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Cognitive and non-cognitive predictors of academic success in higher education: a large-scale longitudinal study

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ABSTRACT

How important are learning strategies or personal attributes for learning outside of domain-specific knowledge or twenty-first-century transversal skills when predicting academic success in higher education? To address this question, we conducted a longitudinal study among 1,681 students at one of the leading universities in Hungary. Students took four tests and questionnaires when they entered the university. They measured knowledge from their previous studies (reading and mathematics), twenty-first-century skills like problem-solving and non-cognitive variables in learning strategies, motivation and attitudes. In the next five years, we followed their academic progress with the aim of detecting cognitive and non-cognitive predictors of academic success toward obtaining a degree and developing training programmes for the most important predictors to boost the probability of academic success. The overarching model, which was controlled for students' socio-economic background, determined 18.4% of the variance in later academic success. Domain-specific knowledge from previous studies and learning motivation emerged as the strongest predictor, learning strategies proved to be the most stable of the other mediating factors as an independent predictor, and twenty-first-century transversal skills proved to be unimportant in earning a university degree. Results highlight the importance of transforming higher education so that it is consistent with the expectations of the twenty-first-century labour market, a future-fit education in Hungary.

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academic success; higher education; cognitive and non-cognitive predictors; domain-specific knowledge; 21st-century skills; learning strategies

Introduction

Across the globe, one of the main objectives of higher education is to increase the percentage of young people with university degrees (Diaz Lema et al. 2023). This requires actions that make it possible for students not only to access university, but also to successfully complete it (Roberts 2011). As a result – beyond the issue of rapid technological development and its effect on the behaviour, traits and expectations of current generations – we are facing a continuously changing higher education environment.

In Hungary, where the present study was conducted, there were about 100,000 students in higher education 30 years ago, mostly in full-time programmes. Twenty years after the millennium, there

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are approximately three times more, with one third of them being part-time students. In 1990, there were 170,000 children enrolled in the first grade, while this number is 90,000 today because of the population decline that has been part of the demographic changes in Europe. In 1990, 36% of the students applying to higher education were admitted, while this rate is almost two times higher today at 70%. That is, out of the significantly fewer students enrolled in public education, significantly more students are entering higher education, and, in the context of lifelong learning, more and more individuals are returning to higher education at a later stage in life, resulting in significantly different students in higher education in many respects. It should also be noted that there are vastly more international students at Hungarian universities than there were in 1990 (OECD 2019), there are far more non-state schools, and many more Hungarians are studying abroad. As a consequence of these developments, the composition of students has been continuously changing in the last few decades, not only in Hungary, but also internationally, including their expectations, learning methods, knowledge, opportunities and abilities. On average, 31% of students dropped out of tertiary education in 2010 (OECD 2010), while (OECD 2022) 32% of them failed to complete their course in postsecondary public institutions by the end of the theoretical duration of the programme in 2022.

In this constantly evolving environment, higher education institutions must make considerable efforts – based on the latest research results – to reduce dropout rates and, at the same time, boost admission rates while continuously improving completion rates, which are among the lowest in the OECD (OECD 2017).

Academic success can be described as a complex web of factors that involve personal, academic, organisational, pedagogical and social dimensions (e.g. Alyahyan and Düştegör 2020; Diaz Lema et al. 2023) and interact with and influence each other (York, Gibson, and Rankin 2015). These predictors are important, as they provide insights into an individual's potential for academic performance and success in higher education settings. In order to optimise and reduce the complexity of this phenomenon, most studies focus on one type of predictor and the acquisition of the first twenty credits as extremely important milestones during university studies (Clercq, Galand, and Frenay 2017; Díaz et al. 2020). There is a lack of longitudinal studies that involve the multidimensionality of these predictors. To achieve this, extensive longitudinal research has been initiated at one of the leading universities in Hungary to identify these predictors, with appropriate trainings in modifiable cognitive and non-cognitive factors, including competencies, which are highlighted as key in the marketplace of the twenty-first-century. The results of this study build the bases of students' personalised suggestions, feedback and offered targeted online and/or face-to-face training programmes and courses which should increase the probability of successful completion and graduation.

Predictors of academic success in higher education

Several classifications of predictors of academic success exist (Alyahyan and Düştegör 2020; Van Rooij, Jansen, and van de Grift 2018), but they can basically be divided into two parts: cognitive and non-cognitive predictors.

