EARLY ALERT OF THE ACADEMICALLY AT-RISK ADULT LEARNER IN HIGHER EDUCATION

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Abstract

Universities today have a different landscape than they did a generation ago. Globalisation towards a growing technology and knowledge-centric economy has heightened the demand for highly skilled and knowledgeable workers. To take advantage of this economy, education reforms are required for an educated and skilled workforce. These reforms would include widened access of education to non-traditional communities, such as the adult learners. These learners are often working adults enrolled in part-time programmes, and some are returning to education after a break of a few years [1]. The influx of adults to higher education presents key challenges to the institutions where they matriculate.

There is a need for an early alert system to identify adult learners who struggle with the transition from work to university. Beck and Davidson [2] defined an early alert system as “mechanism for identifying students most likely to fail academically or to encounter serious problems assimilating into the college environment” (p. 709). Predictive modelling is used to identify learners at-risk so as to provide timely intervention. Predictive models have no impact on academic success without effective intervention strategies aimed at supporting the at-risk learner. This paper describes a pilot project of an early-alert system in a Singapore university for adult learners in the Business School.

The early alert system is based on predictive modelling to identify learners who may be at-risk. The population that is used to build the predictive model are adult learners who completed 25 credit-units (cus) and are completing the next 25 cus of a 130 cus part-time bachelor degree program in the Business School. The 34 input variables used to construct the predictive model are from 623 adult learners who enrolled in July 2015, January 2016, July 2016, January 2017, July 2017 and January 2018 semesters. The input variables can be broadly categorised into Demographics & Work Background variables (e.g. age and gender), Prior Education variables (e.g. polytechnic GPA, ‘O’ level Math and English grades) and University variables (e.g. Discipline enrolled and Years into Degree).

The model is then validated based on 533 adult learners enrolled from January 2016 to July 2018 semesters, who are in phase 2 as at July 2018 semester (i.e. completed at least 25cus, yet to complete 50cus) and finally deployed on 558 adult learners enrolled from July 2016 to January 2019 semesters, who are in phase 2 as at January 2019 semester. The results are displayed in a dashboard that allows users to identify the adult learners that are predicted to be at-risk for intervention.

Various levels of intervention strategies will be used. Some adult learners will be receiving an email from their Heads of Programme while others will be monitored. Results from the various strategies will be explained and the implications of the results will be discussed.

Keywords: adult learner, academically at-risk, predictive modelling, intervention.

1 INTRODUCTION

Higher education plays a pivotal role in enhancing the society’s competitive advantage. The growing technology and knowledge-centric economy is increasingly dependent on skilled and talented workforce. Many societies are also facing key population changes. Singapore’s society is aging at the same time that the birth rate is falling [3]. The Singapore educational landscape is facing challenges of rapidly changing demographics. A key pressure felt in the higher education sector is the increasing participation rate of adult learners. The fastest growing population in higher education is the working adult learner [4]. This is significant, as more adults who have been out of school for some years are turning to higher education institutions to start, continue or complete undergraduate degrees. The influx of adults to higher education presents key challenges to the institutions where they matriculate. Higher education institutions are challenged to increase the overall student success rate.

1 Refer to section 1 (Introduction) on definition of ‘phase’
Having access to a rich technological data source potentially enables higher education institutions to develop an early alert system to effectively identify adult learners who struggle with the transition from work to university. Beck and Davidson [2] defined an early alert system as “mechanism for identifying students most likely to fail academically or to encounter serious problems assimilating into the college environment” (p. 709). “A robust early warning system uses readily available student data and validated indicators of risk to identify students who are at risk of dropping out of school so that they can be matched with appropriate supports and interventions” [5]. Predictive modelling is used to identify learners at-risk so as to provide timely intervention.

The aim of this research is to develop an early alert system to identify adult learners who are at-risk when they are pursuing their degree studies in a Singapore university that caters mainly to adult learners. The early alert system developed is made up of three components – Modeling the at-risk population, Deployment in a Dashboard and Intervention Strategies.

It is envisioned that the at-risk modelling is to be carried out in 4 phases to cover the adult learner’s journey in the university as shown in Fig. 1 above. The typical part-time basic degree consists of many 5 credit-units (cus) courses and one or two 10 cus courses to make a total of 130 cus. Phase 1 covers adult learners who have done up to 25 cus of courses. This corresponds roughly to their first semester in the university although some learners may take two to three semesters as they might be encountering heavy demands from their workplaces. Phase 2 will be for learners who have completed the first 25 cus and embarking on their next 25 cus. This will roughly be those in their second to fourth semesters. Phase 3 covers those in the middle of their degree journey and phase 4 covers those in their final 50 cus of courses.

