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Ádám Kocsis & Gyöngyvér Molnár

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Factors influencing academic performance and dropout rates in higher education

Ádám Kocsis [a] and Gyöngyvér Molnár [b]

[a]Doctoral School of Education, University of Szeged, Szeged, Hungary; [b]Institute of Education, University of Szeged, Szeged, Hungary

ABSTRACT

The aim of this study was to identify and evaluate the most frequently used research methods and factors influencing academic performance, based on a pool of 95 studies, published after 2012. We considered only peer-reviewed papers containing 78 empirical and 17 meta-analytic studies. Our theoretical background lies in the different approaches of the terms 'university dropout' and 'academic performance'. After the systematic analysis we ascertained the most commonly used methods are Educational Data Mining (EDM) algorithms (decision tree, logistic regression and neural networks) and Structural Equation Modelling (SEM). The strength of the predictive power depends on the dataset, however Support Vector Machines, Multilayer Perceptron, Naïve Bayes algorithm were found to be the most precise in prediction. Regarding factors influencing academic performance we derived our results based on 600,000 university students. Considering the data from meta-analyses and systematic reviews, reaching up to 900 studies, we found grade point average (GPA), obtained credits (ECTS) and gender to be the most consistent and decisive predictors of academic performance. Nevertheless, GPA and ECTS (as output variables) are mediated by student factors (intrinsic motivation, self-regulated learning strategies, self-efficacy, prior education) and throughput factors (work, finances, academic engagement). We had contradictory results on age and family background.

KEYWORDS

Dropout; academic success; research methods; background factors

Introduction

Research for the reasons behind dropout have been conducted since the 1920s (Behr et al., 2020). The expansion of higher education has resulted in a growing demand for university graduates in the labour market, however dropout rates in higher education are also rising by an average of about 30 per cent (OECD, 2019), influencing almost all universities around the globe. On the one hand, this percentage should be lowered, but on the other hand the increased number of undergraduate students cannot be guaranteed the very same level of knowledge given by the university. The significance of

CONTACT Ádám Kocsis kocsis.adam@edu.u-szeged.hu Doctoral School of Education, University of Szeged, Petofi S Sgt, Szeged 30-34, Hungary

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lowering the dropout rate and raising students' academic success, in other words, of recognising the factors behind lagging academic performance among undergraduate students ahead of time, has become increasingly important from the perspectives of policy makers, higher education institutions and students (Behr et al., 2020).

However, these procedures create a series of unfortunate events: (1) policy makers are pressuring higher education institutions to flood the labour market with skilled workforce and are trying to optimise the financial background of universities; (2) higher education institutions have to adapt their strategies to the socio-political changes (expansion of higher education) and the expectations of policy makers (need for qualified workforce), so they may lower the requirements to obtain a diploma; (3) the more students start studying in higher education, the more diverse problems and socio-political issues appear. So university dropout/academic success has become a complex, multi-layered phenomenon. Both international and national studies have different results on the background variables of dropout and academic success, so, due to the constantly changing background features and variables, it will always be a serious issue to be examined (Behr et al., 2021, Rump et al., 2017).

In the first part of this study, as a theoretical basis, we outline the different approaches to academic performance (university dropout and academic success). However, we must first state that the different cultural backgrounds, regulations, education systems and policies make comparisons more difficult, and the factors influencing university dropout have been constantly changing as time has passed (Li & Wong, 2019). It is therefore always a relevant aim for the institution to identify the background variables of retention and academic success because it requires effort to lower dropout rates. It is also relevant for university students to gain more knowledge and secure a better position in the ever-changing labour market.

In the second part of this study, our aim was to map and evaluate the most prevalent research methods used in cross-sectional and longitudinal empirical studies on academic performance. In the last part of the study, we examine and synthesise the empirical studies and compare them to the meta-analytic studies regarding factors behind academic performance. We identify the 'core factors' associated with academic dropout/success and build our model based on 95 publications.

Theoretical background

Defining university dropout

The first comprehensive theoretical framework of dropout was created by Tinto (Tinto, 1975). Based on social academic integration, he examined dropout from a sociological point of view. His variables included family background, personal characteristics and prior academic achievement (PAA) as input factors. He stated that the interactions between students and the university are the main contributors to dropout. His model was validated by his own research, but Tinto (2006) claimed that the different perspectives used in examining dropout placed limits on his early model of retention. These limits were recognised by Bean back in the 1980s, so as a supplement to Tinto's model (including university as an organisation and attitudes-interactions), Bean's model of attrition (Bean, 1980) stated that 50 per cent of university grades can be explained by PAA (high school grades and ACT scores). He also took environmental variables (family, work and the military) into consideration, thus asserting that university has little control over them.

