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Predicting students' short- and long-term academic achievement in higher education: A cross-classified multilevel study

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A B S T R A C T

This study investigates the influence of secondary education (SE) and higher education (HE) study programmes on both the short-term (one year) and long-term (three years) academic achievement of HE students. It also examines the impact of various background, cognitive, and non-cognitive factors, controlling for SE and HE programmes. Based on a representative dataset (N = 24,183), this study employs cross-classified multilevel models with a random interaction effect between SE and HE levels. Results show that both SE and HE study programmes impact short- and long-term achievement in HE. The impact of SE programmes is smaller on long-term achievement, while that of HE programmes remains stable. Notably, the alignment between SE and HE programmes, is increasingly important in the long run. The study also highlights that background, non-cognitive and cognitive factors significantly predict academic achievement in both time frames, with important variations in their impacts on short- and long-term outcomes.

Educational relevance statement: Having a clear perspective on the key determinants of academic achievement in higher education (HE) is crucial to support students during their difficult transition to HE. The present study addresses important gaps in the existing literature by analysing the influence of secondary education (SE) and higher education (HE) programmes on *both* short- and long-term academic achievements of HE students. It also examines the impact of a wide range of background, cognitive, and non-cognitive factors on these academic achievement measures, controlling for the effects of SE and HE programmes. The study reveals several important findings, among which: (1) An included interaction term between random variances at the SE and HE programme levels (in a cross-classified multilevel model) increasingly predicts academic achievement over time, suggesting the necessity of aligning SE and HE programmes. This is particularly relevant for SE administrators and counsellors developing study choice guidance trajectories for students; (2) There is evidence of a cumulative effect of SES risk factors in HE, with the influence of these background variables on academic achievement intensifying over time; (3) Cognitive and non-cognitive factors assessed at the end of SE significantly influence academic performance over a three-year period in HE, in addition to their impact on short-term academic achievement. This underscores the predictive validity of these measures and underscores their inclusion in online assessment tools designed to support SE students intending to pursue HE.

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1. Introduction

The transition to higher education (HE) is a challenging process for many students. Consequently, success rates in HE are typically low. Statistics from the Organisation for Economic Cooperation and Development (OECD, 2019) showed that in participating countries only 39 % of students graduated within the theoretical duration of the study programme; moreover, 12 % dropped out before the start of the second year. In Flanders (Belgium), there is an open access HE system. This means that students with any secondary degree can enrol for basically any HE study programme, except for Dentistry, Medicine, Veterinary studies and select art studies. Aside from these exceptions, there are no central exams at the end of secondary education (SE), and no entrance exams or SE Grade Point Averages (GPA) required for admission; additionally, HE tuition fees are very low. This open access system is meant to advance social mobility by stimulating HE participation, also among socioeconomically disadvantaged groups. However, as a consequence, timely graduation is also lower than the OECD average, at a mere 33 %. Informing students about skills and abilities related to achievement is therefore crucial in such open access HE systems.

Going back to influential models such as Tinto's (1975) theoretical model of dropout, several studies have investigated the contribution of entry factors to academic achievement in HE (Richardson et al., 2012; Robbins et al., 2004; Schneider & Preckel, 2017). Several meta-analyses show that both cognitive factors, e.g. verbal ability and pre-HE achievement, as well as non-cognitive factors such as motivation, self-efficacy and learning strategies are important determinants of achievement (Credé & Kuncel, 2008; Richardson et al., 2012; Robbins et al., 2004). In addition to these individual characteristics the contextual diversity on both the levels of students' SE and HE tracks also impacts students' academic achievement (De Clercq et al., 2013; De Clercq, Galand, et al., 2021; Fonteyne et al., 2017; Schelfhout, Wille, et al., 2022; Willems et al., 2021). However, more research is necessary on the interplay between contextual and individual characteristics in their contribution to achievement. For example, students from a language-heavy SE programme might have more success in HE programmes requiring knowledge of languages. In addition to this lack of research into the combined influence of contextual and individual characteristics, few studies examined the impact of these factors on long-term academic achievement. As De Clercq, Jansen, et al. (2021) pointed out, studying the transition to HE requires longitudinal approaches as this transition can be considered as a process, not a state. Identifying how pre-entry factors impact both short- and long-term achievement could help (re) shape student preparatory and support programmes to increase students' achievement rate more efficiently.

This study therefore investigates how pre-entry student characteristics and the combination of SE and HE study programmes as well as their interaction contribute to the prediction of both short- and long-term study achievement in a representative sample from several Flemish SE and HE institutions; typically renowned European university colleges and universities.

2. Predicting academic achievement in higher education

Several theoretical models emphasised the importance of accounting for pre-entry characteristics in the prediction of achievement. Tinto's (1975, 1993) influential model of student dropout, for example, accounted for individual attributes such as demographic variables, abilities, family backgrounds and educational variables, such as pre-HE achievement. More recent studies also addressed the importance of non-cognitive factors such as self-efficacy and motivation (Richardson et al., 2012; Schneider & Preckel, 2017; Van Rooij et al., 2017). Tinto's aforementioned model was further refined in other models, all using an input-throughput-output structure (Biggs et al., 2001; Braxton et al., 2000; Tinto, 1993).

2.1. Cognitive factors

Cognitive ability is often established as one of the strongest predictors of achievement (Kuncel & Hezlett, 2010; Roth et al., 2015). General measures of intelligence and general cognitive ability (g) also relate to success in the academic domain (Busato et al., 2000; Kuncel et al., 2004; Kuncel & Hezlett, 2010; Richardson et al., 2012). Schneider and Preckel (2017), for example, showed a medium effect of standardised measures of intelligence on academic achievement ($d = 0.47$). Also tapping into cognitive ability are university admissions tests. More restricted HE systems use tests such as the SAT that often focus on verbal and math ability as proxies of general intelligence (Sedlacek, 2011). Richardson et al. (2012) showed that SAT and ACT show medium-sized correlations with tertiary GPA. More recently, Schneider and Preckel (2017) found a large effect of admissions tests (ACT, Scholastic Aptitude Test (SAT)) in their systematic review of academic achievement meta-analyses ($d = 0.79$). Performance in SE was also often used as an indication of general cognitive ability (De Clercq, Galand, et al., 2021); in the meta-analysis of Richardson et al. (2012) high school GPA was correlated significantly and with a medium effect size to tertiary GPA, while A level points (United Kingdom) showed small positive average correlations. A systematic review of studies carried out in Flanders (Belgium) and the Netherlands also proved secondary school GPA and secondary school coursework to be consistent predictors of students' GPA in HE (van Rooij et al., 2017).

As has been mentioned earlier, in the Flemish context no admissions tests such as SAT or ACT are used, however, several mostly cross-sectional studies showed that general, non-binding and non-obligatory tests of verbal and mathematical skills have also proven to be valuable as predictors of success of the first year in HE. Fonteyne et al. (2015, 2017) showed that the results of a basic mathematics skills test are related to first-year students' academic achievement. Fonteyne et al. (2017) for example found significant correlations between a mathematics test and first-year GPA between 0.21 and 0.33 in the faculties of Psychology, Arts, Law, and Pharmaceutical sciences. Schelfhout, Wille, et al. (2022) found a somewhat lower, but still significant correlation with first-year students' GPA ($r = 0.16$). In a study by Vandervieren and Casteleyn (2020) first-year students' numerical literacy also correlated weakly, but significantly with their achievement, both measured as GPA ($r = 0.27$) and percentage of credits obtained ($r = 0.22$). In addition to numerical skills, language proficiency measures have also shown to predict general academic achievement in the Flemish context. Academic language proficiency, for example, showed weak to moderate correlations of around 0.30 with academic achievement of first-year students, most of which are considered native speakers (De Wachter et al., 2013; Heeren et al., 2021; Heeren, 2024; De Moor & Colpaert, 2019); a result that was also found in other educational contexts (i.e.: Elder et al., 2007; Van Dyk, 2015). Writing ability also is related to first-year achievement (Kuiken & Vedder, 2021), as is vocabulary knowledge (Fonteyne et al., 2017; Schelfhout, Wille, et al., 2022; Vandervieren & Casteleyn, 2020). Vocabulary knowledge is indeed an interesting variable as it has shown to be a strong predictor of other language skills as well as language proficiency in general (Qian & Lin, 2019).

