Frontline Learning Research
An official journal of EARLI

Frontline Learning Research Special Issue Vol.9 No.2 (2021) 28 - 49
ISSN 2295-3159

# Predicting freshmen's academic adjustment and subsequent achievement: differences between academic and professional higher education contexts

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*Article received 18 March 2020 / Article revised 28 August / Accepted 4 December / Available online 12 March 2021*

## Abstract

*This study tests an integrative model, which delineates how students' academic motivation, academic self-efficacy and learning strategies (processing strategies and regulation strategies) at the end of secondary education impact academic adjustment in the first semester of the first year of higher education (FYHE) and subsequent academic achievement at the end of the FYHE, in two types of HE programmes. More precisely, the present study explores the extent to which the explanatory values of aforementioned determinants of academic adjustment and academic achievement differ across academic (providing more theoretical and scientific education) and professional (offering more vocational education that prepares students for a particular occupation, such as nursing) programmes. Hereto, multiple-group SEM analyses were carried out on a longitudinal dataset containing 1987 respondents (Academic programmes: N=1080, 54.4%; Professional programmes: N=907, 45.6%), using Mplus 8.3. Results indicate differences in the predictive power of determinants under scrutiny between professional and academic contexts. Firstly, learning strategies and motivational variables at the end of secondary education have more predictive power in the prediction of FYHE academic adjustment in the academic programmes than in professional programmes. Secondly, our results indicate that academic adjustment in the first semester of the FYHE influences academic achievement to a bigger extent in professional programmes than in academic programmes. Moreover, these differences across HE contexts were found after controlling for prior education. Implications of the findings are discussed.*

*Keywords*: Learning strategies; motivation; academic adjustment; first-year academic achievement; programme diversity

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## 1. Introduction

Over the years, democratisation of higher education (HE) around the world has led to a substantial increase and diversification of the student population enrolling in HE (Schuetze & Slowey, 2002). This seems to be accompanied by low study success rates, early drop-out and study delay of students in the first year of higher education (FYHE). For example, in Flanders (Dutch speaking part of Belgium), only 48.6% of freshmen successfully complete their required coursework in the FYHE (Declercq & Verboven, 2014). This has extensive psychological and financial costs for the individual student, the family and society (OECD, 2013). As such, more insight into factors that facilitate freshmen's transition process to HE can give rise to an increase in the academic achievement of these students (Briggs, Clark, & Hall, 2012).

In recent decades, several lines of research have argued that non-cognitive factors such as learning strategies and motivational and adjustment variables are important determinants of students' academic achievement in the FYHE (e.g. Bailey & Phillips, 2016; Credé & Kuncel, 2008; Richardson, Abraham, & Bond, 2012; Robbins et al., 2004). This body of research, however, has been mostly carried out in academically oriented HE programmes (offering more theoretical and scientific education), leaving professionally oriented HE contexts (offering more vocationally oriented education that prepares students for a specific occupation) rather underexplored (for an exception, see Vanthournout, Gijbels, Coertjens, Donche, & Van Petegem, 2012). This paucity of research in professional HE contexts is certainly remarkable, given that a significant part of adolescents worldwide enrols in professional HE programmes (OECD, 2009), for example, in Flanders, 54.4% of the HE student population participate in professional HE (Flemish Government, 2019). Moreover, previous research points out that institutional and disciplinary differences might influence the interrelationships between variables in a predictive model of academic achievement (e.g. De Clercq et al., 2013). Simply assuming that the aforementioned determinants of academic achievement have the same predictive value in professional and academic FYHE contexts, thus, seems to neglect this important source of meso-level diversity.

Therefore, this study sets out to investigate to what extent the predictive power of learning strategies (processing strategies and regulation strategies), motivational variables and academic adjustment in predicting FYHE students' academic achievement differs across academic and professional HE contexts, using an integrative, longitudinal research design. In what follows, we firstly describe how HE in Flanders is organised, after which we briefly describe the main constructs and expected relationships under study – albeit as we will point out - have been investigated in predominantly academic HE contexts, with little attention to academic adjustment as an intervening variable for academic achievement in the FYHE.

## 2. Research context: Flemish HE system

As in many other European HE systems (such as Germany, the Netherlands, Finland, Denmark and Portugal), Flemish HE is provided by two types of institutions: universities and university colleges. Universities offer academically oriented HE programmes, which provide mainly theoretical and scientific education. They typically prepare students for a succeeding master programme and correspond to the Bologna two-cycle programmes (bachelor and master, encompassing a total of 4 or 5 years; The Bologna Declaration, 1999). University colleges, on the other hand, are specialised institutions that organise so called 'professional bachelor programmes', which are mainly designed for learners to acquire the knowledge, skills and competencies specific to a particular occupation, such as nursing or social work (Camilleri, Delplace, Frankowicz, Hudak, & Tannhäuser, 2014). These vocational programmes offer a direct access to the labour market and are in line with the Bologna first cycle programmes (one cycle of 3 years).

Academic and professional bachelor programmes have different aims and expectations of students, and typically differ from each other with regard to their curricular organisation. In professional programmes, theory and practice are combined through the use of student-centred learning methodologies such as: simulations, working with real-life materials and workplace learning settings (e.g. long-term internships, machinery to repair, assignments for translators, see also Camilleri et al. 2014). In academic programmes, then, subject matter is more abstract and often less practical. Also, the teaching speed is higher, research activities and large-scale lectures are more common, and more independent learning and scientific research attitudes are expected from students in these academic programmes (van Rooij et al., 2017).

## 3. The pivotal role of academic adjustment in predicting academic achievement

Academic adjustment is generally described as the extent to which a student successfully copes with the various educational demands and characteristics of the new HE environment, and comprises components such as motivation to learn, taking action to meet academic demands, having a clear sense of purpose, management of expectations, and general satisfaction with the academic environment (Baker, McNeil, & Siryk, 1985; Baker & Siryk, 1999; Gerdes & Mallinckrodt, 1994). Today, it is well established from a variety of studies that academic adjustment is imperative in the prediction of students' academic achievement in the FYHE: students who are more academically adjusted drop out less often (Bean, 1980; Kuh, Kinzie, Buckley, Bridge, & Hayek, 2006) and achieve better grades (Bailey & Phillips, 2016; Petersen, Louw, & Dumont, 2009; Prospero & Vohra-Gupta, 2007; Severiens & Wolff, 2008; Wintre et al., 2011). Considering this importance of academic adjustment in the prediction of freshmen's academic achievement, it is not surprising that a considerable number of studies on the first-year transition experience treat this construct as an important outcome in its own right (e.g. Garriott, Love, & Tyler, 2008; Rice, Vergara, & Aldea, 2006).