As measurement tools and technology were improving, the late 2000s brought the emergence of psychological and economic models (Musso et al., 2020; Srairi, 2022). Thus, nowadays mixed and comprehensive models are used to identify the cognitive, affective and environmental factors and even log file data behind academic performance (Alyahyan & Düştegör, 2020). Behr et al. (2020) separated the definition of dropout into two parts, depending on the underlying dataset: the macro point of view, using a nationwide survey data, is called system departure; and the micro point of view, using the university's data, is called institutional departure. Relying on this distinction, we can approach the problem transition. Thus, depending on the research questions and the focus of our research (micro/macro/individual), we can decide to regard a transition as dropout or not (Heublein, 2014; Pusztai et al., 2019). Behr et al. (2020) introduced four different perspectives of dropout: sociological, psychological, economic and the phase model, the latest approach. The phase model is divided into three phases: pre-university, within-university and a decision-making phase. The first phase is tied to student factors. The second phase is linked to the within-university period, which relies on the student's internal factors and factors external to the university. Basically, the decision-making process and the final decision are based on these two phases.

Components of academic success

The main difference between university dropout and academic success is that academic success can be measured by two comparable factors as a determinant of student success: obtained credit points (ECTS) and (cumulative) grade point average ((C)GPA), and, similarly to university dropout, this is also a complex phenomenon (York et al., 2015). It can be described as a measurable list of factors influencing each other (Alyahyan & Düştegör, 2020) containing 'academic achievement, attainment of learning objectives, acquisition of desired skills and competencies, satisfaction, persistence, and post-college performance' (York et al., 2015, p. 5). On the basis of York et al. (2015), Farruggia et al. (2018) added other factors related to academic success: academic mindset (self-efficacy), academic perseverance (grit), learning strategies, social skills and academic behaviour. Van Rooij, Brouwer, et al. (2018) expanded this model. They considered academic success as a long decision-making process and divided it into three parts: input factors (secondary school GPA, gender, conscientiousness, self-efficacy and intrinsic motivation); throughput factors (number of contact hours, study load, academic adjustment, lack of self-regulated learning, attendance and observed learning activities); and outcome variables (GPA, ECTS and persistence). This model was created on the basis of a meta-analysis, which was the starting point of their empirical research (van Rooij, Jansen, et al., 2018). This is in line with the phase model of university dropout (Behr et al., 2020) but takes outcome variables into consideration as decisive factors influencing the decision made to remain at university or to leave. In line with their findings, the theory developed by Alyahyan and Düştegör (2020) expanded York et al.'s (2015) model and considered five dimensions that influence academic performance: the student's environment, student demographics, PAA, psychological attributes and the student's activity logs (Figure 1).

Figure 1. A broad variety of factors potentially impacting students' academic success (based on Alyahyan & Düştegör, 2020).

In conclusion, different layers of both definitions were provided from the beginning of Tinto's comprehensive study. The more information we can measure, the more complex the definitions will be. Thus, the definition of both aspects of academic performance depends on the research questions/aims, the dataset (nationwide/more than one university/one university) and perspective (micro/macro/individual) of the research. As a self-criticism, after 30 years of research, Tinto stated: 'despite our many years of work on this issue, there is still much we do not know and have yet to explore. More importantly, there is much that we have not yet done to translate our research and theory into effective practice' (Tinto, 2006, p. 2).

Aims

This clarification of the two approaches to academic performance brought us to determine the aims of our study. Broadly speaking, the objective was to find the most frequently used research methods and to identify the most influential factors that affect academic performance based on the empirical research and studies available in the literature. More particularly, we aimed to:

(1) identify and evaluate the most frequently used research methods to examine the characteristics of success and/or failure of academic performance;

(2) highlight the most important student- and non-student-related characteristics associated with success and/or failure of academic performance based on earlier studies from the last ten years; and
(3) build a model by identifying and evaluating the most important student- and non-student-related characteristics affecting academic success and/or failure based on earlier studies from the last ten years.

Method

The Educational Resources Information Center (ERIC), the Scopus databases, Google Scholar and Semantic Scholar were used in developing the scientific foundation of the analyses under investigation. By filtering the relevant literature, we applied a systematic, multi-layered and strategic approach. First, we filtered the available literature on academic performance using the keywords 'academic success' and 'university dropout'. Second, the search was narrowed by adding the keywords 'factors' and 'higher education'. The number of hits still exceeded 8,000, indicating the importance of the topic. At the third layer, we restricted the pool of the analyses on peer-reviewed research focusing on cross-sectional/longitudinal studies and meta-analyses carried out after 2012, written in English or Hungarian and available online (2,800 papers). Based on the abstract search, we excluded papers without a higher education context or without empirical data. Finally, we excluded papers with a small sample size ($N < 50$). We examined these aspects of academic performance to further clarify the factors behind them. The final pool consisted of 95 publications: 55 cross-sectional and 15 longitudinal studies, 7 studies connected to EDM, as well as 18 meta-analyses/systematic reviews. For easier replicability, we have included online supplementary material (see S1; organised by categories) – they were taken into consideration in the analysis. The reference section contains every paper our key arguments were based on. As the methodologies executing a cross-sectional and a longitudinal study or writing a meta-analysis based on existing studies strongly differ, before synthesising the findings, we decided to analyse these two groups of papers separately. With meta-analyses and systematic reviews, the sample size was defined by the number of studies analysed, and we retained the variables (if available) and research methods. Figure 2 visualises the process of the research method we used.

