Smart Learning Environments

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Reducing dropout rate through a deep learning model for sustainable education: long-term tracking of learning outcomes of an undergraduate cohort from 2018 to 2021

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Abstract

In recent years, initiatives and the resulting application of precision education have been applied with increasing frequency in Taiwan; the accompanying discourse has focused on identifying potential applications for artificial intelligence and how to use learning analytics to improve teaching quality and learning outcomes. This study used the established dropout risk prediction model to improve student learning effectiveness. The model was based on the academic portfolios of past students and built with statistical learning and deep learning methods. This study used this model to predict the dropout risk of 2205 freshmen enrolled in the fall semester of 2018 (graduated in June 2022) in the field of sustainable education. A total of 176 students with a dropout risk of more than 20% were considered high-risk students. After tracking and the appropriate guidance, the dropout risk of 91 students fell from > 20% to < 20%. To discuss the results from the perspective of gender and financial disadvantages, the improvement rate of the dropout risk for male students was 10.2% better than that of female students at 2.9%. The improvement rate in dropout risk for students with disadvantageous financial situations was as high as 12.0%, surpassing the 5.9% rate among general students. Overall, the dropout rate in the second year of the 2018 freshman cohort was lower than that of the 2016 and 2017 freshman cohorts. A predictive model established by statistical learning and deep learning methods was used as a tool to promote precision education, accurately and efficiently identifying students who are having difficulty learning, as well as leading to a better understanding of AI (artificial intelligence) in smart learning for sustainable education.

Keywords: Precision education, Deep learning, Individual dropout risk, Academic dropout, Sustainable education

Introduction

Precision education

In approximately 480 BC (before Christ), Confucius proposed the concept of teaching without classification. This initiative was pivotal and greatly influenced modern approaches to education and teaching. In addition to developing teachers' understanding of educational concepts and improving their educational levels, modern education includes the fundamental goals of respecting students' individuality, cultivating responsibility, acknowledging students' differences, and adjusting teaching to match student aptitude (Fan, 2019). Generally, to teach students according to their aptitude, personalized and differentiated educational methods should be employed to ensure that every student can achieve optimal learning outcomes. However, because manpower and material resources are limited, personalizing teaching methods according to student aptitude is frequently an ideal rather than a practice. One of the pathways of educational governance transformation involves the privatization, marketisation, digitization, and datafication of education on various digital platforms. The core concept of precision education shares similarities with the four steps of precision medicine: diagnosis, prediction, treatment, and prevention. By applying these steps, students' learning behaviors, learning environments, and learning strategies can be analyzed and discussed. Research topics encompass governance, policies, technology, and instructional practices. Regarding the findings on intelligent assessment, they include adjusting instructional strategies, predicting learning outcomes, and providing timely guidance to enhance students' learning effectiveness (Yang et al., 2021). Precision education is an emerging educational model that is evidence-based and rapidly gaining prominence. It relies on statistical and mathematical models to track, calculate, and predict individual behavior, facilitating more effective personalized behavior management, optimization, instruction, and learning (Mertanen et al., 2022). Customization is at the core of precision, and for "precision education" to be implemented, students must be taught through customized educational methods. To achieve this customization, data science, such as big data analysis, can be employed. In addition, students can be divided into groups, stratifications, and distributions according to their abilities, learning interests, and future career planning. The current graded English teaching in Taiwan's university system serves as a clear example of this. Precision education generally refers to teaching students in accordance with their aptitudes. Every student is an independent learning individual; they differ in their abilities to learn and absorb knowledge. From the perspective of learning engagement in individual students, their abilities are reflected in their individual learning performances, for both overall learning outcomes and individual subjects. However, in conventional educational systems, all students are provided with the same teaching materials, and they must follow the same instructions and learning process taught by a single teacher. This form of educational system ignores students' individual differences.