This latter body of research has unveiled that students' learning strategies and motivational variables, on their turn, have considerable impact on first-year academic adjustment (e.g. Baker, 2004; Cazan, 2012). Moreover, previous research in academic HE contexts has suggested that academic adjustment is a mediator of the effects of several learning strategies and motivational variables on academic achievement (Petersen, Louw, & Dumont, 2009; van Rooij, Jansen, & van de Grift, 2018), which further highlights the pivotal role of the academic adjustment construct in first-year students' transition process. For instance, van Rooij and colleagues (2018) found that *intrinsic (autonomous) motivation* and *self-regulated study behaviour* did not influence academic achievement directly, but through academic adjustment. However, the work of Peterson et al. (2009), who also investigated the mediating role of first-year students' academic adjustment, suggests that this construct is not a "pure" mediator on academic achievement. Indeed, these authors found that the effects of students' *intrinsic motivation* and *identified regulation* (together *autonomous motivation*) and *self-esteem* were mediated by adjustment, while *extrinsic regulation* (*controlled motivation*) and *academic overload* (being unable to cope with the academic workload) had a direct impact on academic achievement.

This rationale leads us to the integrative conceptual model adopted in the present study, which delineates that students' learning strategies (deep processing, surface processing, self-regulation, lack of regulation), academic motivation, and academic self-efficacy have an impact on academic adjustment in the first semester of the FYHE and subsequent academic achievement (Fig. 1). Acknowledging that academic adjustment might not be a pure mediator on academic achievement (Peterson et al., 2009), the model also includes direct paths between the exogenous variables and academic achievement. Furthermore, as it is clear from previous studies that students' prior secondary education tracks might influence academic adjustment and achievement as well (e.g. De Clercq et al., 2013; Vermunt, 2005), in the present study, we have included this factor as a control variable. Finally, for the design of the present study, we adhere to the suggestion of van Rooij et al. (2018) that research on this matter should

be conducted longitudinally and should *"start measuring motivational and behavioural variables in secondary school and investigate how they relate to adjustment and student success outcomes later in university*" (p. 763).

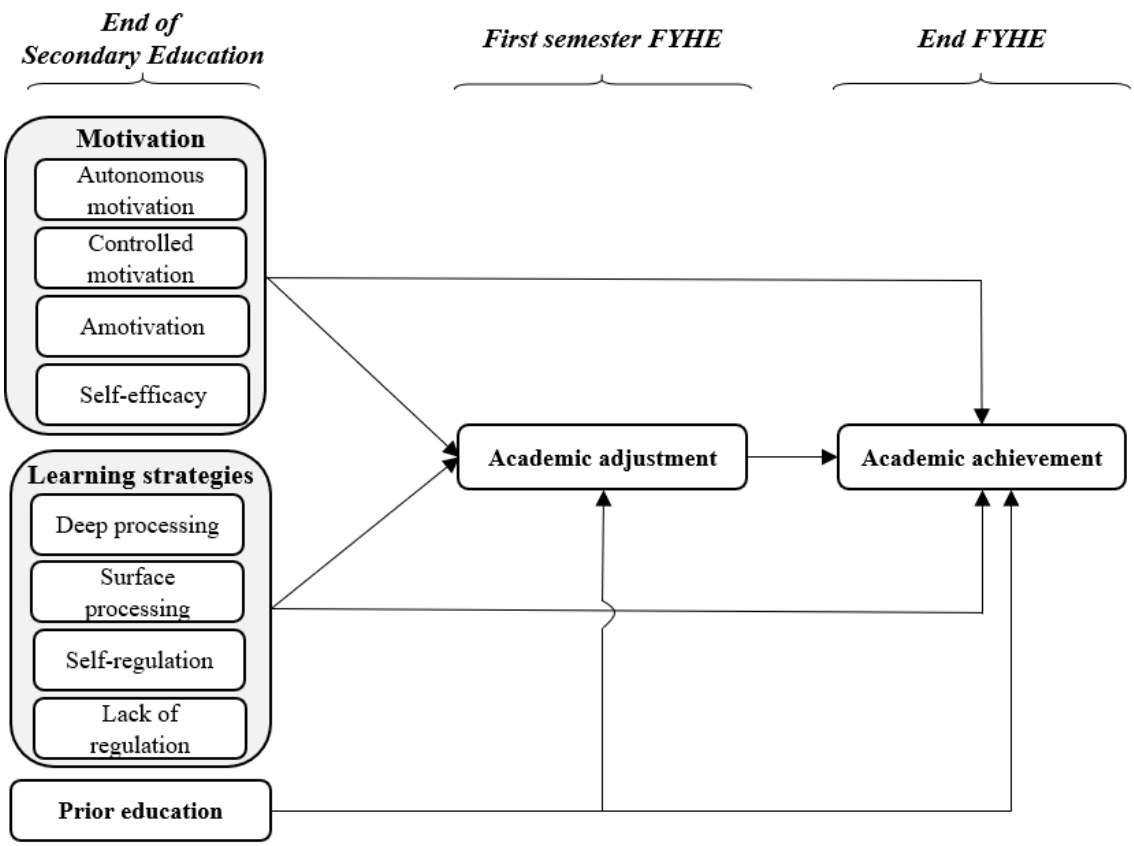


*Figure 1.* Conceptual model of learning strategies and motivational variables affecting academic adjustment and subsequent academic achievement.

From the above, it is clear that one might expect a positive relationship between academic adjustment and academic achievement. The subsequent paragraphs further detail on the hypothesised interrelations between motivational and learning related variables on the one hand, and academic adjustment and achievement on the other hand. The hypothesised directions of the associations in the conceptual model (Fig.1) are summarised in Table 1.

## 4. Motivational and learning related determinants of academic adjustment and academic achievement

### 4.1 Academic motivation

It has previously been observed that FYHE students' *academic motivation* (Deci & Ryan, 2000) is linked to academic adjustment. For instance, Clark, Middleton, Nguyen, & Zwick (2014), Petersen et al. (2009) and van Rooij et al. (2018) reported a positive relation between types of autonomous motivation and academic adjustment. Amotivation, on the other hand, has been found to be associated

with lower academic adjustment (Baker, 2004). Research further shows that students who are more autonomously motivated have higher academic achievement than students who are more controlled motivated or more amotivated (e.g. Bailey & Phillips 2016; Guay, Ratelle, Roy, & Litalien, 2010). Finally, a number of studies revealed a negative association between amotivation and students' academic achievement (e.g. Prospero & Vohra-Gupta, 2007; Vanthournout et al., 2012).

### 4.2 Academic self-efficacy

*Academic self-efficacy* (further shortened to self-efficacy) is defined as individuals' beliefs that they can successfully perform given academic tasks at designated levels (Schunk, 1991). This construct has repeatedly been identified as one of the strongest determinants of academic achievement in the FYHE (e.g. Richardson et al. 2012; Robbins et al. 2004). Furthermore, Cazan (2012) and Chemers, Hu, & Garcia (2001) demonstrated that self-efficacy was strongly and positively related with academic adjustment. Van Rooij et al. (2018), however, did not find a significant relationship between self-efficacy and academic adjustment, after controlling for intrinsic motivation, self-regulation and degree programme satisfaction. Thus, the specific role of self-efficacy, especially after controlling for additional concepts, remains inconclusive.