Results and discussion

Discovering and evaluating the methods in the empirical research on academic performance

The first research goal was related to the most frequently used research methods. There is a huge variety of methods used from very basic descriptive analyses (Sibanda et al., 2015) to state-of-the-art statistics. Descriptive statistics and correlations were used from the beginning of the 1970s (Tinto, 1975). Then, in the early 2000s, as models of and approaches to academic performance were becoming more complex and multi-layered, the advancement of technology made it possible to conduct a complicated analysis. Researchers were given the opportunity to exploit the benefits of educational data mining (EDM) (e.g. Aulck et al., 2017; Westrick et al., 2021). This is a technique used in education to

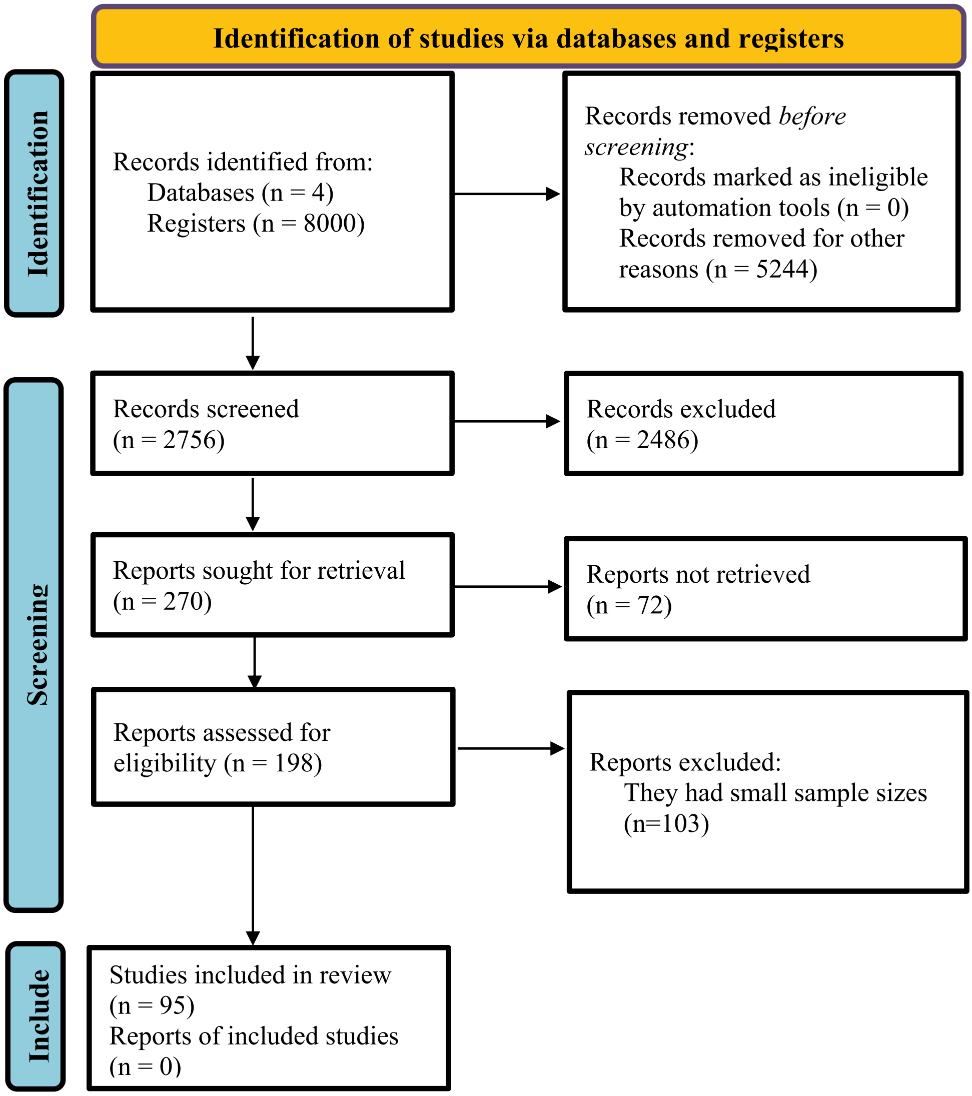

Figure 2. The process of the research method (based on page et al., 2021; S1).

extract meaningful information, patterns and relationships among variables in an enormous educational dataset (Agrusti et al., 2019). Although it existed back in 1999, the expanded use of EDM, used to identify reasons behind academic performance, became popular in the late 2000s (Jayaprakash, 2018). EDM involves both data mining tools and algorithms. WEKA, SPSS, Rapid Miner and R are the most widely used data mining tools (e.g. Alban & Mauricio, 2019; Diaz Pedroza et al., 2019; Syahira et al., 2019).

