International Jl. on E-Learning (2022) **21**(4), 337-357

Contextualisation of Predictor Variables for Students' At-Risk of Dropping Out of University

SONWABO JONGILE
Cape Peninsula University of Technology (CPUT), South Africa
jongiles@cput.ac.za

The value of fostering predictor variables for students at-risk of dropping out of university has received increased attention in higher education settings internationally, but the research on the efficacy and transferability of the variables between contexts remains limited. The purpose of this article is to offer a conceptual perspective on the efficacy and transferability of the predictor variables from which they are originally developed to other contexts that is not the same as their origin. The researcher reviewed literature on a number of predictor variables that contribute to the successful identification of at-risk students. The methods used to track down literature were: an extensive search of the World Wide Web (WWW) for journal articles, books, master's and doctoral thesis; library databases; and a systematic follow up of key research texts related to the topic under investigation. Factors similar to the country context, the paradigm shift from traditional to online learning; and the increase in using Blended Learning practices empirically influence the efficacy and transferability of the predictor variables once applied in diverse contexts that are not the same as the context of conception. As a result, HEIs need to customize the variables based on the context of their students.

Keywords: at-risk students, contextualization, learning analytics, predictor-variables.

INTRODUCTION

The term "at-risk" became widely used in the 1980s and was applied to students who are at risk of not succeeding and graduating (Narrz'ello, 2014). The application of data analytics in identifying students at-risk of failing and those who face conditions that threaten their potential to complete their studies has been one of the motivating factors and an important area of focus in Learning Analytics (LA) internationally for the reason that it addresses large scale issues relating to increasing student retention, improving student success; and easing the burden of accountability (Dietz-Uhler & Hurn, 2013). Ferguson (2012) explained learning analytics as it was first defined in the International Conference on Learning Analytics and Knowledge (LAK), "the measurements, collection, and analysis and reporting of data **about learners and their contexts**, for purposes of understanding optimising learning and the environment in which it occurs".

Analytic solutions are the inception of LA which has recently emerged in the education domain in the aftermath of the successful application of data analytics in business organisations (Jayaprakash, Moody, Lauria, Regan, & Baron, 2014). Broadly, LA is a multi-disciplinary field involving artificial intelligence, machine learning, and statistics that harness predictive analytics to support the learning process (Chatti, Dyckhoff, Schroeder, & Thus, 2012). Predictive analytics is a process in which Higher Education Institutions (HEIs) identifies insights from student data using predictor variables with aims to mitigate early interventions from meaningful patterns of datasets. In this situation, predictor variables are defined as the characteristics that are manipulated to identify students with a high probability of failing, including those who face conditions that threaten their potential to complete their studies and graduate. Literature affords a flood of predictor variables that contribute to the successful identification of students at-risk from LA using the data generated by the integrated institutional information systems (Lourens & Bleazard, 2016).

In the past two decades or so, a vast majority of Higher Education Institutions (HEIs) have shared many evolutional formations relating to interest, investments, and implementation of Information and Communication Technologies (ICTs) to improve operational efficiency, increase management effectiveness, and to improve competitiveness amongst universities (Kelly, et al., 2017). The intention to improve operational efficiency included automation of information-based processes (Banker, Kauffman, & Morey, 1990). While the intention for increased management effectiveness included the Institutional Management Systems (IMS) to satisfy information requirements for decision making and to encourage administrative reforms, the systems included the Enterprise Resource Planning (ERP) systems - to manage university enrolment, student records (Student Information Systems- SIS), financial aid, finance, and human resources (Brainbridge, Melitski, Zahradnik, Lauria, & Baron, 2015). Whereas the intention to improve competitiveness included Strategic Information Systems (SIS) by changing the nature of business, that is, the use of Learning Management Systems (LMSs) - which changed the way lecturers teach and students learn (Conijn, Snijders, Kleingeld, & Matzat, 2017); and the Marks Administrative Systems (MAS)– for the facilitation of student marks and performance (Peppard & Ward, 2016).

As a result, Systems Integration (SI) soon became a key factor in joining together the different types of university systems, activities as well as hardware, software, and human resources to produce a cohesive flow of data and a central database (Prencipe, Davies, & Hobday, 2003). The paradigm shift from traditional to online learning and the increase in using Blended learning Practices has drastically changed the way HEIs function (Chaubey & Bhattacharya, 2015). Doolan and Guiza (2015) defined blended learning as the use of ICTs to supplement traditional learning methods to enhance the teaching and learning experience. With the increase in the adoption of the LMSs and the institutional information systems mentioned in the previous section, HEIs have substantive data describing students' online and blended learning behaviors, as well as conditions that are external to students' learning activities (Lawson, Beer, Rossi, Moore, & Fleming, 2016). But, the substantive data generated by the integrated LMS and the institutional administrative systems make analysis and interpretation difficult and burdensome (Pardo & Kloos, 2011). Hence the examination of predictor variables that contribute to the successful identification of students at-risk of failing and those who face conditions that threatens their potential to complete their studies and graduate.

The value of forecasting predictor variables for students at-risk has received increased attention in many educational settings, but the research on the efficacy and transferability of the variables is limited (DeZure, et al., 2012). The purpose of this research was to offer a conceptual perspective to guide the enquiry regarding the efficacy and transferability of the predictor variables that contribute to the successful identification of at-risk students from which they are originally developed to the different academic contexts in which they are introduced.