### 4.3 Learning strategies

In the learning pattern model, developed by Vermunt (1998), learning strategies are described to encompass both cognitive processing strategies and regulation strategies. Firstly, *processing strategies* refer to those thinking activities and study skills students apply whilst studying (Vermunt, 1998). Generally, two qualitatively different types of cognitive processing are discerned in educational literature, namely deep and surface processing (e.g. Vermunt & Donche, 2017; Vermunt & Vermetten, 2004). Deep processing refers to the use of learning activities that lead to meaningful learning and in-depth understanding of the learning content, such as relating and structuring. Surface processing refers to the use of learning activities like memorizing that lead to the learning of superficial features of a study task, also described as root learning (Vermunt & Vermetten, 2004).

Traditionally, it has been argued that the use of deep processing strategies leads to high academic achievement, while surface processing strategies entail lower academic achievement (Vermunt & Donche, 2017). Two important meta-analyses in the field corroborate this idea, as they found those relationships to be significant, albeit small (Dent & Koenka, 2016; Richardson et al., 2012). However, the findings of studies on the direction of the relationship between cognitive processing and academic achievement in studies can also be inconclusive. For instance, it has been argued that surface learning, in some situations, might be advantageous to the learner (see Dinsmore & Alexander (2012) for an elaborate exposition). Further, associations between cognitive processing strategies and academic adjustment have been less investigated. Nevertheless, previous research has demonstrated that students who lack appropriate study skills in HE are at risk of having problems with their academic adjustment (Abbott-Chapman, Hughes, & Wyld, 1992). Therefore, we hypothesise that deep and surface processing strategies will be related to academic adjustment.

Secondly*, regulation strategies* are defined as those activities that students use to harness their cognitive processing strategies (Schunk & Zimmerman, 2012). Students who are more self-regulated are able to actively steer their own learning processes through activities such as planning tasks, monitoring progress, and diagnosing problems. Lack of regulation, on the other hand, refers to an absence of clarity on how to steer the learning process (Vermunt & Donche, 2017).

Several studies have found self-regulation to be positively related to both academic adjustment (Cazan, 2012; Hurtado et al., 2007; van Rooij et al., 2018) and academic achievement (e.g. Dent & Koenka, 2016; Richardson et al., 2012). Although lack of regulation has repeatedly been found to affect academic achievement in a negative fashion (e.g. Donche & Van Petegem, 2010; Vermunt, 2005), to

our knowledge, there has been no investigation of the relationship between lack of regulation and academic adjustment in professional and academic programmes. Considering the 'deficit'-character of the construct, we theoretically expect that lack of regulation is negatively associated to academic adjustment.

Table 1
*Hypothesised directions of the relationships under study*

| | Academic adjustment | Academic achievement |
|---|---|---|
| Motivation | | |
| *Autonomous motivation* | + | + |
| *Controlled motivation* | - | - |
| *Amotivation* | - | - |
| *Self-efficacy* | + | + |
| Learning strategies | | |
| *Deep processing* | + | (+) |
| *Surface processing* | - | (-) |
| *Self-regulation* | + | + |
| *Lack of regulation* | - | - |
| Academic adjustment | | + |

## 5. Exploring programme diversity: a meso-level study

When reviewing the literature on determinants of academic adjustment and academic achievement, it becomes apparent that relatively few studies have tackled these relationships in the specific setting of professional HE. Indeed, the vast majority of studies on the relationships under scrutiny (Fig.1) have been carried out in academically oriented programmes (e.g. Petersen et al., 2009; van Rooij et al., 2018).

Several scholars, however, have established that disciplinary differences influence the learning environments wherein students reside in terms of, for instance; requirements of students, assessment systems, study goals and teaching methods (Becher, 1994; Braxton & Hargens, 1996; Young, 2010). Moreover, previous research has suggested that such variations in environments might influence interrelationships between non-cognitive variables and academic achievement. An example of this *disciplinary diversity* is provided by De Clercq et al. (2013) who investigated whether freshmen's background, study choice process, experience of the university, motivational beliefs, learning strategies, and behavioural engagement had similar predictive power in two university disciplines: science and physical education. The authors found several differences in the effects of those determinants; in physical education courses, for example, self-efficacy was the most powerful predictor of academic achievement, whereas intention to persist was the most powerful determinant in the science discipline. Another study by Lizzio, Wilson, & Simons (2002) showed that relationships between university students' prior achievement, learning strategies and academic achievement varied between faculties of humanities, science, and commerce. This also concurs with the study by Fonteyne, Duyck & De Fruyt (2017), who found that the predictive power of background, cognitive, personality, metacognitive, self-efficacy and motivational factors on academic achievement varied considerably across various academic study disciplines, such as psychology, criminology, history, and pharmaceutical sciences. However, students' academic adjustment, as a possible mediator in further understanding the effects of entry characteristics on academic achievement, was not taken into account in these studies.

Moreover, professionally oriented programmes have distinctive aims and expectations of students and typically adopt different didactical approaches than academically oriented programmes

(Camilleri et al., 2014; see also "Research context: Flemish HE system"). We therefore expect that such *programme diversity* could influence relationships in a predictive model of academic achievement as well. Determinants of academic adjustment and academic achievement might, thus, have a dissimilar predictive value in both contexts.

Therefore, the aim of this study is to explore this programme diversity, by comparing the impact of the different determinants depicted in the conceptual model (Fig.1), in professionally and academically oriented programmes. The following two research questions are central to this study:

RQ1: *To what extent is the explanatory value of secondary students' academic motivation, academic self-efficacy and learning strategies (processing and regulation strategies) in the prediction of first-year HE academic adjustment, different between professional and academic FYHE programmes?*

RQ2: *To what extent is the explanatory value of secondary students' academic motivation, academic self-efficacy, learning strategies and subsequent first-year academic adjustment, in the prediction of first-year HE academic achievement, different between professional and academic FYHE programmes?*

## 6. Method

### 6.1 Respondents & Procedure

The data stem from a longitudinal research project on students' transition from secondary to HE in Flanders. In this project, students from 32 randomly selected secondary schools (offering a mixture of secondary education (SE) tracks; general, arts, technical and vocational) participated and were followed up until the second year of HE. At the end of their last year of SE, students completed questionnaires (both online and paper and pencil) measuring their academic motivation, self-efficacy and learning strategies (wave 1: May/June 2011, $N$=2839). Informed consent and contact information for future research was obtained from 84.1% of these students ($N$=2387). Data obtained from the Flemish government show that 1987 (83.3%) of students who had given their informed consent transitioned to HE, constituting the final sample for this study. A small majority of these students ($N$=1080, 54.4%) started an academic bachelor programme, whereas 907 (45.6%) opted for a professional bachelor programme. At a second wave, during the first semester of the FYHE, students' academic adjustment was mapped out in an online questionnaire. Several communication channels were used to reach respondents (letter, e-mail, SMS, phone call after repeated non-response), making this an intensive data collection that extended over three months (October - December 2011). In the second wave of the study, 604 (30.4%; academic programmes: $n$=331; professional programmes: $n$=273) of the 1987 students who transitioned to HE completed the academic adjustment scale. Table 2 shows the proportions of respondents' prior education tracks in both academic and professional HE programmes, and compares these with the corresponding student proportions in the actual Flemish population in academic year 2010-2011, as reported by Glorieux, Laurijssen, & Sobczyk (2014). As no students from the vocational SE track completed the academic adjustment scale in HE, this group of students is not represented in the present study.