Precision education has been adopted for many years in advanced countries. It is mainly used to assist in facilitating the learning and growth of children with learning disabilities or dyslexia, aiming to understand the important indicators of learning disabilities at an individual level through additional data collection (Hart, 2016). For example, children have a higher likelihood of being diagnosed with dyslexia if their immediate family members have dyslexia. Precision education involves implementation of measures centered on personalized learning to improve learning outcomes. However, implementation of such an educational system is slow and arduous; it requires educational researchers to evaluate and analyze the crucial factors in learning. Successful personalized intervention also requires extensive time and resources, and these interventions must be updated consistently based on the latest evidence (Hart, 2016). Precision education has been used abroad for early diagnosis of childhood learning problems. In Taiwan, through the compulsory national educational system, students with special learning problems at and below high school level can be identified and appropriate teaching strategies and learning environments can be provided for them. At higher educational levels, precision education can be employed to similarly identify and address academic and nonacademic problems in undergraduate students to improve their learning behaviors, attitudes, and outcomes. Lu et al. (2018) collected data on 21 learning behaviors related to blended learning and established a highly accurate predictive model of students' final exam scores to identify crucial factors affecting semester performances. In recent years, initiatives and the resulting application of precision education have been applied with increasing frequency in Taiwan. The accompanying discourse has focused on the identification of potential applications for artificial intelligence and how to best use learning analytics to improve teaching quality and learning outcomes. One study used deep neural network models to import students' learning behaviors to the MOOCs (Massive Open Online Courses) platform to predict learning outcomes, assist instructors in identifying underperforming students, and provide them with help in a timely manner (Lee et al., 2021). These initiatives revealed that precision education could be used for early detection of high-risk students with poor learning performances. Artificial intelligence analysis could be employed to establish risk predictors for poor learning performance, identify high-risk students, and enable prompt intervention to improve teaching quality and student learning outcomes (Yang, 2021). Artificial intelligence can be applied in precision education for adaptive and personalized learning analysis to enable early identification of high-risk students with poor learning performances; furthermore, it can provide immediate assistance in improving teaching quality and learning outcomes. This article argues for a novel governance structure known as precision education governance. By leveraging big data and algorithms, with the aid of behavioral science and life sciences, precision education governance aims to guide and predict human behavior.

Academic dropout rates

Information technology is advancing at an unprecedented pace. New technologies, devices, applications, tools, and, most importantly, new ways of thinking are being introduced every day. The primary information technologies in smart education involve the collection of learning activity data and the use of learning analytics for guiding educational decisions. Additionally, data obtained from the educational environment is analyzed to understand learners' behavioral patterns and improve the educational setting. The framework of smart education emphasizes the role of various information and communication technologies in education, highlighting the importance of new or improved instructional and learning methods. It underscores the need for a coherent integration of information and communication technologies with appropriate teaching approaches (Demir, 2021). Predicting the future success of students poses a significant challenge in higher education management. However, with the current application of machine learning methods such as artificial neural networks, Naive Bayes, and support vector machine, predicting student behavior, attitudes, and performance becomes feasible. By understanding the factors that influence college students' performance, proactive measures can be taken to improve learning outcomes (Veluri et al., 2022).

Managers of academic affairs in universities are highly concerned with reducing suspension and dropout rates and maintaining retention rates. The Ministry of Education in Taiwan has identified this as a performance indicator for evaluating teaching performance in universities. Studies have noted that students' academic self-efficacy and academic engagement is affected by family and teachers. In teacher–student relationships, teacher support positively affects students' academic self-efficacy and thereby affects academic achievement (Pan et al., 2017). A study explored the effects of undergraduate students' academic emotional indicators (enjoyment, boredom, and anxiety) and the academic control scale on academic achievement and dropout intention. The findings revealed that anxiety was significantly correlated with dropout intention for both freshmen and sophomores. Students with low anxiety levels were less likely to drop out of school. In addition, enhancing perceived academic control and emotion can reportedly improve academic achievement and dropout intention (Respondek et al., 2017). The purpose of predicting student learning outcomes through learning analytics is to identify potential learning problems, such as the aforementioned, and provide immediate intervention or relevant measures (Tsai et al., 2020). Relevant studies have demonstrated that, through data collected from students' performances in conventional (non-MOOCs) distance learning courses, a predictive model can be constructed using logistic regression and can then be applied in future courses to identify potential dropouts. When such a model is combined with promotion of guidance programs, it can effectively reduce the dropout risk for students in distance learning courses (Burgos et al., 2018). A study adopted a qualitative method, based on focus group technique, and aimed to analyze the factors affecting college dropouts. These factors encompass academic misalignment with initial expectations, financial challenges within the family, and teachers resorting to traditionalist methodologies for the transmission of theoretical content, among others (Santos Villalba et al., 2023). In another study employing a semi-structured interview methodology, the observed reasons for delayed graduation and dropping out included factors such as an inappropriately chosen institution and/or courseload, employment while studying intensively in a higher education institution, participation in a competitive sport, and/or a negative attitude toward learning (Bocsi et al., 2019). Through synthesizing the findings of several studies, expansion in each discrete aspect or the combined aspects of teacher support, student personal factors (e.g., self-efficacy and emotion regulation), and personalized guidance measures can improve student learning outcomes and reduce academic dropout intentions, which then enhances learning motivation and retention rates.

