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Equal opportunities for non-traditional students? Dropout at a private German distance university of applied sciences

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Abstract
Student dropout represents a significant challenge in distance higher education. To better understand this issue, a comprehensive analysis of institutional data, spanning several years from a private German distance learning university of applied sciences, was conducted. The primary objectives were twofold: (1) to pinpoint institutional factors serving as predictors for student dropout and (2) to analyze the underlying psychological mechanisms. The findings indicate that part-time enrollment, age, interruptions, and overdue payments predicted dropout. Conversely, a good match between a student's occupation and the study program, as well as employer reimbursement of study fees, predicted degree completion. Further results suggest that students who recommend the program to others are more likely to succeed. However, those referred by friends are at a higher risk of dropping out. Additionally, poor grades and late submission of the first assignment were identified as predictors of dropout. A noteworthy finding was the interaction between these factors and the student's qualification for studying. Vocationally qualified students tend to submit their first assignment earlier but perform worse academically compared to academically qualified students. Generally, the influence of socio-demographic factors such as the educational background, gender, or nationality was low. This suggests that some of the disadvantages that non-traditional students might face at traditional universities in Germany might cease to exist at private distance universities of applied sciences. The implications of these findings are discussed.

Keywords Distance learning · Dropout · Private university of applied sciences · Asynchronous · Non-traditional students · Distance higher education

Introduction

Distance higher education (DHE) becomes increasingly popular (Dieckmann & Zinn, 2017). It is characterized by the possibility to finish a study degree almost entirely remote. Many distance education institutions furthermore offer an asynchronous mode of studying,

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which enables students to start anytime and study at their own pace. This flexibility is a major advantage of DHE, since it enables the part of society that faces personal circumstances that prevent them from attending traditional universities, to pursue an academic education. The growing demand for academization in the professional world and the need for more flexible study models have also contributed to the steady increase in the number of distance learning students in Germany (Dieckmann & Zinn, 2017). Especially during the Covid-19 pandemic, distance learning formats gained greater attention (S. L. Schneider & Council, 2021). However, studying while working or managing other personal responsibilities can also pose a significant challenge to students, as evidenced by the traditionally low graduation rates at distance universities (Simpson, 2013). This has negative consequences for the individual students, the institutions, and society, as university dropouts often have poorer occupational prospects, universities invest resources into students who do not graduate and there is a need for academically educated personnel on a societal level (Berlingieri & Bolz, 2020; Völk & Netz, 2012). The situation has been particularly concerning in DHE (Radovan, 2019) as demonstrated by the fact that the largest distance university in Germany, the FernUni Hagen reported a dropout rate of approximately 70% (Nolte, 2010) or that the largest DHE institution in the UK, the Open University, had a graduation rate of only 22%, which is well below the lowest graduation rate of face-to-face universities (Simpson, 2013). These factors emphasize the importance of research to understand the factors contributing to dropout and to develop strategies to prevent dropout and foster student success in DHE.

One of the most frequently mentioned factors that might contribute to the high dropout rates in DHE is that distance learning students have limited time available for studying due to conflicts with personal or professional obligations (Simpson, 2013). For example, a survey found that over 80% of distance learners reported that they had too little time to study (Aydin et al., 2019). Other conditions specific to DHE might include the lack of admission requirements, the great amount of time spent on self-study, or the comparably high costs of private distance universities compared to the free education at public universities in Germany. These circumstances characterize DHE but are not the only reason why distance students drop out. Instead, they complement other reasons for dropping out, that also exist in regular study programs: for example, motivational issues, dissatisfaction with the course materials, procrastination, or failed exams (Scheunemann et al., 2022; Xavier & Meneses, 2020). It is well-established that universities must actively support their students to decrease these high dropout rates (Tinto, 2012). Measures that promise to reduce student dropout are early warning systems (Tampke, 2013). For these early warning systems to be of practical relevance, it is needed to first understand the mechanisms that underly dropout factors and then work with institutional data that is readily available for the distance learning universities. This is why the present study aims to identify dropout factors in the data warehouse of a German distance learning university of applied sciences and explain the psychological mechanisms that might underly them.

Dropout in distance higher education

In recent years, research on university dropout in Germany was examined in various psychological studies from different theoretical perspectives, including personality, motivational, and social psychology (Behr et al., 2020; Poropat, 2009; Stein & Trautwein 2002; Suhlmann et al., 2018). Relevant psychological factors include the student's personality, their cognitive competencies, or their academic motivation. Evidence for these factors was also found in distance learning (Almulla & Al-Rahmi, 2023; Chiu, 2022; Kauffman, 2015; Sánchez-Elvira Paniagua & Simpson, 2018). One relevant motivational theory is the situated expectancy-value theory (EVT; Eccles et al., 1983; SEVT; Eccles & Wigfield, 2020). The framework postulates that success expectancy and task value are psychological determinants of achievement-related decision-making, such as performance and engagement in chosen activities (Eccles & Wigfield, 2020). Success expectancy refers to the students' level of confidence in their capacity to achieve a task whereas task values consist of utility value, attainment value, intrinsic value, and cost (Schnettler et al., 2020; Wigfield & Cambria, 2010). Costs include psychological cost, opportunity cost, and effort and are related to the negative consequences of a task (Schnettler et al., 2020). Many studies have used the SEVT in educational research to predict academic outcomes (Schnettler et al., 2020). However, apart from one study concerning online learning engagement in higher education during Covid-19 (Sun et al., 2023), there is limited research in the context of distance learning universities. Social identity theory is positioned within the field of social psychology (SIT; Tajfel & Turner, 2004). Social identity refers to the aspect of a person's self-concept that stems from their perceived affiliation with a relevant social group (e.g., identity as a student; Scheepers & Ellemers, 2019; Turner & Oakes, 1986). Findings by Suhlmann et al. (2018) stated that students who felt that they belonged to their university had higher motivation and satisfaction with the university and lower risks of dropout. Thus, in the context of DHE, incorporating "being a student" into the individuals' self-identity could foster learning behavior and prevent student dropout. However, even though these theories are important for understanding dropout, they are not feasible for distinguishing different dropout factors in the data warehouse of a distance university. For example, the age of a student could be interpreted from various psychological perspectives: Personality changes with increasing age (Allemand et al., 2007; Boyce et al., 2012; Brandt et al., 2023). Furthermore, social identity differs between different age groups (Tanti et al., 2011). Lastly, value-motivational factors change with advanced age (Sigmundsson et al., 2022). To distinguish the factors of a data warehouse in a structured way, instead of multiple theoretical perspectives on dropout, a single *dropout model* is needed.