A pilot of the early alert system is carried out on the Business School for adult learners in phase 2 of their part-time degree journey in the university. The Business School is chosen as it has the largest number of registered adult learners in the university. It has degree programmes in 8 disciplines with more than 85% of the enrolled students being diploma graduates mainly from the 5 local polytechnics while the remaining 15% comes mainly from those with ‘A’ levels. Phase 2 is chosen as the initial at-risk modelling found that the at-risk models for phase 2 are more stable than those in Phase 1 and stability of models translates into producing accurate prediction, which is a vital ingredient for any early alert system.

2 METHODOLOGY

2.1 Modeling the at-risk population

The target population for the implementation of the pilot of the early warning system are the adult learners in the Business School that have completed 25 cus and are in the midst of completing the next 25 cus in their respective part-time bachelor degree programmes.
2.1.1 Data used for Predictive Modeling

Table 1. Samples of input variables used in the 3 categories of input variables.

<table>
<thead>
<tr>
<th>Demographics &amp; Work Background variables</th>
<th>Prior Education variables</th>
<th>University variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>‘O’ level Mathematics grade</td>
<td>Discipline enrolled</td>
</tr>
<tr>
<td>Gender</td>
<td>‘O’ level English grade</td>
<td>Number of course withdrawals</td>
</tr>
<tr>
<td>Marital Status</td>
<td>Polytechnic grade-point-average</td>
<td>Minimum CUs to graduate</td>
</tr>
<tr>
<td>Residency Status</td>
<td>Prior Education Institution</td>
<td>Years into Degree</td>
</tr>
</tbody>
</table>

Records from 623 adult learners, who are enrolled from the last 6 semesters (July 2015 - January 2018) from the target population are extracted with 34 inputs variables. Some of these input variables are shown in Table 1 that are classified into 3 broad categories of variables - Demographics & Work Background variables, Prior Education variables and University variables. For adult learners, Demographics & Work Background and Prior Education variables are usually captured upon enrollment into the university while University variables are gathered throughout the semesters that the adult learners are enrolled in the university. As the adult learners progress through their study in the Business School, one would expect that variables from the Demographics & Work background and Prior Education to dominate in the first few semesters and gradually diminished towards the completion of their studies at the university while the University variables will work in the opposite direction.

The target used for the predictive model is the cumulative grade-point-average-to-date (CGPA-to-date) of the adult learners belonging to the target population which ranges from 0 to 5 in the university. This target is chosen as opposed to a binary target of being at-risk or not so that there is flexibility in the selection of the adult learners for intervention as the cut-off to determine whether one is at-risk can be adjusted depending on the intervention resources at hand. At the same time, the same model can also be used to identify both at-risk and high performing adult learners.

2.1.2 Modeling and Validation

Several models are constructed using the classification and regression tree (CART), chi-squared automatic interaction detection (CHAID), k-nearest neighbour (kNN), neural networks (NN) and regression algorithms that are available in the IBM SPSS Modeler version 18.1. The selected model is the stepwise regression model on the basis of having a relatively low Mean Absolute Error (MAE) at 0.499 among the models that are constructed and also with the interpretation of the model that is not counter-intuitive to conventional wisdom.

In the stepwise regression model, there are 16 significant input variables of which 8 are Prior Education variables followed by 6 being University variables. The top 2 most significant input variables with large absolute values for the coefficients in the regression model are University variables. They are the number of course withdrawals (totalWD) and the ratio of the total number of cus taken to date to the minimum cus needed to complete the degree (CUTaken2MinCU) in decreasing order of significance. TotalWD is positively related to the CGPA-to-date i.e. the higher the number of course withdrawals, the higher is the CGPA-to-date and vice-versa. This results make sense as in the university, course withdrawals allows the adult learners to complete the final assessment, which is typically an examination, the next time the course is offered in the event that the adult learners are not sufficiently prepared to take the examination or are unable to complete the assessment due to last-minute work assignment or overseas trip. CUTaken2MinCU is a proxy for the load that the adult learner is carrying in phase 2 of the academic journey and is negatively related to the CGPA-to-date. The higher the load the adult learner is carrying, the lower the CGPA-to-date and vice-versa.
The selected model is then validated with the 533 adult learners who are enrolled from January 2016 to July 2018 semesters, and are in phase 2 as at July 2018 semester (i.e. completed at least 25CUs, yet to complete 50CUs). The validation MAE is 0.524 which is close to construction MAE. Further validation of the selected model is done by disciplines and as well as by different ranges of the predicted P2CGPA (e.g. predicted P2CGPA of < 2 to predicted P2CGPA of <2.8) as shown in Fig. 2 to ensure that when the selected model is deployed by disciplines in the Business School, there is confidence in the predicted P2CGPA.