The most commonly studied cognitive predictors are (1) grade point average (GPA) and credits earned (ECTS) (e.g. Li and Wong 2019; Naaman 2021; Van Herpen et al. 2020) provided they are used as an indicator of academic success, not as an outcome variable; (2) prior academic achievement (PAA) measured by grades and standardised tests (Richardson, Abraham, and Bond 2012; Westrick et al. 2021), such as school-leaving or college admission exam results, which mostly assess aptitude in areas such as mathematics, reading and writing, explaining 17–25% of its variance (Musso, Rodríguez Hernández, and Cascallar 2020; Pinxten et al. 2015; Westrick et al. 2021); and (3) cognitive abilities, including measures of intelligence, reasoning, critical thinking and problem-solving, twenty-first-century skills, which influence a student's capacity to understand complex concepts and to engage in analytical thinking and problem-solving effectively, but they do not seem to be significant predictors (e.g. Molnár et al. 2021; Pastén 2021; York, Gibson, and Rankin 2015; Zlatkin-Troitschanskaia, Shavelson, and Kuhn 2015).

The most commonly monitored non-cognitive predictors are (1) socio-economic factors (SES), which explain 9–23% of the variance of academic success (Musso, Rodríguez Hernández, and Cascallar 2020; Rodríguez-Hernández et al. 2021); (2) learning and self-regulation strategies (Alhadabi and Karpinski 2020; Farruggia et al. 2018; Musso, Rodríguez Hernández, and Cascallar 2020; Ribeiro et al. 2019), which are also mediating factors for GPA and ECTS and explain 16–26% of the variance of academic success (Aydin 2017; Bäulke, Eckerlein, and Dresel 2018); and (3) motivational factors, such as goal orientation and self-efficacy (Alban and Mauricio 2019; Behr et al. 2020; Bowles and Brindle 2017; Ndoye, Clarke, and Henderson 2020; Rump, Esdar, and Wild 2017; Vanthournout et al. 2012), which explain 9–20% of the variance of academic success (Alhadabi and Karpinski 2020; Azila-Gbettor et al. 2021; Ndoye, Clarke, and Henderson 2020; Rump, Esdar, and Wild 2017), though several studies indicate them as negative (Bäulke, Eckerlein, and Dresel 2018) or non-significant factors (Alban and Mauricio 2019; Li and Wong 2019).

Information on the education system in Hungary: composite entry score and the structure of the various study programmes

After high school, students take school-leaving, or Matura, examinations, whose results are part of the entry score for higher education. From 2005, they consist of five subjects: a written examination in mathematics, oral and written examinations in history, a foreign language, and Hungarian literature and grammar, and a written and/or oral examination in a subject of the student's choice and can be taken at an intermediate or advanced level. Study programmes in each higher education institute determine the necessity of an advanced-level examination in particular subjects. School-leaving exams are evaluated both by grade (from 1 to 5, with 5 being the best) and percentage.

The maximum value for the entry score is 500 and is calculated based on (1) academic results, based on the average of the last two semester grades in Hungarian language and literature, History, Mathematics, a foreign language and a natural science subject as well as school-leaving examination results (max. 200 points), (2) school-leaving examination results in percentage form in two subjects determined by the study programme (max. 200 points), and (3) extra points (max. 100 points, for example, for language skills, competition results, advanced-level examinations and SES) or by doubling the school-leaving examination results with the extra points, which makes it possible to compensate weak general knowledge with strong programme-specific knowledge. For a detailed description of the system, see Molontay and Nagy (2023).

Hungary belongs to the European Higher Education Area and has a multi-cycle higher education system with bachelor's, master's and postgraduate cycles in accordance with the Bologna process since 1999. However, there are some exceptions, including dental and veterinary studies, law, medicine, pharmacy and teacher training, which have a long, single-cycle study structure of five, five-and-a-half or six years of study. Courses can be studied full-time, part-time or through distance learning.

Aims

The aim of the study is to map significant factors that influence students' academic success in higher education today. First, we monitor the predictive power of (a) domain-specific knowledge explicitly taught during previous studies in secondary education (e.g. mathematics and reading); (b) cognitive transversal skills, whose development is not explicitly pursued in secondary education but which play a key role in the twenty-first-century (e.g. problem-solving and inductive reasoning); and (c) non-cognitive factors, which can be modified with targeted training and is strongly connected to the processes of learning: learning strategies, motivation and attitudes. In the second half of the paper, we build an overarching model involving cognitive and non-cognitive factors to predict academic success. The research questions are:

RQ1: To what extent do cognitive and non-cognitive factors each predict academic success?

RQ1a: To what extent does domain-specific knowledge from previous studies predict academic success in higher education?

RQ1b: To what extent does the developmental level of twenty-first-century transversal skills predict academic success in higher education?

RQ1c: To what extent do learning strategies, motivation and attitudes predict academic success at the university level?

RQ2: To what extent does the overarching model of cognitive and non-cognitive factors predict academic success at university? Which factors and what kind of knowledge, skills and attitudes are the most important?

