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Learning Analytics to Inform Teaching and Learning Approaches

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Abstract

Learning analytics is an evolving discipline with capability for educational data analysis to enable better understanding of learning processes. This paper reports on learning analytics research at Institute of Technology Blanchardstown, Ireland, that indicated measureable factors can identify first year students at risk of failing based on data available prior to commencement of first year of study. The study was conducted over three years, 2010 to 2012, on a student population from a range of academic disciplines (n=1,207). Data was gathered from both student enrolment data maintained by college administration, and an online, self-reporting tool administered during induction sessions for students enrolling into the first year of study.

Factors considered included prior academic performance, personality, motivation, self-regulation, learning approaches, learner modality, age and gender. A *k*-NN classification model trained on data from the 2010 and 2011 student cohort, and tested on data from the 2012 student cohort correctly identified 74% of students at risk of failing.

Some factors predictive of at-risk students are malleable, and relate to an effective learning disposition; specifically, factors relating to self-regulation and motivation. This paper discusses potential benefits of measurement of learner disposition.

Keywords: learning analytics, non-cognitive factors of learning, effective learning disposition, academic performance

Learning Analytics to Inform Teaching and Learning Approaches

Introduction

Enrolment numbers to tertiary education are increasing, as is the diversity in student populations (Organisation for Economic Co-operation and Development (OECD), 2013; Patterson, Carroll & Harvey, 2014). This adds to the challenge of both identifying students at risk of failing, and provisioning appropriate supports to enable all students to perform optimally (Mooney, Patterson, O'Connor & Chantler, 2010). Tertiary education providers collect a lot of data on students, particularly activity data from Virtual Learning Environments (VLE) and other online resources (Drachsler & Greller, 2012). As a result, the application of data analytics to educational settings is emerging as an evolving and growing research discipline (Mirriahi, Gasevic, Long & Dawson, 2014; Sachin & Vijay, 2012; Siemens & Baker, 2012). Its primary aim is exploring the value of data gathered in providing learning professionals, and students, with actionable information that could be used to enhance the learning environment (Chatti, Dychhoff, Schroeder & Thüs, 2012; Siemens, 2012).

Models predicting *pass* or *fail* in tertiary education have yielded promising results to date. For example, Romero (2008) reported an accuracy of 62% (n=438) using log data from a VLE. Reported accuracies using log data from intelligent tutoring systems (ITS) are higher; Lauria, Moody, Jayaprakash, Jonnalagadda and Baron (2013) and Jayaprakash, Moody, Lauria, Regan, and Baron (2014) both reported accuracies of 87% based on ITS logs combined with prior academic performance and demographic factors. However, such models are based on data gathered after commencement of course of study. Research from educational psychology suggests non-cognitive factors measureable prior to commencing tertiary education are indicative of potential academic performance. For example, motivational factors such as self-efficacy have significant correlations with academic performance (reviewed in Boekaerts, 2001; Robbins, Lauver, Le, Davis & Langley, 2004). Similarly, research on personality traits such as conscientiousness and openness has also reported significant correlations with academic performance (Chamorro-Premuzic & Furnham, 2004, 2008; De Feyter, Caers, Vigna & Berings, 2012). Learning approach (deep or shallow) and self-regulated learning strategies are also relevant, and have been shown to mediate between other factors (such as factors of personality and factors of motivation) and academic performance (Biggs, Kember & Leung, 2001; Entwhistle, 2005; Swanberg & Martinsen, 2010). In addition, inclusion of non-cognitive factors in models of academic performance has the potential to provide informative feedback on malleable, effective learner dispositions (Knight, Buckingham Shum & Littleton, 2013).

This study investigated if a selection of cognitive and non-cognitive factors of learning, measured prior to or during first year student induction, were predictive of subsequent weak academic performance at the end of year 1. Both regression models of GPA and classification models predicting students at risk of failing were evaluated.

Rationalization of the Study Criteria

In deciding on attributes to include in this study, four key areas were reviewed: aptitude, personality, motivation and learning strategies. These were chosen on the basis of being related to academic performance (Schmitt, Oswald, Pleskac, Sinha & Zorzie, 2009), and measureable in the early stages after student enrolment. All studies cited in this section were based on tertiary education.

There is broad agreement that ability is correlated to academic performance, although opinions differ on the range of sub factors that constitute ability (Flanagan & McGrew, 1998). Cognitive ability tests have been criticised regarding objects of measurement. For example, Sternberg (1999) asserted that high correlation between cognitive intelligence scores and academic performance arise from measurement of the same skill set rather than being a causal relationship. Therefore, many studies have used data already available to colleges to measure ability i.e., grades from 2nd level education or college entrance tests (Schmitt et al., 2009). In a meta-analysis of 109 studies by Robbins et al. (2004), high school GPA or grades was found to have moderate correlation with academic performance (90% CI [0.409, 0.488]).

Factor analysis by a number of researchers has resulted in broad agreement on five main personality dimensions: openness, agreeableness, extraversion, conscientiousness and neuroticism, commonly referred to as the Big Five (Goldberg, 1992). Of the five dimensions, conscientiousness is noted to be the best predictor of academic performance (Swanberg & Martinsen, 2010). For example, Chamorro et al. (2008) reported a correlation of 0.37 (90% CI [0.25, 0.48], n=158) between conscientiousness and academic performance. Openness ranks second. However, there is a lack of consistency in correlations between openness and academic performance (Gray, McGuinness, Owende & Carthy, 2014) as the strength of the correlation is influenced by assessment type. Open personalities do better if assessment is not restricted by rules and deadlines (Kappe & van der Flier, 2010). Studies on the predictive validity of other factors of personality have been largely inconclusive (Gray et al., 2014; Swanberg & Martinsen, 2010).