EDM tools made it possible to examine sample sizes containing data from hundreds of thousands of students. In order to analyse this data, different algorithms were developed, including k-nearest neighbour (KNN), support vector machines (SVM), decision tree, Bayesian networks (BN), (artificial) neural networks (ANN) and logistic regression (Alban & Mauricio, 2019). These are what are called supervised

Table 1. Research methods used in the filtered empirical publications ($N = 128$).

Type of research method	Frequency of research methods (%)
Correlation	20
Structural equation modelling (SEM, including path analysis)	16
Artificial neural networks (ANN)	13
Linear regression	10
Logistic regression	10
ANOVA	8
Decision tree (including random forest)	6
Descriptive statistics (only)	5
Miscellanea	12

data mining techniques (Syahira et al., 2019); nevertheless, they consider linear regression as a data mining process. In Table 1, we summarise the frequency of research methods used in the empirical research on academic performance at university level. Fifty-five per cent of the filtered publications involved more than one research method.

The most frequently used methods are the EDM algorithms: decision tree, 6%; logistic regression, 10%; and ANN, 13%, totalling 30% (if you consider linear regression to be a data mining algorithm, the total rises to 40%). This is contrary to the findings of Agrusti et al. (2019). They analysed 73 documents and found decision tree to be the most commonly used EDM method. Within decision tree, the J48 algorithm was determined to be the most commonly used (Mohamed & Waguih, 2017). Meta-analyses by Alyahyan and Düştegör (2020) and Alban and Mauricio (2019) also agree with them, with decision tree found to be the most frequently used EDM method. In this research, we observed that SEM was the most frequently used research technique (16%), which is a non-EDM but state-of-the-art method. In addition to EDM algorithms and SEM, linear regression (10%) was among the most commonly used research methods. It is important to note filtered publications that used SEM or linear regression (23% in all), with the exception of Akessa and Dhufera (2015), Beyene and Yimam (2016) and Sneyers and De Witte (2017), considered both cognitive (GPA and PAA) and affective factors as well as student demographics.

As an evaluation of the research methods, we have found descriptive statistics and correlation to be outdated. Six per cent of the filtered publications only used descriptive statistics to identify the factors behind academic performance. However, correlation is still a popular research method (20%), but only in six of the filtered publications was it used solely. As for the most frequently used research methods (EDM algorithms), we compared their predictive powers. In our pool, the eight studies implicated the different predictive powers of EDM algorithms on the same dataset. According to Mueen et al. (2016), ANN is the best way to analyse complex data, while MLP has a learning network model for academic classification. Mohamed and Waguih (2017) disagree and claim J48 is a better classifier algorithm than MLP. In addition, the naïve Bayes algorithm is used to supply theoretical solutions (Mueen et al., 2016).

During the comparison, we faced the problem of different values: accuracy, recall, precision, specificity, F-measure and ROC curve. According to Alyahyan and Düştegör (2020), accuracy should be used on almost balanced datasets, recall is used to minimise false negative cases, precision is applied to minimise false positive cases, the F-measure finds the balance between recall and precision, and

Table 2. The predictive power of EDM algorithms.

Reference	Algorithms used	Factors considered	Sample size	Best algorithm and recall (%)
Ahmad and Shahzadi (2018)*	MLP	11	300	MLP − 93.20
Aulck et al. (2017)	LR RF, KNN	10	32,538	LR − 66.59
Bayer et al. (2012)	J48, IB1, PART, SMO, NB	30	775	PART − 92.30
Berens et al. (2019)**	LR, RF, ANN, AdaBoost	17	29,700	RF − 89.01
Díaz et al. (2021)***	C4.5, CART, BN, MLP, KNN, SVM	20	1,055	SVM − 94.6
Hamoud et al. (2018)	J48, random tree, REPtree	24	161	J48–62.10
Mueen et al. (2016)	NB, C4.5 MLP	32	87	NB − 86.30
Rodríguez-Hernández et al. (2021)	GLiM, LR, FLM, GBT, DT, RF, ANN	18	162,030	ANN − 81.50

Notes: ANN = artificial neural network, C4.5 = a decision tree algorithm, CART = a decision tree algorithm, DT = decision tree (not specified), FLM = Fast Large margin (a support vector machine algorithm), GliM = generalised linear model (a logistic regression model), GBT = gradient boost trees (a decision tree algorithm), IB1 = a nearest neighbours algorithm, J48 = a decision tree algorithm, KNN = k-nearest neighbours, LR = logistic regression, MLP = multilayer perceptron, NB = Naïve Bayes, PART = a rule learner algorithm, RF = random forest, SMO = a support vector machine algorithm. *only one method was used. **second semester data is considered. ***median of the five faculties.

the ROC curve summarises the ability of a model. For easier comparison, we present the best algorithms and recall values from the eight publications below (Table 2).