Methods

Participants

Participants in the study were students admitted to a large Hungarian university, starting their studies in the same year and followed in the next five years. Eleven faculties out of the twelve at the university participated in the project. The faculties vary in number of students; that is, the percentages of students from the different faculties are not equally distributed in the sample, as they mirror the distribution of the original population. The target population for the study was 3429 students, of whom 1681 (49.02%) were involved in the analyses and 51% were female. Participants' mean age was 19.86 (SD = 2.11), with most of them having taken their school-leaving examinations in May of the same year. The first point of the data collection was in September, when they entered the university.

Participation was voluntary, and the project was integrated into the educational improvements at the university. Students were notified of the possibility of taking part in the assessment prior to starting their studies. All the participants had turned 18 by the time of the assessment and confirmed with their signature that their data could be used for educational and research purposes at both the faculty and university levels. As an incentive, they received course credit for active participation in the project. Annex 1 contains the descriptive statistics for the demographic variables of participating and non-participating students.

Instruments

Mathematics

Learning mathematics stimulates cognitive development, while mathematics provides knowledge and skills that are essential for everyday tasks. It is one of the most important domains of education in every school system. The test covered the major topics in mathematics learnt in secondary education. Its difficulty level was adjusted approximately to the intermediate-level standards of the school-leaving examination in mathematics. It measured two dimensions: disciplinary knowledge and its application. The number of items and the reliability of the instrument are summarised in Table 1.

Reading comprehension

Reading comprehension is a gateway to learning and developing academic skills at every level of the education system, especially in higher education, where students are required to read constantly and reading encompasses different types of text (Pirttimaa, Takala, and Ladonlahti 2015). The reading comprehension test involved four different types of text (narrative, explanatory, chart and Venn diagram) and corresponding tasks in both continuous and discontinuous formats. Fifty-eight per cent of the items were related to continuous texts, while two fifths measured understanding of discontinuous texts. The test was developed by Hódi and Tóth (2019). The number of items and the reliability of the instrument are summarised in Table 1.

Table 1. Reliability of the tests and questionnaires and other descriptive statistics.

Test		Number of items	Cronbach's alpha	Min.	Max.	Mean	SD
Mathematics		70	0.926	0	100	56.13	18.47
Reading comprehension		72	0.749	0	100	84.44	7.33
Problem-solving		24	0.892	0	100	53.97	22.67
	Knowledge acquisition	12	0.865	0	100	60.53	27.20
	Knowledge application	12	0.783	0	100	47.41	22.78
Inductive reasoning		48	0.868	0	100	65.83	15.45
Learning strategies, motivation and attitudes		78	0.916	1	5	3.56	0.35
Learning strategies	Elaboration	4	0.663	1	5	3.63	0.63
	Planning	8	0.955	1	5	3.70	0.68
	Memorisation (rehearsal)	7	0.763	1	5	3.73	0.64
	Procrastination	4	0.937	1	5	2.72	1.02
	Help – support request	3	0.847	1	5	3.79	0.82
	Time management	4	0.951	1	5	3.48	0.81
Learning motivation	Mastery motivation	5	0.751	1	5	4.11	0.57
	Achievement motivation	6	0.745	1	5	2.92	0.75
Learning attitudes	Effort regulation	15	0.950	1	5	3.71	0.56
	Cooperation	17	0.917	1	5	3.72	0.67
	Openness to problem-solving	5	0.811	1	5	3.81	0.68

Problem-solving

Problem-solving plays an important role in twenty-first-century learning. It was measured via a widely used validated instrument (see Greiff et al. 2013; Molnár, Ahmad Alrababah, and Greiff 2022; Molnár et al. 2017) containing computer-simulated problems developed within the MicroDYN approach (Funke 2001). This type of problem-solving measure enables us to study how knowledge is gathered in new situations and how this knowledge is applied to actually solving a problem, independently of domain-specific content (Molnár, Greiff, and Csapó 2013). The number of items and the reliability of the instrument are summarised in Table 1.

Inductive reasoning

Inductive reasoning is one of the most important reasoning skills with a central role in learning (Hamers, Koning, and Sijtsma 1998; Molnár 2011) and is related to almost all higher-order cognitive skills and processes (e.g. general intelligence, Klauer and Phye 2008; problem-solving, Molnár, Greiff, and Csapó 2013; analogical reasoning, Goswami 1991). The inductive reasoning test was originally developed by Csapó (1997) and further developed, computerised and validated at both the national and international levels in the last 25 years (Mousa and Molnár 2020; Pásztor et al. 2018; Wu, Saleh, and Molnár 2022; Wu and Molnár 2018). The current version contains figural analogies and series and verbal analogies and series. Students were expected to discover the correct relationship between given figures and numbers and select – using the drag-and-drop operation – a suitable figure or number from among the five possibilities provided as their answer. The number of items and the reliability of the instrument are summarised in Table 1.