Quantitative methods are the most commonly used approach in empirical research for Artificial Intelligence in Education (AIEd). The comprehensive results demonstrate four application areas of AIEd in academic support services, institutional services, and administrative services: (1) analysis and prediction, (2) assessment and evaluation, (3) adaptive systems and personalization, and (4) intelligent tutoring systems (Zawacki-Richter et al., 2019) Contemporary research primarily focuses on the phased development of predictive models, with fewer instances of demonstrating the application of research findings in practical institutional strategies. To effectively achieve these goals, the research team of this study has promoted research on precision education and published on this topic with individual dropout risk as the main focus (Tsai et al., 2020).

Under the implied assumption of precision education through which each freshman can learn efficiently under different teaching strategies according to their own learning characteristics, the research team developed a high-risk dropout tracking and guidance system. This study, therefore, which was conducted from September to October 2020 analyzed the output results of the high-risk dropout tracking and guidance system for the freshmen cohort of the 2018 academic year. In addition, this study evaluated the potential applicability and improvement of this artificial intelligence system to strengthen its reliability, security, and trust in order to ensure its continued implementation in the future, with the further benefit of serving as a reference point for institutional research on human-centered artificial intelligence in education.

Materials and methods

Samples

The research samples were taken from freshmen during the fall semester of 2018, as collected from their academic portfolio at the end of the first-year students' initial semester. Relevant data from a total of 2205 freshmen (776 men and 1429 women aged 18–19) were collected, including that of student loan applications, academic performance, number of absences from school, and number of alerted subjects, were substituted into the predictive model (described in subsequent sections).

Prediction model for predicting dropout risk

The authors have used statistical learning (logistic regression) and deep learning (multilayer perceptron) methods to establish a dropout risk prediction model (see Tsai et al., 2020). The model is based on a sample of freshmen enrolled in university from 2012 to 2013. A previous study included a total of 3,769 students to establish predictive models. Based on the research objectives, the study group consisted of 412 students who dropped out between the second and fourth grades, while the control group consisted of 3,357 students who were still enrolled in the second to fourth grades. The study aimed to explore the probability of student learning failure and its influencing factors. Student learning behavior data, including personal background information such as gender, socioeconomic status, and whether they had applied for student loans, were extracted from the school's administrative database for analysis. The analysis also incorporated engagement variables during the first year of study, such as the number of class absences per semester and holding leadership positions, as well as performance variables like semester class rankings and the number of warning subjects per semester. Additionally, data on whether students withdrew during their academic tenure was considered. Through logistic regression analysis, variables significantly associated with withdrawal between the second and fourth grades include students who have availed student loans, students who experienced a decline in their class ranking percentage during the second semester of their first year, students with an accumulated total of more than 20 class absences per semester in the first year, and students with more than 2 warning subjects per semester in the first year. By utilizing logistic regression analysis to identify factors influencing learning failure and providing relevant information for effective machine learning computations, patterns can be discovered to predict learning failure. The established dropout risk prediction model indicates that students with academic performance regression, procuring educational loans, higher absenteeism frequencies, and a greater number of alerted subjects are associated with an increased dropout risk. This information can be utilized as a reference for early intervention and counseling initiatives.

The current study used previously developed predictive models to explore the dropout risk of freshmen in the fall semester of 2018 and provided guidance in reducing dropout risks. First, when freshmen enter sophomores, the demographic information and data on the academic performance of the freshmen were collected, including student loan amounts, semester grades, rate of absenteeism, and number of early warning notices. These data were then substituted into the dropout risk prediction model to generate the predicted dropout risk for each student. Teachers were then given a list of students having a high risk of dropout which also included their learning trajectories; these were delivered as early as possible to provide guidance and improvement strategies based on the students' personal needs. To understand the effectiveness of the model's implementation, the learning status of the high-risk dropout students was consistently tracked until October 2021. In the subsequent transition to the junior and senior, students' learning performance from the previous academic year is used as predictive data to continuously track the risk of withdrawal for each academic year. Each time a student's risk of withdrawal is predicted, it is provided as feedback to both the student and their class advisors.