Table 2
*Proportion of prior education study tracks, in the sample and the Flemish population, across academic and professional HE programmes*

| SE Track | **Academic HE programmes** | | **Professional HE programmes** | |
|---|---|---|---|---|
| | Sample | 2010-2011 Flemish population | Sample | 2010-2011 Flemish population |
| General | 91.02% | 85.20% | 51.27% | 30.40% |
| Arts | .65% | 3.00% | 1.76% | 2.10% |
| Technical | 8.24% | 10.50% | 46.86% | 58.30% |
| Vocational | 0 | .70% | 0 | 8.60% |
| Unknown | .09% | .60% | .11% | .60% |

**6.2 Measures**

Students' motivational characteristics and learning strategies at the end of SE *(Wave1)* were mapped out using scales of the self-report questionnaire 'LEarning strategy and MOtivation questionnaire', which was previously validated in Flanders (LEMO; Donche & Van Petegem, 2008).

*Academic motivation. Controlled motivation* was operationalised by six items, of which 'I am motivated to study, because I am supposed to do this' is an example ($\alpha$=.73). *Autonomous motivation* was also measured by six items, for instance, 'I am motivated to study, because I want to learn new things' ($\alpha$=.83). Finally, *amotivation* was measured using three items, such as 'I am motivated to study…honestly, I don't know; I feel like I'm wasting my time in school' ($\alpha$=.78). Five answering categories were given, ranging from 'Not important at all' to 'Very important'.

*Self-efficacy* is defined more specifically as a student's perception of having the necessary knowledge and skills to carry out learning tasks. The self-efficacy scale exists of four items, for instance 'I have confidence in the way in which I study' ($\alpha$=.84). Items were scored on a five-point Likert scale ranging from 'Completely disagree' to 'Completely agree'.

*Learning strategies.* We opted to measure qualitatively different cognitive processing and regulation strategies. More concretely, s*urface processing* was measured by the 'Memorizing'-scale (e.g. 'I memorise lists of characteristics of a certain phenomenon'; 4 items; $\alpha$=.67), and *deep processing* was measured by the 'Critical processing'-scale (e.g. 'I try to understand the interpretations of experts in a critical way'; 4 items; $\alpha$=.73). On the level of regulation strategies, we measured *self-regulation* (e.g. 'In addition to the compulsory subject matter, I read other books or texts that have to do with the subject matter'; 4 items; $\alpha$=.64), and *lack of regulation* (e.g. 'I notice that it is difficult for me to determine whether I have sufficiently mastered the subject matter; 4 items; $\alpha$=.70). All items are scored ranging from 1 (I never or hardly ever do this) to 5 (I almost always do this).

*Academic adjustment* (*Wave2*) was measured using the 'Adjustment'-scale (6 items, $\alpha$=.76), validated by Torenbeek and colleagues (2010, 2011). An item example is: 'I have experienced some difficulties in adjusting to the teaching approach of my current study programme (Reverse coded)'. Items were scored on a five-point Likert scale, ranging from 'Completely disagree' to 'Completely agree'.

*Academic achievement data* from students at the end of the FYHE (*Wave3*) was obtained from the Flemish government. It was conceptualised as study progress, which is the ratio of credits (ECTS study points) earned by a student versus the credits attempted by that student. Credits are earned when a course is passed, which is when a student scored a minimum of 10 out of 20 on the evaluation for that course.

*Prior education*. Data on students' prior education tracks was obtained from the Flemish government. Flemish SE is provided for young people aged 12 to 18 in four tracks: general SE, technical SE, artistic SE, and vocational SE. As mentioned above, the present study was not able to include students from the vocational SE track. Although differences in the educational tracks in general SE exist, students from the general SE track tend to be more prepared to enrol in an academic HE study programme. All students in the Flemish educational system are free to access either professional or academic HE programs after SE. For use in further analysis, this variable was dummy coded (0=general track, 1=arts/technical track).

### 6.3 Analysis

In the present study, multiple-group structural equation modelling (SEM; Byrne, 2016) is used to examine the fit of the conceptual model illustrated in Figure 1, and to conduct cross-group comparisons between university college students and university students *(RQ1 and RQ2)*. All analyses were carried out in M*plus* (version 8.3). In all models, the maximum likelihood estimator with robust standard errors (MLR) was used, which is robust to non-normality of observations (Muthén & Muthén, 2010). This method also allows for missing data handling; using the complete sample by incorporating data from respondents that did not participate in every wave, which has been found to provide better results in terms of unbiased estimates and statistical power (Enders, 2011).

Global fit of the models is assessed using the 'comparative fit index' (CFI) and 'root mean square error of approximation' (RMSEA). A model has excellent fit when CFI has a value above .95, and RMSEA has a value less than .05. A model has acceptable fit, with a CFI-value above .90, and RMSEA value is less than .08 (Hu and Bentler, 1999).

A prerequisite to conducting substantive comparisons between groups is the establishment of measurement invariance across those groups (Vandenberg & Lance, 2000). Hence, in a first step, we carried out multiple-group measurement invariance testing (Meredith, 1993) to seek evidence that our measurement instrument operates equivalently across the two groups under scrutiny (i.e. do university college students and university students understand all the scales and items in a similar way?). Hereto, four steps were undertaken, in each of which more restricted confirmatory factor analysis (CFA) models are estimated (Byrne, 2016; Vandenberg & Lance, 2000): (1) a *configural invariance* model, wherein only the number of factors and the factor-loading pattern are equivalent across groups. In this stadium, there are no equality constraints imposed on the parameter estimates of the model; (2) a *metric invariance* model requires that only factor loadings are equal across groups; (3) a *scalar invariance* model, wherein intercepts are constrained as well; and (4) a *strict invariance* model, finally, imposes equality constrains on the error variances across groups (Brown, 2014; Gregorich, 2006). When metric invariance is established, this means that the different constructs in the measurement model have the same meaning in the two groups. Scalar invariance, then, implies that the means of the scales across both groups can be compared. Researchers generally agree that assessing scalar invariance is sufficient for establishing measurement invariance (Milfont & Fischer, 2010).

In every proceeding step, the invariance of the factor structure was evaluated by comparing the fit of the more restricted model with the fit of the less restricted model (Byrne, 2016). To this end, we examined changes in the following fit indices: CFI and RMSEA. A decrease in CFI of .01 or more (Cheung & Rensvold, 2002) and an increase in RMSEA of .015 or more (Chen, 2007) was considered as evidence that the invariance hypothesis should be rejected[1]. If scalar measurement invariance was not attained, the model was tested for partial scalar invariance (Byrne, Shavelson, & Muthén, 1989). Hereto, modification indices were examined to identify possible item(s) that induced the lack of equivalence,

[1] For informational purposes, the chi-square difference test ($\Delta\chi^2$) is reported in the results section. A non-significant probability resulting from this test should then indicate non-invariance of the more restricted measurement model. However, the chi-square statistic is sensitive to sample size (e.g. Iacobucci, 2010), and therefore not relied upon in the present study

after which the particular intercepts of these items were allowed to differ between groups. Byrne et al. (1989) and Steinmetz, Schmidt, Tina-Booh, Wieczorek, & Schwartz (2009) suggest that a minimum of two intercepts have to be equal across groups to establish partial scalar invariance of a scale.