Contemporary research has adopted a large number of predictor variables for the at-risk identification process in LA absent of inquiry on the efficacy and transferability of the variables between contexts. For the reason that there are several predictor variables presented by literature, the researcher reviewed the literature on eight (8) predictor variables from two categories. That is, students at-risk of failing: (i) those who have not accessed the institutional LMS over specified period of time, (ii) those with least number of clicks in the LMS, (iii) those who missed deadlines, and (iv) average grade mark performance; as well as students who face conditions that threatens their potential to complete their studies and graduate: (i) linguistic barriers (ii) peer-group interactions (conflicting ethnic and cultural values); (iii) students staying on-campus and their off-campus counterparts (transportation, time and cost); and (iv) pregnancy.

THE PREMISE OF AT-RISK PREDICTOR VARIABLES OF LEARNING ANALYTICS

The review of technology use by underserved students report suggested that the rising number of at-risk predictor variables of learning analytics, specifically those who are not part of the standard population is due to both the academic elements such as below average grade performance, missed deadlines for submissions, not logging-in into the institutional LMS, learning and special education needs; and personal dynamics such as pregnancy, residence, and transportation (Zielezinski & Darling-Hammond, 2016). Therefore, the premise of using predictor variables of learning analytics is to design and propose an integrated model that contribute to the successful identification of students at-risk of dropping out of university due to academic elements and personal dynamics using the data generated by the integrated institutional information systems (Dietz-Uhler & Hurn, 2013). The question is, what are those variables? More importantly, are the predictor variables adequate to identify students at-risk when applied in diverse context that is not the same as the context of conception? Such as the sort driven by the diverse socioeconomic conditions and taxonomies of countries and universities, students' well-fair, taking into consideration the transformative potential of modern teaching and learning practices in higher education.

Predictor variables for students at-risk of failing

Blended learning requires lecturers together with Curriculum Officers (COs) to review their design approaches by means of aligning student activities, assessments, and course outcomes using different ways of student learning such as; learning through acquisition, learning through enquiry, learning through practice, learning through production, learning through discussion, and learning through collaboration together with the different types of conventional and digital learning technologies that serves them (Laurillard, 2013). This requires universities to confront their current assumptions about teaching and learning by means of thoughtful integration of traditional learning experiences with online experiences (Garrisin & Kanuka, 2004). The approach has become a widespread teaching phenomenon and it has been proven to be effective in accommodating a large number of diverse students with dynamic challenges through the incorporation of online teaching resources (Alammary, Sheard, & Carbone, 2014).

Such pedagogical approaches offer universities large volumes of data regarding student behavior in online environments which can be used to predict reasonable variance in students' academic performance. Hence the research on the efficacy and transferability of predictor variables from which they are originally developed to other contexts that is not the same as their origin, specifically those who are not of the standard population. For the reason that there are several predictor variables presented by literature on students at-risk of failing, the researcher reviewed four (4) predictor variables of students at-risk of failing and used South Africa as a country context in which the variables are introduced. That is: (i) those who have not accessed the institutional LMS over specified period of time, (ii) those with least number of clicks in the LMS, (iii) those who missed deadlines, and (iv) average grade mark performance.

Those who have not accessed the institutional LMS over a specified period

Universities are making efforts to support students in their learning to improve retention. Through the use of predictive analytics, universities focus on identifying students who have not accessed the institutional LMS over a specified period with aims to provide support and assist them in greater access to the LMS for greater engagement with their learning (Williams, Morton, Kilgour, & Northcote, 2018). However, the socioeconomic conditions of students in developing countries, including SA permits very limited Internet access. Students rely on the university internet and other external locations with free Wi-Fi, namely the Malls, popular family restaurants similar to MacDonald's, Kentucky Fried Chicken (KFC), and local Internet Cafes (Dillahunt, Wang, Teasley, & S, 2014). This, therefore, minimises their chances to constantly access their courses online.

For that reason, students have developed coping mechanisms in addressing such challenges by assisting each other where more privilege students access the course, by login-in using their smartphones and downloading the materials needed and share the content with peers outside the LMS. Such observation advocates the view that the data collected from the LMS will suggest that the few students that accessed the course online are not at-risk, as opposed to the majority of underprivileged students who never logged-in and flag them as they are at-risk, which may not necessarily be factual. Because of the coping mechanisms that the students have formed in response to their challenge, it might also mean that the students may not be active on the LMS but performing well in terms of task completions and submissions.

Those with least number of clicks in the LMS

Research points out that the minimal number of times that students click on the institutional LMS and the number of times students interact with the content, including the time spent in an online course are all risk indicators of the variance in final grade performance (Smith, Lange, & Huston, 2012). However, Tempelaar, *et al.* (2015) presented arguments to emphasize that the number of clicks in an LMS of eight hundred and seventy-three (873) students in two (2) blended courses could only explain a marginal of four (4) percent of the variance in final exam performance. Bailey *et al.* (2015) additionally advocate that in 51, 306 number of students enrolled in their Massive Open Online Courses (MOOCs), 27, 679 students were active with more than the average number of clicks, yet only 795 completed the course.