Tracking and guidance

This study constructed a precision education platform (as displayed in Fig. 1). Data and dropout rate predictions are updated at an interval of one academic year. The platform provides feedback to students and teachers (i.e., class advisor) on predicted dropout risks, student learning information, and learning trajectories and behaviors, thereby enabling students to self-monitor their learning and teachers to suggest individualized learning directions and guidance measures to efficiently correct students' learning behaviors and improve learning outcomes.

To facilitate students' self-monitoring of their learning progress, a precision educational platform is established, encompassing diagnostic, predictive, counseling, and preventive components. The platform functions by collecting data on students' learning behaviors, conducting future learning prognosis, and providing diagnostic feedback to both students and teachers. Additionally, the developed model for predicting dropout risks is integrated into the platform, enabling early alerts regarding students' course enrollment patterns and academic performance, thus ensuring timely intervention. Leveraging the predictive insights from the dropout prediction system, the platform offers the following functionalities: (1) implementing personalized learning strategy evaluation and improvement mechanisms to cater to students' individual differences; (2) providing timely recommendations on learning pathways, including suitable learning methods, materials, and guidance on when to progress to the next learning objective or select relevant courses for further studies; and (3) alerting teachers about students who are falling behind in their learning or require intervention at appropriate junctures. The precise education platform regularly updates its data on a semester basis, ensuring continuous monitoring of students' learning behaviors.

Fig. 1 The student's interface displays the personal risk assessment and the learning advice from the teacher

The precise education platform provides students with comprehensive personal learning information for self-monitoring, as shown in Fig. 1. This includes records related to dropout risks, course enrollment, volunteer participation, certification exams, and more. Through this system, students can regularly assess their own dropout risk probability for each semester. On the teacher's end, as depicted in Fig. 2, the platform enables teachers to understand the learning status of students in their class and offer timely care and advice. For students at high risk of dropout, teachers provide learning recommendations based on counseling sessions, which are then logged into the system for students to access and review independently.

Teachers play a crucial role at this stage as they are responsible for identifying students who may be facing academic difficulties and guiding them towards appropriate academic support. If a teacher observes that a student's interests lie outside of their current major and they feel uncertain about their life path, the teacher can assist the student in assessing whether the current major is suitable for them and if they can graduate from it. Additionally, the teacher can provide guidance as a mentor by suggesting options such as pursuing a minor, double major, transferring to a different major, or exploring other career paths. If the student faces learning challenges, the teacher can communicate the issues to the relevant academic department or administrative personnel for further assistance. The Table 1 below illustrates the sustainable education and responsible units within the school for various academic and non-academic factors, offering corresponding, sustainable education such as attending

