higher education on the other hand were not significant (respectively, $est=-.034$, $se=.022$, $p>.05$ and $est=.029$, $se=.036$, $p>.05$), indicating that students' growth during higher education is not systematically related to their scores at the wave 1 (start of the last year of secondary education) or wave 3 (start of higher education). This implies that the variation between students in terms of their degree of memorizing remains constant over time.

For the analysing scale, a growth model with free time scores best fitted the data (see Table 2). The results indicate an increasing trend in the analysing scale ($est=.088$, $se=.014$, $p<.001$, see Table 4 and Figure 3). Looking at when this growth occurs, results show a constant trend in analysing secondary education (from wave 1 to 2; λ_1 , $est=-.216$, $se=.277$, $p>.05$). To discern whether there is a significant change during the transition period, the difference between λ_2 and λ_1 is divided by the standard deviation in λ_2 . If the result exceeds 1.96, the lambda is significantly different from the previous (Muthén and Muthén 2010), indicating a significant change during the time form wave

² Whether this leap is significant or not, was tested by re-arranging the factor loadings of the slope in SE in a manner that the intercept was at the end of SE (second wave). In this way, the model compared the intercept in HE (3rd wave) to the value at the second wave. This resulted significant ($est=.146$, $se=.031$, $p<.001$).

2 to 3. Here, the degree of analysing is found to increase during the transition $((2.033-0)/0.256)>1.96$). Afterwards, between December and May of the first year of higher education (from wave 3 to 4), and from May of the first year of higher education to December of the second year (from wave 4 to 5), the degree of analysing anew remains constant. Thus, the results suggest that there is an increase in the degree of analysing, but that this increase occurs during the transition from secondary to higher education.

Regarding the differential growth over time in the analysing scale, results indicate a significant slope variance ($est=.024$, $se=.006$, $p<.001$). This implies that students vary in their growth in analysing over time. Next, the covariance between the intercept and slope is significant and negative ($est=-.024$, $se=.009$, $p<.01$), suggesting that students' scoring higher on analysing at wave 1 increase their reliance on this processing strategy, but to a lesser degree. The same applies in the other direction: students' scoring lower at wave 1 show a greater increase in their degree of analysing. Thus, students' scores on the analysing scale become more comparable over time.

For the critical processing scale, a constant trend is found during the students' last year of secondary education (from wave 1 to 2; λ_1 , $est=.060$, $se=.131$, $p>.05$, see Table 4). During the transition, there is a significant increase in critical processing $((1.609-0)/0.122>1.96)$. The remainder of the first year of higher education, critical processing remains constant again. From the end of their first year of higher education to December of their second year of higher education critical processing increases anew, though, as Figure 3 shows, less strong than during the transition. In sum, the growth in critical processing occurs during the transition phase and from the end of the first year of higher education to December of the second year of higher education.

Examining the parameter estimates on differential growth reveals that students vary in their growth over time ($est=.038$, $se=.009$, $p<.001$). Moreover, there is a negative

covariance between the intercept and slope ($est=-.050$, $se=.014$, $p<.001$), implying that, students' scores on critical processing become more alike over time.

Regarding the relating and structuring scale, results indicated the best fit for a latent growth model with free time scores (see Table 2). Overall, there is an increase in relating and structuring over time ($est=.284$, $se=.020$, $p<.001$, see Table 4). Looking into detail on when this growth occurs, it is noted that during the last year of secondary education, relating and structuring increases ($est=.393$, $se=.100$, $p<.001$). During the transition period relating and structuring augments as well ($(1.767-0.393)/0.088>1.96$). As shown in Figure 3 this increase is at a faster rate than during the last year of secondary education. During the remainder of the first year of higher education, the degree in relating and structuring remains constant. From the end of the students' first year of higher education to December of their second year, there is anew a slight increase in relating and structuring.

Regarding differential growth, the change in relating and structuring over time was found to differ between students ($est=.061$, $se=.011$, $p<.001$). The covariance resulted significant as well ($est=-.070$, $se=.017$, $p<.001$), indicating that students scoring higher on relating and structuring at the first wave (November of the last year of secondary education) tended to increase their relating and structuring to a lesser degree and vice versa.

