Towards Sustainable Education: A Machine Learning Model for Early Student Dropout Prediction in Higher Education Institutions

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Abstract

Sustaining learners through an education cycle is a challenge for institutions at all levels. For higher education institutions, learners are presumed to be mature enough to complete their study courses. However, the challenge of student dropouts is prevalent. This paper seeks to address the key question of why students continue to drop out of learning institutions despite interventions undertaken by stakeholders. The attrition rates are a major concern that requires immediate attention if sustainable education is to be achieved. Dropping out of school is attributed to both individual factors and external factors. However, both require mitigation to save the future of education. This paper presents an analysis of challenges leading to student dropouts sampled from five institutions within the central region of Uganda (532 respondents). In addition, we leveraged the power of artificial intelligence (AI) to design and present a machine learning model for early student dropout prediction so that early interventions can be undertaken.

The study adopted the design science methodology to scientifically support the design and validation of the machine learning student dropout prediction model. The early warning model presents key performance indicators to signal whether a student is predisposed to drop out or on course to completion. This way corrective intervention can be undertaken early enough for likely dropout. The validation experiment conducted on a sample of 523 from the five institutions predicated a dropout of 10%. This proved the concept and the capacity of the model to predict learner dropout from university.

Keywords: *Student dropout; Sustainable education; Early prediction; Machine learning; Algorithm.*

Introduction

Universities and colleges have been at the forefront of developing and dismantling paradigms, according to the history of higher education. They have fostered social change not only through scientific advancements but also through educating thinkers, decision-makers and leaders (Cortese, 2003; Elton, 2003; Lozano, 2006; Tilbury et al., 2005). Higher education can transform the world by educating and enlarging young minds, researching solutions to problems and informing public policy, demonstrating its own comprehension and commitment through careful campus management, and by being an accountable employer and active participant in the local and business communities.

Universities and colleges also have an impact in the age of globalisation through their involvement in offshore collaborations, global procurement, and the instruction of both domestic and foreign students. It is important to consider their potential impact on community development, health and poverty alleviation, in addition to economic development and poverty reduction (Boks & Diehl, 2006; Galang, 2010).

However, in a situation where universities and colleges are now perceived as aggravating the sustainability crisis and perpetuating the ideologies that support our exploitative connections with people and the environment, this catalytic potential needs to be grounded in sustainability of education (Abidin Sanusi & Khelghat-Doost, 2008; Barab & Luehmann, 2003; Huisingh & Mebratu, 2000; Mochizuki & Fadeeva, 2010). The triple bottom-line approach, a sustainability strategy, implementation and cultural change, monitoring and evaluation, and top management commitment are all used by universities to adopt policies and practices that provide sustainable results.

According to the literature, sustainability calls into question the prevalent ideologies, structures, and practices in all social sectors, including higher education (Calder & Clugston, 2003; Lozano, 2006; Merrill et al., 1998).

Therefore, it is not unexpected to see that institutions of higher learning that have committed to sustainability are finding it difficult to make a significant contribution to it (Huisingh & Mebratu, 2000; Lozano, 2006; Su & Chang, 2017). It is relatively easy to start programmes that deal with important sustainability challenges in practice, but these usually focus on minority groups, failing to reach the institution's core of employees, students, and stakeholders, or even to change the institution's culture and practices.

Equally, commissioning a new sustainable structure or creating a specialty course in the field offer some potential to mould beliefs and behaviours, but efforts to mainstream this goal throughout higher education have so far been ineffective. Understanding this difficulty requires understanding that sustainability is more of a journey than a checklist, and that worldviews that permeate thinking and practice must be challenged. Extend the idea of sustainable communities outside universities and colleges requires engaging academic institutions in a drive for interdisciplinarity, participatory pedagogies, "real-world" research, as well as the opening of institutional boundaries.