2.2. Non-cognitive factors

In addition to cognitive factors, research also showed that non-cognitive factors contribute to achievement in HE. Even when controlling for more traditional demographic and cognitive predictors, non-cognitive variables explain additional variance in academic achievement (De Clercq, Galand, et al., 2021; Fonteyne et al., 2017; Richardson et al., 2012; Schelfhout, Wille, et al., 2022; Willems et al., 2021). The present study will focus on students' motivational factors, on the one hand, i.e. self-beliefs, academic motivation and attitude towards school, and learning strategies related to self-regulation, on the other hand, i.e. time management and test strategies. These variables are central to theoretical models predicting achievement such as Zimmerman's model of Self-Regulated Learning (SRL) (Zimmerman, 2002). Differences in self-regulation, according to Zimmerman (2002), can lead to substantial individual differences in learning. Self-regulation can be defined as "the self-generated thoughts, feelings, and behaviors that are oriented to attaining goals" (Zimmerman, 2000, as cited in Zimmerman, 2002).

The SRL-model is considered cyclical with the three phases (forethought, performance and self-reflection) feeding into one another. Self-motivation beliefs such as self-efficacy are part of the forethought phase, they are influenced by prior experiences (self-reflection phase) and determine students' behaviour in the performance phase. Learners who are motivated and set goals will learn in a more self-regulated manner. In the performance phase different learning strategies will be implemented through self-control and self-observation. More regulated learners will adjust their strategies to successfully complete their tasks and be aware of their performance to adjust when necessary. In their systematic review, for example, van Rooij et al. (2017) showed that motivational factors and different learning strategies were related to students' GPA in HE. Schneider and Preckel (2017) also concluded that better achieving students have a higher self-efficacy and a more goal-directed use of learning strategies. Importantly, self-efficacy, motivation and learning strategies are often interrelated and malleable factors that have proven to be related to academic achievement and can be addressed directly in an educational context or in remedial activities (Vermunt & Donche, 2017; Weinstein et al., 2000).

Prior research shows that both academic self-efficacy and academic self-concept can be considered 'self-beliefs' that are related to the academic context (Bong & Skaalvik, 2003; Marsh & Martin, 2011) and are important predictors for academic achievement (e.g. Richardson et al., 2012). Research also showed evidence for a reciprocal relation between academic self-concept and achievement (Bong & Skaalvik, 2003; Huang, 2011; Marsh & Martin, 2011; Wouters et al., 2011). The two concepts are closely related and need some further clarification as they can easily be confused (Marsh et al., 2019). In this study, both self-efficacy and self-concept are studied as general constructs related to school and studying, i.e. the academic domain. Academic self-efficacy, on the one hand, can be considered as a student's perception of having the necessary knowledge and skills to carry out a particular learning task, in this case: the task of studying. Self-efficacy was first coined by Bandura (1977) and reflects people's expectation or conviction regarding their capabilities, i.e. the belief that they can successfully execute the required behaviour to produce certain outcomes in a given context. According to Bandura (1977), self-efficacy determines people's effort and persistence when faced with aversive experiences. In line with this, many studies found a positive relation between academic self-efficacy and achievement (De Clercq, Galand, et al., 2021; Fonteyne et al., 2017; Krumrei-Mancuso et al., 2013; Richardson et al., 2012; Robbins et al., 2004; Schelfhout, Wille, et al., 2022; Willems et al., 2019; Willems et al., 2021). Although self-efficacy is often measured on a specific level, there may be situations where broader measures can be useful. Bandura (1997) pointed out that efficacy beliefs are most effective in predicting performance when assessed at the same level of generality as the task being evaluated. For instance, when the aim is to predict performance on a larger scale, such as course grades (Bong & Skaalvik, 2003).

Academic self-concept, on the other hand,refers to individuals' perceptions about themselves in an academic context and their capabilities. Academic self-concept is therefore a broader, more stable and more generalised perception of one's competence in academic settings, shaped more heavily by social comparisons and influenced by past academic performance (Marsh et al., 2019). Whereas self-efficacy items refer to specific tasks, academic self-concept items typically refer to school work and school subjects (Bong & Skaalvik, 2003). Nevertheless, the constructs are related and share similarities: they are both perceptions of perceived competence that predict future performance, making it difficult sometimes to distinguish them conceptually and empirically (Marsh et al., 2019). Bong and Skaalvik (2003), for example, pointed out that the difference between the two constructs regarding social comparison is one of degree: external sources of information play a role in both but are less powerful for self-efficacy, because it is more strongly influenced by experiences with similar or identical tasks. Therefore, it is important to clearly delineate both concepts and make sure they measure related, but different constructs (Marsh et al., 2019). Nevertheless, it is interesting to include both measures in the prediction of achievement to investigate their possible complementary explanatory value regarding academic achievement.

In addition to self-beliefs, motivational factors also play a role in academic achievement. Students' attitude and motivation towards school and learning, for example, have been shown to be related to achievement (Credé & Kuncel, 2008; Pinxten et al., 2019). In this study 'motivation' was defined as "diligence, self-discipline, and willingness to exert the effort necessary to successfully complete academic requirements" (Weinstein et al., 2016, 8). Academic motivation can thus be understood as students' readiness to invest the necessary effort to fulfill their academic responsibilities successfully and consequently persist towards reaching their academic goals. Students' attitude towards school reflects their "attitudes and interests in college and achieving academic success" (Weinstein et al., 2016, 9). As Weinstein et al. (2016) pointed out, both motivation and attitude are related: if students do not see school as relevant to their life goals and attitudes, they will not be able to generate a sufficient level of effort. When aligned with Zimmerman's (2002) SRL-model, motivation can be seen as part of the forethought phase, more specifically as belonging to learning goal orientation, i.e. valuing the process of learning for its own merits. Attitude towards school, although not mentioned literally in the model, can also be related to the forethought phase, more specifically as the intrinsic value students have towards learning and school. In Zimmerman's model, both intrinsic value and learning goal orientation are considered intertwined, interest in school and its courses will increase motivation to put in effort to learn in a self-regulated manner (Zimmerman, 2002). Both variables also proved to be related to academic achievement: in the meta-analysis of Credé and Kuncel (2008), for example, motivation, as defined above,showed a sample size weighted mean correlation of 0.31 with first-year GPA and attitude a slightly smaller coefficient of 0.23. In a more recent study in Flanders, Pinxten et al. (2019) found a small significant correlation between attitude and the weighted first year GPA of STEM students, while motivation showed a small to medium sized correlation.

Additional non-cognitive variables that have shown a relation to academic achievement are learning strategies related to self-regulation, in this case time management, i.e. students' use of techniques for preparing for and taking tests, and test strategies, i.e. the extent to which students use test preparation and test-taking strategies (Demulder et al., 2020; Vermunt & Donche, 2017; Weinstein et al., 2016). In the SRL-model (Zimmerman, 2002), time management and test strategies can then be seen as belonging to the different task strategies in the performance phase; time management can also be considered as part of self-observation and self-recording, i.e. keeping track of the time spent studying. Credé and Kuncel (2008) found relatively small sample size weighted mean correlations of 0.23 for both variables. In a later study of Pinxten et al. (2019) in Flanders, time management showed a small to medium sized correlation with students' weighted first year GPA, while test strategies showed a small correlation.

2.3. Background factors

When investigating the prediction of academic achievement in HE, it is important to control for students' background factors, as they are also related to achievement. The present study will focus on two commonly used demographic predictors, namely gender and SES (socioeconomic status). Several studies provided evidence for these demographic influences on achievement: women as well as students with a higher socioeconomic status tended to be more successful in their studies

(Glorieux et al., 2015; Richardson et al., 2012; Robbins et al., 2004; Sackett et al., 2009; Van Rooij et al., 2017; Voyer & Voyer, 2014). Additionally, as mentioned above, several studies found evidence that a student's SE educational track is important in the prediction of academic achievement (Fonteyne et al., 2015; Fonteyne et al., 2017; Glorieux et al., 2015; Lacante et al., 2001; Richardson et al., 2012; Schelfhout, Wille, et al., 2022; Van Rooij et al., 2017; Willems et al., 2021).