The most influential model of student dropout is the "Student integration model" by Vincent Tinto (1975). It suggests that student dropout is influenced by two factors: Academic integration, meaning the extent to which students engage in academic tasks (i.e., submit assignments) and social integration, meaning the extent to which students build social relationships and feel included by their peers. Yet, due to the differences regarding student characteristics and the mode of learning, a separate model for explaining dropout in distance learning needed to be designed (Rovai, 2003). That is why Tinto's model was modified; first to account for the special circumstances of non-traditional students (Bean & Metzner, 1985), and subsequently for those of distance learning students (Rovai, 2003). A relatively recent model was put forward by Park (2007) who empirically evaluated Rovai's model for distance learners and altered it accordingly. It still includes elements of Tinto's student integration model but embeds them in a framework of other factors, namely learner characteristics, external factors and internal factors. *Learner Characteristics* (in the following: Student Characteristics) pertain to everything that characterizes a student before the start of a study program. Examples of this are demographic information or their professional background. *External Factors* refer to other aspects of the students' lives that might conflict with their study success. These might include financial difficulties or personal problems. Lastly, everything that characterizes the study experience per se are the *Internal Factors*. These include Tinto's concepts of social and academic integration, as well as student motivation and technical difficulties. Subsequent analyses gathered evidence for this model (Park & Choi, 2009; Radovan, 2019; see Fig. 1 for an overview of Park's model).

The present study

Past research often focused on questionnaires to investigate dropout factors (Heublein et al., 2017a; Vogel et al., 2018). Yet, these might be distorted by psychological biases such as the self-serving bias (Shepperd et al., 2008; Stoessel et al., 2015). Therefore, a data warehouse provided the basis for the present analysis. To the best of our knowledge, the studies that investigated institutional data in the past rarely attempted to analyze them psychologically but rather focused on the statistical properties of the dropout prediction model (e.g., Cannistrá et al., 2022). Furthermore, previous studies that considered dropout from distance learning tended to focus on the first months of studying (Kotsiantis et al., 2003; Queiroga et al., 2020; Utami et al., 2020). Although most dropout happens in this stage (Heublein et al., 2017b), especially in distance learning, there is a considerable part of the student body that does not drop out early but studies for extensive periods of time without earning a degree or even taking an exam (Utami et al., 2020). Since one of the most frequently cited dropout definitions in the German context, by Heublein and Wolter (2011), highlights that student dropout includes everyone who leaves the university without a degree, the present analysis focuses on degree completion. This was only possible because several years of academic records were accessed. To do so, a logistic regression