The challenge is that these must happen in a connected manner. The systemic complexity of this agenda puts pressure on academic silos, power corridors, and the standards and procedures for making decisions. Furthermore, cross-departmental (and faculty) teaching and research, as well as a redefining of the lecturer-student, leader-employee and academia-community ties, all serve as the foundation for sustainability. In other words, transforming a university towards sustainable development necessitates realigning all of its initiatives with a critically reflective mindset that also encourages the creation of interconnected, more sustainable futures.

The multilevelled conventional educational system bases advancement to the following level on satisfactory completion of the one before it. Primary, post-primary, high school and tertiary/higher education levels are the core levels of education. According to experience, learner recruitment is at its peak at entry levels but tends to decline as students advance to higher levels. In particular, there is a declining tendency in the proportion of students who move from the first stage to the last one, demonstrating that students leave school before graduating. Student dropout rates are higher at higher education levels like universities, where they happen early in the academic programmes.

Every third student who enrols in a higher education programme will either transfer to another school or depart without completing it (Vossensteyn et al., 2015). The assumption that pupils at the higher levels of learning are mature enough to understand the purpose of attending school has not yet been confirmed. In addition, graduates of higher education institutions benefit from tax breaks and other advantages like faster economic growth (Kaplan & Haenlein, 2020) and higher productivity compared to non-graduates.

Despite the advantages, many students at university level fail to complete their studies. The long-term effects of dropping out of school do not just relate to the student's future; they also provide a cost challenge for the institution globally (Wild & Heuling, 2020) as well as financial losses because the institution will have already invested in the student. This further leads to misuse public monies, especially those allocated to institutions receiving government support. In terms of economics, dropouts have a nearly two-to-one unemployment rate advantage over college graduates, and they are four times more likely to default on student loans, harming their credit and reducing their career options.

Measures to reduce or mitigate school dropout are a top concern because it is a problem on a global scale. Reduced dropout rates in higher education were a major target for many higher institutions of learning (HEIs) and a significant strategy in Europe's 2020 plan (Vossensteyn et al., 2015). Therefore, early cause factor identification is a key component of mitigation strategies (Cabrera et al., 1992; Spady, 1970; Tinto, 1975). Academic (or institutional) stakeholders, including programme directors and student counsellors, can take prompt corrective action when risk factors are identified early. Although extensive research has been done on the recognised reasons why students leave school, little substantial progress has been made. Many of these are personal, like not paying for education, and external, like peer pressure.

Education stakeholders have taken a great interest in analysing performance qualities utilising academic and non-academic aspects as a result of the paradigm shift towards the computerisation of school data management (Issah et al., 2023). Dropout rates among students are a challenging issue in the educational process, with negative effects on learners, academic institutions, financial resources, and society at large (Fernández-García et al., 2021). Both industrialised and developing nations struggle with it, although the least developed economies are significantly more affected. The ability to foresee the possibility of a student leaving school as soon as feasible is a crucial worry for many education administrators and authorities. Although it is becoming more common, it is still quite difficult to foresee it early enough.

In order to enable early interventions, inform policy and urge focused steps to be taken to support the student in continuing and finishing the course, the goal of this paper is to develop a model to facilitate early prediction of student dropout.

Literature Review

In numerous fields and sectors, including telecommunications, building, transportation, healthcare, manufacturing, advertising and education, artificial intelligence (AI), including machine learning (ML) and deep learning (DL), is regarded as a game-changer (Lee et al., 2018; Reddy et al., 2020). Higher education will increasingly rely on AI since it enables students to take a personalised approach to learning challenges based on their own particular experiences and preferences.

To maximise learning, AI-based digital learning systems can adjust to each student's prior knowledge, rate of learning and intended learning outcomes. Additionally, it has the capacity to examine students' prior academic records in order to pinpoint their areas of weakness and recommend courses that will improve their individualised learning experience (Kokku et al., 2018).

The usage of AI can also speed up ordinary administrative work, freeing up faculty in higher education to devote more time to research and teaching (Pokrivcakova, 2019). Attrition among final-year students has significant effects on both the people and the impacted institutions in today's educational system. In fact, attrition results in costs for all parties, whether in terms of resources, time or money (Gansemer-Topf & Schuh, 2006; Yu et al., 2010). As a result, higher education institutions face a significant difficulty in preventing educational attrition (Zhang et al., 2010).