In addition to SE study programmes, the specific HE programme can also be considered an important contextual variable (De Clercq, Galand, et al., 2021; Fonteyne et al., 2017; Schelfhout, Wille, et al., 2022; Van den Berg & Hofman, 2005). De Clercq, Galand, et al. (2021), for example, showed that 15 % of the variation in students' achievement can be attributed to differences between HE programmes. Herrmann et al. (2017) considered an academic study programme as a nexus of different layers of social practice that determines the ways teaching and assessment are being shaped by both the academic discipline as well as its institutional and departmental cultures and policies. This nested nature of the HE setting benefits from a multilevel approach that investigates the effect of the different predictors within study programmes in a single model. For example, having higher scores on a mathematics test might be more predictive in study programmes relying more on mathematical knowledge, such as physics or chemistry, than in programmes relying more on language ability such as linguistics or law. Context effects may also operate on the level of non-cognitive variables such as motivation or attitudes, for instance, depending on the degree to which a programme fits the interest profile of a student (Schelfhout et al., 2019; Schelfhout, Basleer, et al. 2022).

2.4. Academic achievement

There are different ways of operationalising academic achievement in HE. One measure, also used in models such as that of Tinto (1975, 1993) is whether or not a student drops out (or persists). A downside of this persistence measure, as Vandervieren and Casteleyn (2020) point out, is that this is less useful as a measure of achievement in more flexible HE systems such as in Flanders in which students can compose their own programmes and 'passing a year' is not as clearly delineated. Then, only (delayed) graduation remains as the (longitudinal) outcome. Another commonly used measure of achievement is students' grade point average (GPA), a measure of students' achievement level (Van Rooij et al., 2017). This is the average score across student's courses, usually weighted by the number of credits of the different courses. Another way of operationalising achievement, is study progress, i.e. the percentage of obtained credits. Study progress indicates the extent to which students have progressed in their degree programme (European Union, 2015). In Flanders, where this study was carried out, study progress is the official measure used by the government and the institutions to track students' HE academic achievement, making it an important variable to consider in research. In this study, therefore, study progress will be used as an outcome variable, denoted by the term '(academic) achievement'.

3. This study

Building on prior findings highlighting the incremental value of non-cognitive variables over traditional demographic and cognitive predictors, this study considered background (SES and gender), cognitive (vocabulary, mathematics, and non-verbal reasoning), and non-cognitive variables (academic self-efficacy, academic self-concept, attitude, motivation, time management, and test strategies). The present study built on prior research on various levels. Our study utilised a unique and broad dataset from a very large sample of last-year SE students from across Flanders, tracking their subsequent, including also long-term, HE careers, spanning a multitude of HE programmes. Also, as Flanders has an open access HE system, the sample was not preselected based on admission tests or achievement in SE. This implies that long-term relations may be investigated in a broader range of students entering higher education, including students that would have otherwise not been allowed to enrol, avoiding the range restriction problem that studies in selective access systems suffered from. This might yield more accurate estimations of the predictive value of non-cognitive and cognitive factors (Richardson et al., 2012; Robbins et al., 2004). Indeed, when populations are selected based on tests such as SAT, the variations of variable scores in the population are reduced, as only admitted first-year students are taken into account, so that the correlations between the predictors and the achievement variables will also be reduced, which masks the true importance of variables for academic achievement.

Third, to the best of our knowledge, no studies considered the important influence of the multi-level nature of data encompassing SE and HE programmes *together* in one statistical model. Nonetheless, considering the nested nature of the dataset, in which students completed the measurements in SE and later started HE, a multilevel model that considers both SE and HE study programmes as higher level units, as well as a random interaction between these units, seems to be the most appropriate (Goldstein and Sammons, 1997; Hill & Goldstein, 1998). The random interaction effect can conceptually be understood as the alignment of students' SE and HE programme, accounting for the possibility that HE programmes may have varying effects for students from different SE programmes and vice versa (Leckie, 2013). This might be particularly relevant in an open-access HE system; for instance, a student may find greater success in HE engineering studies if they come from an SE programme with a focus on mathematics and sciences rather than languages, while students coming from a SE programme with less emphasis on mathematics and sciences might be less successful. Lastly, the long-term impact of background-, cognitive-, and non-cognitive factors as pre-entry factors on achievement was seldom explored. Therefore, our analyses focused on assessing their effects on both short- and long-term academic achievement to gain a comprehensive understanding of the longitudinal impact of these variables taking the alignment of SE and HE into account (De Clercq, Jansen, et al., 2021).

The following research questions are central to this study:

RQ1. To what extent do SE and HE study programmes, and their alignment, impact HE students' short- (after one year in HE) and long-term (across three years in HE) academic achievement?

RQ2. To what extent do background-, cognitive-, and non-cognitive factors impact short- and long-term academic achievement, after controlling for SE and HE study programmes?

4. Materials and method

In this section, we report how we determined our sample size, all data exclusions and operations, and all measures in the study. The study was not pre-registered, however, anonymised data and associated statistical codes are available on request from the corresponding author. The data are not publicly available due to privacy and ethical restrictions.

4.1. Participants

In this study, we used a representative Flemish dataset from the Columbus project, a large-scale project in which a self-exploration instrument was developed to support the career decision-making processes of students nearing the end of SE (Demulder et al., 2020). The validated instrument comprises several questionnaires and tests and aims to provide students with personalised feedback, to help them explore their possibilities, strengths, areas for improvement, and to offer them remedial advice. It also serves as a research initiative of the Flemish Department of Education and Training wherein crucial cognitive and non-cognitive pre-entry student variables related to academic achievement in HE are assessed during the last year of SE.

Two cohorts from the Columbus project were used in this study; the first cohort (2016–2017) served as a calibration sample ($N_{16–17}$ = 11,124), while the second (2017–2018) was used as a validation sample ($N_{17–18}$ = 13,059). After the assessment in the last year of SE, the academic achievements of these respondents were tracked throughout their HE trajectories. 1754 students in the calibration sample and 2721 students in the validation sample did not start HE after their last year in SE. For our analyses, only 'full-time' HE students were retained, who according to the Flemish government are students that take up at least 27 ECTS credits in an academic year (Flemish Government, 2023). The term 'full-time', as used by the government, might be slightly misleading in this case as this is less than half the number of credits students enrol for in a normal study trajectory, which is mainly 60 credits in the first year of HE. This cut-off is used by the government to determine whether students are still dependent on their parents so that they are still eligible to receive child allowance. In the calibration sample, 324 students took up <27 credits in the first year, in the validation sample this group consisted of 336 students. As such, the final calibration and validation samples comprised 9046 and 10,002 respondents, respectively.