After this initial testing of the measurement models and their equivalence over students from different types of bachelor programmes, the structural model (Fig. 1) was - as stated above - tested using a multiple-group SEM approach. This allowed us to compare (a) the standardised regression parameter estimates and (b) the explained variances in the endogenous variables in both groups of students. In this study $p < .05$ is used as a criterion of statistical significance. Further, in order to more accurately compare the predictive power - in terms of explained variance - of the factors under study on their respective outcomes across academic and professional programmes, we controlled for prior education, and, subsequently, scrutinised the incremental values of these factors over prior education.

During analyses, we encountered a multicollinearity problem that was induced by high latent correlations between the 'lack of regulation' and 'self-efficacy' variables in the academic ($r$=-.815) as well as in the professional ($r$=-.651) bachelor programme group of respondents. This multicollinearity issue clearly influenced the analyses as theoretically inconceivable parameter estimates emerged when both constructs were included in one predictive model. Since 'lack of regulation' and 'self-efficacy' are theoretically clearly distinctive and both concepts have considerable impact on first-year academic adjustment and academic achievement, we opted to retain both variables in the analysis. Hence, we preferred to break down the model under scrutiny (Fig.1) in two components containing either learning strategies or motivational factors as determinants of academic adjustment and subsequent academic achievement (Fig.2).

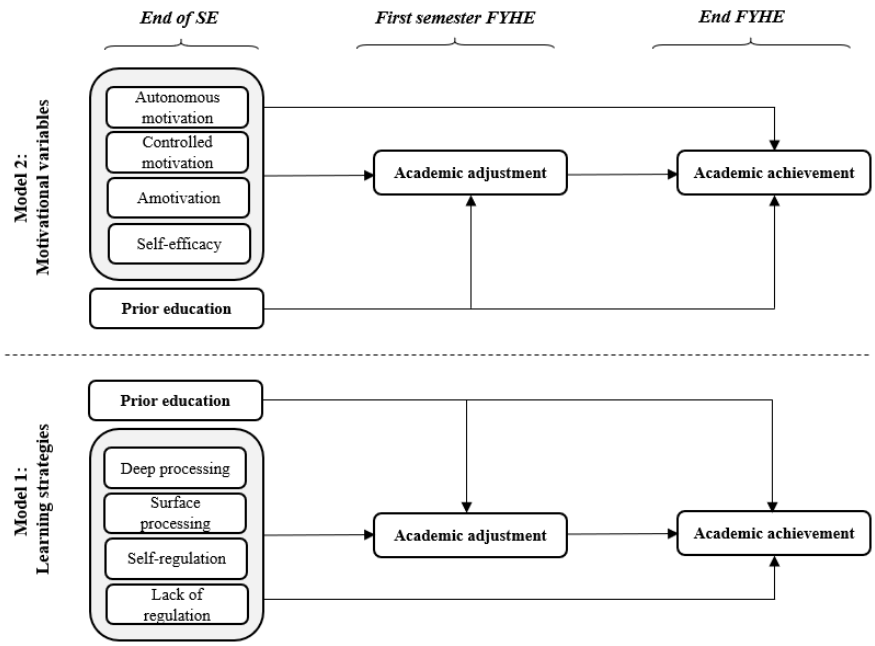


*Figure 2.* Split of the conceptual models of learning strategies and motivational variables affecting academic adjustment and subsequent academic achievement.

## 7. Results

### 7.1 Measurement invariance

Multiple-group measurement invariance analyses were conducted on the two conceptual models (see figure 2 in the method section). In the next paragraphs, we first provide an overview of the results for the learning strategies variables and subsequently for the motivational variables.

#### *7.1.1 Learning strategies*

After adding one error covariance term in the lack of regulation scale, and one in the academic adjustment scale, the configural model for learning strategies showed adequate fit (see Table 3). Next, inspection of the metric model shows that the hypothesis of invariant factor loadings was not rejected (ΔCFI=.003, ΔRMSEA=0). After constraining the intercepts (scalar model), however, model fit decreased significantly (ΔCFI=.016, ΔRMSEA=-.003). We needed to relax constraints on one intercept of the lack of regulation scale, and one of the surface processing scale to improve model fit sufficiently. Subsequently, imposing equality constrains on the error variances across groups did not significantly reduce fit (see Table 3). Thus, results for this model suggest (1) metric invariance for all scales in the model, (2) scalar invariance for deep processing, self-regulation and academic adjustment, and (3) partial scalar invariance for lack of regulation and surface processing.

Table 3
*Results from measurement invariance tests for learning strategies and academic adjustment*

| Model | CFI | RMSEA | ΔCFI | ΔRMSEA | $\chi^2$ | df | $\Delta\chi^2$ | Δ df | p |
|---|---|---|---|---|---|---|---|---|---|
| Configural | .933 | .032 | | | 742.388 | 395 | | | |
| Metric | .930 | .032 | .003 | 0 | 770.750 | 412 | 28.362 | 17 | .041 |
| Scalar | .914 | .035 | .016 | -.003 | 874.256 | 429 | 103.506 | 17 | *** |
| Partial Scalar *[LR[a]]* | .920 | .034 | .010[c] | -.002[c] | 841.912 | 428 | 71.162 | 16 | *** |
| Partial Scalar *[LR] [SP[b]]* | .925 | .033 | .005[c] | -.001[c] | 816.008 | 427 | 45.258 | 15 | *** |
| Partial strict | .919 | .033 | .006 | 0 | 865.602 | 449 | 49.594 | 22 | *** |

*** $p$<.001; [a] LR=One item of Lack of regulation scale freed; [b] SP=One item of surface processing scale freed; [c] The reference point for the calculation of these values is the metric model.

#### *7.1.2 Motivational variables*

In order to achieve adequate fit for the configural model of the motivational variables (see Table 4), we added three error covariances in the autonomous as well as in the controlled motivation scale. Furthermore, one error covariance was added in the self-efficacy scale and one in the academic adjustment scale (the same as in the learning strategies model). As can be seen in Table 4, the results from the measurement invariance tests, thus, provide evidence that strict invariance is established for autonomous and controlled motivation, amotivation, self-efficacy, and academic adjustment.