In order to make better decisions, machine learning models have typically been used to predict student attrition. A computer programme or a certain type of computer system called a "machine learning model" is used to analyse data without involving explicit programming. By finding and nurturing student relationships with the aid of predictive data mining tools suggested by this methodology, a university can reduce student attrition (Delen, 2010) (Delen, 2010).

The first step in enhancing retention policies, such as learning aid or mentorship programmes, is the identification of risk cases. Allocating pedagogical, psychological or administrative resources effectively may benefit from quantifying attrition risks. Addressing attrition issues in higher education institutions is particularly important; attrition is a common domestic phenomenon in higher education, with a high number of students failing to complete their degrees. The job market lacks specialists due to economic expansion and demographic change (Sani et al., 2022).

This paper seeks to leverage machine learning algorithms to predict student attrition issues, as well as to collect knowledge and investigate the student attrition issue, besides developing a model to accurately predict student attrition. This will be achieved by investingating institutional, academic and personal factors that influence student dropout, develop and test an algorithm to predict students likely to drop out of school, and make recommendations for mitigating the challenges.

Objective

This paper is intended to contribute to existing efforts related to learner dropout from school. Specific reference is made to higher institutions of learning. The paper proposes an early dropout prediction model supported by an algorithm that employs machine learning to mine and analyse data to support prediction. This way, we contribute to education sustainability through prediction and the recommendation of timely corrective interventions. Specifically, the paper is intended:

a) To study the key institutional, academic and personal factors that influence student dropout and suggest mitigative measures.

b) To establish the requirements necessary for developing a learner dropout prediction algorithm

c) To develop a predictive algorithm that can correctly predict learners' who are likely to drop out of school.

d) To recommend the development of an early learner dropout prediction model.

Methodology/Approach

The design science method was used to support the design, development and validation of the learner dropout prediction model. The methodology allows for the methodical production of information about a phenomenon leading to the design of an artifact (Peffers et al., 2007, 2014). It extends the scientific study of design and the use of design processes in the scientific creation of knowledge. In order to design, develop and evaluate the prediction model artefact to support timely intervention options for people who are at risk of failing, the methodological view serves as a suitable research paradigm. Design science proposes six steps: 1) During problem identification, the focus centres on the issue of continuous student dropout from the university; 2) To achieve the study purpose, the study objectives are defined, where the main objective is to develop a machine learning-based model for early prediction of learner dropout at higher education institutions. The consequential outcome is to undertake early interventions to support sustainable education; 3) The intended artifact is designed and supported by relevant requirements; and 4) The prediction model has to be evaluated or validated.

Sample data and population

Data was collected from a sample of 532 continuing and final-year students. Data was also extracted from exit surveys used by some of the institutions. The data described the institutional efforts, academic intentions of the learners along with personal and institutional characteristics. Data preparation for machine learning methods was done following the ETL (extract, transform and load) process. In order to make the data compatible with the machine learning algorithms, it was cleaned up, outliers removed, and then converted.

Data collection was supported with a questionnaire whose reliability was tested using the Cronbach alpha coefficient (Cronbach, 1951), which yielded a value of 0.821. Being above 0.7, the instrument was found to be adequate (Nunnally & Bernstein, 1994). While validity was tested using Bartlett's test of sphericity, the outcome was found to be significant at a level of 0.05 because the constructive validity significance level is $P<0.05$.

To ensure the artefact reliability to identify students at risk, stages for designing and developing an AI-based model using integrated DSR methodology are outlined. The process deployed the use of big data analytics over a range of AI techniques to achieve predictive accuracy, moderating classifier algorithm parameters, tuning the dataset, and applying ML algorithms to choose the best key predictive attributes. The application of DSR for predictive artefact design justifies technology-based innovations in non-information system disciplines such as education (Muhammad et al., 2020; Shah & Michael, 2016). For accuracy purposes, two design and development phases were employed. The predictive model was intended to warn stakeholders by promptly pointing out learners with challenges, and to offer timely and necessary assistance in terms of corrective actions to sustain academic progress. Data was mined from learner records without specific limitation to academic performance.