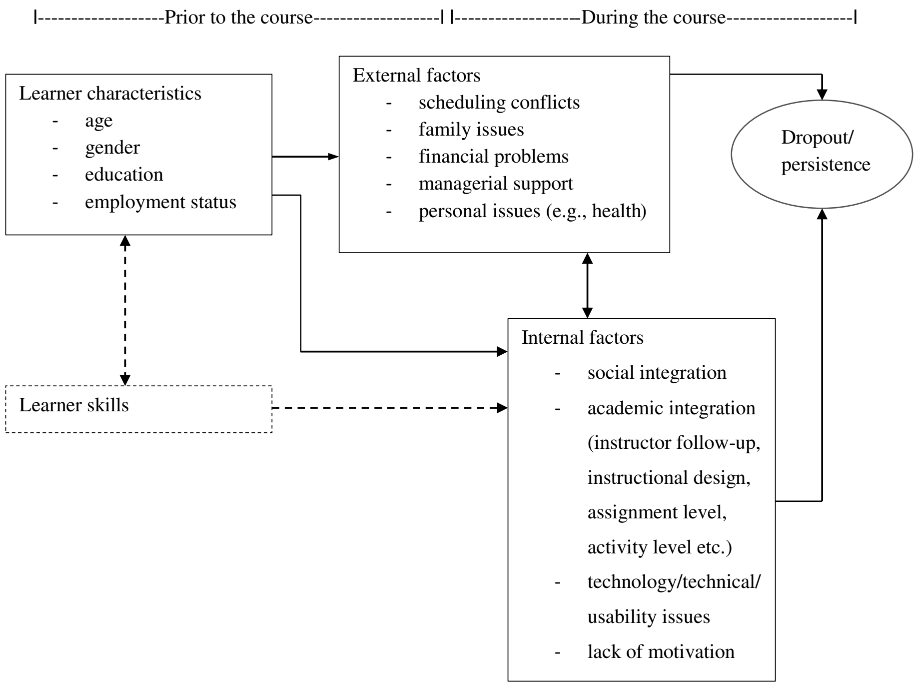


Fig. 1 Park's (2007) dropout model

analysis was performed. The identified factors were allocated to the dropout model by Park (2007) to ease their theoretical interpretation. Furthermore, as past research indicates that effective student support is needed as early as possible (Simpson, 2013; Tinto, 2012), the analysis was divided into factors that can already be collected before the start of the course (first step) and factors that can only be collected afterwards (second step). Special attention was furthermore put on minority groups of non-traditional students (foreign students, older students, vocationally qualified students, females) in the student body, since these groups often actively choose to pursue an academic degree in the distance learning format (Dieckmann & Zinn, 2017). Therefore, the interactions between socio-demographic variables and the other factors were investigated in the third step of the regression model. The study followed an exploratory approach to investigate the psychological properties that are predictive of student dropout at the distance university APOLLON. The literature about student dropout in DHE is limited. Therefore, the purpose of the present study was to gather preliminary information about student dropout in DHE and to investigate whether our findings align with previous research about student dropout at traditional universities.

Method

Dataset

The data for the present study was sourced from the data warehouse of the APOLLON University. The APOLLON University is a distance learning university of applied sciences that focuses on the public health sector, economics, and social study programs. It was founded in 2005, and as of 2021, there were more than 3800 actively enrolled students at the university. In Germany, universities of applied sciences also enable students who did not finish high school to obtain an academic degree. Consequently, the student body is very diverse from a socio-demographic perspective.

Data extraction was carried out in November 2021 and the sample was composed of students who started their studies between 2006 and 2017. However, to comply with data protection regulations, data of students whose records exceeded the ten-year mark were excluded from the data warehouse. Thus, only students who were still enrolled at the university from any point in time after November 2011 were included, which is $N=5796$. Incomplete data sets were excluded prior to the statistical analysis. Furthermore, all students who started their studies after December 2017 were excluded. Thus, the students had at least four years to graduate. This ensured that the data set was not distorted by the strong growth of the university in recent years and the disproportionately increasing number of dropouts. This was necessary because a degree is always associated with several years of study (average study time to degree: 38.31 months; $SD=9.36$), whereas dropouts can occur already after the first binding contract period of 6 months has expired. Furthermore, to ensure anonymity, 14 students from a very small master program had to be removed from the dataset (master of gerontology). In the data set, 69.5% of the students were identified as female and 30.5% as male. The most frequent occupation of the students was in health care and nursing (24.1%). The average age of the students at the start of their contract was 31.21 years ($SD=8.19$). 87.6%

were Bachelor students and 12.4% were Master students. Furthermore, of all Bachelor students for that the qualification was registered ($N = 4705$), 75.9% qualified with their school degree (academically qualified) and 24.1% qualified through an apprenticeship in connection with work experience (vocationally qualified). Furthermore, with 90.3% most students were German and only 9.3% were from other countries.

Operationalization of dropout

To determine reliable predictors for dropout in DHE, a dropout definition is needed. According to Heublein's definition (Heublein & Wolter, 2011), only students who leave university without a degree and do not start studying elsewhere are considered dropouts. We defined leaving the university without earning a degree as dropout (i.e., institutional attrition; Heublein & Wolter, 2011), for practical reasons. Students who left the university and continued their studies at other institutions or might return to their studies in the future were thus inevitably considered as dropouts in the analyses. This interpretation is in line with earlier research (Schneider et al., 2019). Yet, students who did not leave the university and merely changed their study program were not classified as dropouts. Only their most recent contract was considered, which ensured that each student could only be listed once as a dropout. A distinction had to be made between properly enrolled and provisionally enrolled students. The provisionally enrolled students included students who quit after a trial-month of their studies and students who wanted to qualify vocationally for their study program but did not pass a mandatory placement test within the first six months of studying. Only properly enrolled students were analyzed. In addition, some students who were found to have circumvented the admission requirements were removed. Once students terminated their contract, or their contract expired, they met clear criteria to be classified as dropouts. This also included students who terminally failed their exams or failed to pay their tuition fees before earning a degree.

Predictors

A total of 19 predictors for dropout were included in the model. Based on Park's dropout model (2007), these predictors were divided into internal factors, external factors, and student characteristics. Furthermore, a distinction was made between variables that could be collected before the start of the course and variables that were only collected after the start of the course (see below). This approach was inspired by previous studies examining dropout in distance learning (see Kotsiantis et al., 2003).

Student characteristics In the analysis, demographic variables such as age, gender (1 = female), and the nationality of students (1 = German) were included. Previous studies found that older students, male students, and foreign students are at increased risk for dropout (Belloc et al., 2010; Ghignoni, 2017; Müller & Schneider, 2013). It was also considered whether the students qualified for university academically with their (high) school diploma or vocationally, through a combination of professional training and work experience. In Germany, there is a hierarchy of school degrees with only the highest degree enabling the students to apply to any university without limitation. If students earn the next highest degrees, they might still be able to apply to universities of applied sciences or specific study programs, depending on their major subjects in school. Any of these groups will be referred to as academically qualified students in the following. If students did not finish high school at all, they might finish an apprenticeship and can be admitted to universities of applied sciences when they gained at least five years of work experience. They will be referred to as vocationally qualified students. Past research indicates that vocationally qualified students might at times be at a particular risk of dropping out (Heublein et al., 2017a).