The argument suggests that there is a minimal correlation between the number of clicks in the LMS and student performance in an exam nor the overall final grade mark. Given the socio-economic conditions in South Africa, the underprivileged students who eventually get to access their online courses on-campus or in alternative locations, may click all over the contents of the course in an attempt to familiarise themselves with the system, apart from the reality that there are not enough ICT skills in South Africa (Kirlidog, van der Veyver, Zeeman, & Coetzee, 2018) . In doing so, predictive analytics will register the number of clicks accomplished and automatically move the student out of the at-risk list. In the meantime, students who are familiar with the system log-in, access the course content, click on the content they need and logout. Such students have greater chances of being sent emails suggesting interventions as they may be identified as at-risk due to the minimal number of clicks in the LMS. The same applies to lecturers who promise students to load content at specific times and end up not doing so; students will keep on logging-in and scrutinizing the course pages to see if the lecturer has not loaded the content as promised. Such behavior creates false records while compromising the power of 'least number of clicks' predictor variable.

Those who missed deadlines

Falkner's (2012) findings maintain that knowledge upon the timeliness of initial submissions of any marked activity and current course level provides a reliable guide to student performance. Though this may be a noble predictor of at-risk behavior, it also makes sense to factor that it is ceremonial for SA students to submit at the last minutes, allowing the possibilities of an unsuccessful submission once the students encounter technical and administrative glitches. Furthermore, universities can place a considerable amount of effort to support activity preparations; and substantial technical and administrative support in advance when identifying 'missed deadline' as an at-risk behavior else the prediction could be improbable (Judd, Kennedy, & Cropper, 2010).

Every so often the activities given to students in various subjects in the course program is more than their capacity, resulting in either missed deadlines or poor quality of the activities submitted and consequently leading to poor grades. Therefore, the predictive capacity of this predictor variable requires a holistic view of students' trajectory within the course and the provisions made by Faculties and departments to support and ensure activity submission. Besides, the transition from traditional to online, and the increase in using Blended learning practices has up to now been experimental for both lecturers and students. Access to computers and smartphones, the skills gap in computer literacy when typing assignments, dispensation of submission of activities in more than one subject in a course, and the shortage of computer labs and lab-assistants even after hours are some of the severe challenges still faced by South African universities which compromise the predictive capacity of students who missed deadline variable.

Those with less than average grade mark performance

The different ways in which online learning and blended practices are adopted and applied in course-specific context is imperative for any predictive analytics research to consider before the log-data can be merged to create a generalized model for predicting grade mark performance (Gasevic, Dawson, Rogers, & Gasevic, 2016). For example, Falakmsir and Jafar (2010) examined student performance on activities that affect their final grades, while Macfadyen and Dawson (2012) made use of the LMS tool use frequency to predict student achievement. Specifically, both studies hold the position that student participation in discussion forums was the best predictor of their students' final grade.

Unwin, *et al*. (2010) reported on a survey of 358 respondents across African countries into their usage of LMSs and the results exposed that most lecturers in Africa have little knowledge or interest of use when it comes to the LMS. Their study acknowledged human capacity development and infrastructural constraints as a base to the reason why lecturers are not interested to make use of the LMS. In the meantime, the extent to which HEIs make use of the LMS is imperative for any predictive analysis before considering predicting student grade mark performances. Hence, Venter, *et al*. (2012) suggest certain initiatives to assist in increasing the perceived usefulness of the institutional LMS first, before considering examining any predictor variables regarding student performance.

Predictor variables for students who face conditions that threaten their potential to complete their studies

Apart from predictor variables of students at-risk of failing, the research furthermore acknowledged the conditions that threaten student's potential to complete their studies and graduate. The use of datasets generated by the integrated institutional information systems through application, registration, blended learning, and adaptive learning consents universities the information they need to contextualize their predictor variable identification process based on their student conditions. The research therefore offers conceptual perspective on students who face conditions that threaten their potential to complete studies by reviewing four (4) predictor variables and used South Africa as a country context in which the variables are introduced. That is: (i) linguistic barriers (ii) peer-group interactions (conflicting ethnic and cultural values); (iii) students staying on-campus and their off-campus counterparts (transportation, time and cost); and (iv) pregnancy. What was more but not covered in this research were additional risk conditions that are external to students' academic and social trajectories, yet in some way linked into their taxonomy, for example, chronic illness, troubled household functioning, death in the family, low socioeconomic status, amongst other categories of risk factors.

Those with linguistic barriers

South African HEIs have become universities of choice for Lecturers and students hailing from both international and African countries, impeded by an array of challenges which includes limited English proficiency (Ralarala, Pineteh, & Mchiza, 2016). However, given the eleven (11) official languages it cannot be ignored that South Africa is country rich in cultural diversity and South African students face the same challenge. The main challenge is that the majority of students in SA and international students have English as a second and even a third language, yet most of the SA universities are recognized as English speaking universities (Ralarala, Pineteh, & Mchiza, 2016).

To understand the extent to which the predictive capacity of linguistic barrier as a predictor variable, social exclusivity, and cultural integration need acknowledgment (Cummin, 2008). For example, approaches similar to adaptive learning have knowledge of the diversity in the cohorts of students in terms of limited English proficiency, therefore the predictive capacity is within identifying and logically move students facing this challenge through a learning path, targeting their experience of acceptance and inclusion by also considering conditions that may affect completion and success (Becker, et al., 2017).