To evaluate the model, a variety of evaluation experiments shall be conducted with carefully planned phases, including evaluation based on actual data from higher education institutions. To assess the effectiveness and usability, the model artifact was integrated into institutional learning management systems (LMS) and other supporting systems. Recommendations are further presented as best practices for support structures to deal with the school dropout challenge.

Findings/Results

To understand the magnitude of the challenge, a preliminary investigation was conducted using a sample of 532 university students randomly selected from both private and government universities within the central region of Uganda. The actors responsible for learner dropout were categorised into academic and non-academic. The findings showed that non-academic factors contribute more to learner dropout than academic factors. Figure 1 summarises the outcomes where the non-academic factors for learner dropout were 320 (60%) compared to academic factors, where the response was 212 (40%).

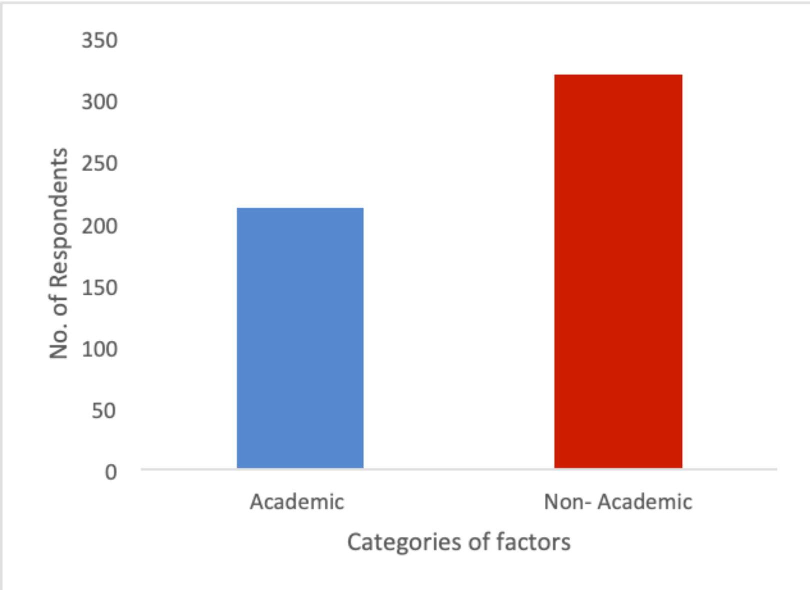

Figure 1: Categories of factors for learner dropout

Specifically, to understand the magnitude and contribution of academic factors responsible for learner dropout, the participants indicated a number of factors, which are summarised in Figure 2. As Figure 2 shows, the key academic factors for learner dropout included the lack of free lunch at school (18%), lack of teacher support (15.4%) and poor learner attendance. Many students fail to raise tuition fees, and once balances accumulate learners tend to abandon studies. With regard to learner support, at the higher institutions of learning, learner independence tends to overshadow their need to seek support from tutors. Eventually some perform poorly, accumulate retakes and eventually drop out. The high level of independence causes some learners to skip classes, which eventually retards their academic performance.

However, other factors, too, had a contributory effect on dropout, including lack of scholastic materials and a low-grade point average, both rated at 11.3%, the number of disciplinary referrals such as when a student is involved in a malpractice (10.3%), and being subjected to disciplinary actions such as suspension for one or two academic years. Such students may never return to school. The lack of support programme placements (9.4%) such as counselling or career guidance, and the number of grade retentions such as retakes (which contributes 8.5%) are also factors considered to lead to school dropout.