The accuracy of the prediction rate of the EDM method was always higher than 60% (all studies analysed by EDM). The best predictor appeared to be SVM, but we have some notes on this result. First of all, every study found a different EDM algorithm to be the best predictor, so based on these data we cannot decide which is the most effective in predicting academic success/university dropout. Mueen et al. (2016) found the Naïve Bayes algorithm, on the same dataset, outperformed decision tree and ANN in predicting student performance, considering student demographics, PAA and the students' activity logs (classification by Alyahyan & Düştegör, 2020). Their research was carried out with a small sample size ($N = 60$). Based on a large sample size ($N = 162{,}030$) and the same background variables, with the exception of activity logs, Rodríguez-Hernández et al. (2021) and Siri (2015) reinforce ANN as the most precise way to predict academic performance, taking F1 scores into consideration. However, Díaz et al. (2021) also agreed on the effectiveness of decision tree (KNN also) and found ANN to be less effective in predicting student performance ($N = 1055$; same variables as Rodríguez-Hernández et al., 2021). In line with Mueen et al. (2016), the meta-analysis by Alyahyan and Düştegör (2020) also found that seven out of the 16 presented studies showed NB to be the best predictor. The analysis by Syahira et al. (2019) compared eight studies on student retention, and their results showed that DT algorithms outperformed NB, KNN and SVM in three out of eight cases and that an improved DT algorithm could predict performance with precision of 92.50 and 97.50%.

However, EDM methods have their drawbacks. They require a huge amount of different background variables, and ANN needs to be learnt to analyse a dataset. Furthermore, the data collection and data transformation phases are time-consuming periods (Mueen et al., 2016). Chinsook et al. (2022) raises the concern of privacy problems with EDM analyses. EDM methods are on the edge of ethical boundaries, and undergraduate students perceive a loss of freedom while under surveillance during their library and study time (as logfiles are analysed) (Binjubeir et al., 2019).

All in all, the appearance of EDM data collecting tools and algorithms have prompted researchers to expand the sample size and the spectrum in analysing the factors behind academic performance. Based on our research, the most frequently used research methods to examine the characteristics of success and/or failure of academic performance proved to be EDM methods (30%), SEM analyses (16%) and linear regression (10%). As regards the predictive strength of the research method, the proper choice depends on the perspective and the dataset in the study. With regard to student performance, student demographics, PAA and affective student factors, the most significant EDM methods are SVM, MLP, Naïve Bayes and decision tree. A non-EDM method, SEM, proved to be the most adequate statistical tool because it does not require extensive databases to achieve a precise predictive result. We have to note that we have to reduce the quantity of missing data and check the multicollinearity of the variables while using SEM (Cascallar et al., 2014).

The most important student- and non-student-related characteristics affecting success and/or failure based on earlier studies

To address our second research aim, we looked for reasons behind academic performance in the empirical studies. In order to monitor the generalisability of the research results, we first have to take a look at the sampling procedure in the studies under investigation.

In the systematic review process, we filtered 77 empirical, cross-sectional or longitudinal studies. The 55 cross-sectional studies published results based on responses from more than 255,000 undergraduate students. However, a large amount of data ($N = 215{,}000$) comes from three studies (Berens et al., 2019; Pellagatti et al., 2021; Rodríguez-Hernández et al., 2021). The 16 longitudinal studies under investigation analysed responses from more than 350,000 undergraduate students. Please note that Westrick et al. (2015, 2021) build their publication on the same data collection using the same sample, so we have taken their sample size into consideration only once. In total, the filtered studies thus reached more than 600,000 undergraduate students in order to monitor student- and non-student-related characteristics affecting academic success and/or failure in higher education.

In the empirical publications, some factors have been investigated more thoroughly than others. We summarised the frequency of the factors that were examined by the filtered publications based on the five dimensions of academic performance created by Alyahyan and Düştegör (2020) (see Table 3). Eighty per cent of the studies investigated more than one factor category.

The percentages for psychological student factors, academic achievement and student demographics were nearly the same (32%, 31.5% and 31.5%, respectively). A student's environment and e-learning activity only appeared in 4.5% of the filtered publications. Our findings are in line with Li and Wong (2019), who demonstrated that interest towards psychological attributes and outcomes grew in the 2010s, as well as student factors connected to academic performance (Gallego et al., 2021). This is contrary to the findings of Alyahyan and Düştegör (2020), who found the frequency of PAA at 44%, student demographics at 25%, a student's environment at 17%, psychological factors at 11% and e-learning activity at three per cent.