Self-regulated learning and study-related resources: Learning strategies, motivation, attitudes

Self-regulated learning strategies and study-related resources are used to assist students in learning effectively; they entail the cognitive, metacognitive, behavioural, motivational and emotional/affective aspects of learning (Panadero 2017). The learning strategies, motivation and attitudes questionnaire contains statements developed and adapted by D. Molnár and Gál (2019). The statements were evaluated on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). Based on Pintrich's (1999) model of self-regulated learning, the statements for monitoring learning strategies covered cognitive strategies, metacognitive awareness and resource management. Statements on cognitive strategies are tied to the selection, encoding and organisation of information (e.g. memorisation and planning; Artelt et al. 2003; Weinstein, Husman, and Dierking 2000).

Statements on metacognitive awareness and regulatory strategies pertain to the planning, monitoring and evaluation of learning processes (e.g. elaboration and need for help; Adams and Blair 2019; Winne and Perry 2000), while statements on resource management strategies encompass the management of external factors and internal resources (e.g. time management) (Pintrich 2000). Statements on learning motivation monitored factors that examine why students learn, why they start and maintain their learning, and what they believe about their ability to learn subject matter. Statements on learning motivation involved mastery and achievement motivation (D. Molnár 2013). Learning attitudes encompassed factors that measured students' attitudes towards learning, such as cooperation with peers (Kuger et al. 2016) and openness to different problem situations (D. Molnár and Gál 2019). The analysis focused on areas where effective intervention and improvement are possible. Table 1 summarises the areas covered in the analysis, the number of items per area, reliability indices and other descriptive statistics.

Procedures

The assessments involving two testing sessions of two hours each were carried out in a large computer room at the university's Learning and Information Centre during the first two weeks of the semester. The tests and questionnaires, measuring mathematics, reading comprehension, problem-solving, learning strategies, motivation and attitudes and related background factors (mothers' education and number of books at home) were administered online with the eDia online platform (Csapó and Molnár 2019). Students had a total of two times 120 min to complete it. At the beginning of the testing sessions, participants were provided instructions on the user interface, including warm-up tasks. Immediate average achievement-based feedback was provided after they completed each of the tests along with detailed feedback with normative comparative data on their performance via e-mail a week after the data collection was closed.

The general and follow-up educational data (e.g. entry score, length of studies, student's faculty, academic track, attempted course credits each semester, corrected credit index in each semester, level of training – dropped out, still studying or degree received) were provided by the university's Office of the Director of Academic Affairs.

Data from the achievement tests were transformed to a 500(100) scale so that the university means were set to 500 with Rasch scaling. MPlus software (Muthén and Muthén 2012) was employed to conduct the structural equation modelling. A full SEM (structural equation model) was used to investigate the roles of the cognitive, non-cognitive and demographic predictors on students' later academic success. Academic success as a latent variable was defined by the corrected credit index[1] for the first and second semesters, by the global corrected credit index (GCCI) based on the five-year follow-up and by the official status of the student (dropped out, still studying or degree received) controlled for the length of the training. χ^2 values, an absolute fit index (the root mean square error of approximation, RMSEA) and two incremental fit indices (the Tucker–Lewis Index, TLI, and the comparative fit index, CFI) were computed to evaluate model fit. A TLI and CFI larger than 0.90 paired with a RMSEA less than 0.08 are commonly considered as an acceptable model fit (Yu 2002). Modification indexes (MI) were used to add arrows to the model and improve the model fit. Only significant coefficients were published in the SEM models.

Results

Mathematics, reading comprehension and previous studies are important factors in predicting academic success

A full SEM model was used to explore the predictive power of previous studies for academic success in higher education (see Figure 1). Academic success as a latent variable was defined by four manifest variables: the corrected credit index for the first two semesters, GCCI and the official status of the