3.2. Regulation strategies

For the self-regulation scale, a growth model with free time scores was most suitable (see Table 2). The parameter estimates indicate that on average over a period of 12 months self-regulation increases by .302 ($se=.020$, $p<.001$, see Table 4). Examining when this growth occurs, reveals that during secondary education, self-regulation remains constant ($est=.085$, $se=.096$, $p>.05$). As shown in Figure 3, during the transition from secondary education to higher education, there is a significant jump in self-regulation ($(1.619-0)/0.114>1.96$). During the remainder of students' first year of

higher education, self-regulation remained constant, to subsequently increase anew from the end of the students' first year of higher education to the start of their second year of higher education, though less strongly then during the transition.

Concerning differential growth in self-regulation, students were found to differ in their growth over time ($est=.051$, $se=.011$, $p<.001$, see Table 4). The insignificant covariance ($est=-.007$, $se=.014$, $p>.05$) indicates that this growth is unrelated to the students' score on self-regulation in November of their last year of secondary education.

Last, for the lack of regulation scale, a cubic growth trend represented the data best (see Table 2). The results of this model indicate a negative linear slope ($est=-.384$, $se=.121$, $p<.01$, see Table 5), a positive quadratic parameter ($est=1.034$, $se=.153$, $p<.001$) and a negative cubic growth parameter ($est=-.379$, $se=.049$, $p<.001$). Figure 3 shows that during the last year of secondary education, students' lack of regulation remains constant. During the transition period up to the start of the second year of higher education, the degree of lack of regulation increases. Subsequently, up to December of the second year of higher education, students' lack of regulation decreases.

Regarding differential growth in the lack of regulation scale, results indicate that students vary in their linear and quadratic growth (respectively $est=.406$, $se=.175$, $p<.05$ and $est=.061$, $se=.028$, $p<.05$, see Table 5). The variance of the cubic growth trend was insignificant and had to be constrained to zero to improve the model fit. Results also show that students scoring higher on the lack of regulation scale at the start of the last year of secondary education show a stronger decrease during the last year in secondary education ($est=-.243$, $se=.096$, $p<.05$). Thus, as shown in Figure 3, over the last year of secondary education, the differences between students in terms of lack of regulation diminished.

The covariance between the intercept and the quadratic growth parameter was not significant ($est=-.060$, $se=.036$, $p>.05$, see Table 5), while the covariance between the linear slope and the quadratic growth parameter was at the verge of significance ($est=-.131$, $se=.067$, $p=.053$). Interpreting this as significant, this suggests that students showing a less steep decreasing linear slope tended to score lower on the quadratic growth parameter. In other words, students who decreased less in their lack of regulation during their last year of secondary education tended to show a more modest increase in their lack of regulation during the transition and their first year of higher education. The same applies in reverse: students who initially decreased stronger on the scale later showed a stronger increase. Therefore, and in contrast to the last year of secondary education, during the transition and their first year of higher education, students' scores on lack of regulation become less comparable over time.

3.3. *Comparing the strength in growth*

To allow for comparison of the strength in growth across scales, standardised slopes were retrieved. This was, however, not possible for the memorizing and the lack of regulation scales, given that for both scales, one variance parameter had to be constrained to zero (see note 2 with Table 3 and section 3.2 respectively).

For the scales that were best estimated using a growth model with free time scores, the standardised slopes could be calculated and are provided in Table 4. Results indicate that the increase in self-regulation is the most noteworthy ($std. est=1.343$, $se=.156$, $p<.001$), followed by the increase relating and structuring ($std. est=1.150$, $se=.111$, $p<.001$) and in critical processing ($std. est=1.130$, $se=.139$, $p<.001$). Though significant as well, the increase in analysing was only about half of the size of those of the other scales ($std. est=0.569$, $se=.085$, $p<.001$).

4. Discussion

Research on the experience of the transition period from secondary to higher education highlights the importance of the change in T/LE (Christie et al. 2008; Cree et al. 2009), which may affect students' learning strategies. The present research is innovative in the way that it investigates the average and differential growth in learning strategies during the transition from secondary to higher education.