Adaptive learning, in this context, is a pedagogical approach for both formal and informal learning in support of student self-regulated learning and for more effective learning experiences (Dabbagh & Kitsantas, 2012). In this case, it can mean providing students with recorded classroom lecturers, sign students to programs of academic literacy, providing more supportive content, and exposing students with linguistic barriers to multi-lingual glossary resources. By doing so, SA universities can be able to identify students with linguistic barriers and provide provision very early in their academic trajectory, which may offer 'linguistic barrier' predictive capacity based on the context of the students in question.

Peer-group interactions (conflicting ethnic and cultural values)

Another predictor variable suggested by literature as a risk indicator is peer-group interactions. According to Tinto (1976), peer-group interactions result in collective affiliation, each of which can be viewed as important social rewards that become part of the person's generalized evaluation of the costs and benefits of university attendance and that modify his educational and institutional commitments. Lecturers generate the data collected from records of social interaction practices, namely, the discussion forums, number of consultations with lecturers and departments, send an email, peer and self-assessments, to name a few. However, countries similar to South Africa have numerous social risk factors, such as conflicting ethnic and cultural values or traumatic peer exchanges and social interactions (King, 2004)-meaning that some students may request to submit a group assignment individually, or may not be able to participate in group activities (especially those that involve touching), discussions or even address peers of certain gender in the discussion forums.

Therefore, limit their participation in peer-group interactions- however, it might factor that the same student would be progressing well in other academic activities, even with the tasks that were meant to be done as a group. Besides, students may be prejudiced against gay and lesbian lecturers which in some way provide perspective in why some students do not consult, amongst other things (Ewing, Stukas Jr, & Sheehan, 2003). Thus this article puts forward arguments as to why peer-group interactions and consultation logs may not necessarily be resilient predictors based on a beehive of cultures, including language in contexts similar to SA.

Students staying on-campus and their off-campus counterparts

An additional predictor variable highlighted by literature as a risk indicator is the issue between students staying on-campus and their off-campus counterparts, thus looking at their academic achievements provides perspective into the problem. In a study conducted by Frazier (2009), it was revealed that there are no significant differences in grades for students that lived on-campus and their off-campus counterparts. At this instance, the reality of these findings provides support to the argument that educational context is shifting in terms of teaching and learning practices. Thus, the predictor variables identified based on students staying on-campus against those staying off-campus cannot be applied in any setting, without consulting the nature and context of a specific university, above all its teaching and learning practices. For an example, students residing over sixty (60) kilometers away from campus may no longer concern themselves with missing the first period, similar to lecturers who offer first period classes with the majority of students residing off-campus.

Current teaching and learning practices, similar to blended learning and adaptive learning allow flexible practices similar to class-lecture recordings and podcasting. Flexible learning allows technology-enhanced pedagogical approaches to generate better learning and teaching experiences for lecturers, specifically for their students (Ng, Lam, Ng, & Lai, 2017). These approaches not only offer interventions to students who have missed classes due to distance and transport hurdles, but also contributes to those students, and from time to time lecturers, who never did English as a first language. Lecturers can record their lectures using a podcast, make use of an adaptive release approach to release the content to the students that missed class, including those struggling with the English language and other international students. This enables them to play, pause, and rewind the podcasts as many times as they may need to. Which then brings us back to the argument presented earlier that, predictor variables such as on-campus and off-campus residence, including English not being the first language of the majority in some universities, are losing their predictive power over innovative approaches similar to blended learning, flexible learning, and adaptive learning.

Additionally, Muslim *et al.* (2012) observed that off-campus students face inconveniencing challenges that affect their wellbeing associated with their living environments. The question is, what good is a student staying on-campus but starving, compared to a well-fed student staying off-campus? What predictive capacity does an on-campus and off-campus students have on University of South Africa (UNISA)- predominantly a distant learning university, compared to the Cape Peninsula University of Technology (CPUT), Stellenbosch, University of Cape Town (UCT) or the University of the Western Cape (UWC) students- predominantly contact universities; even though that they are in the same province? Now, these are the relevant questions that South African higher education practitioners should take into consideration when classifying the efficacy and transferability of on-campus and off-campus variables that are developed to identify students who face conditions that threaten their potential to perform well and complete their studies.

Pregnancy

During traditional teaching and learning practices, unplanned pregnancy posed numerous challenges, namely: academic program needed to be disrupted with financial costs incurred by the institution, the family and the individual (Naidoo & Kasiram, 2014). On the other hand, recent developments in online, adaptive learning, and an increase in blended learning and teaching and learning practices lessen the predictive power of pregnancy as a condition that threatens students to complete their studies and graduate. However, the challenges faced by South African students and the institutions regarding the implementation of these innovative teaching practices are still blurred, which makes it difficult for students to fully rely on blended learning.

The problem could come from the student with no internet access at home, no computer or a smartphone to complete tasks; or from the lecturer who is still resistant in blending their teaching practices- which puts pregnancy as a predictive variable in an uneven position. For example, even though it can be assumed that both the lecturer and the individual are without any challenges regarding online and blended learning practices, the individual still need to be stress-free with lots of rest during pregnancy. And after pregnancy, individuals still need to go back to class, go home, attend to the baby, and also be a baby to her parents in terms of helping them with cooking and cleaning in the house. This can put lots of stress in one person based on time, cost and pressure.