Table 3. Frequency of the factors behind academic performance in the filtered empirical publications ($N = 152$).

Factor category	Factor description	Frequency (%)
Psychological	Big-Five personality characteristics, Coping strategies, Engagement/adjustment, Grit, Motivation, Problem-solving skills, Satisfaction, Self-efficacy, Self-regulated learning strategies, Stress	32
(Prior) academic achievement	High school background (high school results and type), Admissions test results University-data: semester GPA, CGPA, ECTS	31.5
Student demographics	Gender, Age, Race/ethnicity, Socioeconomic status, Parents' education and occupation, Family size, Family income, Finances, Peers	31.5
Student's environment	Type of programme/curriculum	4.5
Student e-learning activity	Number of logins, Number of tasks, Number of tests, Assessment activities, Number of discussion board entries, Number of accesses of the virtual classroom	0.5

Table 4. Percentage frequency distribution of factors behind academic performance in the filtered empirical publications ($N = 153$).

Factor category	Factor description	Frequency (%)	Correlation range	Path range
Psychological	(intrinsic) Motivation	15	.14–.36	.16–.16*
	Self-regulated learning strategies (SRLS)	12	.057–.44	.12–.53
	Self-efficacy	7	.17–.39	.15–.55
	Satisfaction	4	.26–.57	.32–.50
	Big-Five personality characteristics (only conscientiousness)	3	.24–.47	.41–.41*
	Engagement/adjustment	3	.31–.60	.18–.76
	Stress	3	.30–.30*	NI
	Problem-solving skills	1	NI	NI
	$\sum$	48		
(Prior) academic achievement	Semester GPA, CGPA	12	.25–.28	.21–.49
	High school results (HSGPA) and type	8	.28–.62	.13–.35
	ECTS	7	.43–.59	.22–.22*
	Admissions test results	2	.25–.51	.48–.48*
	$\sum$	29		
Student demographics	Family background (family income, family size, parents' education and occupation, socioeconomic status)	9	.081–.56	.11–.72
	Gender	8	.27–.31	.11–.14
	Finances	4	.16–.16*	NI
	Age	2	.014–.51	.09–.17
	$\sum$	22		
Student's environment	Type of programme/curriculum	1	NI	NI
	$\sum$	1		

Notes: NI = no information was found in the filtered publications; *Data is derived from only one publication.

To add further implications of the factors associated with academic performance, in Table 4 we present the frequency and strength of the identified factors associated with academic performance considering both cross-sectional and longitudinal studies. We took factors into account which had the strongest influence on academic performance based on the results of the filtered empirical publications. The correlations and path ranges of the variables are calculated to dropout intentions OR GPA OR ECTS, because GPA and ECTS are considered as a level of academic success (York et al., 2015). The only case in which it was a dependent variable is when it was part of the model and not the outcome of academic performance. It is important to note that our data are derived from empirical studies where correlations or path coefficients were implicated and significant. We did not consider signs because they could not have been interpreted due to the difference between university dropout and academic success. Correlation and path ranges are shown based on the lowest and highest values in our pool of empirical studies.

According to the analyses, the most frequently identified contributor to academic performance was intrinsic motivation (15%), SRLS (12%), GPA/CGPA (12%) and family background (9%). Moreover, we found psychological factors tend to have a greater influence on academic performance than academic achievement and student demographics; all in all, in 48 per cent of the cases, a psychological factor had the largest contribution to university dropout/success (e.g. Le et al., 2020; Respondek et al., 2020). Rodríguez-Hernández et al. (2021) found a combination of PAA, student demographics and university background to be the most significant predictor: their cumulative value was over 70%, although they did not take psychological characteristics into consideration during their research.

To identify the strength of the factors, we analysed their correlations and path ranges. Based on our results, became apparent that the most consistently influential factors were GPA/CGPA, ECTS and gender, with a medium-sized correlation to academic performance. It is important to note, in the case of dropout, the acquisition of the first 20 credits was found to be crucial. Every psychological factor, HSGPA and admissions test results had a medium-sized consistency with small to medium-sized correlations, and we had the most contradictory results for family background and age (see Table 5).

Our secondary analysis to fulfil the third research aim was based on 17 meta-analyses and systematic reviews, which summarised the results of more than 900 empirical studies, spanning over 50 years of research on academic performance. The findings of the meta-analyses/systematic reviews confirmed our results based on the empirical studies.