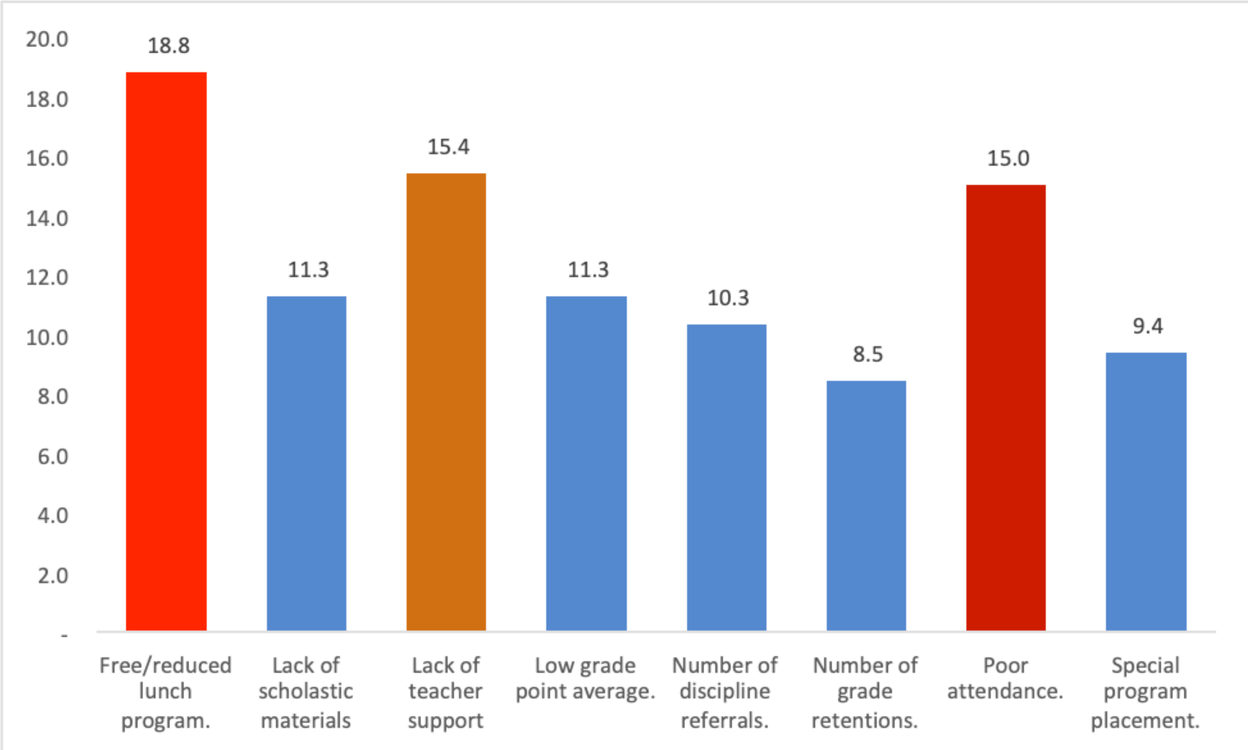

Figure 2:Academic factors for learner dropout

Relatedly, it was revealed that several non-academic factors are responsible for learner school dropout, as presented in Figure 3. Among the outstanding factors, the respondents indicated social factors (21.6%) such as family commitment and social life. In addition, work related factors and peer pressure (15%) also highly contribute to school dropout.