Furthermore, previous education of the students, namely, whether they already completed an apprenticeship (1 = yes) or completed a university degree (1 = yes) before studying was also considered. Past research showed that dropout is higher in bachelor degrees than in master degrees (Heublein & Wolter, 2011), yet because of the inclusion of the previous study degree, no additional differentiation between bachelor and master programs was made. Lastly, it was investigated how well their occupation fits their study program. To approximate this, a rating scheme was developed in which every study program and every occupation was rated regarding health-, economic-, social- and technological relevance. This rating was based on a number of 0 (indicating no relevance), 1 (indicating some relevance), and 2 (indicating high relevance). The rating of the study programs was administered in close communication with the student service department of the university. The rating of the occupations was applied by two researchers separately. Inter-rater reliability was moderate ($\kappa = 0.553$). Subsequently, the rating was compared, and conflicting ratings were adjusted; again, in agreement with the student service department who, through extensive personal contact, is familiar with the student's backgrounds. Eventually, a score was calculated by adding the values for the four categories. The maximum possible score would have been 8, yet no combination exceeded a score of 4 since no study program addressed all four fields. To the best of our knowledge, this fit between the student and the occupation was not investigated before.

External factors From the perspective of the situated expectancy-value theory (SEVT; Eccles & Wigfield, 2020), the opportunity costs for studying are largely influenced by time conflicts with other areas of life. An approximation of this is the mode of studying, since students who study full-time might have a tighter schedule. However, students, who opt for the part-time mode of studying, might already have less study-time available to begin with. Past research suggests that students who work more than 20 h a week are at a higher risk of dropping out (Hovdhaugen, 2015). Furthermore, financial difficulties are a dropout risk (Vogel et al., 2018). Hence, delinquency with and the reduction of study fees were considered, as well as the reimbursement of the study fees by the employer. As students collect more credits, the opportunity costs associated with dropping out increase. Thus, receiving a credit transfer from earlier studies was assumed to be a student success factor. Past research furthermore found that students from the countryside were more successful than students from urban areas (Glaesser, 2006). In the analysis, this effect was investigated by considering the population density of the place of residency of the students. A distinction was made between low, medium, and high population densities. This was calculated based on data of population densities corresponding to all counties of Germany, provided by the Statistical Bureau of the Federal Republic of Germany (Statistisches Bundesamt (Destatis), 2021) and then matched with the administrational data in the data warehouse. The rationale was that students from densely populated regions like large cities may have the option to change to local traditional universities while students from sparsely populated regions would have to commute or move to study at traditional universities. Lastly, putting one's studies on hold by making use of the option to pause the payment for the study program was considered an indicator of both time and financial difficulties.

Internal factors Previous studies indicate that the career interests and intentions of students are moderated by their friends' interests (Robnett & Leaper, 2013; Tey et al., 2020). Moreover, longitudinal studies suggest that families influence the conceptualization of the field of interest, whereas friends and peers have an important impact on informing decisions about what constitutes the appropriate career path (Brooks, 2003). Therefore, it was investigated whether being referred by a friend who already studies at the university predicts dropout. During the enrollment process, the student service flagged every student who was referred by a friend with a note. By filtering this note, it was possible to identify those students. Similarly, the student service flagged the studying friend that recommended the studies, since they received a financial reward. These factors were considered an approximation for social integration, since they indicated that students knew at least one other person at the university. After the course start, factors of academic integration were approximated by considering the grade of the first exam and the time that passed until the first exam was submitted. The latter was considered as an indication of procrastination. Earlier studies investigated the time it took for students to enroll in a course to approximate this phenomenon with institutional data (Schneider et al., 2019; for an overview of all predictors please see Table 1).

Statistical analysis

The data was analyzed with a binary logistic regression. This analysis has proven efficient in predicting student dropout (Mduma et al., 2019; Stoessel et al., 2015) and occasionally produced even better results than more complex machine learning algorithms (Aulck et al., 2017). In addition to this analysis method, various descriptive analyses (e.g., mean values or standard deviations) and *t*-tests were carried out to investigate associations between the variables.

The analyses were computed with IBM SPSS statistics (Version 24).

Results

Assumption check

In the variable set were some minor deviations from normality. Yet, a certain deviation from normality is acceptable for regression analyses on large data sets (Blanca Mena et al., 2017). For this analysis, the collinearity diagnosis showed that the assumption of no multicollinearity was fulfilled (tolerance > 0.899).

Step 1: predictors before the start of the course

Internal factors Contrary to expectations, being referred to university by a friend significantly predicted dropout ($ß = 0.728$ $p < 0.01$), not student success (i.e., degree completion).