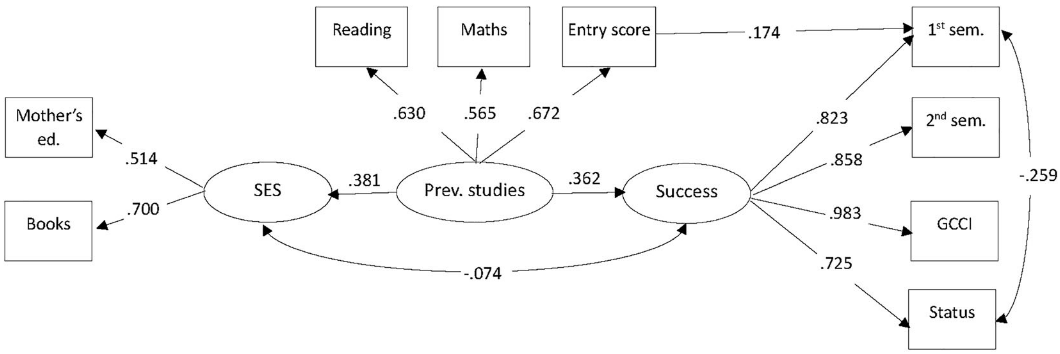

Figure 1. Domain-specific knowledge as a predictor of academic success in higher education controlled for students' socio-economic background: The full SEM model.

student (see Procedures part). Knowledge from previous studies as a latent variable was defined by the level of students' reading comprehension, mathematics knowledge and entry score as manifest variables. Because of the selectiveness of the Hungarian school system, which is mostly based on parents' education and socio-economic status (SES) (Csapó, Molnár, and Kinyó 2008; Csapó et al. 2014), we controlled domain-specific school knowledge as a latent factor of SES, which was built on mother's education and number of books at home. The controlled model fitted the data well ($\chi^2 = 338.51$, CFI = .956, TLI = .929, RMSEA = .093, C.I. = .084.101) and explained 13.1% of the variance of academic success. Previous school knowledge predicted later academic success at a medium level ($\beta = .362$), while university entry score (mostly containing information about students' GPA and results on the school-leaving examinations) predicted student's corrected credit index for the first semester at a low level ($\beta = .174$). The first-semester corrected credit index correlated negatively with the present status of the students after five years ($r = -.259$).

twenty-first-century transversal skills are basically not necessary for academic success in the twenty-first century

Two highly correlated ($r = .722$ on a latent level) but distinct transversal skills that play an important role in learning were assessed as a measure of twenty-first-century transversal skills, problem-solving and inductive reasoning. A full SEM model was used to explore their predictive power on academic success at a latent level (see Figure 2). The model had good model fits ($\chi^2 = 144.609$, CFI = .984, TLI

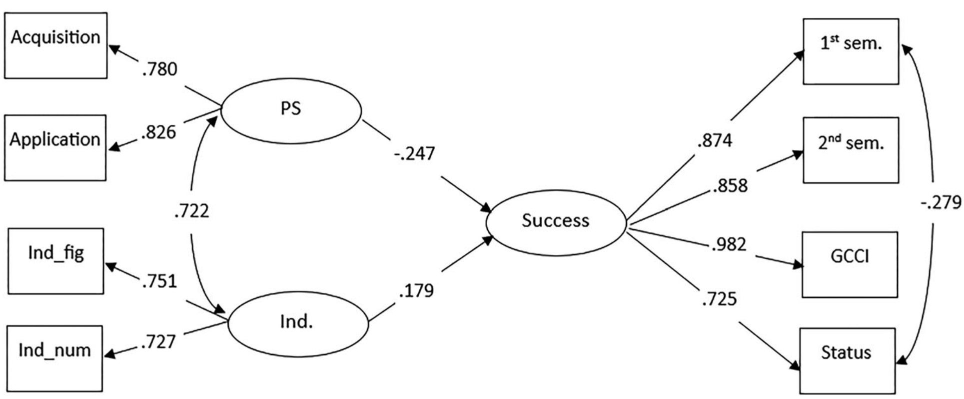

Figure 2. Twenty-first-century transversal skills as a predictor of academic success in higher education: The full SEM model.

= .971, RMSEA = .069, C.I. = .059–.080). Problem-solving and inductive reasoning only explained 2.9% of the variance of academic success, and the path coefficient was negative ($\beta = -.247$) for problem-solving and positive but very low ($\beta = .179$) for inductive reasoning. A large amount of variance remained unexplained.

Learning strategies, motivation and attitudes are predictive factors of academic success at university level

The full SEM model (see Figure 3) fitted the data well ($\chi^2 = 650.33$, CFI = .953, TLI = .936, RMSEA = .067, C.I. = .062–.072) and explained 16.8% of the variance of academic success. Not all the manifest and latent factors proved to be significant. As a latent factor, learning strategies built on planning, memorisation, elaboration, time management, asking for help and procrastination proved to have the lowest but significant predictive power for later academic success ($\beta = .220$). As a latent factor, learning motivation built on achievement motivation and mastery motivation proved to be the most important predictor ($\beta = .512$) of later academic success. Finally, learning attitude at a latent level defined by openness to problem-solving, cooperation and effort had a significant but negative path as regards learning success ($\beta = -.497$).