THE EFFICACY AND TRANFERABILITY OF PREDICOTR VARIABLES IN SOUTH AFRICAN CONTEXT

It was reported that 47.9% of South African university students do not complete their studies (South African Department of Higher Education and Training, 2015). The challenges regarding low course completion rates as well as overall university retention exert from a variety of factors. These factors include high failure rates that may lead to academic exclusion (Akoojee & Nkomo, 2007), financial constraints where students don't have funding to see them through after enrolling for a course (Letseka & Maile, 2008), lack of first-year experience preparedness (de Klerk, Spark, Jones, & Maleswena, 2017), students hopping from one course to another and students not getting enough support from their universities (Roger, 2003).

The Council of Higher Education (2010) in South Africa has found that students enter universities from positions of extreme inequality in terms of financial pressures, lack of academic preparedness- both social conditions and teaching and learning background. The effects of financial pressures can force students to either commit to a part-time job or take a gap year to raise funds. Pantages and Creedon (1975) found employment responsibilities to influence student retention. For example, results from their study advocated the view that full-time students who worked more than 15 hours per week were more likely to withdraw than those who worked less. While the effects of social conditions can either discourage or encourage student commitment to graduate when the student has experienced underprivileged teaching and learning or substantial financial problems (Scott, Yeld, & Hendry, 2007).

The South African higher education, in response to historic conditions, has increased enrollment to address issues of equity; but failed to address the equally important issue of ensuring equity in success for the enrolled students (Mohamedbhai, 2014). Such disputes led to the recent and ongoing #FeesMustFall movement which has addressed varied issues confronted by enrolled students in South African higher education relating to food and housing, curriculum transformation, financial barriers, and the issues concerning inclusion and exclusion (Dominguez-Whitehead, 2017). For many years, each of the above-mentioned disputes has become a common approach when identifying predictor variables for at-risk students in SA higher education, specifically for poor and working-class students.

Two years back (2017), the former President of the Republic of South Africa, Jacob Zuma announced a fee-free education beginning in the year 2018 for poor and working-class students. More attention was put on the socio-economic impact fee-free education will have on access to higher education for poor and working-class SA higher education students, with limited measures to ensure student retention aimed at improving student success and throughput. There is a persisting need for SA universities to comprehend the predictive capacity of the predictor variables developed to identify at-risk students using predictive analytic approaches that facilitates comprehension in context of SA students to minimize the potential waste of time, effort, and public funds spent on students who subsequently do not complete their studies (Chui, Fung, Lytras, & Lam, 2018). For that reason, universities across SA need to account for their enrolled student at-risk identification processes by interrogating the predictor variables presented, with the view to develop a customizable model adequate for SA student context.

RESULTS

Empirical evidence in learning sciences confirm that student success in higher education is a combination of students' identities, dispositions, and attitudes (Shum & Crick, 2012). Therefore, research on predictor variable of learning analytics should be cumulative with educational data studies that highlight student behaviors based on student identities, dispositions and attitudes to assess the at-risk factors in their courses. That is:

- students who have not accessed the institutional LMS over a specified period,
- students with the least number of clicks in the LMS,
- students who missed deadlines,
- students with average grade mark performance,
- students with linguistic barriers,
- peer-group interactions (conflicting ethnic and cultural values),
- students staying on-campus and their off-campus counterparts (transportation, time and cost); and
- pregnancy for identifying at-risk students.

The premise of these educational data analytics for at-risk students in higher education are to predict student success by examining the predictor variables that contribute to the successful identification of at-risk students using student-produced data from the integrated institutional information systems, frequently absent of a conceptual context to guide the inquiry (Mattingly, Rice, & Berge, 2012). That is, should any of the predictor variables be applied in dissimilar contexts, their predictive capacity becomes fragile for the novelty and complexity of context in which they are introduced. For that reason, inquiries from universities on the predictor variables that contribute to the successful identification of at-risk students have a duty to reflect conceptually, on the student dynamics similar to country context (access to the Internet, ICT skills, crime ratio), the paradigm shift from traditional to online learning (innovative teaching and learning pedagogies); and the increase in using Blended Learning practices.

As a result, the predictor variables are not just searched from the literature, but profound interrogations on the efficacy, transferability, and just how they affect the student dynamics within the context in which they are introduced. For example, universal research findings on students with below-average marks show that the key contributing factors that influence below-average marks are derived from numerous factors, such as lack of subject interest, poor teaching strategies by lecturers, poor relationship with the lecturers, unfavorable learning environment, too much socialization, and necessary part-time jobs (Wadesango & Machingambi, 2011). Therefore, contextualization of 'students with below average mark' variables must take effect on course-to-course bases before the log-data can be merged to create a generalized context; for the reason that how traditional, online, and blended learning practices are adopted vary in each course (Gasevic, Dawson, Rogers, & Gasevic, 2016).

Furthermore, the UNESCO report suggested that an inclusive higher education system would allow opportunities for exceptional grade marks, access, exclusion or suspension free atmosphere, participation, multilingualism, and success irrespective of the student socio-economic background (Unesco, 1994). At a conference proceeding, Devlin (2010) argued that in an increasing number of enrolled students, it is applicable for universities to work towards a successful experience for all students. That is, those who are not part of the standard population, but study alongside conventional students, yet measured by same scale. For instance, Okioga (2013) noted that the conventional student parents are more engaged in their children's education and development as opposed to students who are not part of the standard population. Commonly, students from low socio-economic backgrounds are the first in their families (first generation) to attend university, both parents and siblings never attended university hence the lack of parental engagement. Therefore, obtaining a holistic view on the (mis)recognition of students who are not part of the standard population is essential in identifying who they are and how they access and encounter their studies (Fataar, 2018).