### 2.2 Deployment in a Dashboard

![Dashboard Image]

Figure 2. Validation of the selected model by different ranges of the predicted P2CGPA and different disciplines in the Business School.

<table>
<thead>
<tr>
<th>Discipline</th>
<th>P2CGPA (predicted)</th>
<th>n</th>
<th>MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>2.74</td>
<td>440</td>
<td>0.524</td>
</tr>
<tr>
<td>&lt;2.8</td>
<td>2.84</td>
<td>346</td>
<td>0.5221</td>
</tr>
<tr>
<td>&lt;2.5</td>
<td>2.82</td>
<td>220</td>
<td>0.5094</td>
</tr>
<tr>
<td>&lt;2.3</td>
<td>2.58</td>
<td>128</td>
<td>0.5363</td>
</tr>
<tr>
<td>&lt;2.0</td>
<td>2.04</td>
<td>32</td>
<td>0.59095</td>
</tr>
</tbody>
</table>

Grand Total: 230,560,638, 440, MAE: 0.524
Park and Jo [6] have looked at the various genres of learning analytics dashboards that have appeared in the literature on the basis of target users and intended goals. The implementation here would fit into the category where the target users are only for teachers as opposed to those targeting students or a mix of teachers and students as the main goal of the dashboard is to facilitate the identification and intervention of at-risk learners. In the Business School, the dashboard deployed would be used mainly by the school faculty such as the Heads of Programme of the various disciplines to identify the at-risk learners and effect the appropriate intervention.

Deployment involves using the selected predictive model to generate the predicted P2CGPA (Predicted P2CPGA) on 558 adult learners who are enrolled from July 2016 to January 2019 semesters, who are in phase 2 as at January 2019 semester. Fig. 3 shows the screenshot of dashboard deployment used in the pilot. The dashboard allows the users to visually look at selected statistics and charts that are interactively linked to one another. The main advantages of using the dashboard for deployment is that it allows users to explore and profile the population that the selected model is being deployed on and also it allows users to identify the population for intervention through the use of filters.
2.2.1 Profiling the Population for Deployment

Fig. 3 shows the average predicted P2CGPA to be at 2.74 with a minimum value of 0.45 and a maximum value of 4 and the average intake age to be 27.4 years old for the 558 adult learners. In terms of disciplines, the top three disciplines are the Business discipline with 32.8% or 183 adult learners being in degree programmes followed by 14.5% (81) and 11.8% (66) being enrolled respectively in the Logistics and Security Studies disciplines.

2.2.2 Identifying the population for intervention

As the current policy for academic counselling for at-risk adult learners are based on achieving CGPA-to-date of less than 2.3, the population for intervention identified by the early alert system based on the predicted P2CGPA would want to reach out to adult learners that are not covered by the current policy. Hence the population for intervention identified by the early alert system is based on the following conditions – predicted P2CGPA of less than 2.3 (those predicted to be at-risk) and CGPA-to-date of greater than 2.3 (those not covered by the existing academic counselling policy). Fig. 4 shows how the screenshot of how the two filters are applied to the scatterplot of CGPA-to-date vs Predicted P2CGPA using the dashboard. Upon applying the filters, the dashboard immediately reflects that there are 30 adult learners in the population for intervention in the thick black rectangle.

The flexibility afforded in this implementation is that if there are insufficient resources to tackle the population for intervention, one could adjust the filter on the predicted CGPA to say less than 2.2.
Conversely, if there were more resources available to tackle the population for intervention identified, one could adjust the filter on the predicted P2CGPA to say less than 2.5.

2.2.3 Profiling the population for intervention

Fig. 5 shows the dashboard with the 30 adult learners in the population for intervention identified with an average of 2.13 for the predicted P2CGPA. The top 3 disciplines are Accounting, Business and Finance forming 20%(6), 16.7%(5) and 16.7%(5) of the population for intervention. Another observation is that every adult learner in this population will show a decrease in their CGPA from CGPA-to-date to the Predicted P2CGPA with the maximum difference being as large as 2.04 and the smallest being 0.14.

2.3 Intervention Strategies

2.3.1 Monitoring the actual P2CGPA vs predicted P2CGPA

The first intervention is to monitor the actual P2CGPA against the predicted P2CGPA. This is applied to all 30 adult learners in the population for intervention. The respective Heads of Programme are briefed on the early warning system, given access to the dashboard and also given the data of the adult learners that predicted to be at-risk from their disciplines. They are told to monitor these predicted at-risk adult learners and report any incidents involving them.