The overarching model with cognitive and non-cognitive predictors of academic success controlled for SES explains one fifth of academic success

The full SEM model (see Figure 4) fitted the data well ($\chi^2 = 1404.85$, CFI = .932, TLI = .913, RMSEA = .058, C.I. = .055–.060) and explained 18.4% of the variance of academic success. (Please note that, because of the high complexity of the full model, Figure 4 contains just the paths and covariance arrows between the latent variables.) The latent variable of previously acquired, domain-specific school knowledge defined by standardised test results in mathematics and reading comprehension and students' entry score proved to be the strongest predictor ($\beta = .293$)

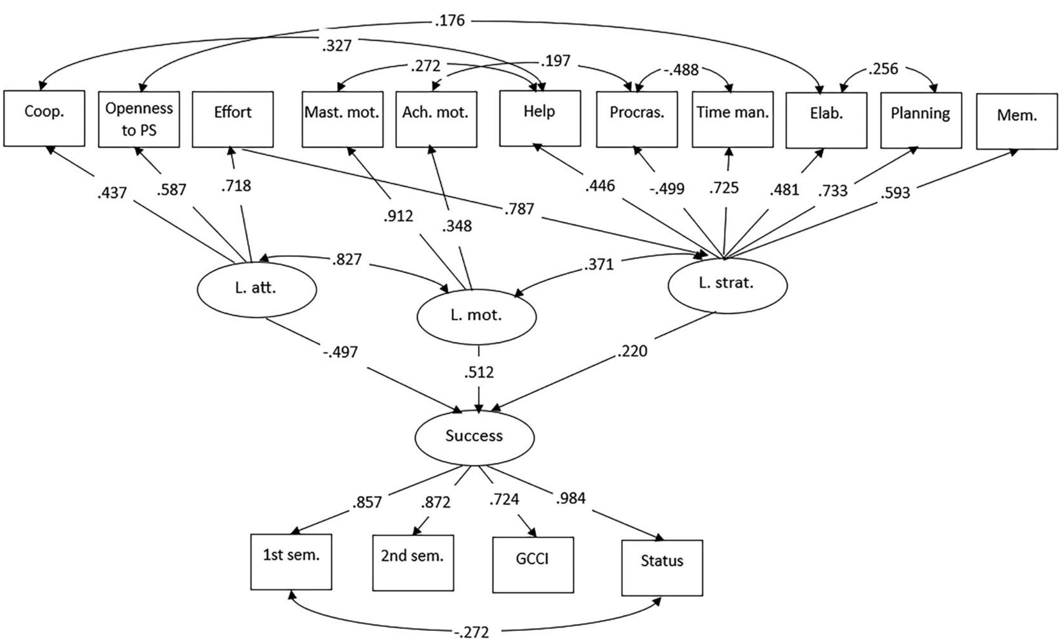

Figure 3. Learning strategies, motivation and attitudes as predictors of academic success in higher education: The full SEM model.