According to Toetenel and Rienties (2016), HEIs are to transform their practices by adapting to the shifting educational context through learning analytics, to identify common pedagogical patterns for improving retention. As a consequence, the conceptual perspective on the adoption of predictor variables for the identification of at-risk students, especially those who are not part of the standard population, can reject the 'one predictor variable suits all' approach and consider reviewing adoption process based on who the students are and how they encounter their studies.

CONCLUSION

The emergence of LA in HEIs is aimed at advancing data-driven decision making using predictor variable that contribute to the successful identification of at-risk students. Despite the fact that student academic performance and their level of commitment towards course completion are moderate determinants of student decision to dropout, financial hardship exerts a powerful influence, especially those who are not part of the standard population (Bennett, 2003).

Based on the outcome from reviewing the literature on the efficacy and transferability of the predictor variables for students at-risk of academic failure and those who face conditions that threaten their potential to complete their studies, the importance of country context, shift in teaching and learning practices and the socioeconomic status of Higher Education students were acknowledged. For that reason, research proposes some suggestions for South African HEIs and others all over the world to evaluate the predictive capacity of the predictor variables by assessing their calibration (the premise between the observed outcomes and the prediction) and discrimination (the predictor variable's ability to discriminate between high and low risk students), before the predictor variables are used in the at-risk prediction process (Pavlou, et al., 2015).

The process is described as model validation. We conclude that if South African HEIs and others all over the world could validate the predictive capacity of the adopted at-risk predictor variables based on the challenges faced by their student, taking into consideration the shift in educational context in terms of teaching and learning practices and the increase in blended learning practices; then they can provide better predictions and informed choices about their interventions.

Limitations and implication for further research: Further predictor variables that are external to students' academic and social systems, but more linked to their socio-economic positions, for example, chronic illness, troubled household functioning, death in the family, low socioeconomic status, amongst other categories of predictor variables were not queried in this research. Perhaps further research on how universities can create provisions to collect data on variables such as the sort mentioned in the previous section, in order to track how students cope; especially those who experience such trials during their student-experience but still want to succeed.

Also, some researchers propose theoretical reasoning above data reasoning in learning analytics, to explain in theory, the processes of interaction between students and the universities, and distinguish between those processes the predictor variables that effect the different forms of dropout behaviour. (Tinto, 2017).

References

Akoojee, S., & Nkomo, M. (2007). Access and quality in South African higher education: the twin challenges of transformation. *South African Journal of Higher Education, 21*(3), 385-399.

Alammary, A., Sheard, J., & Carbone, A. (2014). Blended learning in higher education. *Australasian Journal of Educational Technology , 30*(4), 440-454.

Bailey, H., Rubinstein, B. & Zhang, R., 2015. Identifying At-Risk Students in Massive Open Online Courses. Australia, Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence, pp. 1749-1755.

Banker, R., Kauffman, R., & Morey, R. (1990). Measuring Gains in Operational Efficiency from Information Technology: A study of the Positran Deployment at Hardee's Inc. *Journal of Management Information Systems, 7*(2), 29-54.

Becker, S., Cummins, M., Davis, A., Freeman, A., Hall, C., & Ananthanarayanan, V. (2017). *NMC horizon report: 2017 Higher Education Edition.* Texas: The New Media Consortium.

Bennett, R. (2003). Determinants of Undergraduate Students Drop Out Rates in a University Business Studies Department. *Journal of Future and Higher Education, 27*(2), 123-141.

Brainbridge, J., Melitski, J., Zahradnik, A., Lauria, E. J., & Baron, J. (2015). Using Learning Analytics to Predict At-Risk Students in Online Graduate Public Affairs and Administration Education. *Journal of Public Affairs Education, 21*(2), 247-262.

Chatti, M., Dyckhoff, A., Schroeder, U., & Thus, H. (2012). A Reference Model for Learning Analytics. *International Journal of Technology Enhanced Learning, 4*(5-6), 318-331.

Chaubey, A., & Bhattacharya, B. (2015). Learning Management Systems in Higher Education. *International Journal of Science Technology & Engineering, 2*(3), 158-162.

Chui, K., Fung, D., Lytras, M., & Lam, T. (2018, June 27). Predicting at-risk university students in a virtual learning environment via a machine learning algorithm. *In Press*, pp. 1-7.

Conijn, R., Snijders, C., Kleingeld, A., & Matzat, U. (2017). Predicting Student Performance from LMS Data: A Comparison of 17 Blended Courses Using Moodle LMS. *IEEE Transactions on Learning Technologies, 10*(1), 17-29.

Cummin, J. (2008). *BICS AND CALP: Empirical and theoretical status of the distction* (2nd ed.). (B. Street, & N. Hornberger, Eds.) New York: Encyclopedia of Language and Education.

Dabbagh, N., & Kitsantas, A. (2012). Personal Learning Environments, social media, and self-regulated learning: A natural formula for connecting formal and informal learning. *The Internet and Higher Education, 15*(1), 3-8.

de Klerk, D., Spark, L., Jones, A., & Maleswena, T. (2017). Paving the Road to Success: Reflecting critically on year one of an undergraduate student support programme at a large South African university . *Journal of Student Affairs in Africa, 5*(1), 1-13.