4.1. Average short term growth during the transition

Results of the present study show that when students make the transition in learning environment from secondary to higher education, for all seven scales, there is a strong increase, labelled 'transition jump'. This contradicts the view that a new educational context makes students rely more strongly on their usual way of going about learning (Cliff 2000; Segers et al. 2006) and confirms that a new educational context induces a period of friction, which stimulates students to adjust their learning strategies (Vermunt and Vermetten 2004). Possibly, the first year in higher education demands more deep and self-regulated learning in addition to greater reliance on analysing and learning some content by heart. However, if the first year in higher education requires students to rely more on memorizing than in secondary education, we would expect the high level of memorizing to be maintained throughout the first year. This is not the case. In addition, the friction hypothesis does not appear sufficient to explain the transition jump in the lack of regulation scale.

An alternative explanation may be anxiety, which has previously been found to be associated with student learning (Tooth et al. 1989). Possibly, uncertainty and stress about the learning required in the new educational context, as described in qualitative research (Cree et al. 2009), may leave students experiencing a greater lack of regulation in their learning. The uncertainty may also have motivated students to maximize their chances by augmenting their use of both deep and stepwise processing activities.

4.2. Average growth during the transition period

Regarding the growth in learning strategies during the entire transition period (spanning from the onset of the students' last year of secondary education up to halfway through their second year in higher education), the increase in critical processing and relating and structuring confirms hypothesis 1 of an evolution in the direction of deep learning. This is in line with research by Severiens et al. (2001) and Vermunt and Minnaert (2003). For both scales however, this change only takes place from the end of the first year in HE onwards (see Figure 3). Put differently, during the first year, students' degree of critical processing and relating and structuring on average remains constant. Given that the latter scale has been found predictive of study success (Vanthournout et al. 2012), a continuous increase would have been more desirable.

With regard to the memorizing scale, students displayed a sharp increase in their degree of memorizing during the transition. Yet, due to the decreasing trends during both secondary and higher education, there was an overall decrease from the first to the last wave (see Figure 3), confirming the findings by Vanthournout (2011). At the start of their second year of higher education, students, on average, relied less on memorizing than at the start of their last year of secondary education, which is in line with hypothesis 1. The increase in self-regulation during the 25 months of the study is in line with hypothesis 2 and prior findings by Severiens et al. (2001), Vanthournout (2011) and Vermunt and Minnaert (2003).

The results for the analysing and lack of regulation scales, however, contradict both hypotheses. In contrast to prior research findings (Marambe 2007; Severiens et al. 2001; Smith et al. 2007; Vanthournout et al. 2011), analysing was found to increase during the transition. However, this increase is only about half of the size of those noted for the deep processing and self-regulation. Students' lack of regulation

increased during the transition from secondary to higher education as well as during their first year of higher education. Although it later decreased, students' lack of regulation at the last wave was higher than at the first wave, which is in line with findings by Marambe (2007).

In sum, though the results for the analysing and lack of regulation scales are contrary to expectations, the results for four scales (critical processing, relating and structuring, memorizing and self-regulation) are in line with hypotheses 1 and 2. As such, results partially confirm the change in students' learning strategies in the direction of deep and self-regulated learning.

To foster understanding of the observed patterns, it would be worthwhile to include predictors of growth. Literature exploring the fit in the T/LE between secondary and higher education appears of specific value here. It suggests that students benefit from learning environments not too dissimilar from those that they are already acquainted with in secondary education. If the resemblance in T/LE is high, students need less time to adjust (Torenbeek et al. 2010). Future research should focus on whether the degree of similarity of the T/LE to secondary education is related to growth in their learning strategies over time.

4.3. Results on differential growth

Results for the differential growth during the transition period suggest that, except for the self-regulation scale, the change over time is related to the score on the intercept. For the analysing, critical processing and relating and structuring scales, students' scores became more comparable over time. This implies that during the transition from secondary to higher education, students scoring lower on these scales increase at a faster pace (and vice versa). Put differently, for the deep processing scales, students with poorer initial learning skills in terms of lifelong learning, catch up on their peers.

The fact that some scales show differential growth is in line with prior research findings by Phan (2011) and Vanthournout (2011). As such the present research base seem to indicate that there is differential growth for some scales: critical processing and analysing showed a differential growth pattern both in the present study and the one by Vanthournout (2011). However, only for the analysing scale, both studies agree on a growth trend towards more comparable scores over time.