Separately, when the results are released in mid-June 2019, the actual P2CGPA will be available that will be compared to the predicted P2CGPA to see how the prediction compares. Similar to the validation MAE, the corresponding monitoring MAE and the monitoring MAE of the different ranges and different disciplines can be calculated and compared to the construction MAE of 0.499 and validation MAE of 0.524. This will boost the confidence in the use of the selected model among the users of the early alert system.

2.3.2 Email contact to selected disciplines in the population for intervention

This intervention is based on [7] that identified positive interactions, encouraging faculty-student interactions through email and connecting existing support services to students as ingredients of successful intervention.

In the pilot, the 8 adult learners in the Business, Business Analytics and Security Studies disciplines are sent email through the Heads of Programme between the fourth to sixth weeks of the semester with the following content:
• How’s the going so far? (positive interactions)
• In order to sustain your effort your journey all the way to the end, I would like to bring your attention to the following support that we have for part-time students... (connecting existing support services to students)
• If you still need assistance or wish to clarify any queries you may have, you can contact (encouraging faculty-student interactions)

The email does not mention that the adult learner is at-risk in order to avoid alarming the adult learner and avoid any concerns of adverse effect on the adult learner.

3 RESULTS OF INTERVENTIONS TO-DATE
To-date, there are only results from the email contact. The relevant Heads of Programme have reported that the email contact has been ignored by all eight adult learners. This is not surprising as even the email to invite adult learners to contact the Head of Programme arising from the current academic policy for academic counselling when their CGPA-to-date is less than 2.3 is routinely ignored with only a handful of adult learners responding to the email.

Feedback provided from a briefing conducted with the Business School mentioned that the email sent to the adult learners in the population for intervention should reference to triggers for interventions, as mentioned by [8], or study difficulties as documented by [9]. Mention of these in the email to the targeted adult learners will prompt them to act on the email. Examples of triggers for intervention are not accessing the Learning Management System (LMS) or the course material within the first 7 days of the course start date. Examples of study difficulties are poor performance or non-submission of course continuous assessments such as online quizzes or tutor-marked assignments.

4 FUTURE WORK
Although all the results from this pilot are not in yet, the following improvements to the early warning system for wider implementation to other schools in the university have been identified. They are:

4.1 Improved modelling
Arising from the feedback mentioned in Section 3, the next round of at-risk modelling should include University variables that can be extracted from the LMS. Inputs variables dealing with access to the LMS, access to the course material and related items, access to assessments and assessment performance should be extracted and used for the at-risk modelling. This may lead to a more accurate at-risk model and increase the email response by customising the emails with mentions of triggers of intervention and student difficulties, where applicable.

4.2 Timely email contact
According to [7], they mentioned that “timely deployment allows a student more time to address the problem”. In subsequent deployment of the dashboard, the deployment can be done 2 weeks after the available of the examination results. This will allow the email contact to be initiated by the first week of the semester to enable the targeted adult learner more time to respond.

4.3 Personal follow up to the email contact
To address the problem of non-response to the email contact, a follow-up telephone contact will be initiated by the faculty in the school. Up to 3 attempts of such telephone contacts will be made as any more may be construed as harassment, as mentioned by [8].

4.4 Use of self-assessment tool
One modification to the email content besides connecting existing support services is to point the targeted adult learner to a self-assessment tool such as the Learning and Study Strategies Inventory (LASSI) as suggested in [7] that will enable the adult learners to uncover deficiencies in their learning and study habits and also understand their learning styles. With this knowledge, they would be able to leverage on the relevant workshops (e.g. writing or English workshops) offered by the respective support services (e.g. Teaching and Learning Centre).
5 CONCLUSIONS

The findings of this study suggest that use of an early alert system may provide meaningful ways to support the adult learners in higher education. Predictive analytics allows for intervention and support systems to take place before the learner fails or withdraws from the programme. Early alert systems can be a powerful and influential tool and educators as well as administrators would require adequate training to optimise the system. Gatta [10] reminds us that, “Many school system leaders describe their organization as data rich and information poor,” where “the key to leveraging analytics is asking the right questions.”

As educational institutions rely more and more on technology, educators will need to reinvent teacher and administrator training programmes for the complexity of using technological tools to solve complex educational issues. The complexity, power, and influence of predictive analytics will require more than simply having access to an early warning system. Institutions must employ diverse tools to better understand and embrace adult students’ overall needs to increase student success.

REFERENCES