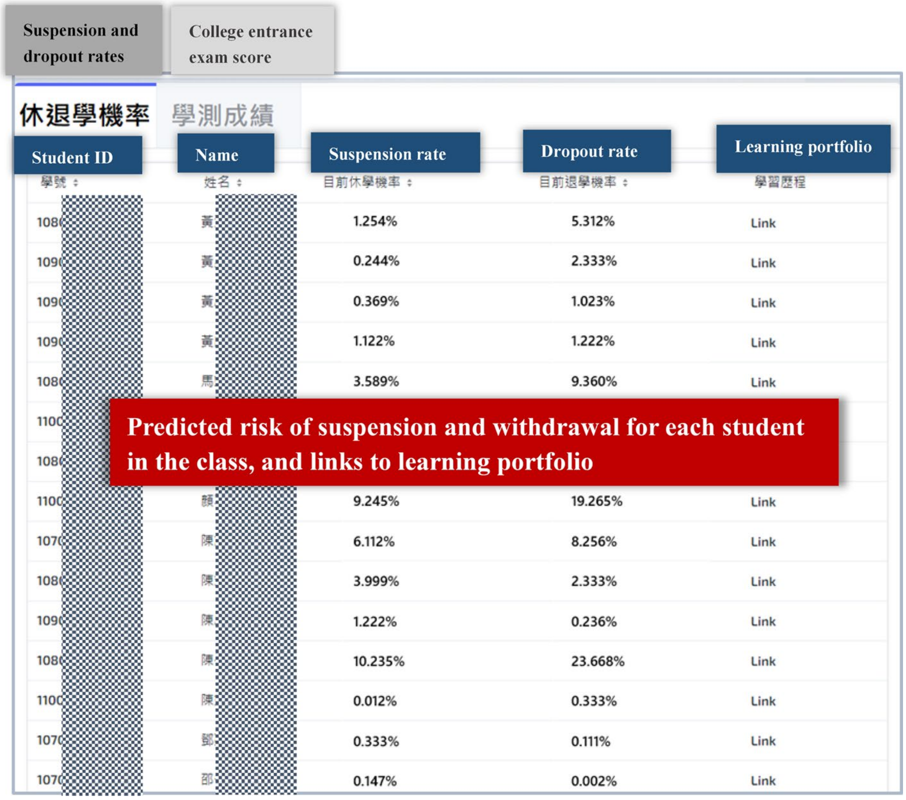

Fig. 2 On the teacher interface displays the dropout risk probabilities for each student in the class

Table 1 Factors affecting dropping out and mechanisms for improvement

Categories	AI predictive variables	Sustainable education	Responsible units
Academic-related	Academic performance Early warning subjects	Academic advising, career counseling	Instructors, departments, academic affairs office, career team
Non-academic-related	Economic weakness	Apply for student loans, scholarships, and part-time jobs	Instructors, academic affairs office, student affairs office
	Absence	Roll call system, Internet addiction therapy, career counseling	Instructors, student affairs office, career team, internet addiction prevention center
	Others	Social Caring	Instructors, caring group

after-school tutoring, referring students for mental health counseling, or providing treatment for internet addiction.

Results

The sample data of 2205 freshmen in the 2018 academic year were substituted into the prediction model. After computing by statistical learning and deep learning methods, the probability of each student being predicted as dropouts can be obtained. The same prediction results of the two methods revealed that 448 students (297 men and 151 women) had a dropout risk of over 10% (as shown in Table 2). Taking into account the dropout rate of sophomore students in previous years (sophomore dropouts/sophomore

Table 2 Number of 2019 sophomores as categorized by dropout risk

Predicted dropout risk	< 10%	10–15%	15–20%	20–25%	> 25%
Number of students	1757	162	110	37	139

enrollees), it has been observed to be approximately 8%; as such, this proportion is adopted as the threshold for high-risk counseling and tracking. Therefore, in this study, out of the 2025 freshmen as derived from the predictive model (Tsai et al., 2020), the top 176 students at high risk (constituting roughly 8% of the incoming cohort) exhibit predicted attrition probabilities exceeding 20%. Of these 488, the 176 students with a dropout risk of more than 20% were considered high-risk students. By the end of this study, due to the efforts of several parties, such as the Student Affairs Department, Academic Affairs Department, and teachers, the dropout status of the 176 high-risk students had changed.

To assist students in reducing the risk of dropping out, teachers employ several approaches. They proactively strive to understand the students' situations, engage in individual conversations, and create opportunities for emotional bonding between teachers and students. By adopting a multifaceted empathetic approach, teachers provide assistance and offer academic support channels to improve learning outcomes. They collaborate closely with parents to enhance the learning experience and address individual students' emotional or other internal needs. When dealing with students' emotional or other internal needs, teachers may refer them to resource centers, harnessing the collective efforts of the school and parents to improve students' academic performance.

When this high-risk cohort entered the second year, 31 of the students dropped out. The distribution of their predicted dropout risk is indicated in Table 3. As observed from Table 3, the actual dropout rate increases as the predicted risk intervals widen (*p* value for the trend, 0.0044). This demonstrates the model's efficacy in accurately identifying high-risk students. The research sample was subsequently comprised of 145 high-risk students. The results at the end of the first semester of the second year were used to predict the distribution of the dropout risk. As indicated in Table 4, the dropout risk of 91 students fell from > 20% to < 20%, with the rates for 50 of these students decreasing to < 10%. A subsequent total of 54 high-risk students were consistently tracked. In the

Table 3 Distribution of students' second-year outcomes across different predicted dropout risk intervals (2019)

Predicted dropout risk	20–30%	30–39%	40–49%	50–59%	60–69%	70–79%	Subtotal	*p* value*
Number of dropout students(%)	4(7%)	4(15%)	4(13%)	5(23%)	8(40%)	6(38%)	31(100%)	0.0044
Number of enrolled students(%)	55(93%)	23(85%)	28(88%)	17(77%)	12(60%)	10(63%)	145(100%)	

* Cochran–Mantel–Haenszel Statistics was used to test trend distribution in dropouts and Predicted risk levels. A two tailed p value < 0.05 was considered statistically significant