Department of Education, 2001. Higher Education Institutional Plans: An Overview of the First Planning Phase, Pretoria: The Republic of South African Department of Education.

Delvin, M. (2010). Non-traditional achievement: Theory, policy and practice in Australian higher education. *13th Pacific Rim First Year in Higher Education Conference.* Brisbane.

DeZure, M., Van Note Chism, N., Deane Sorcinelli, M., Cheong, G., Ellozy, A., Holley, M., & Atrushi, D. (2012). Building international faculty-development collaborations: The evolving role of American teaching centres. *Change: The Magazine of Higher Learning, 44*(3), 23-33.

Dietz-Uhler, B., & Hurn, J. (2013). Using Learning Analytics to Predict (and Improve) Student Success: A Faculty Perspective. *Journal of Interactive Online Learning, 12*(1), 17-26.

Dillahunt, T., Wang, B., Teasley, & S. (2014). Democratizing higher education: Exploring MOOC use among those who cannot afford a formal education. *The International Review of Research in Open and Distributed Learning, 15*(5), 178-196.

Dominguez-Whitehead, Y. (2017). Food and housing challenges: (Re)framing exclusion in higher education. *Journal of Education*(68), 149-169.

Doolan, M. & Guiza, M., 2015. Towards a Novel Methodology for Adopting Blended Collaborative Learning Solutions. Nassau: Bahamas, 10th International Conference on e-Learning: ICEL 2015.

Ewing, V., Stukas Jr, A., & Sheehan, E. (2003). Student prejudice against gay male and lesbian lecturers. *The Journal of Social Psychology, 143*(5), 569-79.

Falakmasir, M., & Habib, J. (2010). Using educational data mining methods to study the impact of virtual classroom in e-learning . USA: Educational Data Mining .

Falkner, N. & Falkner, K., 2012. A fast measure for identifying at-risk students in computer science. New Zealand, Proceedings of the ninth annual international conference on International computing education research.

Fataar, A. (2018). Placing Students at the Centre of the Decolonizing Education Imperitive: Engaging the (Mis)Recognition Struggle of Students at the Postapartheid University. *A Journal of the American Educational Studies Association, 54*(4), 1-14.

Ferguson, R. (2012). Learning analytics: drivers, developments and challenges. . *International Journal of Technology Enhanced Learning* , 304-317.

Fournier, H., Kop, R., & Sitlia, H. (2011). The value of learning analytics to networked learning on a personal learning environment. Canada: ACM: Digital Libraries.

Frazier, W., 2009. A study of themed residential learning communities at a Midwest four-year university: North Dakota State University. North Dekota: Proquest.

Garrisin, D., & Kanuka, H. (2004). Blended learning: Uncovering its transformative potential in higher education. *The Internet and Higher Education, 7*(2), 95-105.

Gasevic, D., Dawson, S., Rogers, T., & Gasevic, D. (2016). Learning analytics should not promote one size firts all: The effects of instuructional conditions in predicting academic success . *Internet and Higher Education , 28*, 68-84.

Jayaprakash, S., Moody, E., Lauria, E., Regan, J., & Baron, J. (2014). Early Alert of Academically At-Risk Students: An Open Source Analytics Initiative . *Journal of Learning Analytics, 1*(1), 6-47.

Judd, T., Kennedy, G., & Cropper, S. (2010). Using wikis for collaborative learning through contribution. *Australasian Journal of Educational Technology, 26*(3), 341-354.

Kelly, N., Montenegro, M., Gonzalez, C., Clasing, P., Sandoval, A., Jara, M., . . . Alarcon, R. (2017). Combining event- and variable- centred approaches to institution- facing learning analytics at unit of study level. *The International Journal of Information and Learning Technology, 34*(1), 63-78.

King, N. (2004). Advising underprepared students. NACADA: Summer Institute on Advising.

Kirlidog, M., van der Veyver, C., Zeeman, M., & Coetzee, W. (2018). Unfulfilled need: reasons for insufficient ICT skills in South Africa. *Information Development, 34*(1), 5-19.

Laurillard, D. (2013). *Teaching as a design science: Building pedagogical patterns for learning and technology.* New York: Routledge.

Lawson, C., Beer, C., Rossi, D., Moore, T., & Fleming, J. (2016). Identification of 'at-risk' students using learning analytics: the ethical dilemmas of intervention strategies in a higher education institution. *Educational Technology Research and Development , 64*(5), 957-968.

Letseka, M., & Maile, S. (2008). High university drop-out rates: A threat to South Africa's future. Pretoria: Human Science Research Council.

Lourens, A., & Bleazard, D. (2016). Applying predictive analytics in identifying students at risk: A case study. *South African Journal of Higher Education , 30*(2), 129-142.

Macfadyen, L., & Dawson, S. (2012). Numbers are not enough: Why e-learning analytics failed to inform an institutional strategic plan. *Journal of Educational Technology & Society, 15*(3), 149-163.

Mattingly, K., Rice, M., & Berge, Z. (2012). Learning analytics as a tool for closing the assessment loop in higher education . *Knowledge Management & E-Learning: An International Journal , 4*(3), 236-247.