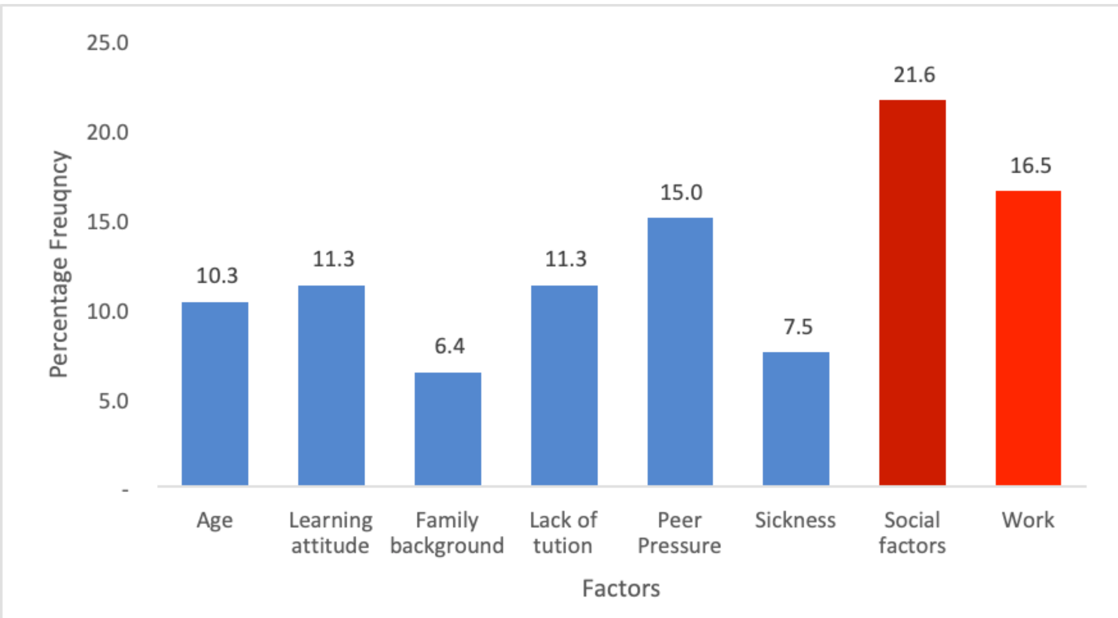

Figure 3: Non-academic factors for learner dropout

Learning attitude and lack of tuition fees averagely (11.3%) contribute to school dropout, according to the respondents. The factors that least contributed to dropout include a learner's age (10.3%), sickness (7.5%) and family background (6.4%). The learner's age involves scenarios where learners are above the average learners' age in their study group. Such learners tend to fail to connect with the other learners and are sometimes too bored to continue with school.

The respondents were engaged on the probable mitigation factors to cub school dropout. Several propositions were made which were presented as action points on what stakeholders should do. These are categorised into what sponsors/parents can do, what students can do, and what the institutions can do. The responses are presented as follows:

The learners were engaged to respond to what they thought their parents should do to save the situation. The responses are summarised in Table 1. Among the recommendations, the respondents strongly agreed (64.7%) to the need for parents to communicate with the learners. This way, the parents would know the challenges learners may be encountering and support them to stay in school. The learners also agreed that there is need for their parents to be supportive (66.2%) and for counselling about career prospects (66.9%).

Table 1: What parents should do

Parents should	Strongly Disagree	Disagree	Not sure	Agree	Strongly agree
Be supportive	4.1	6.4	1.9	66.2	21.4
Communicate with learners	-	-	8.3	27.1	64.7
Counsel learners about career realities	5.6	-	3.8	66.9	23.7
Encourage a break at the point of quitting	77.6	4.1	-	10.3	7.9

Source: Primary data

However, some learners strongly disagreed regarding the need for a break at the point where a student is discovered to be likely to drop out (77.6%). The respondents felt that such a break would instead clearly make learners relax and possibly fail to resume school.

Relatedly, learners were further engaged on what they thought institutions should do to alleviate the challenges leading to school dropout. The responses are summarised in Table 2.

Table 2: What institutions should do

Institutions should	Strongly disagree	Disagree	Not sure	Agree	Strongly agree
Adopt active learning	0.6	2.6	3.8	75.2	17.9
Adopt early-intervention strategies	0.4	6.2	1.9	65.8	25.8
Develop mentoring/tutoring programmes	6.2	2.3	-	41.4	50.2
Lower study costs	-	-	-	6.0	94.0
Provide family support systems	0.4	5.6	6.2	43.2	44.5
Support learner mental health	-	5.1	3.8	45.1	46.1
Support learner to make informed decisions	4.1	8.1	1.9	63.9	22.0
Use life coaches	2.1	4.1	1.9	38.5	53.4