Table 1 Allocation of analyzed predictors to Park ‘s (2007) dropout model

	Internal factors	External factors	Characteristics
Before course start	Referred by friend	Discounts; reimbursement of study fees; credit transfer; mode of studying (full-/part-time); population density	Age; gender; nationality; previous vocational training; previous university degree; qualification; match of program and occupation
After course start	Grade of first exam; month of first exam; recommendation	Overdue payments, interruptions; reduced fees	

List of the 19 predictors for student dropout categorized according to the model of Park (2007)

External factors The logistic regression indicates that students studying part-time dropped out more frequently than students studying full-time (ß = -0.567, $p < 0.001$). Whether the students received discounts for their studies (ß = -0.050, $p = 0.644$) was no significant indicator of academic success, even though, when omitting other factors, receiving a discount predicted degree completion ($t(4261) = 3.01$, $p < 0.01$, $d = 0.11$). Getting previous credits transferred was no significant predictor in the model (ß = -0.114, $p = 0.360$). The population density of the students' place of residency, approached significance (ß = -0.108, $p = 0.065$). Getting the study fees reimbursed by the employer was a significant success factor ($\beta = -0.327$, $p < 0.05$).

Student characteristics Previous study degree completion was a significant predictor of academic success, yet the completion of an apprenticeship was not ($\beta = -1.181$, $p < 0.001$ for study; $\beta = -0.143$, $p = 0.294$ for apprenticeship). In line with this, there are significant differences between the dropout rates of the Bachelor's and Master's courses at the APOLLON University ($t(959.46) = 7.66$, $p < 0.001$, $d = 0.328$). In contrast to previous studies, older age predicted study dropout ($\beta = 0.203$, $p < 0.001$; Park & Choi, 2009) but nationality did not ($\beta = 0.127$, $p = 0.407$). Also, the coded match of the occupation with the course of study significantly predicted dropping out (ß = -0.180, $p < 0.001$). The qualification for studying was no significant predictor for dropping out (ß = 0.152, $p = 0.155$). Ultimately, gender was also not identified as a predictor for dropping out (ß = -0.163, $p = 0.103$).

Model before the start of the course The model that only contained variables that were already available before the courses started was statistically significant, χ^2 (12, N = 5796) = 150.61, $p < 0.001$. It had a prediction accuracy of 61.7%. For comparison, an earlier prediction of dropout in distance learning (Kotsiantis et al., 2003) had a similar prediction accuracy of 63% before course start. Nagelkerke's R squared was 0.084.

Step 2: predictors after the start of the course

Internal factors Being referred by a friend also remained a significant dropout predictor after course start. The month of submission of the first examination was a strong predictor for dropout (ß = 0.182, $p < 0.001$). Within the first six months, the dropout rate increased with every month of delay of the first submission. Furthermore, the first exam grade predicted dropout as well (ß = 0.284, $p < 0.001$). Worse grades in the first exam were associated with higher dropout rates. Contrary to being referred by someone else, recommending a friend to study was a strong predictor for student success (ß = -0.965, $p < 0.001$).

External factors All external factors that were significant before the start of the courses remained significant after the start of the courses. The corresponding values can be found in Table 2 in the Appendix. An external factor that was identified as a significant predictor for dropping out during the course was financial difficulties, which were operationalized by overdue payments ($\beta = 0.902$, $p < 0.001$). Reduced study fees, which are also related to financial problems, were not significant in the model ($\beta = 0.241$, $p = 0.188$). Interrupting the study program was furthermore a particularly strong predictor ($\beta = 0.892$, $p < 0.001$).

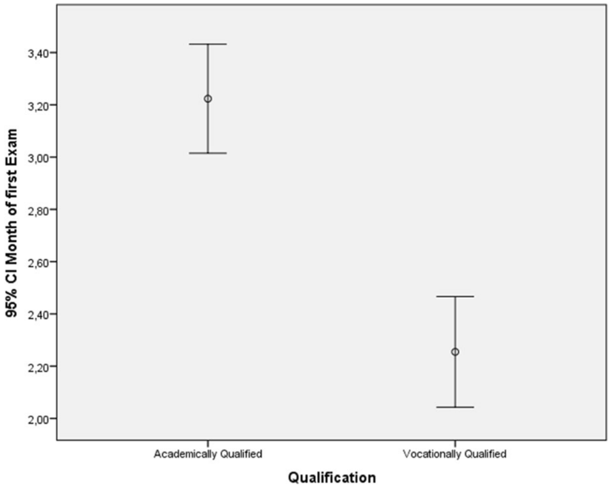


Fig. 2 Month of the first exam among academically and vocationally qualified students

Student characteristics After adding the variables after course start, gender was a significant predictor (β = -0.143 $p < 0.05$), with males dropping out more frequently. Also, nationality became significant ($\beta = 0.409$, $p < 0.05$), with German students dropping out more frequently than foreign students. For all other characteristics before the start of the course, significance levels did not change.

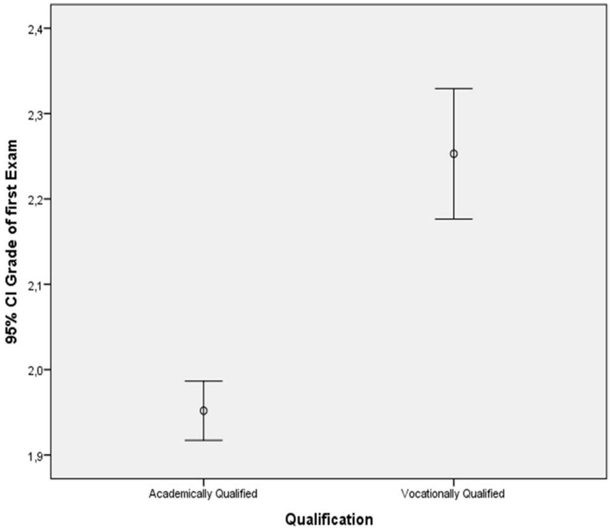
Model after the start of the study The extended model improved significantly χ^2 (7, $N = 5796$) = 355.45, $p < 0.001$. Yet, it had only moderate predictive power. With 70.6% it was already better than the previous model and the difference also showed a significant result ($p < 0.001$). Although Nagelkerke's R square tripled, it was still in the low to moderate range at 0.258. It was also significantly lower than the prediction of Kotsiantis et al. (2003), who achieved a forecast accuracy of 83% in distance learning, or by Kemper and colleagues (2020), who achieved an accuracy of over 95% in face-to-face studies – though using a different methodology (i.e., decision trees).