Ethical review and approval was not required for this study on human participants in accordance with the local legislation and institutional requirements. The datasets on which this study is based are part of a larger project, Columbus, commissioned by the Flemish Ministry of Education and Training. Written informed consent was obtained from all participants. When registering, students agree to the terms and conditions formulated in collaboration with the Data Protection Officer of the Ministry of Education and Training and in accordance with the General Data Protection Regulation (GDPR). The Ministry strictly follows the principles of the GDPR when processing personal data. The sharing of personal data requires a protocol. The extensive Columbus protocol (January 27, 2021) can be found at https://data-onderwijs.vlaanderen.be/documenten/bestand.ashx?id=13051

The respondents in these samples were nested in both SE and HE study programmes (see Table 1 for *N* of the grouping variables), which were provided from an administrative database from the Flemish government. Regarding secondary school classification, Belgium has a tracked educational system, in which secondary school students choose for academic, technical, artistic, or vocational studies and within each of these educational types can further choose a study field. For some examples, within academic studies students can focus on sciences, economics, or languages; within technical studies students can focus on electromechanics, tourism, or wellness sciences; within artistic studies students can focus on drama, architecture, or fine arts; and within vocational studies students can focus on landscaping, cosmetology, or childcare. As academic and technical studies offer the most possibility for higher education studies, the majority of students in our sample were in either academic (61.3 %) or technical (35 %) study fields, with small percentages studying artistic (1.7 %) and vocational (2 %) topics. In higher education, students can pursue a programme of study leading to an academic or professional bachelor degree. For academic degrees (leading to ISCED level 7) students can pursue many options within Sciences (i.e psychology, medicine, communication sciences, etc), Arts (i.e. linguistics, philosophy, history, etc.), or Law; in university colleges offering programmes that lead to ISCED levels 5 and 6, students can pursue studies within these fields at a less theoretical and more applied level, for instance nursing, business management, social work, or digital media, to name a few of many options. Sixty-eight percent of the students over the two cohorts hailed from schools that participated in both academic years examined in this study, while 32 % of students came from a school that only participated in either cohort 16–17 or cohort 17–18. Female students in the calibration and validation sample constituted 57.4 % and 58.5 % of all respondents, respectively, which is representative for Flemish higher education participation. On average, the age of respondents was 18 years, and the average birthday in the two cohorts differed by nineteen days relative to each cohort's respective year.

It is essential to highlight that the effective implementation of multiple imputation (as described in the 'Analyses' section) required the creation of two distinct datasets within each cohort. One dataset was specifically tailored for assessing short-term academic achievement, while the other was dedicated to investigating long-term academic achievement. It is worth noting that a substantial number of students withdrew from HE between the first and third years in our study samples ($N_{16–17}$ = 1112; $N_{17–18}$ = 842). As a result, these respondents were intentionally excluded from the long-term academic achievement datasets. This exclusion is due to the fact that data needs to be at least missing at random for multiple imputation to be accurately implemented (Peng et al., 2016), and as such it would not be correct to impute variable values for students for whom data was missing because of the non-random decision to drop out of higher education, which is obviously related to the independent variables.

4.2. Measures

4.2.1. Student background factors

In this study, we have incorporated students' gender and socioeconomic status (SES) as key background variables. The Flemish government utilises four SES risk indicators in the domain of education to determine eligibility for supplementary equal opportunity government funding (Flemish Government, 2018). These indicators encompass the following criteria for identifying students at risk: (1) students who either do not use Dutch, the language of instruction, within their household, or students who exclusively communicate in Dutch with only one out of three family members (with siblings being counted as one family member in this calculation); (2) students whose mother's highest level of education is a primary school degree; (3) students residing in neighbourhoods characterised by educational delays; and (4) students receiving a study allowance during their SE. These four SES indicators were provided by the database on education of the Flemish government and were included in the analyses as dichotomous variables. In cohort 16–17, the percentage of students with each of the risk factors was (1) 8.9 %, (2) 13.7 %, (3) 19.5 %, and (4) 25.7 %, while in cohort 17–18 the percentages of students per risk category were (1) 7.9 %, (2) 12.3 %, (3) 16.8 %, and (4) 21.2 %.

4.2.2. Cognitive measurements

Cognitive abilities of students were conceptualised in terms of (1) numerical skills, (2) vocabulary knowledge, and (3) non-verbal reasoning. The test measuring *numerical skills* used in this study comprises 25 items on basic mathematics and algebra in seven mathematical topics (Fonteyne et al., 2015): numerical knowledge and order of operations, operations with decimals, operations with brackets, operations with fractions, and algebra (unknown variables, proportions, and the rule of three). The items of this test were based on the subject-specific learning objectives for the third grade of the general SE track.

Vocabulary knowledge was measured using LexTALe, a lexical decision task using yes/no answers (Lemhöfer & Broersma, 2012). The test consists of 60 items of which 40 words and 20 nonwords. The measure provides an indication of students' vocabulary knowledge and general language proficiency. The test, originally developed as a measure for L2 students is found to be relatively easy for L1 students (Vander Beken & Brysbaert, 2018) but nevertheless has shown relatively small but significant correlations with first-year achievement in several university faculties (Fonteyne et al., 2017; Schelfhout, Wille, et al., 2022).

Non-verbal reasoning was measured using a test called 'Rules', inspired by the Raven Standard Progressive Matrices (SPM) (Raven et al., 1998). The Raven SPM was developed to measure fluid intelligence (*Gf*), a measure of cognitive ability which consists of meaning-

Table 1
N of grouping variables in both cohort 16–17 and cohort 17–18.

	Cohort 16–17 (calibration)		Cohort 17–18 (validation)	
	Short-term academic achievement sample	Long-term academic achievement sample	Short-term academic achievement sample	Long-term academic achievement sample
SE study programmes	93	83	85	77
HE study programmes[1]	139	173	142	176

[1] *Note:* For short-term academic achievement analyses, the HE study programme in the first year is considered, while for long-term academic achievement analyses, the HE study programme in the third year is considered.

making ability and reproductive ability, i.e. being able to reproduce information and acquired skills. This measure was also strongly related to general cognitive ability, i.e. Spearman's *g* (Kvist & Gustafsson, 2008; Raven, 2008). The advantage of this Raven-like test is that it is easy to administer and, as it is non-verbal, can be used in different language contexts.[2] Table 2 shows the number of items, mean and standard deviation as well as Cronbach's alpha for the cognitive tests used in both the calibration and the validation sample.

4.2.3. Non-cognitive measurements

The data collection process in this study is founded on the online Columbus instrument, which encompasses a total of 25 non-cognitive variables. However, incorporating this extensive set of variables into our analysis would not be advisable due to the potential introduction of redundancy effects. Such a scenario could arise because these variables would need to compete for a relatively limited portion of unique variance in the dependent variable, as indicated by previous research (Cohen et al., 2013; Grewal et al., 2004). In light of this consideration, and in line with our research questions, we followed the approach employed by Richardson et al. (2012) and Robbins et al. (2004) by adopting a selective process for the inclusion of non-cognitive variables. Specifically, we chose to retain only those non-cognitive variables showing a correlation coefficient of 0.10 or higher with short- and long-term academic achievement in both of our study samples. Consequently, the following non-cognitive variables were included as predictors in our regression models: Academic Self-efficacy, Academic Self-concept, Attitude, Motivation, Time-management, and Test strategies.

These six non-cognitive variables were measured using scales from two instruments: the validated LEarning strategy and MOtivation questionnaire (LEMO; Donche et al., 2010) and the Learning And Study Strategies Inventory (LASSI; Weinstein et al., 2016). To measure self-concept, an adjustment of the academic self-concept subscale developed by Wouters et al. (2011) was included. Table 3 shows the number of items, an item example, and the reliability of these variables in both the calibration and validation dataset, as well as the source of the scale. As Marsh et al. (2019) pointed out the importance of avoiding too much overlap between the Self-efficacy and Self-concept scales, correlations between the two scales were also calculated. With a correlation of 0.620 ($p < .001$, $N = 8391$) in the calibration dataset, and 0.618 ($p < .001$, $N = 9081$) in the validation dataset, both scales, although they do show some expected overlap with 38 % shared variance, clearly measure distinct constructs.

Table 2
Number of items (# Items), mean (*M*), standard deviation (*SD*), and Cronbach alpha (α) of the cognitive scales in both calibration and validation samples.

Scale	# Items	*M (SD)* Calibration	*M (SD)* Validation	α Calibration	α Validation
Numerical skills	25	17.42 (5.58)	17.29 (5.76)	0.87	0.87
Vocabulary[1]	60	85.01 (9.58)	85.40 (10.94)	0.71	0.66
Non-verbal reasoning	28	19.93 (4.98)	19.48 (5.27)	0.81	0.81

[1] Note. Vocabulary scores are expressed as percentages.