Table 4 Distribution of predicted dropout risk for students in their third year (2020)

Predicted dropout risk	< 10%	10–20%	> 20%
Number of students	50	41	54

Table 5 Number and percentage of dropouts in freshman cohorts from 2016 to 2018

Academic year	2016	2017	2018
Number of freshmen	2379	2361	2334
Freshman	76 (3.2%)	92 (3.9%)	47 (2.0%)
Sophomores	159 (6.7%)	172 (7.3%)	144 (6.2%)

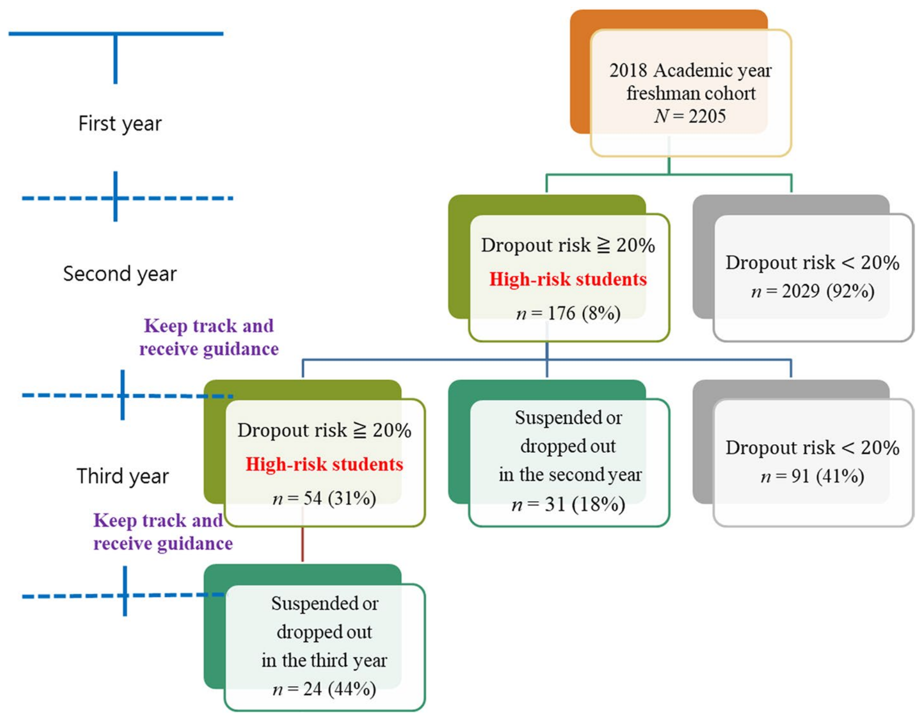

Fig. 3 Cohort tracking freshmen with high risk of dropout in the 2018 academic year

third year, 24 students were suspended or dropped out. When compared with freshman cohorts for the 2016, 2017, and 2018 academic years, the 2018 cohort had a lower dropout risk in the second year, as presented in Table 5.

As presented in Fig. 3, for the freshmen admitted in the 2018 academic year, the overall spectrum of the dropout risk changed during the 2020 academic year. The freshman cohort from the 2018 academic year will continue to be tracked and receive guidance in future semesters. During the academic years 2018–2021, out of a total of 2029 students categorized as the non-high-risk group, 154 students withdrew, resulting in a dropout rate of 7.58%. For the students who dropped out, their reasons for suspension or dropout were collected from our databases for institutional research and are displayed in Table 6.

According to the analysis of the institutional research, sex was a common confounder, particularly with respect to academic and learning performance. Therefore, the influence of sex differences on dropout risks were also analyzed. In addition, the dropout circumstances of students with financial difficulties were investigated. For high-risk students who dropped out in the second year, the tracking results for sex and disadvantaged financial situation (as shown in Table 7) demonstrated that, under the monitoring and

Table 6 Primary reasons for suspension and dropout in the 2019 academic year

	Number of students Third year	Number of students Fourth year
Reason for suspension		
Health-related factors	2	0
Mismatched interest	3	5
Maladaptation	2	0
Failed examination	2	0
Study abroad	1	0
Poor academic performance	0	1
Reason for dropout		
Failure to earn two-thirds of total semester credits	2	9
Work-related factors	0	1
Failed examination	0	1
Transfer (transfer to another university)	9	2
Transfer (internal course transfer)	6	1
Other factors	4	4
Total	31	24