Richardson et al. (2012) investigated factors that influence GPA and found conscientiousness, self-efficacy and SRLS to be the most significant but demographic factors to be less significant in influencing GPA (as a mediator). Alban and Mauricio (2019) confirmed the mediating role of self-efficacy in GPA, which is consistent with previous studies (e.g. Naaman, 2021 ; Schneider & Preckel, 2017; van der Zanden et al., 2018). Aydin (2017) disagreed with the importance of self-efficacy in the case of academic success. Our results for ECTS were also in agreement with those from previous research (Li & Wong, 2019; van der Zanden et al., 2019). Moreover, PAA affected both GPA and ECTS (Richardson et al., 2012). Further, the meta-analyses/systematic reviews strengthened our findings in connection with HSGPA and high school type (e.g. Li & Wong, 2019; Schneider & Preckel, 2017). Rodríguez-Hernández et al. (2020) stated that HSGPA and high school type are more important than family background and GPA. Kappe and van der Flier (2012) and

Table 5. Correlation difference of factors behind academic performance in the filtered empirical publications.

Difference in correlation			
Factor category	Small ($\Delta<.2$)	Medium ($.2<\Delta<.4$)	Large ($.4<\Delta$)
Psychological		(intrinsic) Motivation, SRLS, Self-efficacy, Satisfaction, Conscientiousness, Engagement	
(Prior) academic achievement	GPA/CGPA, ECTS	HSGPA, Admissions test results	
Student demographics	Gender		Family background, Age

Ibrahim et al. (2014) examined the effects of the Big Five personality traits on GPA and concluded that conscientiousness had the strongest correlation with academic performance (.18–.46), similarly to our results (.24–.47). It was in line with Koning et al. (2012) and later confirmed by Ambiel et al. (2018) and Khan (2018), but questioned by Osamika et al. (2021). The importance of conscientiousness was also emphasised by other meta-analytic studies (e.g. Kehm et al., 2019). The findings of the empirical studies on satisfaction and engagement/adjustment (e.g. Soares et al., 2021; Truta et al., 2018; Willems et al., 2019, 2021) were also confirmed by the secondary analysis (Alban & Mauricio, 2019; Aljohani, 2016).

Nevertheless, we had inconsistent results on (intrinsic) motivation. Some studies found the role of motivation to be decisive (Behr et al., 2020; van der Zanden et al., 2018). However, Richardson et al. (2012) used the term 'motivational factors' to cover self-efficacy, self-esteem and goal orientation in addition to types of motivation. They state that self-efficacy and grade goal were the strongest predictors of GPA from among the 'motivational factors'. In addition, Alban and Mauricio (2019) and Li and Wong (2019) did not even consider intrinsic motivation to be a contributor to academic performance.

A possible explanation for the contradictory results for SES and age is that these are the most frequently analysed factors in connection with academic performance (Alban & Mauricio, 2019). Richardson et al. (2012) found family background has a weak connection with academic performance, and this was later confirmed by a systematic review by Rodríguez-Hernández et al. (2021). However, Aljohani (2016) found this factor to be a strong contributor. This was confirmed by Alban and Mauricio (2019) and Li and Wong (2019). The empirical studies thus also had mixed results with regard to age and family background (e.g. Brooker et al., 2017; Shawwa et al., 2015; Zotti, 2015). Student work and finances were not strong contributors in the empirical studies and the secondary analysis. Aljohani (2016) and Bowles and Brindle (2017) emphasised the significance of financial aid; however, Aldahmashi et al. (2021) did not consider income as a decisive factor. Larsen et al. (2013) had mixed results for student work but stated that more than 20 hours of employment per week increases the probability of university dropout.

To sum up, based on an evaluation of 77 empirical papers and 18 meta-analyses published in the last ten years, we can conclude that the most important student- and non-student-related characteristics affecting success and/or failure of academic performance can be described in a model – using the classification developed by van Rooij, Brouwer, et al. (2018) – consisting of input, throughput and output factors (see Table 6).

Our results showed GPA/CGPA, ECTS and gender thoroughly influenced academic performance. While gender, intrinsic motivation, SRLS, self-efficacy, conscientiousness, engagement/adjustment, stress, HSGPA and high school type, and admissions test results showed some inconsistency, with a small- to medium-sized effect on academic

Table 6. A model of factors influencing academic performance based on the filtered publications.

Input: student factors	Throughput factors	Output: academic performance
Ability: problem-solving (skills)	Engagement	(C)GPA
Demographic factors: age, gender, family background	Work	
Prior education: HSGPA, high school quality	Finances	ECTS
Personality: SRLS, intrinsic motivation, conscientiousness, self-efficacy		

performance. We thus decided to include them in the final summary model. Furthermore, concerning age and family background (family income, family size, parents' education and occupation, and SES), our results were ambiguous and contradictory (Casanova et al., 2018; Larsen et al., 2013; Merchán-Clavellino et al., 2019; Páramo et al., 2017). However, we decided to include them due to cultural considerations.