The fact that there is decreasing variability in students' critical processing, relating and structuring and analysing is remarkable given that students were studying in relatively homogeneous settings in secondary education and subsequently spread out over different study domains in higher education. If these domains affect students' learning strategies (e.g., Vermunt 2005), more variation between students rather than less is expected. Possibly, by choosing the study domain of their interest, students that initially score lower have greater interest in the content of their learning when compared to their secondary education. This can have motivated them towards deeper processing and a higher degree of analysing.

Students' scores for the lack of regulation scale also became more similar during the last year of secondary education. However, during the transition and during their first year of higher education, differences between students in terms of their lack of regulation increased again. Given that lack of regulation has previously been found to be related to drop-out as well as study success (Vanthournout et al. 2012), this finding gives reason for concern. Students, who made good progress decreasing their lack of regulation during the last year of secondary education, contradict this progress during their transition to higher education.

There may possibly be a subgroup of students for whom learning strategies were less crystallized at the end of secondary education, making them more vulnerable to stress and uncertainty due to the change in T/LE when transitioning to higher education. Future research should set out to explore whether there are latent classes in growth

over time using growth mixture modelling (Duncan et al. 2006; Jung and Wickrama 2008). If found, class membership can then be used as a predictor for drop-out and academic achievement. This can help to answer the question of which change trajectories lead to a higher probability of drop-out and which growth trends are associated with higher academic achievement.

4.4. Limitations and future research

A limitation of the present study concerns the attrition issue common to longitudinal studies, especially when long time intervals are involved. Some students were unreachable during the three waves after secondary education and thus were not included in the study. This attrition issue and the fact that the present study is the first to examine the change in learning strategies during the transition period from secondary to higher education, underlines the need for replication research to confirm the findings.

A second limitation concerns the absence of effect size for latent growth models (Richardson 2013). For the growth models with free time scores, standardised slopes were provided to allow for comparison of the strength of the change across scales. However, the meaningfulness of this change is open for debate. Given the importance for applied research and practice, methodological research on measures of effect size for latent growth models is called for.

4.5. Implications for practice

The detected transition jump has important implications for student guidance. The period of encounter with the new educational context of higher education appears ideal for remedial action. Firstly, increased malleability in learning strategies can be used to direct students towards more effective learning strategies. Secondly, students were found to increase learning strategies detrimental to lifelong learning skills as well. The reliance on memorizing and reports on lack of regulation also increase during this

stage. This should not be viewed as a temporary upsurge: on average, at the start of the second year of higher education, the degree of memorizing and lack of regulation is still higher compared to at the end of secondary education. As such, the results of the present study suggest to schedule study skills guidance at the onset of the first year of higher education.

A second implication for practice regards the content of learning strategies guidance. The present study measured growth in students' learning strategies, but it remains unclear whether students themselves were aware of those changes. In addition, it remains unclear whether students are conscious of desirable learning strategies and their association with drop-out and academic achievement (e.g., Mäkinen et al. 2004). An important step in guiding students towards adopting more beneficial learning strategies thus appears to be in raising their awareness by presenting them with results obtained from repeated measurement of their learning strategies over time and contrasting these to results from research on student drop-out and study success.

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Figure 1: The five measurement waves over time
 (SE=Secondary Education, HE=Higher Education)

Figure 2: E
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(A), quadratic (B), cubic (C), piecewise (D), discontinuous piecewise growth model with free time scores (F)

Figure 3: Average and individual estimated growth trajectories per learning strategy scale

Table 1: Learning strategy scales of the ILS-SV questionnaire, number of items, item examples (translated from Dutch) and range of scale reliability

Scales	Items	Item example	Cronbach's Alpha
Processing strategies			
Stepwise processing			
Memorizing	4	I learn definitions by heart and as literally as possible.	.64-.74
Analysing	4	I study each course book chapter point by point and look into each piece separately.	.62-.69
Deep processing			
Critical processing	4	I try to understand the interpretations of experts in a critical way.	.69-.76
Relating and structuring	4	I compare conclusions from different teaching modules with each other.	.68-.72
Regulation strategies			
Self-regulation	4	I use other sources to complement study materials.	.61-.69
External regulation	6	I study according to the instructions given in the course material.	.56-.61
Lack of regulation	4	I confirm that I find it difficult to establish whether or not I have sufficiently mastered the course material.	.69-.75