4.2.4. Academic achievement

Academic achievement variables were provided by the Flemish government. Academic achievement was operationalised as study progress, which is the number of ECTS study points obtained by a student in a period of time, divided by the total number of credits registered for in that period. Short-term academic achievement encompassed credits earned and registered for after the first year of HE, while long-term academic achievement comprised the **cumulative** credits obtained and registered for across the initial three years of HE. In other words, first year study progress is included in the three-year study progress variable. The three-year timeframe for long-term study progress aligns with the theoretical duration for obtaining a bachelor's degree.

5. Analyses

As respondents are nested within SE and HE study programmes, our data exhibited a multilevel organisation (Goldstein, 2011). However, as mentioned earlier, these data are not structured in a 'strict' hierarchical fashion, as SE study programmes are not nested within HE study programmes or vice versa. Rather, students from different SE tracks can attend different HE study programmes, and as such respondents are simultaneously nested within multiple non-hierarchical settings. Fig. 1 serves as an illustration of the general principle of the nested nature in a cross-classified multilevel model. Cross-classified multilevel models allow to account for such a two-level structure, with students at level 1 nested within the cells of a second level cross-classification (Goldstein, 1994; Rasbash & Goldstein, 1994). Ignoring this cross-classified structure can lead to biased standard error estimates and variance components (Meyers & Beretvas, 2006; Thomas and Heck, 2001).

To answer RQ1, for both short- and long-term academic achievement, we estimated four consecutive mixed effects null-models using the lme4 package in R (Bates et al., 2009), and tested which fitted best to the data. The first null-model (M01) is a strict hierarchical null model that included only SE programmes as second level units. The second model (M02) contains only HE programmes at level two. Model three (M03) is a cross-classified multilevel null-model, containing both SE and HE programmes as second level units. The fourth null-model (M04), then, is a cross-classified multilevel null-model with random interaction effect between the second level units. Including the random interaction effect in M04 allows for modelling that HE programmes are likely to have different effects for students from different SE programmes and vice versa (Leckie, 2013; Shi et al., 2010). By comparing these models, insight is gained into the question whether, how, and to what extent

[2] A pilot study was conducted correlating the new 'Rules' test and SPM. A Spearman correlation of 0.62 was found ($p = .000$, $n = 76$). Van Cauwenberghe et al. (under review) further investigated and confirmed its validity.

Table 3
Number of items (# It), item example Cronbach alphas (α), and source of the non-cognitive scales.

Scale	# It	Item example	$\alpha_{Calibration}$	$\alpha_{Validation}$	Source
Academic Self-efficacy	4	I think I can study well.	0.88	0.88	LEMO
Academic Self-concept	7	I'm doing well in school.	0.85	0.85	Wouters et al. (2011)
Attitude	6	I would rather no longer attend school.	0.61	0.60	LASSI
Motivation	6	Even if I don't like a task, I can push myself to work on it.	0.73	0.73	LASSI
Time-management	6	When I decide to study, I determine in advance how long I will study and I stick to it.	0.70	0.70	LASSI
Test strategies	6	It is difficult for me to adapt the way I study to the different types of subjects.	0.67	0.67	LASSI

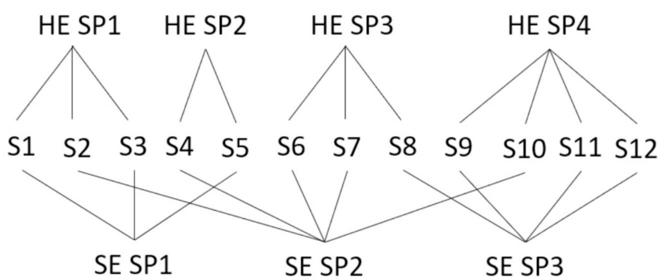

Fig. 1. An illustration of the cross-classification principle: 12 Students (S) at Level 1 are nested within a SE study programme (SE SP) and HE study programme (HE SP) cross-classification at level 2.

both higher levels (SE and HE study programmes) jointly impact short- and long-term achievement.

Continuing from these analyses, to answer RQ2, again, four progressively built models were estimated. The first model is the null-model that in previous analyses deemed to be best-fitting. In a next step, a random intercepts model (M1) is estimated by adding the background variables to the null-model. Consecutively, the abovementioned cognitive (model M2) and non-cognitive (model M3) variables were added, and the fit of all these models was compared both in the 2016–2017 and in the 2017–2018 cohort. These analyses were all carried out in R.

For the comparison of different models, the information-theoretic approach to model selection is applied (Anderson, 2008; Burnham et al., 2011), in which the Akaike's Information Criterium (AIC; Akaike, 1973) takes a pivotal role. In short, after fitting each of the above-described models to the data, the AIC of each fitted model is estimated, and models are ranked in order of ascending AIC values (highest AIC value at the bottom). As such, the top-ranked model is best in approximating full reality (Anderson, 2008). Next, based on the differences in AIC values between the compared models, several AIC effect sizes are computed to quantify the strength of evidence for each model (van Daal, 2020): (1) differences in AIC (Δ AIC); (2) weight of evidence (w); and (3) evidence ratio (E). These AIC effect sizes are described in Table 4.

To accurately compare the fit of the different mixed effect models, they need to be estimated on identical samples. However, as Little's (1988) test statistic showed to be significant in our data, we could not assume that the missingness in our data was completely at random (MCAR), and therefore a listwise deletion might produce bias in our sample (Myers, 2011). In this case, multiple imputation (MI) is a powerful method for handling missing data in statistical analysis. MI involves generating several plausible values for the missing data, creating multiple completed datasets (in the present study 5), on which multilevel analyses are executed separately. The resulting estimates are then aggregated using Rubin's Rules, which are designed to incorporate proper uncertainty into final estimates when dealing with missing data. This approach effectively mitigates bias in parameter estimates (Rubin, 2004).

Table 4
AIC effect sizes.

AIC effect size	Description
Differences in AIC (Δ *AIC*)	Expresses the distance in *AIC* between the best fitting model (lowest *AIC*) and each other model: $\Delta\ AIC = AIC_i - AIC_{best}$ As $\Delta\ AIC$ increases, the plausibility of model *i* to be the best approximation of reality decreases.
Weight of evidence (*w*)	Expresses for each candidate model the probability of being the best model in approximating full reality. It is the likelihood of a model I divided by the sum of the likelihoods of all of the candidate models (e.g., $w_y = 0.50$ corresponds to a probability of 50 % that model *y* is the best model.)
Evidence ratio (*E*)	Expresses the difference in AIC between two models in odds. Can be calculated by dividing the likelihood of the best-fitting model by the likelihood of model *i*.

It should be noted here that for the calculation of pooled *AIC* test statistics and marginal (addresses the variance attributed to only fixed effects) and conditional (incorporates both fixed and random effects; see Nakagawa & Schielzeth, 2013) R^2 values, Rubins rules were not applied, as – to our knowledge – there is no means to extract such values from the mixed-methods models used (lme4 package in R). Therefore, AIC test statistics and R^2 values were extracted from each of the five individually imputated datasets, after which they were averaged (Van Ginkel et al., 2020). Further, it is also worth mentioning that, given the absence of missingness in both the outcome variable (academic achievement) and cluster variables, the null models are estimated using the non-imputed dataset (as there is no need for pooling according to Rubin's rules).

6. Results

6.1. *Impact of SE and HE study programmes on short- and long-term academic achievement*

The results provide clear evidence that the cross-classified multilevel null-models with random interaction effect between the second level units (M04, see Supplementary Table 1) are best fitting with the data, both for short- and long-term academic achievement. This is true for cohort 16–17 as well as cohort 17–18. Let us illustrate this by focusing on the sample of cohort 16–17, for short-term academic achievement; Model M04 is ranked as the most plausible, as it demonstrated the lowest *AIC* value. The other candidate models are >1000 times less likely to be the best fitting model (E > 1000). Furthermore, model selection uncertainty for model M04 is virtually non-existing ($w = 1$), and thus, M04 was retained for further analyses.

Followingly, we investigated the ICC values for the different grouping variables of the models, in explaining short- and long-term academic achievement (See Supplementary Table 2). In every sample analysed, we observed substantial increases in the ICC values of both grouping variables when simultaneously incorporating SE and HE study programmes in the cross-classified models (Models M03 and M04), as compared to the strict models where SE and HE programmes were included separately (Models M01 and M02). This indicates that we would underestimate the explained variance in academic achievement by SE and HE study programmes, when considering them separately in our analyses.