Source: Primary data

The respondents strongly agreed that institutions should lower costs (94.0%) related to learning since a high number of students drop out due to lack of tuition fees. In addition, the learners agreed (75%) that institutions should adopt active learning in which a learner will be fully engaged and contribute to the learning process. In the same way, the respondents advocated for early intervention (65.8%) once a slump in a student's learning process is detected as well as the need for support to the learner to make informed decisions (63.9%). Many times, learners, owing to their age, make wrong decisions that impact their stay in school. Therefore, 46.1% strongly agreed that institutions should support their mental well-being. This can be through mental welfare programmes and campaigns against drug abuse. Moreover, the need for

family support systems (44.5% strongly agreed) can help, since many learners can be affected by social factors that may pull them out of school. The respondents further strongly agreed (50.2%) that institutions should develop mentorship programmes which inspire learners and direct them towards achieving their life-time goals. This was strongly supported, as the respondents strongly agreed to the use of life coaches (53.4%). Life coaches speak to the life of learners and inspire them to remain focused in life.
Learners are core to the effort of education life cycle sustainability. The respondents were asked on the contribution of learners to this effect. The response is summarised in Table 3.

Table 3: What Learners should do

Learners should	Strongly disagree	Disagree	**Not sure**	**Agree**	**Strongly agree**
Engage in other activities	7.5	5.6	6.2	24.6	56.0
Monitor my performance	3.8	5.6	2.1	27.1	61.5
Seek help	0.4	0.8	3.8	15.0	80.1
Set life goals	-	-	15.0	75.2	9.8
Set study goals	1.1	1.7	5.5	22.6	69.2

Source: Primary data

The respondents strongly agreed that learners should seek help (80.1%), especially at the point where they are struggling and are likely to drop out of school. In addition, the respondents strongly agreed (69.2%) that setting study goals is an important factor for staying in school. Once students aim to attain their study goals, this becomes a motivation to sustain their learning. The ability to monitor the performance of the learner was ranked at 61.5%, implying that learners should be empowered to monitor their performance as a way to encourage their progression. This can be achieved through formative feedback and the use of electronic tools such as discussion forum feedback. The respondents strongly agreed that there was need to be engaged in other activities (56%) as a way to keep them motivated. Such activities may include outdoor sports and physical education activities. Lastly, the respondents agreed (75.2%) that setting life goals was a strong factor. Life goals are objectives in life that learners want to achieve.

The results have indicated the feelings of the learners towards sustaining education. Paramount among them is the need for them to monitor their performance, set life goals and get support from both parents and their learning institutions. These factors are considered to be key indicators for sustaining learners in school. Once a slump is detected, it can be an early warning of likely dropout from school.

Discussion

Besides academic performance as a key indicator of learner dropout (Al-Hamad et al., 2021; Alshurideh et al., 2021), preliminary findings revealed other factors, including student's family, attendance, cost of learning, and education level of parent (Saeed Al-Maroof et al., 2020; Shahzadi & Ahmad, 2011). The existent works on the subject of academic dropout can be categorised as follows:

Students' personal factors: Gender, age, learning disability (if any), prior education history, discipline history (Daud et al., 2017; Gkontzis et al., 2018; Mitra & Goldstein, 2015) have been found to determine learner stay in school. This resonates well with primary findings where it was established that learner attitude and family background are key determinants for one to stay or drop out of school.

Financial and professional status: These include family income, family assets, work experience and current employment status (Daud et al., 2017). The primary findings revealed that the cost of learning in terms of tuition fees was a key factor in school dropout. It was suggested that lowering the cost highly contributes to sustainable education as per the primary data findings in Table 2.