Table 4
*Results from measurement invariance tests for motivational variables and academic adjustment*

| Model | CFI | RMSEA | ΔCFI | ΔRMSEA | $\chi^2$ | df | $\Delta\chi^2$ | Δ df | p |
|---|---|---|---|---|---|---|---|---|---|
| Configural | .93 | .043 | | | 1.384.466 | 514 | | | |
| Metric | .93 | .044 | 0 | -.001 | 1403.976 | 534 | 19.510 | 20 | .489 |
| Scalar | .928 | .043 | .002 | .001 | 1453.800 | 554 | 49.824 | 20 | *** |
| Strict | .926 | .043 | .002 | 0 | 1509.784 | 579 | 55.984 | 25 | *** |

*** *p*<.001

## 7.2 Multiple-group SEM

### *7.2.1 Learning strategies*

In a next step, a multiple group SEM analysis containing the learning strategies component (Model 1 in Figure 2) provided satisfactory fit (*CFI*=.911, *RMSEA*=.031). Parameter estimates of this model (Table 5) demonstrate that students' first-year academic achievement is related with their prior education (dummy coded; 0=general SE) in both the academic (*β*=-.149, *p*<.001) and professional (*β*=-.215, *p*<.001) contexts, indicating that students from more academically preparing study tracks in secondary education (general education), achieve better in first-year HE. Further, it appears that academic adjustment is a direct significant (positive) determinant of academic achievement in academic (*β*=.290, *p*<.001) programmes, as well as in professional (*β*=.334, *p*<.001) programmes. Academic adjustment is, in its turn, significantly and negatively associated with lack of regulation in both types of programmes (acad.: *β*=-.430, *p*<.001; prof.: *β*=-.253, *p*=.004). Finally, prior education predicts academic adjustment in professional programmes (β=-.248, *p*<.001), but not in academic programmes (β=-.096, *p*=.135).

Table 5
*Results of the multiple-group SEM analysis for learning strategies; standardised parameter estimates and explained variances ($R^2$) in academic and professional programmes*

| | **Academic programmes** | | **Professional programmes** | |
|---|---|---|---|---|
| | *B* | *p* | *β* | *p* |
| **Academic adjustment** | | | | |
| *Deep processing* | -.031 | .761 | .075 | .586 |
| *Surface processing* | -.081 | .244 | .016 | .867 |
| *Self-regulation* | .186 | .087 | .055 | .730 |
| *Lack of regulation* | -.430 | .000 | -.253 | .004 |
| *Prior education*[a] | -.096 | .135 | -.248 | .000 |
| *Explained variance ($R^2$)* | *20.5* | | *12.7* | |
| **Academic achievement** | | | | |
| *Deep processing* | .047 | .407 | .006 | .941 |
| *Surface processing* | .037 | .402 | .018 | .703 |
| *Self-regulation* | -.069 | .262 | .049 | .562 |
| *Lack of regulation* | .018 | .754 | -.007 | .902 |
| *Academic adjustment* | .290 | .000 | .334 | .000 |
| *Prior education*[a] | -.149 | .000 | -.215 | .000 |
| *Explained variance ($R^2$)* | *11.2* | | *19.9* | |

[a] Dummy coded: 0=general SE

In order to accurately compare the predictive power, in terms of explained variance, of learning strategies, motivational variables and academic adjustment on their respective outcomes across academic and professional programmes, we contrasted the incremental values of these factors over prior education, which are calculated in Table 6 (i.e. *ΔR² learning strategies* in the prediction of academic adjustment, and *ΔR² learning strategies + adjustment* in the prediction of academic achievement). Results show that the larger regression coefficients of learning strategies in the prediction of academic adjustment in the academic group, are also reflected in the explained variances (*ΔR² learning strategies*)**.** Learning strategies at the end of SE predict over double the amount of variance in first-semester academic adjustment in academic programmes (19.4%) in comparison to professional programmes (7.2%). Table 6 further shows that in professional HE, 3.1% more variance in academic achievement is explained by learning strategies and academic adjustment (11.1%), compared to the academic context (8%). Further analyses (see 7.2.3 Incremental value of academic adjustment) will show that this latter difference in incremental value can be completely attributed to the increase in explained variance of academic adjustment, not learning strategies.

Table 6
*Calculation of incremental value (ΔR²) of learning strategies and academic adjustment over prior education*

| | **Academic programmes** | **Professional programmes** |
|---|---|---|
| **Academic adjustment** | | |
| $R^2$ prior education | 1.1 | 5.5 |
| $R^2$ prior education + learning strategies[a] | 20.5 | 12.7 |
| $\Delta R^2$ learning strategies | **19.4** | **7.2** |
| **Academic achievement** | | |
| $R^2$ prior education | 3.2 | 8.8 |
| $R^2$ prior education + learning strategies + adjustment[a] | 11.2 | 19.9 |
| $\Delta R^2$ learning strategies + adjustment | **8** | **11.1** |

[a] As also reported in Table 5.

### *7.2.2 Motivational variables*

The motivational variables model (Model 2 in Figure 2) had satisfactory fit as well (*CFI*=.924, *RMSEA*=.039). Parameter estimates of this model (Table 7) demonstrate that prior education relates to adjustment in academic ($\beta$=-.128, $p$=.043) as well as in professional ($\beta$=-.276, $p$<.001) programmes. Next, self-efficacy had a significant positive effect on academic adjustment in the academic programmes ($\beta$=.266, $p$<.001), but not in the professional programme group ($\beta$=.088, $p$=.285). Controlled motivation was significantly and negatively related with adjustment in both types of programmes (acad.: $\beta$=-.188, $p$=.024; prof.: $\beta$=-.189, $p$=.028). Academic adjustment, subsequently, positively predicted academic achievement in the academic programmes ($\beta$=.215, $p$=.001) as well as in the professional programmes ($\beta$=.333, $p$<.001). Further, next to the indirect effect through academic adjustment in the academic group, self-efficacy also has a direct positive impact on academic achievement in the academic ($\beta$=.134, $p$=.002) and in the professional group ($\beta$=.117, $p$=.014). Finally, prior education was also related to academic achievement in both types of programmes (acad.: $\beta$=-.160, $p$<.001; prof.: $\beta$=-.213, $p$<.001).

Table 7
*Results of the multiple-group SEM analysis for motivational variables: parameter estimates and explained variances in academic and professional programmes*

| | Academic programmes | | Professional programmes | |
|---|---|---|---|---|
| | *β* | *p* | *β* | *p* |
| **Academic adjustment** | | | | |
| Autonomous motivation | -.049 | .595 | -.013 | .910 |
| Controlled motivation | -.188 | .024 | -.189 | .028 |
| Amotivation | -.043 | .686 | -.073 | .497 |
| Self-efficacy | .266 | .000 | .088 | .285 |
| Prior education | -.128 | .043 | -.276 | .000 |
| *Explained variance ($R^2$)* | 14 | | 14.8 | |
| **Academic achievement** | | | | |
| Autonomous motivation | -.014 | .774 | .060 | .262 |
| Controlled motivation | .008 | .861 | .043 | .430 |
| Amotivation | -.053 | .318 | .033 | .605 |
| Self-efficacy | .134 | .002 | .117 | .014 |
| Academic adjustment | .215 | .001 | .333 | .000 |
| Prior education | -.160 | .000 | -.213 | .000 |
| *Explained variance ($R^2$)* | *12.1* | | *21.8* | |

Similar to the learning strategies model, we observed that the incremental value of motivational variables in the prediction of academic adjustment, over prior education (Table 8), is larger in academic programmes (12.9%) relatively to professional programmes (9.3%). However, this difference across programmes (3.6%) is smaller than that in the learning strategies model (12.2%). Furthermore, motivational variables and academic adjustment together, in the professional programmes were able to predict 13% of variance in academic achievement, over and above prior education. This is 4.1% more variance than was predicted in the academic contexts, where the increase in explained variance of these variables over prior education was 8.9%. Again, this latter difference in incremental value is attributable to the increase in explained variance of academic adjustment (see 7.2.3 Incremental value of academic adjustment).