In examining model M04 more closely, several distinctions between short- and long-term outcomes emerge. Although we reference the results of the calibration sample (cohort 16–17) here, findings for the validation sample (cohort 17–18) are analogous and can always be found in the table presenting the corresponding results. First, the influence of the SE study programme on long-term academic achievement (ICC = 0.05) appears to diminish when juxtaposed with its short-term effects (ICC = 0.27). Second, the impact of the HE study programme rather demonstrates stability over a three-year span (Short-term ICC = 0.12; Long-term ICC = 0.15). Intriguingly, the random interaction effect between the SE and HE study programmes gains importance over the long term (Short-term ICC = 0.02; long-term ICC = 0.08), suggesting an increasing importance of the alignment between the two programmes as students advance in their HE trajectories.

6.2. Impact of background-, cognitive-, and non-cognitive variables on short- and long-term academic achievement

Building up from the multilevel null-models that incorporate a random interaction effect (M04; see Supplementary materials), the findings indicated that the random intercepts models including all student-level predictors (background, cognitive, and non-cognitive variables; denoted as models M3) provide most optimal fit to the data (See Supplementary Table 3). This holds true for both short-term and long-term academic outcomes and is consistent across both the 16–17 and 17–18 cohorts. To exemplify, when examining the 16–17 cohort's short-term academic achievement, Model M3 emerges as the most credible according to the AIC index. In contrast, the alternative models are over 1000 times less probable to best fitting (E > 1000). Additionally, there is negligible model selection uncertainty for Model M3 (w = 1), leading to its selection for subsequent analyses.

In Tables 5 and 6, the pooled fixed and random effects' parameter estimates for the short-term and long-term M3 models are presented, accompanied by their pooled 95 % confidence intervals for cohort 16–17 and cohort 17–18. When examining cohort 16–17 in relation to short-term academic performance, it becomes clear that all background variables exhibit a negative fixed effect, and inferences can be made with regard to these estimates beyond the sample at hand. For the cognitive variables, significant positive relationships are evident for mathematics and reasoning. However, the effect of vocabulary is not generalizable to the broader population. Lastly, among the non-cognitive factors, all variables except test strategies significantly predict short-term academic achievement, with academic self-concept emerging as the most important predictor.

Upon contrasting the effects of background, cognitive, and non-cognitive variables on long-term achievement against those on short-term achievement, distinct patterns become evident. Firstly, the impact of background variables appears to intensify over the long term, in both calibration and validation samples. Specifically, being male or being at risk due to any of the SES factors increasingly predicts a negative trajectory for long-term academic achievement compared to short-term outcomes. Conversely, the influence of cognitive factors assessed at the end of SE generally wanes over time, though they remain present. The analyses regarding the non-cognitive variables provide a somewhat less clear picture across the two cohorts. It does seem evident that the effect of academic self-concept appears to decline over time, and the effect of attitude vanishes entirely. The effects of academic self-efficacy and time management remain stable or slightly intensify.

Table 7 delineates both the marginal and conditional R^2 values for models M1 (comprising solely background variables), M2 (background + cognitive variables), and M3 (background + cognitive + non-cognitive variables). These values are provided for both cohorts and for both short- and long-term academic achievement. Firstly, our final M3 models explain a considerable proportion of the variance in the outcome variables. In the 16–17 cohort, the models account for 44.6 % of the variance in short-term and 39.5 % in long-term academic achievement. Additionally, the marginal R^2 values, which highlight the explained variance ascribed solely to fixed effects, affirm that both cognitive and non-cognitive variables contribute distinctively to the variance in short- and long-term academic achievement. For instance, in the 16–17 cohort, the added value of cognitive variables beyond background variables amounts to 1.8 % in predicting short-term academic achievement. Similarly, the incremental contribution of non-cognitive variables, when considered alongside background and cognitive variables, is 3.6 %. Furthermore, when considering long-term academic achievement, cognitive ($\Delta R^2 = 1.3$ %) and non-cognitive ($\Delta R^2 = 3.5$ %) variables also have incremental value. Of course, one should also keep in mind that these analyses also accounted for SE and HE programmes.

Table 5
Estimates (Est.) and 95 % confidence intervals (95 % CI) of the fixed and random effects of the short- and long-term M3 models, for cohort 16–17.

Cohort 16–17	Short-term		Long-term	
	Est.	*95 % CI*	*Est.*	*95 % CI*
Fixed effects				
Intercept	−0.096	−0.243 | 0.051	0.113	0.025 | 0.200
1. Background				
Gender (female)	−0.221	−0.266 | -0.176	−0.299	−0.348 | -0.250
Home language (no risk)	−0.239	−0.311 | -0.168	−0.442	−0.523 | -0.361
Degree mother (no risk)	−0.182	−0.239 | -0.125	−0.206	−0.271 | -0.141
Neighbourhood (no risk)	−0.123	−0.172 | -0.075	−0.195	−0.249 | -0.141
Study allowance (no risk)	−0.143	−0.190 | -0.097	−0.195	−0.248 | -0.143
2. Cognitive				
Math	0.078	0.050 | 0.105	0.045	0.016 | 0.074
Vocabulary	0.021	−0.000 | 0.042	0.029	0.006 | 0.052
Reasoning	0.034	0.012 | 0.056	0.031	0.005 | 0.057
3. Non-cognitive				
Academic self-efficacy	0.062	0.032 | 0.092	0.078	0.046 | 0.110
Academic self-concept	0.117	0.091 | 0.143	0.057	0.030 | 0.084
Attitude	0.042	0.019 | 0.065	−0.003	−0.028 | 0.022
Motivation	0.026	0.001 | 0.051	0.026	−0.002 | 0.055
Time management	0.037	0.012 | 0.062	0.049	0.023 | 0.076
Test strategies	0.002	−0.025 | 0.029	−0.001	−0.026 | 0.025
Random effects	σ^2		σ^2	
SE programme	0.258		0.030	
HE programme	0.183		0.097	
SE programme * HE programme	0.015		0.069	
Residual	0.710		0.739	

Note. The cognitive and non-cognitive variables are standardised values.

7. Discussion & conclusion

While a substantial amount of previous research has explored the determinants of academic success in HE, this research has overlooked the multi-level nature of data encompassing *both* SE and HE programmes, typically only focused on entry-level predictors at the start of HE, and seldom addressed long-term HE achievement in relationship with pre-entry student factors measured in SE. This study addresses these limitations by analysing the influence of SE and HE programmes on both the short-term and long-term academic achievements of HE students, in a very large sample that was longitudinally tracked after a broad (non-)cognitive assessment. It therefore examines the impact of a wide range of background, cognitive, and non-cognitive factors on these academic achievement measures, controlling for the effects of SE and HE

Table 6
Estimates (Est.) and 95 % confidence intervals (95 % CI) of the fixed and random effects of the short- and long-term M3 models, for cohort 17–18.

Cohort 17–18	Short-term		Long-term	
	Est.	*95 % CI*	*Est.*	*95 % CI*
Fixed effects				
Intercept	−0.128	−0.277 | 0.020	0.139	0.053 | 0.226
1. Background				
Gender (female)	−0.252	−0.296 | -0.207	−0.295	−0.342 | -0.249
Home language (no risk)	−0.216	−0.288 | -0.144	−0.474	−0.552 | -0.396
Degree mother (no risk)	−0.223	−0.282 | -0.165	−0.250	−0.314 | -0.187
Neighbourhood (no risk)	−0.104	−0.153 | -0.055	−0.133	−0.186 | -0.080
Study allowance (no risk)	−0.141	−0.187 | -0.095	−0.181	−0.231 | -0.131
2. Cognitive				
Math	0.064	0.036 | 0.091	0.037	0.010 | 0.063
Vocabulary	0.008	0.011 | 0.027	0.009	−0.017 | 0.035
Reasoning	0.046	0.020 | 0.071	0.012	−0.013 | 0.037
3. Non-cognitive				
Academic self-efficacy	0.092	0.065 | 0.119	0.094	0.064 | 0.123
Academic self-concept	0.100	0.076 | 0.124	0.044	0.018 | 0.070
Attitude	0.039	0.015 | 0.062	−0.024	−0.049 | 0.001
Motivation	0.025	−0.000 | 0.050	0.054	0.027 | 0.081
Time management	0.011	−0.014 | 0.037	0.042	0.017 | 0.068
Test strategies	0.006	−0.019 | 0.031	−0.008	−0.033 | 0.017
Random effects	σ^2		σ^2	
SE programme	0.238		. 035	
HE programme	0.198		0.083	
SE programme * HE programme	0.017		0.058	
Residual	0.738		0.759	

Note. The cognitive and non-cognitive variables are standardised values.