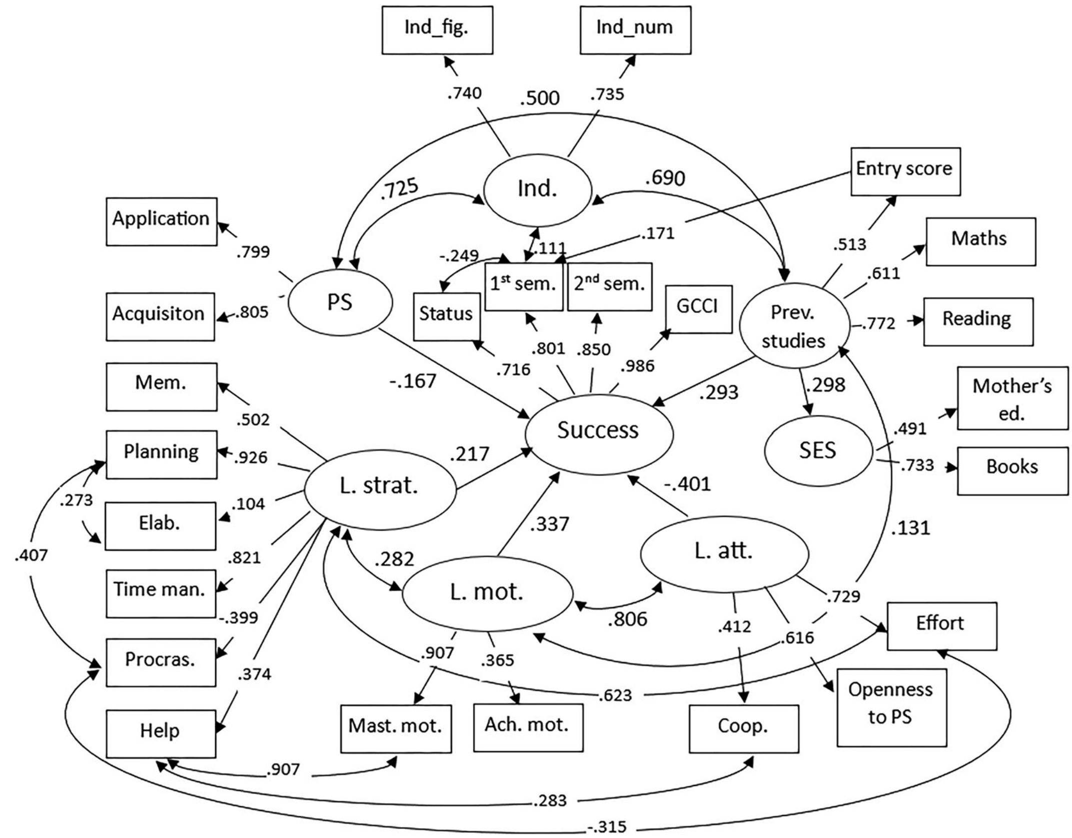

Figure 4. The overarching model contains domain-specific knowledge, twenty-first-century skills and learning strategies, motivation and attitudes as predictors of academic success in higher education: The full SEM model.

of academic success, while twenty-first-century transversal skills were not conducive to earning a degree in higher education; however, they correlated strongly with previous school learning (r = .500 for problem-solving and r = .690 for inductive reasoning). Specifically, students' problem-solving skills negatively predicted their later academic success (β = −.167), and their level of inductive reasoning proved to be a non-significant factor; however, it correlated strongly with previous academic success (r = .690). Among non-cognitive factors, learning strategies (β = .217) and learning motivation (= .337) had positive predictive power for academic success on a latent level, while learning attitude had negative predictive power (β = −.401). However, the latter two constructs were strongly correlated (r = .806). Students' entry score predicted their quality achievement in the first semester at almost the same level as their level of inductive reasoning skills (β = .171 and .111, separately). SES was not a significant influential factor at university level.

Discussion

Prediction of academic success in higher education represents one of the major goals in psychological and educational research in higher education. Because of the constantly changing circumstances (e.g. demands of the marketplace, trends in technological developments and type of study) and participants (e.g. in expectations, age and available opportunities), it requires continuous research. Recent developments cannot be based on research results from a decade ago.

The first purpose of this study was to investigate the relative contribution to academic success of (1) domain-specific knowledge, that is, knowledge learnt and explicitly developed in secondary education, (2) twenty-first-century transversal skills and (3) learning strategies, motivation and attitudes. The factors proved to be predictive of academic success at different levels if measured alone, accounting for 13.1, 2.9 and 16.8% of its variance, respectively.

We confirmed previous research results, which considered general and domain-specific knowledge as a promising predictor, since students with a solid foundation in domain-specific knowledge are better equipped to engage in the subject matter, understand it and earn higher grades. They generally achieve higher results in the first semester ($\beta = .172$) and are more successful, independently of the study programme ($\beta = .362$). Indeed, achieving good grades and accumulating an adequate number of credits in the first semester can provide a sense of accomplishment and reassurance, and they demonstrate that the student is capable of meeting the academic requirements of the programme. However, they do not guarantee continuous academic success and graduation at the end of the training ($r = -.259$). A large amount of variance remained unexplained (86.9%), thus indicating that domain-specific and general disciplinary knowledge plays an important role, but it is essential to recognise that academic success is multidimensional and influenced by various other cognitive and non-cognitive factors.

Nowadays, many study programmes incorporate interdisciplinary approaches and provide education that goes beyond narrow specialisation to ensure students are well-rounded and prepared in a rapidly changing world. Thus, we expected that twenty-first-century transversal skills, especially inductive reasoning and problem-solving, would have a high predictive power for academic success in higher education. We detected a positive but very low predictive power for inductive reasoning in academic achievement and a stronger but negative path for problem-solving. This means that students equipped with higher-level twenty-first-century skills have generally no advantage at university level; moreover, good problem-solvers have higher chances of dropping out than graduating in the current system. The two constructs explained just 2.9% of the variance of academic success, which also indicates that study programmes in Hungary should be further revised to better respond to labour market demands and expectations and foster twenty-first-century skills.