Step 3: interactions

The interactions were inserted to investigate relationships between the different clusters of variables. Some were also based on previous research results: Stoessel et al. (2015) reported interactions of various socio-demographic factors in an evaluation of a survey that was completed by graduates and dropouts of the Fernuniversität Hagen. However, our closest approximations of their interaction of the migration background (nationality in our data set) and the gender of the respondents, as well as the interaction between nationality and age were not significant (β = -0.161, $p = 0.659$ and $\beta = 0.007$, $p = 0.977$ respectively). Thus, these results were not replicated in our data set. However, the inclusion of the interaction terms led the age, nationality and gender variables to become non-significant ($\beta = 0.206$, $p = 0.360$ for age, $\beta = 0.526$, $p = 0.428$ for nationality and $\beta = 0.206$, $p = 0.360$ for gender).

When comparing academically qualified and vocationally qualified students, a significant interaction regarding the time of submission of the first exam was found. Vocationally qualified students submit their first exam significantly earlier (t = 4.961, df = 2699.76,

Fig. 3 Grade of the first exam among academically and vocationally qualified students



$p < 0.001$, d = 0.21). However, academically qualified students achieve better grades (with 1 being the best and 5 being the worst grade in the German higher educational system) in their first exam (t = 7,934, df = 3721, $p < 0.001$, d = 0.30; see Figs. 2 and 3 for error bars illustrating the effects). After adding the interactions, the qualification for university was now significant (ß = -0.429, $p < 0.05$). Thus, when controlling all other factors, vocationally qualified (and thus non-traditional) students complete their studies more frequently than academically qualified students.

Model with interactions The inclusion of the interaction terms improved the model slightly but significantly χ^2 (3, $N = 5796$) = 16.65, $p < 0.001$. It now had a predictive accuracy of 70.3% and Nagelkerke's R square of 0.270. An overview of the final regression model is given in Table 2 (see Appendix).

Discussion

The present study yielded various new insights into student dropout in distance learning and raised many new questions. Generally, all sectors of dropout factors that were found in earlier research also yielded good predictors in this analysis. These included the educational and demographic background of students, financial problems, and time conflicts, as well as indicators of social, and academic integration, and motivation. The major findings include that studying parttime, being older, and interrupting one's studies were predictors of dropout. A good match between a student's job and the study program on the other hand was a predictor for student success. Regarding social integration, it was found that recommending the studies to someone else was a success factor; however, being referred by a friend was a predictor for dropout. Furthermore, bad grades and late submission of the first assignment are predictors for dropout. An interaction between these factors and the qualification for studying was found. Vocationally qualified students submit their first assignment significantly earlier but receive significantly worse grades than academically qualified students. The detailed findings will be discussed in the following section.

Student characteristics

There were several important findings regarding the educational and professional background of the students. The finding that students who completed a university degree before course start are more successful could be explained by the greater academic competence which the students acquired in their previous studies. This confirms earlier results from regular universities where master programs have lower dropout rates than bachelor programs (Heblein & Wolter, 2011). Conflicting with this view is the finding that vocationally qualified students are similarly as successful as academically qualified students. Interestingly, when all other factors are controlled, being vocationally qualified is an even stronger predictor for success. This contrasts previous findings from research at face-to-face universities, where vocationally qualified students were found to be less successful or at most equally as successful compared to academically qualified students (Majer, 2018). It is also in conflict with psychological theories of cognitive performance, according to which students with higher school degrees should be more successful (Behr et al., 2020). However, assuming that a higher school degree is an indication of greater academic competence, this confirms earlier findings from Park and Choi (2009) who found that there is little research indicating that learner skill is related to dropout in distance learning. Thus, this finding might indicate a distinct suitability of distance learning to vocationally qualified students. Yet, there might be various other explanations for this finding. Students who are vocationally qualified are necessarily engaged in employment within their area of study and may have assimilated their vocational identity into their social identity. This integration could explain why being vocationally qualified correlated with success, highlighting the intertwining of their educational and professional identities. Belonging to a group was positively correlated with academic motivation and lower intention to drop out in earlier research (Suhlmann et al., 2018). The result could also be explained from the perspective of the situated expectancy-value theory. Vocationally qualified students may have higher success expectancy because they already have more work experience; thus, their confidence in the capacity to achieve a task (the degree) could be higher. Moreover, their utility value may be higher, because vocationally qualified students see the practical value of the degree as a chance to further qualify in their occupation. This is also consistent with previous research showing that professionally qualified students are more extrinsically motivated (Majer, 2018). Considering that non-traditional students still have to overcome many educational obstacles in contemporary society (Tinto, 2012), the findings suggest that at least once they passed the entrance exam, they are equally as, if not more successful as academically qualified students. This finding should be further investigated in future research.