Table 2: Fit indices for the best fitting latent growth model per learning strategy

	Accepted model	χ^2	df	p	CFI	NNFI/TLI	RMSEA (90% conf. interval)
Memorizing	Discontinuous piecewise growth model	234.815	148	***	.973	.966	.031 (.023-.038)
Analysing	Growth model with free time scores	244.005	151	***	.965	.956	.031 (.024-.038)
Critical processing	Growth model with free time scores	194.020	151	*	.986	.983	.021 (.011-.030)
Relating and structuring	Growth model with free time scores	190.965	150	*	.984	.980	.021 (.010-.029)
Self-regulation	Growth model with free time scores	167.097	149	.148	.994	.992	.014 (.000-.024)
Lack of regulation	Cubic growth trend	296.002	149	***	.954	.941	.040 (.033-.046)

*** $p < .001$; * $p < .05$

Table 3: Parameter estimates for the discontinuous piecewise growth model

	Slope SE	Intercept HE	Slope HE	Var Intercept SE	Var Intercept HE	Var slope HE	Cov Intercepts SE & HE	Cov Intercept SE & slope HE	Cov Intercept HE & slope HE
Memorizing	-0.313 (.060)***	-0.010 (.031)***	-0.104 (.032)***	0.278 (.032)***	0.281 (.043)***	0.063 (.077)	0.267 (.030)***	-0.034 (.022)	0.028 (.036)

SE=Secondary Education, HE=Higher Education; *** $p < .001$; ** $p < .01$; Note1: In a latent growth model with underlying measurement model (to test for measurement invariance over time), the intercept during SE is zero. Therefore, it is not provided. Note2: the slope variance during SE is constrained to zero, given there were two measurement moments during SE.

Table 4: Parameter estimates for the growth models with free time scores *** $p < .001$; ** $p < .01$; * $p < .05$; ° Mplus provides a significance test for

	λ_1°	λ_2°	λ_3°	λ_4°	Slope	Std. Slope	Var Intercept	Var slope	Cov
Analysing	-0.216 (.277)	2.033 (.256)*	1.869 (.238)	2.08 (.000)	0.088 (.014)***	0.569 (.085)***	0.190 (.027)***	0.024 (.006)***	-0.024 (.009)**
Critical processing	0.060 (.131)	1.609 (.122)*	1.491 (.121)	2.08 (.000)*	0.221 (.018)***	1.130 (.139)***	0.371 (.040)***	0.038 (.009)***	-0.050 (.014)***
Relating and structuring	0.393 (.100)***	1.767 (.088)*	1.816 (.088)	2.08 (.000)*	0.284 (.020)***	1.150 (.111)***	0.329 (.040)***	0.061 (.011)***	-0.070 (.017)***
Self- regulation	0.085 (.097)	1.619 (.114)*	1.705 (.107)	2.08 (.000)*	0.302 (.020)***	1.343 (.156)***	0.274 (.032)***	0.051 (.011)***	-0.007 (.014)

the λ 's, indicating whether the λ is significantly different from zero. This is relevant for λ_1 , given that the factor loading for wave 1 is zero. For the other λ 's, it is of more interest whether the score differs from the previous λ , suggesting whether there is an increase or decrease in the scale. This is calculated by the difference in λ /the standard deviation. If the result exceeds 1.96, the lambda is significantly different from the previous (Muthén and Muthén 2010). In table 5 we provide this significance, instead of the results provided in the Mplus output; Note: In a latent growth model with underlying measurement model (to test for measurement invariance over time), the intercept is zero. Therefore, it is not provided.

Table 5: Parameter estimates for the cubic growth model

	Linear	Quadratic	Cubic	Var Intercept	Var Linear	Var Quadratic
Lack of regulation	-0.384 (.121)**	1.034 (.153)***	-0.379 (.049)***	0.453 (.065)***	0.406 (.175)*	0.061 (.028)*

*** $p < .001$; ** $p < .01$; * $p < .05$; Note: In a latent growth model with underlying measurement model (to test for measurement invariance over time), the intercept is zero. Therefore, it is not provided.