Table 7 Effects of sex and financial factors on dropout risk during the academic years 2019–2020

	Third semester ($n = 2205$)			Fourth semester ($n = 2174$)			Reduction rate (%)
	Current student	High-risk cohort for dropout		Current student	High-risk cohort for dropout		
	Number of students	Number of students	Percentage (%)	Number of students	Number of students	Percentage (%)	
Sex							
Male	776	125	16.1	758	44	5.9	− 10.2
Female	1429	51	3.6	1416	10	0.7	− 2.9
Disadvantaged financial situation							
No	1865	154	8.3	1839	44	2.4	− 5.9
Yes	340	22	15.0	335	10	3.0	− 12.0

guidance of this system, the dropout risk reduction rate for male students was 10.2%, whereas that for female students was 2.9%. The dropout risk reduction rate for students with poor financial situations was as high as 12.0%, which outperformed the 5.9% rate of general students.

Discussion

This study found that as the first-year academic portfolio of freshmen was substituted into the predictive model, it was calculated that students who are at high risk of dropout were accurately identified. Through the intervention of individualized improvement strategies, 41% of students with a high risk of dropping out of school successfully reduced their chances of dropping out, and such students also had reliable attendance.

As found in Lee et al. (2021), teachers can use artificial intelligence systems to identify poorly performing students and provide them with additional timely assistance to create a learning-teaching environment that benefits both students and lecturers. The research conclusion in Tempelaar et al. (2021) has the same concept; in precision education, we are not concerned with the group level, but the individual level. It is this individual difference and intervention that can be effectively improved. In recent years, immense progress has been made in the application of big data and artificial intelligence in education. This highlights a new trend in educational research. Artificial intelligence and big data can facilitate embedding data collection into educational technology, and modern computing technology is making big data analysis a reality (Luan et al., 2020). To prevent retention rates from decreasing, the goal of university admission departments should be to not only focus on recruiting talented students; they should also include provision of excellent education. The research team of this study began implementing precision education in 2019. Through establishment of an academic affairs database, individual dropout risks (e.g., failure risk) could be predicted. In early research by Purnell et al. (2010), it was posited that the early detection of students' learning difficulties allows students to understand their own learning goals; through support channels such as learning skills assistance, counseling and study groups from schools and teachers, learning outcomes can be effectively improved. Similarly, within research on early warning systems for students at high risk of academic challenges, strategies have been implemented to mitigate students' fears of course failure and subsequent dropout. These interventions include mentor involvement alongside the alerts. Notably, research findings have indicated that adopting relatively straightforward intervention approaches can exert a positive influence on students' learning outcomes (Jayaprakash et al., 2014). Aligned with previous research practices, each student not only views their individual dropout risk but also receives recommendations for their learning path. Class advisors offer guidance and facilitate referrals to relevant support units.

The results of this study indicate that a student's sex and financial situation may affect the results of the tracking and guidance system. Therefore, these two factors were compared (as shown in Table 4). The results revealed that the tracking and guidance system was more likely to reduce dropout risks in men and in students with financial difficulties. In the future, the effects of sex and financial situations should be considered in tracking and guiding freshman cohorts. In most developed countries, the academic performance of female students in elementary school is more favorable than that of male students (Organisation for Economic Co-operation and Development [OECD], 2012). However, a reversal has also occurred in many countries, with male students having higher academic performance than female students in 1970 (Almås et al., 2016). Chang (2020) studied dropout rates and compared the grade point averages and course pass rates of graduates and academic dropout students from the 2011 academic year to that of 2019. The results indicated that the grade point averages and the course pass rates of dropout students at National Central University and National Chengchi University were lower than those of the graduates. In addition, among the students at Chung Yuan Christian University who failed to earn one-half of their total semester credits, the proportion of students with financial difficulties was considerably higher in some departments. Among dropout students in Soochow University, the highest proportions had student loans, were men, were in the mathematics or science departments, were transfer students, had applied for suspension, and had lower test scores.