Table 8
*Calculation of incremental value ($\Delta R^2$) of motivational variables and academic adjustment over prior education*

| | Academic programmes | Professional programmes |
|---|---|---|
| **Academic adjustment** | | |
| $R^2$ prior education | 1.1 | 5.5 |
| $R^2$ prior education + motivation[a] | 14 | 14.8 |
| $\Delta R^2$ motivational variables | **12.9** | **9.3** |
| **Academic achievement** | | |
| $R^2$ prior education | 3.2 | 8.8 |
| $R^2$ prior education + motivation + adjustment[a] | 12.1 | 21.8 |
| $\Delta R^2$ motivation + adjustment | **8.9** | **13** |

[a] As also reported in Table 7.

*7.2.3 Incremental value of academic adjustment in predicting academic achievement, over prior education, learning strategies and motivation*

The motivational variables model (Table 7) showed that, in addition to academic adjustment, self-efficacy was a significant direct predictor of academic achievement. Moreover, we know that the non-significant effects of the determinants of academic achievement presented in Table 5 and 7 have a small impact on the reported explained variances as well - in addition to the significant effects. Hence, these considerations bring about the question of what the 'net' impact of academic adjustment on academic achievement is in terms of explained variance, and to what extent this is different between academic and professional programmes. Therefore, we also examined a model containing only the direct impact of the learning strategies and motivational variables on academic achievement (Models B in Table 9 and 10), wherein academic adjustment was not included as predictor of achievement. This allowed us to estimate the explained variances ($R^2$) of learning strategies and motivational variables in academic achievement, and consequently the incremental value ($\Delta R^2$) of academic adjustment in the predictive model. Our calculations show that the difference in explained variance in academic achievement in the learning strategies model, between academic and professional contexts ($\Delta R^2$=3.1%, see Table 6), can be completely ascribed to the incremental value of academic adjustment, as can be seen in Model C of Table 9 (9.8% - 6.7%). Indeed, learning strategies have identical incremental value over prior education in both academic and professional programmes (Model B, Table 9: $\Delta R^2$=1.3).

Table 9
*Calculation of incremental value ($\Delta R^2$) of academic adjustment in predicting academic achievement, over prior education and learning strategies*

| | **Academic programmes** | | **Professional programmes** | |
|---|---|---|---|---|
| | $R^2$ | $\Delta R^2$ | $R^2$ | $\Delta R^2$ |
| **Academic achievement** | | | | |
| *Model A*: $R^2$ prior education | 3.2 | / | 8.8 | / |
| *Model B*: $R^2$ prior education + learning strategies | 4.5 | ***1.3*** | 10.1 | ***1.3*** |
| *Model C*: $R^2$ prior education + learning strategies + adjustment | 11.2 | ***6.7*** | 19.9 | ***9.8*** |

Closer inspection of Table 10, then, shows that the difference of 4.1% explained variance in academic achievement in the motivational variables model (see Table 7), can also be attributed to the fact that academic adjustment predicts more variance in professional programmes ($\Delta R^2$=9.4%), relative to academic programmes ($\Delta R^2$=3.9%); a difference of 5.5%. However, given that learning strategies have a larger incremental value over prior education in academic programmes ($\Delta R^2$=5%), in comparison to professional programmes ($\Delta R^2$=3.6%) - a difference of 1.4% - this larger predictive value of academic adjustment in professional programmes is slightly compensated.

Table 10
*Calculation of incremental value ($\Delta R^2$) of academic adjustment in predicting academic achievement, over prior education and motivation*

| | **Academic programmes** | | **Professional programmes** | |
|---|---|---|---|---|
| | $R^2$ | $\Delta R^2$ | $R^2$ | $\Delta R^2$ |
| **Academic achievement** | | | | |
| *Model A*: $R^2$ prior education | 3.2 | / | 8.8 | / |
| *Model B*: $R^2$ prior education + motivation | 8.2 | ***5*** | 12.4 | ***3.6*** |
| *Model C*: $R^2$ prior education + motivation + adjustment | 12.1 | ***3.9*** | 21.8 | ***9.4*** |

## 8. Discussion and conclusion

This study set out to explore whether the determinants in our conceptual model (Fig. 1) have dissimilar predictive power in professional HE programmes, in comparison with more academically oriented programmes. More specifically, we examined (1) to what extent the explanatory value of secondary students' academic motivation, academic self-efficacy and learning strategies in the prediction of first-year HE academic adjustment, was different between these two types of programmes, and (2) whether secondary students' academic motivation, academic self-efficacy, learning strategies and subsequent first-year academic adjustment, are similarly or differently predictive for academic achievement within the two different HE programmes. We examined these relationships and differences in explanatory value of determinants, controlling for students' prior education track. In what follows, we discuss the resulting parameter estimates of the multi-group SEM-models in relation to previous research, after which we further focus on the differences in predictive power between academic and professional HE contexts.

### 8.1 Identified relationships in academic and professional HE contexts

Our results indicate that academic adjustment in the first semester of the FYHE exerted the largest influence on academic achievement in both academic and professional programmes; students who feel more academically adjusted to their new learning environment in the first semester of HE will obtain a higher percentage of their credits at the end of their first year. This result corroborates the findings of several previous studies in academic HE contexts (Bailey & Phillips, 2016; Petersen et al., 2009; Prospero & Vohra-Gupta, 2007; Severiens & Wolff, 2008; Wintre et al., 2011). The only other direct and positive significant predictor of academic achievement in both HE contexts was self-efficacy which is also in line with former studies (Richardson et al., 2012; Robbins et al., 2004).

However, as our study went beyond the consideration of separate direct effects by modelling the relationship between variables within integrated models, we could also identify some motivational and learning strategy variables that influenced academic achievement indirectly, through their impact on academic adjustment. Firstly, students in academic programmes who had more confidence in their way of studying (self-efficacy) at the end of SE felt more academically adapted in the first semester of the FYHE, which contradicts the findings by van Rooij et al. (2018), but are in line with findings from other research (Cazan, 2012; Chemers et al., 2001). This latter relationship was non-significant in professional programmes. Further, for both academic and professional HE programmes, results confirm the hypotheses that students who have difficulties in steering their own learning process (lack of regulation) and those for whom the drivers for studying were more determined by external sources (controlled motivation) at the end of SE, felt less adapted to their new learning environment. A strength of the present study is that all the above relationships were present after controlling for the expected effect of the prior SE education track which students followed.