Academic background: These include admission scores, information regarding schools the student has attended in the past, enrolment options and enrolment year (Gkontzis et al., 2018; Mitra & Goldstein, 2015). The academic background was found not to matter as per the academic data. However, student engagement with support systems such as learning management systems (LMSs) and virtual learning environments

– numbers and patterns of login activity, time spent online, information regarding the submission of assignments, activity on discussion forums, engagement with course materials, self-assessment quizzes (Conijn et al., 2016; Gkontzis et al., 2018; Nespereira et al., 2016) – was a key factor, where primary data indicated that learners should be engaged in active learning to participate in knowledge creation and in monitoring their own performance.

Course engagement and motivation: Pass/fail status, grades, completed assignments, student course history, reflections and self-assessments, number of credits enrolled in, number of lost courses and attendance statistics (Chounta et al., 2020; Mitra & Goldstein, 2015; Niitsoo et al., 2019) all affected the ability of the learner to stay in school. To this effect, primary data revealed that when learners are engaged actively their motivation to stay in school improves. It further revealed that engagement in extra activities such as physical education improves their motivation.

The predictive model

To predict the likelihood of dropout, machine learning techniques were employed. Specifically, the random forests, decision trees, the Bayesian classifier, the support vector machine, the K-nearest neighbour and logistic regression were adopted for their effectiveness in supporting prediction (Gilbert, 2017; Kemper et al., 2020; Wan Yaacob et al., 2020).

The collected raw data is represented as follows, with various measures:

- X = State of academic performance (Satisfying, Normal, Not satisfying)
- M = Marital status (Married, Not married)
- F = Fees status (Sponsored, Full payment, Partial payment)
- FB = Family background (Educated, Not educated)

Before being used for developing a predictive mathematical model, the collected raw data must be pre-processed to avoid the cases in which one variable receives a higher or lower weight for its coefficient due to its initial low or high. The model is supported by an algorithm to sort and process data to provide output.

Algorithm 1: Dropout prediction Algorithm

```
Result: Show a combination of dropout
initialization;
X, F, M, FB;
State.start X_{i-n}, F_{i-n}, M_{i-n}, FB_{i-n}
X_{i-n} = Grade(Satsifactory, Normal, NotSatsifying)
F_{i-n} = Fees(Sponsored, Fullpay, Partial, NonPayment)
M_{i-n} = state(Married, NotMarried, Divorced)
FB_{i-n} = Cat(Educated, NotEducated)
while Check state of key indicators do
    if state = " " then
        print .state X_i, F_i, M_i, FB_i
        Provide reasoning and advice;
    else
        next record;
    end
end
```

To develop the predictive model, several of mathematical modelling techniques such as multiple linear regression (MLR), multilayer perception (MLP) network, radial basis function (RBF) network, and support vector machine (SVM) were used. We aimed to predict student academic performance by developing a set of validated mathematical models and then identifying the most appropriate model(s) for use in prediction.

The combinations were selected from for their reasonable ability to predict the learner willingness to progress with their studies. The model was trained based a prepared dataset (Yen & Lee, 2006). This involved the use of the algorithm to discover trends related to learner dropout. The algorithm specifically targeted the provision of support to instructors to identify students with early dropout risk in the semester and recommend corrective action to prevent the chance of dropping out.

Conclusion

Learners in higher education institutions in Uganda experience various challenges resulting from conflicting interests as they learn to manage the demands of their course, the desire to succeed and the pressures of life. For many, such challenges force them out of school; whereas others reluctantly drop out. The paper aimed at identifying why students drop out of higher education institutions. We presented the challenges responsible for learner dropout and suggested mitigation measures from the perspectives of the learners, institutions and parents/sponsors. In addition, the paper explored the role technologies such as artificial intelligence (AI) and its techniques such as machine learning could play in sustaining learners in school. Further, a model supported by an algorithm for early prediction of the likelihood of students to drop out of school was presented as a way to sustain education management. The prediction intelligence of the algorithm was based on both academic and non-academic factors as a way to leverage the existent models that were constrained to academic performance factors only. Specifically, an algorithm supports data mining and analysis to enhance prediction. This is a work in progress, whose initial output is the prediction algorithm that will inform the model yet to be presented and validated.

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