According to the latest statistics from the Ministry of Education in Taiwan, 166,562 undergraduate students dropped out in the 2018 academic year, which is 13.38% of the total number of undergraduate students (1.24 million students). The ratio for this year is the highest to date, indicating that 1.3 out of every 10 students in the 2018 academic year dropped out. The main reasons were work-related factors, mismatched interests, poor academic performance, and financial difficulties. Therefore, the Ministry of Education has asked universities to expand the flexibility of their courses to help students with mismatched interests study double majors and interdisciplinary studies. In addition, a NT$400 million stipend is provided to help financially disadvantaged students obtain on-campus part-time jobs instead of off-campus part-time jobs, enabling them to focus on their academic performance. As for the reasons why students dropped out in the 2018 school year, they were mainly work-related factors, interest mismatch, poor academic performance and financial difficulties. The Ministry of Education has also proposed a new syllabus for the 12-year national education system and a new system for the Joint University Entrance Examination that will go into effect in 2022 and will better account for mismatched interests in students. Universities actively plan flexible course modules for freshmen to reduce occurrence of deferred graduation and dropouts (Lin & Wu, 2020). Retention rates can also reflect continued attendance of students. In the 2018 academic year, the retention rate of full-time bachelor's degree students (in 140 universities) was 90.4%, indicating that approximately 10% of students dropped out. Among the included universities, public universities had a retention rate of 94.3%, which was 5.7% higher than that of private universities (88.6%). With respect to school systems, the retention rates for regular universities and technical colleges were 91.5% and 89.2%, respectively. The results reveal the essentiality of maintaining retention rates, especially under the circumstances of sub-replacement fertility and high dropout rates.

According to statistics from the National Center for Education Statistics in the United States, the failure graduation rate of students from low-income families was five times that of middle-income families and six times that of high-income families (Sikhan, 2013). Moreover, Letseka and Breier (2008) reported that higher education data in South Africa indicated that 50% of students dropped out from higher education institutions in the first three years, with approximately 30% dropping out in the first year. This indicates that evaluation of students' financial situations when they demonstrate poor academic performance is necessary. If high dropout risks cannot be reduced, the Academic Affairs Division may encounter difficulties in management and operation. Furthermore, because many dropouts have financial difficulties, they will further be unable to achieve social mobility due to not having completed their studies and graduated successfully (Kearney, 2015). To address the needs of economically disadvantaged students, their foundation must be strengthened to ensure equal learning opportunities. A basic principle is to provide assistance and guidance to replace part-time work with study, so that students with financial difficulties can balance academics and livelihood. This includes offering academic tutoring, diverse lectures and practical courses, employment consulting services, mentoring students to participate in domestic and international design or entrepreneurial competitions, and overseas learning opportunities. Additionally, providing financially disadvantaged students with long-term study resources, such as loaned laptops, can assist their academic studies.

In recent years, several studies have discussed the phenomenon of dropping out (Chang, 2020; Her & Lin, 2017; Her et al., 2021). At our university, precision education has been implemented to the extent of our capacity to do so, not only within the framework of dropout issues, but also with regard to implemented grouping, stratification, distribution, and graded teaching to ensure that students with different learning performances can learn according to their abilities. In addition, we conducted a study using an innovative model in the hopes that more students at our university would successfully complete their studies. This high-risk dropout tracking and guidance system was developed at the university. Despite the valuable findings, our study is subject to certain limitations due to the waiting time required for data collection. It is necessary to collect the academic portfolio to predict the dropout risk after the second year. If the data can be traced back to the learning process of high school, we can predict the learning behavior of each student when freshmen enter the university, and promote precision education of teaching students in accordance with their aptitude as soon as possible. In summary, this study applied a statistical learning and deep learning prediction model to predict the dropout risk of a freshman cohort in the given academic year. This study predicted the dropout risk for each student in their second to fourth years (or their completion rates) based on their learning engagement data. Furthermore, this study performed tracking and guidance to ensure each student had a higher probability of completing their studies. Under the current wave of sub-replacement fertility, the decline in the number of new students and high dropout rates have worsened the situation. This study indicates that assisting students in learning and maintaining the retention rate through precision education practices may mitigate the effects of sub-replacement fertility.

Abbreviations

AI	Artificial intelligence
AIEd	Artificial intelligence in education
BC	Before Christ
MOOCs	Massive open online courses
OECD	Organisation for Economic Co-operation and Development

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Author contributions
TNW initialized the study and wrote the manuscript; YTS was responsible for administrative process communication and wrote the manuscript; CHC revised the manuscript and made corrections before submission; YTS and CHC have made equal contributions to this article; KFW and BLC provide technical support; and YHC conducted the statistical analyses. All authors read and approved the final manuscript.

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Availability of data and materials
The datasets generated and/or analysed during the current study are not publicly available due to the data is owned by the service organization of the corresponding author, but are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests.

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