The influence of demographic variables was relatively low. Higher age was a predictor of an increased dropout risk, which contrasts findings from Stoessel et al. (2015) who found that older students were more successful at the Fernuniversität Hagen. This discrepancy might be explained by the more practical focus of universities of applied sciences compared to the more theoretical universities like the Fernuniversität Hagen. For students of the former the degree might be more important for their career. Gender and nationality of the students had a weak influence that was only visible in the second step of the regression model. There, female students and foreign students were more likely to graduate. This also contradicts findings from Stoessel et al. (2015) who found that being a student with a migration background and being female were dropout risks. The differing results could also be explained by the differing nature between the universities, with the Fernuniversität Hagen being a public distance university with a more theoretical focus and the APOLLON university being a private distance university of applied sciences with a more practical focus. Taken together, these results indicate that demographic diversity may play a reduced role at universities of applied sciences in DHE, compared to traditional study programs, potentially due to the more autonomous way of studying.

External factors

Data from the data warehouse supports previous subjective notions, that external factors play a major role in distance learning (Klinke & Pundt, 2022). In line with earlier research, the analysis showed that various external factors had a significant influence on student dropout (Park & Choi, 2009), as for example financial issues and time conflicts. Generally financial difficulties (i.e., being overdue with the study fees) predicted dropout. Financial support in the form of getting the study fees reimbursed by the employer was a predictor of student success. Yet, the latter might also be explained by greater performance pressure induced by the funding of the employer. In general, these effects were only moderate and in the case of discounts and halved study fees, vanished once more predictors were considered.

The approximations for time conflicts were very strong predictors, which confirms earlier research (Vogel et al., 2018). The finding that part-time students drop out more often would be plausible when one assumes that students who are already busier due to their background tend to choose the part-time variant of their studies. Therefore, the underlying motive could still be a lack of time. That students from rural regions are slightly more successful is in line with research from regular universities (Glaesser, 2006). The perspective of SEVT's opportunity costs may be used to explain it, as there are less educational options in rural areas than in urban areas. By far the strongest predictor was interrupting the studies. This factor can be linked to financial difficulties, time conflicts, or other personal problems. Because of its strong predictability, it should be viewed as a red flag for student dropout and a hint that students may need more support with regard to those factors. Since the data did not reveal the reasons why interruptions are such a strong predictor, further research is needed.

Internal factors

Internal factors were of special interest. Social integration was found to be important in distance education in earlier research (Vogel et al., 2018). However, regarding social integration, the results in the present analysis seem ambivalent. Recommending the university to a friend is a predictor for student success while being the student who is referred to the university is a predictor for dropout. This finding might be explained in several ways. It could be assumed that students who are referred to the university were less autonomous in their decision to study and thus less intrinsically motivated. Students who successfully refer someone also get a bonus from the university which might cause them to be biased in their recommendation. Yet this would not explain why students who recommend the studies are more successful, since discounts per se were not found to be a predictor of student success. Overall, these results indicate that in DHE the individual satisfaction and motivation for studying might be more important than the mere connection to other students. However, further research is needed to investigate this assumption.

Furthermore, the relevance of the point in time at which the first exam is submitted, and the grade of this assignment, is in line with research that proposes that procrastination and achievement motivation influence student success in distance learning (Kauffman, 2015; Klingsieck et al., 2012). This suggests, that DHE institutions should consider advising their students to not postpone their assignments for too long. The interaction showing that professionally qualified students submit the first examination faster, but academically qualified students achieve better grades might have two explanations. On one hand it might indicate systematic differences between the two groups of students. On the other hand, it might be due to the special admittance procedure that vocationally qualified students need to undergo before admission to university. Within the first six months of studying, they need to pass a certain number of courses to be properly enrolled. This time pressure might suppress the students' procrastination tendencies and motivate them to hand in assignments earlier while compromising on the grades. Students who qualify for university with a high school degree do not have this time pressure. Future research should re-evaluate this finding, also regarding its potential influence on self-regulation strategies, which were key to success in distance education in earlier research (Radovan, 2011).

Complete model

Overall, the prediction model improved remarkably after course start, which confirms earlier research. Still, it needs to be noted that most of the analyses are in the range of weak to moderate effect sizes. Due to the limited control over the mentioned external influences on the students, the overall model is also weaker than comparable models (Kemper et al., 2020; Kotsiantis et al., 2003).

Limitations

Several limitations need to be addressed. The effects of the analyses were small. Even though statistically small effects can be highly relevant on a large scale (Greenwald et al., 2015), considering this and that the effects only represent statistically controlled associations, no causal conclusions can be drawn. In addition to this, due to their exploratory nature, prediction models develop greater predictive power retrospectively compared to the prediction of future data, as they are prone to overfitting (Behr et al., 2020). However, especially in distance learning, this is inherent to institutional data which can only serve as an approximation of the underlying psychological mechanisms. The most important factors for dropout in distance learning, namely personal problems (Klinke & Pundt, 2022), cannot be observed this way and future questionnaire-based research should aim to take these into account. The present study also only took a limited part of the impact of social-political decision-making into account. Future research should take the impact of social-political decision-making on dropout intentions into consideration. Another limitation of the study is its generalizability. The study used institutional data of the APOLLON distance university of applied sciences. The results were representative of student dropout at the APOLLON university, because the data warehouse of the university was used. However, the results of this cannot be generalized to distance university students in general, because the APOLLON distance university is a German distance university of applied sciences with a very specific focus on health economics. Findings of this study should only be viewed as approximates for distance universities in different contexts.