Mohamedbhai, G. (2014). Massification higher education institutions in Africa. *International Journal of African Higher Education, 1*(1), 59-83.

Muslim, M., Karim, H. & Abdullah, 2012. Satisfaction of Students' Living Environment between On-Campus and Off-Campus Settings: A Conceptual Overview. Procedia-Social and Behavioral Sciences, 68(1), pp. 601-614.

Naidoo, P., & Kasiram, M. (2014). Exploring unplanned pregnancy amongst university students. *Sicial Work/Maatskaplike Werk, 42*(3), 341-354.

Narrz'ello, G. (2014). At-risk students . In D. Levinson, P. Cookson, & A. Sadovnik (Eds.), *Education and sociology: An encyclopedia* (p. 49). New York: Routledge.

Ng, R., Lam, R., Ng, K., & Lai, I. (2017). Identifying the Needs of Flexible and Technology Enhanced Learning in Vocational and Professional Education and Training's (VPET) Workplaces. In *New Ecology for Education- Communication X Learning* (pp. 107-117). Singapore: Springer.

Okioga, C. (2013). The Impact of Students' Socio-economic Background on Academic Performance in Universities: A Case of Students in Kisii University Collage. *American International Journal of Social Science* , 39-46.

Pantages, T., & Creedon, C. (1975). Studies of college attrition: 1950-1975. *Review of Educational Research* , 49-101.

Pardo, A., & Kloos, C. D. (2011). Stepping out of the box. Towards analytics outside the Learning Management System. Spain: Semantic Scholar .

Pavlou, M., Ambler, G., Seaman, S., Guttmann, O., Elliot, P., King, M., & Omar, R. (2015). How to develop a more accurate risk prediction model when there are few events. *British Medical Journal*, 1-6.

Peppard, J., & Ward, J. (2016). *The strategic management of information systems: Building a digital strategy.* John Wiley & Sons.

Prencipe, A., Davies, A., & Hobday, M. (2003). *The Business of Systems Integration.* OUP Oxford.

Ralarala, M., Pineteh, E., & Mchiza, Z. (2016). A CASE STUDY ON THE LANGUAGE AND SOCIAL-CULTURAL CHALLENGES EXPERIENCED BY INTERNATIONAL STUDENTS STUDYING AT CAPE PENINSULAR UNIVERSITY OF TECHNOLOGY. *South African Journal of Higher Education , 30*(4), 231-255.

Roger, B. (2003). Determinants of Undergraduate Student Drop Out Rates in a University Business Studies Department. *Journal of Future and Higher Education, 27*(2), 123-144.

Scott, I., Yeld, N., & Hendry, J. (2007). *Higher Education Monitor 6: a case for improving teaching and learning in South African higher education.* Pretoria: Council of Higher Education.

Shum, S., & Crick, R. (2012). Learning dispositions and transferable competencies: pedagogy, modelling and learning analytics. *In Proceedings of the 2nd international conference on learning analytics and knowledge* (pp. 92-101). ACM.

Siemens, G. (2012). Learning analytics: envisioning a research decipline and a domain of practice. *In Proceedings of the 2nd international conference on learning analytics and knowledge* (pp. 4-8). ACM.

Smith, V., Lange, A., & Huston, D. (2012). PREDICTIVE MODELING TO FORECAST STUDENT OUTCOMES AND DRIVE EFFECTIVE INTERVENTIONS IN ONLINE COMMUNITY COLLEGE COURSES. *Journal of Asynchronous Learning Networks, 16*(3), 51-61.

South African Department of Higher Education and Training. (2015). *Statistics on Post-School Education and Training in South Africa: 2013.* Pretoria: Department of Higher Education and Training.

Tempelaar, D., Rienties, B., & Giesbers, B. (2015). In search for the most informative data for feedback generation: Learning analytics in a data-rich context. *Computers in Human Behavior , 47*, 157-167.

Tinto, V. (2017). Reflections on student persistence. *Student Success, 8*(2), 1-8.

Toetenel, L., & Reinties, B. (2016). Analysing 157 learning design using learning analytic approaches as means to evaluate the impact of pedagogical decision-making . *British Journal of Educational Technology* , 981-992.

Unesco. (1994). *The Salamanca Statement and Framework for action on special needs education: adopted by the World Conference on Special Needs Education.* Spain : UNESCO.

Unwin, T., Kleessen, B., Hollow, D., William, J., & Oloo, L. (2010). Digital learning management systems in Africa. *Open Learning: The Journal of Open, Distance and e-Learning , 25*(1), 5-23.

Venter, P., van Rensburg, J., & Davis, A. (2012). Drivers of learning management system use in a South African open distance learning institution. *Australasian Journal of Educational Technology , 28*(2), 183-198.

Wadesango, N., & Machingambi, S. (2011). Causes and Structural Effects of Student Absenteeism: A Case of Three South African Universities. *Journal of Social Sciences, 2*(26), 89-97.

Williams, T., Morton, J., Kilgour, P., & Northcote, M. (2018). How engaged are our students? Using Analytics to Identify Students At-risk. *EdMedia and Innovative Learning: Association for the Advancement of Computing in Education* , 122- 128.

Zielezinski, M., & Darling-Hammond, L. (2016). *Promising practices: A literature review of technology use by underserved students.* California: Stanford Centre for Opportunity Policy in Education.