Table 7
Marginal and conditional R^2 for short- and long-term achievement in cohorts 16–17 and 17–18.

		Short-term			Long-term		
		M1*	M2*	*M3**	M1*	M2*	*M3**
Cohort 16–17	Marginal R^2	0.038	0.054	*0.090*	0.074	0.087	*0.122*
	Conditional R^2	0.401	0.374	*0.446*	0.333	0.325	*0.395*
Cohort 17–18	Marginal R^2	0.036	0.048	*0.082*	0.064	0.069	*0.102*
	Conditional R^2	0.380	0.362	*0.431*	0.319	0.312	*0.373*

* Note. M1 = Model 1: solely background variables; M2 = Model 2: background + cognitive variables; M3 = Model 3: background + cognitive + non-cognitive variables.

programmes. Our study extends the previous research by employing cross-classified multilevel modelling with a random interaction term between SE and HE levels, utilizing an exceptionally extensive and representative dataset (encompassing two separate cohorts), enabling highly robust analyses.

7.1. Impact of SE and HE study programmes on short- and long-term academic achievement

In addressing the first research question on the influence of SE and HE study programmes on the short- and long-term academic achievement of HE students, the findings of the cross-classified multilevel null-models with random interaction effect between the second level units, indicate that both SE and HE programmes affect academic achievement in both time frames. These analyses reveal that while the SE programmes' impact is more pronounced in short-term achievement, it diminishes in the context of long-term achievement. This finding aligns with existing literature that identifies pre-HE tracks as a significant predictor of first-year academic achievement (Fonteyne et al., 2015; Fonteyne et al., 2017; Glorieux et al., 2015; Lacante et al., 2001; Richardson et al., 2012; Schelfhout, Wille, et al., 2022; Van Rooij et al., 2017), while research on its long-term effect is scarce.

Furthermore, while the HE programmes' impact on academic achievement (De Clercq, Galand, et al., 2021; Van den Berg & Hofman, 2005) remains consistent over time, the random interaction between SE and HE study programmes gains greater importance in the long-term perspective. This interaction term can conceptually be understood as the alignment between SE and HE programmes (Leckie, 2013; Shi et al., 2010). For instance, it stands to reason that a language- or mathematics-focused SE programme may impact achievement differently, depending on what HE programme a student enrols in. Indeed, a student who pursues a mathematics programme in HE might achieve better results with a background in mathematics from their prior education. The finding that the random interaction effect gains more importance over the longer term implies that the alignment between SE and HE programme is particularly decisive for academic achievement over a three-year span, rather than just in the first year. This may be surprising as first-year graduation could imply that sufficient skills and knowledge were acquired to initiate the program, and disadvantaged students from poorly aligned SE programmes receive the same HE input after this first-year test. This rationale does not seem to hold. This might instead suggest that the prior skills and knowledge acquired in SE may become increasingly relevant and beneficial throughout the duration of an HE programme, or alternatively, there might be some sort of cumulative effect of gaps in foundational knowledge and skills across time. This area warrants further exploration in future research endeavours.

7.2. Impact of background-, cognitive-, and non-cognitive variables on short- and long-term achievement

When looking at the extent to which background-, cognitive-, and non-cognitive variables impact short- and long-term academic achievement, after controlling for SE and HE study programmes, several patterns became evident. The most comprehensive model (including all predictor variables) was found to fit the data best, and shows that, after controlling for SE and HE study programme, background, cognitive, and non-cognitive variables remain important predictors of short- and long-term achievement. Exploration of the marginal and conditional R^2 values revealed that each category of variables uniquely contributes to explaining the variance in the academic achievement outcomes (e.g., Credé & Kuncel, 2008; Richardson et al., 2012).

Firstly, and as expected, the background variables (gender and SES) all had an impact: academic achievement is significantly lower for male students, students who speak another language at home, whose mother had not obtained a SE degree, who came from a neighbourhood with study delays and who receive a study allowance (Glorieux et al., 2015; Richardson et al., 2012; Robbins et al., 2004; Sackett et al., 2009; Van Rooij et al., 2017). Interestingly, when comparing their effect on the short and long-term, background variables seem to become more important over time in both the calibration and validation sample. This trend aligns with existing literature on the compounding impact of SES-related risk factors in younger children's educational trajectory (e.g., Atkinson et al., 2015), suggesting that such cumulative effects persist also into HE (Lardy et al., 2022).

Regarding the cognitive variables assessed at the end of SE, this study aligns with prior research in showing a positive effect of numerical skills and non-verbal reasoning on short-term academic achievement (e.g., Fonteyne et al., 2015, 2017; Kuncel & Hezlett, 2010; Schneider & Preckel, 2017). However, diverging from previous findings, the current investigation does not provide robust evidence to support the notion that vocabulary knowledge significantly influences academic achievement at the end of the first year of HE (Fonteyne et al., 2017; Schelfhout, Wille, et al., 2022; Vandervieren & Casteleyn, 2020). This finding may be attributed to the comprehensive set of control variables included in our study, which extends beyond the scope of many other studies, also encompassing factors such as students' home language and accounting for the variance associated with SE and HE programmes. Furthermore, the results of the effects of all the cognitive variables on long-term achievement suggest that the influence of these factors assessed at the end of SE generally diminishes thus indicating a washing-out effect of these variables as students advance in their studies. It is plausible that more specialised knowledge and skills imparted in HE, as opposed to the broader competencies acquired in SE, hold greater importance for long-term success in higher education, which presents an intriguing avenue for future research. It should also be mentioned here that that there was limited control over the administration conditions of the cognitive tests (although classroom administration was strongly recommended, students could also complete the tests at home), which might have impacted the predictive value of the measures. Nonetheless, despite this limitation, our study found incremental value in the cognitive measures even within the 'messy' real-world setting of our research.

Further it was observed that most of the non-cognitive variables, are, as expected, positively related to short-term academic achievement. Students displaying higher levels of academic self-efficacy and self-concept, attitudes, motivation, and time management skills at the end of SE, tend to perform better at the end of the first year of HE (Credé & Kuncel, 2008; De Clercq, Galand, et al., 2021; Fonteyne et al., 2017; Krumrei-Mancuso et al., 2013; Richardson et al., 2012; Robbins et al., 2004; Van Rooij et al., 2018; Vermunt & Donche, 2017; Willems et al., 2019; Willems et al., 2021). Emerging as important predictors were academic self-beliefs, encompassing academic self-efficacy and self-concept. This aligns with extant literature (e.g., Willems et al., 2019; Richardson et al., 2012). With respect to the results found for motivation, it has to be noted that this study has used a particular operationalisation of this concept. A broader conceptualisation of motivation, also capturing quality of motivation (e.g. autonomous motivation; Deci & Ryan, 2000), for instance, would provide an interesting avenue for further research. Contrary to previous studies (Pinxten et al., 2019), the study found that test strategies did not significantly predict short-term academic achievement. The long-term analysis provides a somewhat less clear picture across cohorts. There does appear to be a diminishing effect of academic self-concept, while the predictive value of attitude recedes entirely. This pattern may be partially attributed to the dynamic nature of these variables, as they tend to evolve during a student's academic trajectory (e.g., Kyndt et al., 2015; Bong & Skaalvik, 2003). Intriguingly, the impacts of academic self-efficacy and time management, either remain consistent or intensify over time, which further underscores the value of assessing these student variables at the end of SE.