Implications

The focus of future support offers should be on the internal factors that can directly be monitored and influenced by the distance universities. These include, above all, the psychological and social conditions for dropping out. While previous research showed that having a study partner has positive effects on academic achievement (Pinnell et al., 2021; Putri & Nuraini, 2022), our mixed results regarding social connection of students (positive for students who recruit friends for the studies, but negative for the ones being recruited) highlight, that these initiatives should remain on a voluntary basis. The finding that the grade of the first exam and the point in time when it is submitted, make a considerable difference for student success, should be of special concern. This suggests that institutions should consider investing more resources in the support of their students early on in their studies. This support should prevent them from delaying the submission of the first assignment for too long. The support could also entail changing the official first grade to pass or fail, to ensure that most students will have a rewarding experience with their first mandatory assignment. Furthermore, the implementation of soft commitments, which were found to be an efficient means to increase student engagement in earlier research (Behlen et al., 2021), could be considered here. The results also suggest that students who do not work in a field related to their studies might need special attention. Lastly, putting the studies on hold should be viewed as a red flag for student dropout. From past research, it appears that those students who need support the most seek it the least and vice versa (Tinto, 2012). Educational implications of the study are that distance universities could use counseling to support students at risk of dropping out. Thus, distance learning institutions should invest resources into actively reaching out to at-risk students for support, for example by phone (Simpson, 2013). The present study yielded many predictors that can serve as approximates for other distance learning institutions to identify these students and understand their motives for dropping out.

Appendix

Table 2 An overview of the final regression model

Block	Variables	Step 1					Step 2					Step 3				
		B	*SE*	*W*	*OR*	*p*	*B*	*SE*	*W*	*OR*	*p*	*B*	*SE*	*W*	*OR*	*p*
Before	German (nationality)	.13	.15	.69	1.14	.41	.41	.17	5.80	1.50	*	.53	.66	.63	1.69	.43
Course-start	Age	.20	.06	11.14	1.23	***	.21	.07	10.69	1.24	**	.21	.22	.84	1.23	.36
	Gender	-.16	.10	2.66	.85	.10	-.27	.11	6.36	.76	*	-.14	.35	.17	.87	.68
	Credit transfer	-.11	.12	.84	.89	.36	-.14	.13	1.03	.87	.31	-.14	.14	1.13	.87	.29
	Previous degree	-1.18	.19	39.94	.31	***	-1.07	.20	28.61	.34	***	-1.06	.20	28.29	0.35	***
	Previous vocational training	-.14	.14	1.10	.87	.29	.05	.15	0.13	1.06	.72	.05	.15	.11	1.05	.74
	Study mode (full-/part time)	-.57	.09	40.32	.57	***	-.63	.10	41.48	.54	***	-.63	.10	41.63	.53	***
	Employer reimbursement	-.33	.13	5.87	.72	*	-.35	.15	5.61	.70	*	-.35	.15	5.54	.71	*
	Population density	-.11	.06	3.42	.90	.06	-.09	.06	1.87	.92	.17	-.08	.06	1.52	0.92	.22
	Qualification (Acad./Voc.)	.15	.11	2.02	1.16	.15	.09	.12	.60	1.09	.44	-.43	.17	6.05	0.65	*
	Match	-.18	.05	13.50	.84	***	-.15	.05	8.57	.86	**	-.16	.05	8.55	0.86	**
	Discounts	-.05	.11	.21	.95	.64	.02	.12	.03	1.02	.85	.01	.12	.01	1.01	.93
	Referred by friend	.73	.22	10.72	2.07	**	.74	.24	9.32	2.09	**	.72	.24	8.74	2.05	**
After	Halved fees						.24	.18	1.73	1.27	.19	.25	.18	1.89	1.29	.17
Course-start	Overdue payment						.90	.16	30.91	2.46	***	.92	.16	31.44	2.50	***
	Interruption						.89	.10	83.77	2.44	***	.90	.10	84.25	2.46	***
	Recommended to friend						-.96	.15	42.00	.38	***	-.96	.15	41.28	0.38	***
	Grade of first exam						.28	.05	29.97	1.33	***	.27	.05	26.26	1.31	***
	Month of first exam						.18	.02	71.16	1.20	***	-.13	.08	2.58	.88	.11
Interactions	Age x German											.01	.23	.00	1.01	.98
	Gender x German											-.16	.36	.19	0.85	.66
	Qualification x month of first exam											.29	.07	15.00	1.33	***
	Nagelkerke's R^2	.08					.26					.27				
	Classification accuracy (%)	.62					.71					.70				

The whole logistic regression model. *B*, logit coefficient; *SE*, standard error; *W*, Wald- χ^2 statistic; *OR*, odds ratio; *p*, *p*-value

* $p<.05$; ** $p<.01$, *** $p<.001$

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Declarations

Competing interests The authors declare no competing interests.

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Relevant research in the field of Psychology of Education:

Eckert, M., Scherenberg, V., & Klinke, C. (accepted for publication). How a Toke-Based Game May Elicit the Reward Prediction Error and Increases Engagement of Students in Elementary School. A Pilot Study. Frontiers in Psychology.

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Bettina Schreyögg:
No publications.

Katharina Fischer:
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Marcus Eckert:

Relevant research in the field of Psychology of Education:

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