Students reporting higher self-efficacy in learning are more successful, make more effort to complete tasks (Olivier et al. 2019), have more control over their learning, and are generally more self-confident (Luszczynska, Gutiérrez-Doña, and Schwarzer 2005; Martos et al. 2021). This means self-regulated learning strategies and learning resources play an important role in learning success, which was partially confirmed by our results. The learning strategies, motivation and attitudes we monitored explained 16.8% of the variance of academic success, which is at about the same level as the explained variance of domain-specific and general knowledge and which is significantly larger than the predictive power of twenty-first-century skills. Learning motivation defined by mastery and achievement motivation had a strong predictive power for final academic success, and learning strategies proved to be important factors. Learning attitudes were determined by effort, cooperation and openness to problem-solving; that is, constructs closely related to twenty-first-century skills had a negative predictive power for later academic achievement.

The overarching model explained less than one fifth of the variance of academic success (18.4%) and not one third of it, as expected by simply adding the results of the separately built models, indicating the very complex phenomenon of academic success in higher education and the necessity of monitoring it in a complex way, not just focusing on single domains of learning.

Learning motivation and domain-specific knowledge dominated as predictors; however, their predictive power dropped, including other cognitive (e.g. problem-solving) factors in the model. The predictive power of inductive reasoning became non-significant in the complex model; that is, other learning-related cognitive and affective factors absorbed its predictive power. The most stable predictive factor proved to be learning strategies, whose path coefficients remained almost the same in the stand-alone and complex models, indicating their stable importance and necessity for development consistent with academic success. Against our expectations, twenty-first-century skills, specifically skills which make it possible to learn in unknown situations, emerged as almost unimportant factors in academic success as well as learning attitudes, thus confirming earlier research results and highlighting the importance of study programme revisions to better respond to the demands of the twenty-first-century labour market. However, though not directly monitored, it is a very positive result of the present analysis that SES proved not to be a significant influential factor at university level; that is, differences brought from home are equalised at the level of higher education.

Limitations

The study sample may lead to limitations and generalisability of the results at a population level. We used a non-representative convenience sample from one of the highest-ranked universities in Hungary. We followed participants' academic track record for five years. There are many participants in the system because of the length of their training (e.g. medicine) or due to a changed study track. We analysed all the students collectively, independently of their field of study and the expectations of the different courses of study and some majors presumably rely on more problem-solving, critical thinking and other twenty-first-century skills than others. We focused on problem-solving and inductive reasoning within the scope of twenty-first-century skills, areas that only represent a subset of that broad category. We focused on constructs which can be modified with specialised face-to-face or online training.

Conclusion and further studies

This five-year longitudinal study investigated students' cognitive and non-cognitive skills to monitor their predictive power on later academic track and university graduation. Specifically, we monitored students' level of domain-specific knowledge on entering higher education, the level of twenty-first-century transversal skills and the type of learning strategies, motivation and attitudes to ascertain the causes behind a lack of successful completion of studies. The factors proved to be predictive of academic success at different levels if measured alone, thus accounting for 13.1, 2.9 and 16.8% of its variance, respectively. A large amount of the variance remained unexplained in the overarching model (81.6%), indicating the complexity of this phenomenon, the low level of predictability and the high level of mediating roles of different factors, which can be examined with significant limitations when separated from each other. Learning motivation and domain-specific knowledge proved to be the most dominant predictors and learning strategies the most stable predictor. Contrary to our expectations, twenty-first-century transversal skills emerged as unimportant factors, thus highlighting the significance of transforming higher education in accordance with the expectations of the twenty-first-century labour market in Hungary, and success in the first semester does not guarantee continued academic success or graduation. Next, we will develop face-to-face and online courses to facilitate students' academic success in higher education in general and after division-level analyses in particular in cooperation with the university's education council.

Note

1. "Government Decree 76/2006. § 24(3) A student's quantitative and qualitative academic performance during a semester is measured by the credit index and the corrected credit index. The credit index is calculated by multiplying the credit point value of the subjects completed during the semester and the grades awarded to them, which is then divided by the thirty credit points that indicate a student's standard study progress during a semester. The corrected credit index is calculated by dividing the number of credit points attempted in a given semester by the number of credit points earned in the same semester, which is, in turn, multiplied by the value of the credit index. The global corrected credit index is used to measure the student's qualitative and quantitative academic performance over a span of multiple semesters. The global corrected credit index is calculated in the same way as the corrected credit index except that it is thirty credit points per semester that have to be considered;

moreover, the credit points attempted and subsequently earned are to be considered within the entire period." Source: Nftv: Act CCIV of 2011 on National Higher Education.

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Annex 1. Demographic variables of participating and non-participating students.

	Participating ($N = 1681$)				Non-participating (1732)					
	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD	t	p
Sex	1	2	1.51	0.5	1	2	1.56	0.5	−7.4	<.001
Age	18	47	19.86	2.11	18	53	20.71	2.99	3.05	<.01
Entry score	280	493	381.6	50.27	280	488	369.0	48.40	9.62	<.001