By investigating the pre-entry characteristics and influence of SE and HE study programmes on the short- and long-term achievement of HE students, this study also contributes to the construction of theoretical models on the transition from SE to HE (Biggs et al., 2001; Braxton et al., 2000; Tinto, 1975, 1993; Van Rooij et al., 2017). It specifically adds a layer of complexity to the conceptualization of pre-entry characteristics. Where these models typically characterise pre-entry-characteristics such as cognitive variables, motivational variables and pre-HE education as singular variables, our study clearly shows that the individual characteristics, i.e. the non-cognitive, cognitive and demographic variables, are not stand-alone but are nested within the educational contexts of both SE and HE. Moreover, the results show that they can be considered as true pre-entry characteristics in the sense that they can provide meaningful information to students before HE enrolment. Furthermore, this study also shows the importance of taking measures of both short- and long-term academic achievement into account in a theoretical model. While, as Van Rooij et al. (2017) point out, short-term achievement might be a strong predictor of long-term achievement, this study showed that the predictive nature of pre-entry variables changes over time, emphasizing the importance of adding a measure of long-term achievement into theoretical models of achievement in HE.

7.3. Limitations of the present study

In interpreting the results of this study, it is important to acknowledge various limitations. First, the Columbus instrument, the source of this study's data, should not be regarded solely as a collection of tests and questionnaires. Its primary objective is to provide SE students with feedback on the assessed variables, enabling them to undertake remedial action to enhance their transition to HE, if necessary. Consequently, participation in the Columbus programme may itself act as an intervention and was also set up to be one, potentially diminishing the impact of these variables on student achievement for some students. Students received feedback after completing the tests in SE. In 2016–2017 Columbus was administered as a pilot and students only received limited feedback in the second half of the school year. The feedback contained an explanation of the test content of the different measures and why they are important for HE study success. The feedback on the non-cognitive variables provided remedial tips. The feedback in 2017–2018 was more extensive as it was based on the pilot in 2016–2017. Students additionally received scores on all the cognitive variables and feedback was norm-referenced and compared to the students from the previous cohort, both the group as a whole as to students from the different SE study tracks. However, there was no information on students' follow-up actions or how they acted on the feedback. Despite a possible interference from the feedback, the extensive dataset obtained from the Columbus instrument, as well as the calibration-validation design, enabled an exceptionally robust analysis, revealing meaningful effects. However, conducting a parallel study in which students do not receive feedback would be worthwhile to accurately determine its actual effects.

Secondly, the research considered the diverse contexts within students' educational trajectories, focusing on the multilevel structure of the data regarding SE and HE programmes. The results highlight the importance of this approach, as a considerable proportion of variance is attributable to these levels and their interplay. However, the current study incorporated only student-level predictors (i.e., background, cognitive, and non-cognitive factors) in the analysis. Consequently, it does not provide specific insights into how particular context variables at the institutional level, such as average class size or evaluation methods in different programmes, influence academic achievement in both the short and long term (De Clercq, Galand, et al., 2021; Van den Berg & Hofman, 2005). Future research should delve deeper into these aspects.

Thirdly, academic achievement was operationalised by the ratio of credits earned/credits attempted. We believe that this outcome measure is an important indicator of students' 'achievement' in HE, and it also is the official indicator of study success in Flanders. Nonetheless, as mentioned earlier various other operationalisations of academic achievement (even more long term) could be worthwhile to investigate, and conceptually have different meanings. An often-used example in this regard is 'grade point average' (GPA), which also account for the specific grades obtained by students in different courses within in a study programme, and as such not only captures the progress a student makes, but also the "quality" of academic success. Another commonly used outcome variable is 'drop-out', which can be adopted to shed light on variables crucial for identifying students at risk of leaving HE entirely. Other, less examined examples include 'time to graduation' which measures the duration a student takes to complete a bachelor's degree, or the 'frequency of reorienting' in HE. Each of these operationalizations has its own merits and potential insights into student achievement.

Fifthly, it has to be taken into account that data collection took place throughout the last year of SE. It was, therefore, impossible to impose fixed time slots or fixed waves as schools were free to fill in their own study choice trajectory during the final year of SE. Students may therefore have completed the different tests at different moments in time. However, despite the possible differences in timing, it was always strongly emphasised in the guidelines that the administration of the different tests and questionnaires had to be in controlled conditions, i.e. in a classroom under supervision. Additionally, the vocabulary test in the validation sample and the Attitude and Test strategies questionnaires show an internal consistency smaller than 0.70. Although it is within the acceptable range for studies at group level for which no binding advice is given (Evers et al., 2015), further research should look for ways to increase the reliability. Nevertheless, the analyses point out that the measures were indicative of future results, yielding models that were predictive of achievement.

Lastly, the longitudinal tracking of respondents from both calibration and validation cohorts in HE extended over three years, encompassing the academic years 2019–2020 and 2020–2021, during which the COVID-19 pandemic occurred. Notably, the first lockdown in Belgium began on March 18th, 2020, approximately two months before the final HE examination period in June. It is important to acknowledge that this unprecedented event may have impacted the relationships between our predictors and long-term academic achievement.

7.4. Implications for practice

Notwithstanding the limitations as outlined above, our conclusions entail different practical implications. First, the substantial influence of SE programmes on early academic achievement indicates the importance of a student's specific SE programme in overcoming the initial hurdle into HE, making it a crucial choice in their preparation for HE. Furthermore, our findings show an increasing importance across time of the *interaction term* between random variances at the level of SE and HE programmes, in predicting academic achievement. This suggests that SE and HE programmes should be well-aligned, an important consideration for administrators and counsellors in SE that develop study choice guidance trajectories for students. Conversely, it might also suggest that successfully completing the first year in HE does not necessarily resolve misalignments between SE and HE programmes. Furthermore, the substantial impact of SE programmes on *early* academic achievement, indicates that a student's specific SE programme is important to take the first hurdle into HE, and thus is an important choice in their preparation towards HE.

Second, our analyses suggest a potential cumulative effect of SES risk factors in HE, as the influence of these background variables on academic achievement appears to intensify over time. While further investigation is necessary, it is important for HE personnel to understand that certain student disadvantages may initiate a chain reaction or domino effect, where one negative factor leads to another and may cluster over time, as supported by existing literature (e.g., Atkinson et al., 2015). In this context, the provision of (social) support throughout the entire HE programme is vital to enable certain struggling students to attain academic success (Noyens et al., 2019; Schneider & Preckel, 2017).

Finally, this study demonstrates that various cognitive and non-cognitive factors assessed at the end of SE significantly influence academic performance across a three-year period in HE, in addition to their impact on short-term academic achievement. This finding underscores the predictive validity of these measures, suggesting the importance of their inclusion in online assessment tools designed to support SE students who intend to pursue HE. Indeed, students in the course of their career exploration, should delve into these variables to enhance their preparedness for the transition to HE. Also, identifying and addressing problematic scores in these areas before the transition to HE can facilitate pre-emptive interventions (e.g., providing automised feedback), thereby potentially increasing the likelihood of academic success in HE.

CRediT authorship contribution statement

Jonas Willems: Writing – review & editing, Writing – original draft, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jordi Heeren:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Conceptualization. **Alicia Ramos:** Writing – review & editing, Validation, Formal analysis. **Nicolas Dirix:** Writing – review & editing, Methodology. **Karine Verschueren:** Writing – review & editing, Validation, Resources, Methodology, Conceptualization. **Wouter Duyck:** Writing – review & editing, Validation, Resources, Investigation. **Lieve De Wachter:** Writing – review & editing. **Marlies Lacante:** Funding acquisition. **Sofie Van Cauwenberghe:** Writing – review & editing. **Lien Demulder:** Writing – review & editing. **Veerle Vanoverberghe:** Writing – review & editing. **Vincent Donche:** Writing – review & editing, Validation, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to further improve scientific writing. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.lindif.2025.102697.

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