In contrast to previous research, several variables were not significantly associated with academic adjustment in either HE programmes: autonomous motivation (Clark et al., 2014; Petersen et al., 2009; van Rooij et al., 2018), amotivation (Baker, 2004) and self-regulation (Cazan, 2012; Hurtado et al., 2007; van Rooij et al., 2018). The hypothesis that deep and surface processing at the end of SE influences FYHE academic adjustment (Abbott-Chapman et al., 1992) was not supported by our data either.

Thus, similar to the study by van Rooij et al. (2018), which highlighted the pivotal role of academic adjustment in predicting achievement in university, we found academic adjustment to be an important mediator of the effects of several motivational variables and learning strategies on academic achievement. Interestingly, however, while van Rooij and colleagues did not find evidence of self-efficacy being related with academic adjustment nor with academic achievement, the present study found that students' self-efficacy of studying, especially in HE academic programmes, to be positively associated with academic achievement both directly and indirectly, through academic adjustment.

### 8.2 Differences between academic and professional programmes

In line with previous work on *disciplinary diversity* of HE programmes influencing interrelationships between non-cognitive variables and academic achievement (De Clercq et al., 2013; Fonteyne et al., 2017; Lizzio et al., 2002), the present study provides empirical evidence that also HE *programme diversity* (academic vs. professional) influences relationships in predictive models of academic achievement. The fact that the size of regression coefficients varies over academic and professional programmes, is an important first indication that learning strategies, motivational variables, and academic adjustment affect their respective outcomes differently in both HE contexts. Furthermore, one relationship - between self-efficacy and academic adjustment - was significant in academic programmes, but not in professional programmes.

The value of investigating the diversity between HE programmes on the meso-level, is also further evidenced by the differences in explained variance across both groups. Firstly, learning strategies and motivational variables at the end of SE seem to have more predictive power in the prediction of FYHE academic adjustment in the academic context (motivational variables: $\Delta R^2$=12.9%; learning strategies: $\Delta R^2$=19.4%) than in the professional context (motivational variables: $\Delta R^2$=9.3%; learning strategies: $\Delta R^2$=7.2%). In this light, especially lack of regulation and self-efficacy proved to have important differential effects in both contexts.

Secondly, our results suggest that academic adjustment in the first semester of HE influences academic achievement to a bigger extent in professional programmes than in academic programmes. Indeed, the incremental value of academic adjustment on academic achievement in terms of explained variance, was relatively larger in the professional programmes (motivational variables model: $\Delta R^2$= 9.4%; learning strategies model: $\Delta R^2$=9.8%), compared to the academic programmes (motivational variables model: $\Delta R^2$= 3.9%; learning strategies model: $\Delta R^2$= 6.7%). Finally, after controlling for prior education, students' learning strategies seem to have an identical predictive power regarding academic achievement in both HE programmes ($\Delta R^2$=1.3%), while motivational variables and more specifically self-efficacy, predicts academic achievement to a slightly larger extent in academic versus professional programmes (acad.: $\Delta R^2$=5%; prof.: $\Delta R^2$=3.6%).

### 8.3 Implications, limitations and perspectives

The results of this study indicate that scholars investigating students' transition into HE should be attentive for the possible influences of the specific HE programme or educational context wherein research is carried out. Indeed, our study strengthens the idea that predictive models of academic achievement developed in academic programmes should not be imprudently applied in professional programmes - considering that the predictive power of the included variables in this study varies across the two contexts. Further research is needed to accurately establish (1) why learning strategies and motivational variables at the end of SE seem to affect FYHE academic adjustment to a bigger extent in academic programmes than in professional programmes and (2) why academic adjustment seems to have more predictive power in the prediction of FYHE academic achievement in the professional context relative to the academic context.

Several theoretical models point at the importance of both the learning environment and student characteristics in the development of students' learning processes (e.g. Biggs, 1987), motivation (e.g. Deci & Ryan, 2000) and FYHE adjustment (e.g. Tinto, 1975). In this regard, it should be noted that, although we did control for students' prior education - which is an important student characteristic, it remains unclear whether the unveiled differences in predictive power of the abovementioned determinants emerge from differences between the HE programmes (contextual), or differences between students within the two systems (individual).

With reference to the contextual characteristics, it remains unclear whether and how specific aspects of the learning environments under scrutiny (e.g. aims, expectations of students, assessment

methods or didactical approaches) might have been moderating the relationships in the predictive model. Possibly, compared to students in academic contexts, students in professional contexts might get a clear-cut indication of how well they are functioning, much earlier on in their programme (due to, for instance, different evaluation periods/feedback loops). This, then, would entail professional bachelor students to be able to make a more accurate assessment of their own academic adjustment, which could explain the larger effect of academic adjustment on achievement in professional contexts. Another hypothesis we introduce here, is that there might be more demanding requirements related to regulation in academic HE programmes, so that a higher level of lack of regulation at the end of SE impacts academic adjustment to a larger extent in academic HE programmes, relative to professional contexts.

Some limitations of the present study need to be highlighted. Firstly, although this study adopts a longitudinal research design and, thus, enables further understanding of the directionality of effects, it does not allow for causal interpretation (Cohen, Manion, & Morrison, 2011). The results and conclusions should therefore be interpreted cautiously.

A second limitation concerns the adopted academic adjustment scale. This measure was developed in an academic context, and therefore, we cannot guarantee that this measure is a valid representation of academic adjustment in professional contexts. Indeed, it is conceivable that the academic adjustment construct in professional programmes comprises sub-facets specific to that context, which are not accounted for in the present study. Nonetheless, the items of the adopted scale are drawn up rather generally (another item example is: "*I have the impression that I experience too many difficulties for my studies in higher education*."), and measurement invariance analyses have shown that the meaning of items of the adopted academic adjustment scale is equivalent for students from the two types of programmes (full scalar invariance was established).

Finally, although this study demonstrated the significance of diversity on the level of study programmes (academic vs. professional) in predicting academic adjustment and achievement, additional studies need to explore the effect of discipline diversity within the professional HE context (Becher, 1994). This would help us to establish a greater degree of accuracy and understanding of the matter at hand.

Based upon the results of this study, we suggest that (especially professional) HE administrators should be attentive to the pivotal role of freshmen's academic adjustment in the first semester of the FYHE. Also, next to academic adjustment, coaching and guidance initiatives aimed at facilitating the academic transition in the FYHE should particularly target students' self-efficacy, lack of regulation, and controlled motivation, which - especially in academic HE programmes – have considerable impact on academic adjustment. This is promising, as previous longitudinal research has shown that these latter variables are malleable, and not fixed pre-entry characteristics (e.g. Vermunt & Donche, 2017).

## Keypoints

- The present study provides empirical evidence that HE programme diversity (academic vs. professional HE programmes) influences the relationships in predictive models of academic achievement.
- Learning strategies and motivational variables at the end of SE have more predictive power in the prediction of FYHE academic adjustment in academic HE programmes, relative to professional HE programmes.
- Academic adjustment in the first semester of the FYHE influences academic achievement to a bigger extent in professional programmes than in academic programmes.
- These differences across HE contexts were found after controlling for prior education, and adopting a longitudinal, integrative study design.

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