Lastly, we also added problem-solving (skills) because of evidence from recent studies (Molnár et al., 2021) on their importance as a mediating factor of academic performance, which has received relatively little attention based on the filtered publications. Please note that SLRS, motivation, self-efficacy and conscientiousness are not disjunctive categories (Alhadabi & Karpinski, 2020; Azila-Gbettor et al., 2021; Kusurkar et al., 2013; Mujica et al., 2019; Séllei et al., 2021).

Conclusions

From the theoretical background, we concluded that it is not possible to provide a universal definition of either university dropout or academic success or a universal approach to them because of the complexity of the phenomenon. Basically, the definitions are influenced by the perspective of the investigation. However, two points should be noted. First, university dropout/academic success are both decision-making processes based on individual reasoning. Second, the focus of the research (micro/macro/individual) has to be clarified to make the comparison more precise. After the filtering process, we analysed 77 empirical studies and 18 meta-analyses and systematic reviews from the last ten years to identify the most frequently used research methods and factors influencing academic performance.

The first research aim was to monitor and evaluate the research methods used in empirical research on the factors influencing academic performance and dropout rates in higher education. We concluded, in the beginning, that these were descriptive statistics, with correlations using data collected in small-scale studies. As technology has advanced, sample sizes have grown larger. Nevertheless, samples are still convenience-based, and the opportunity to use predictive models, such as SEM and EDM tools and algorithms, has emerged. However, the research methods are closely related to the research questions, according to the filtered empirical publications. Based on our results, the most frequently used EDM tools are WEKA, SPSS, Rapid Miner and R. Forty per cent of our empirical study pool used EDM algorithms, of which neural networks were most frequently used. Nonetheless, our results are contradictory because decision trees were found to be the most commonly used algorithm (Mueen et al., 2016; Syahira et al., 2019). As regards the evaluation, SVM, MLP, Naïve Bayes and decision tree as well as SEM, a non-EDM method, proved to be the most adequate statistical tools in predicting academic performance. These are all predictive methods; however, SEM focuses on the personal data of an individual and does not require big data databases for analysis.

Our second and third research aims were tied to factors influencing academic performance. After our evaluation of the empirical and meta-analytic studies, we came to the conclusion that GPA, ECTS and gender are the strongest predictors of academic performance. Although GPA and ECTS are output factors, we also have to consider throughput factors which contribute to GPA and ECTS.

Beyond our research aims, we concluded there is a lack of comparability in our pool of studies, with 90% of the empirical studies using different measurement tools. In order to facilitate a comparison, we suggest establishing a theoretical framework and generalised questionnaires to make comparison and research work easier.

Limitations

According to the Scopus database, approximately 5,000 studies were published in 2020 with the keywords 'university dropout', 'academic success' and 'higher education'. We need to broaden our study by involving scholarly databases and research engines. Moreover, the databases from six of the longitudinal studies were established before 2012, but the publications were written after 2012 (Aina, 2013; Murray, 2014; Musso et al., 2013; Rocha-Ruiz et al., 2018,; Westrick et al., 2015, 2020). Considering the fact the cross-sectional studies were more up-to-date, we plan to involve more, and more recent, longitudinal studies on this topic. There were 17 empirical studies which were taken into consideration both in our analysis and the systematic reviews. Although it can cause a slight distortion, we wanted to implicate the original sources as well.

While university students cannot be considered as a homogeneous block of people (Molnár et al., 2021), we still used cumulative data in this study. Thus, no distinctions were made between the students' academic processes (Syahira et al., 2019) and areas of study. While our model is based on the international literature, an examination of academic performance being so complex, the cultural and political differences as well as language barriers make it impossible to build a universal model of dropout, not to mention various measurement tools, technological improvements and the Covid-19 pandemic. We would add to this the lack of representative samples in the empirical research on academic performance.

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Notes on contributors

Ádám Kocsis is a PhD. student of Gyöngyvér Molnár. He started his academic studies in 2020 and has been examining the research methods and decisive factors behind university dropout and academic success.

Gyöngyvér Molnár is a full professor and the head of Institute of Education and the head of the Doctoral School of Education at the University of Szeged in Szeged, Hungary. She is the co-chair of the Presidential Committee on Public Education of the Hungarian Academy of Sciences. Her main areas of interest include: technology-based assessment, improving cognitive skills, studying the quality of school learning, and the potential for using ICT in education – all of which are aimed at improving the quality of learning. She heads eDia, an online diagnostic testing system used in numerous countries. In 2016, she won the Apáczai Csere János Prize for her outstanding scholarly work in support of educational practice; in 2020 she received the Innovation Award of the University of Szeged; in 2022 the Researcher of the Year Award of the University of Szeged. In 2023, her research team received the Fáy Educational Innovation Award.

ORCID

Ádám Kocsis http://orcid.org/0009-0008-4469-598X
Gyöngyvér Molnár http://orcid.org/0000-0003-4890-6904

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