Motivation is currently explained by a range of complementary theories, which in turn encompass a number of factors, some of which have been shown to be relevant, directly or indirectly, to academic performance (discussed in Gray et al., 2014). Robbins et al. (2004) meta-analysis of 109 studies found self-efficacy had the strongest correlation with academic performance in tertiary education (90% CI [0.444,0.548]). Covington (2000) argued that motivation in itself is not enough; a student must also self-regulate the learning task. This is done by planning their learning, using study time effectively (study effort) and continually monitoring and evaluating the quality of their own learning (metacognitive self-regulation) (Schunk, 2005; Zimmerman, 1990). A longitudinal study of first year students (n=581) found self-test strategies[1] (r=0.48, p<0.001, 90% CI* [0.426,0.531]) and monitoring strategies (r=0.42, p<0.001, 90% CI* [0.426, 0.531]) were more strongly correlated with academic performance than effort strategies (r=0.24, p<0.01, 90% CI* [0.175, 0.303]) (Ning & Downing, 2010).

The relationship between academic performance and temperament or motivation can also be mediated by approach to learning task (Chamorro-Premuzic & Furnham, 2008; Diseth, 2011). Marton & Säljö (2005) classified a students' approach to learning as either shallow (memorise content) or deep (aim to understand content). Later studies added strategic learners (Entwhistle, 2005, p. 19) who will adopt either a shallow or deep learning approach depending on the requisites for academic success. Cassidy (2011) found correlations with GPA were similar for both a strategic (r=0.32, p<0.01, 90% CI* [0.16,0.46], n=97) and deep (r=0.31, p<0.01, 90% CI* [0.15, 0.45], n=97) learning approach when using separate scales for each approach. However, Gray, McGuinness, Owende and Hofmann (2016) reported that when a single scale was used, requiring respondents to select one of the three learning approaches, then only a deep learning approach had positive correlation with academic performance (r=0.234, 95% CI [0.18, 0.29], n=1207).

The Study Dataset

The study participants were first year students at the Institute of Technology Blanchardstown (ITB), Ireland. The admission policy at ITB supports the integration of a diverse

[1] CI* denotes CI was not provided by the author, and was calculated in R (V 3.0.2) using CIr in package *psychometric*.

student population in terms of age and socio-economic background. Course entry requirements are generally lower than corresponding university courses (Mooney et al., 2010).

Each September 2010 to 2012, all full-time, first year students at ITB were invited to participate in the study by completing an online questionnaire developed for the study. This was administered during first year student induction. A total of 46% of full-time, first year students participated in the study (n=1,207). Participants ranged in age from 18 to 60, with a mean age of 23.27 (standard deviation, *s*=7.3); of which 355 (29%) students were mature (23 and over[2]), 713 (59%) were male and 494 (41%) were female. Students were enrolled on a range of courses in the disciplines of Business (n=402, 33%), Humanities (n=353, 29%), Information Technology (n=239, 20%), Engineering (n=172, 14%) and Horticulture (n=41, 3%).

The study dataset included data from three sources: student registration; non-cognitive factors of learning self-reported during first year induction; and exam results from first year of study at ITB, supplied by the college. Study factors are in italics in following sections.

Student Registration Data

Registration data included *age*, *gender* and prior academic performance. Access to full time college courses in Ireland is based on academic performance in the leaving certificate (or equivalent), a set of state exams at the end of secondary school. Students typically study seven subjects, which must include mathematics, English[3] and a foreign language. Subjects can typically be studied at higher or ordinary level. College places are offered based on CAO[4] points, an aggregate score based on grades achieved in a student's best six subjects, range [0,600]. Points are accumulated for grades ≥ 40%.

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[2] This is a state-wide definition of a mature student. Their entry requirements are less strict.
[3] The English syllabus focuses on critical literacy and a respect and appreciation for language (www.education.ie).
[4] CAO: Central Applications Office, who process applications for undergraduate courses in Ireland.

The study dataset included *CAO points*, points in *mathematics* and points in *English* for each student. Points achieved in additional subjects (53 in total) were included as average points achieved by subject category. The Department of Education in Ireland groups leaving certificate subjects into six categories based on subject content.[5] These were combined to create three categories as follows: *applied* (artistic and practical categories); *humanities* (humanities, languages and social categories); and *methodical* (mathematics, science and business categories). Many science and business subjects are numerate based, however the two most popular electives in the methodical category did not have a significant mathematics component, namely Biology (51% of students) and Business (48% of students). All subjects in the applied category had a significant practical component, however 43% of participants did not have a grade for this category of electives, limiting its usefulness.

Descriptive statistics for study factors of prior academic performance in Table 1 confirmed a student population with a weaker prior academic profile compared to university students as reported in Mooney et al. (2010). Of particular note was the low average points in mathematics (mean, m=23.8, equivalent to 55%-59% in an ordinary level paper) which was significantly lower than all other subject areas.

Additional Non-cognitive Factors Gathered

Table 2 gives descriptive statistics for the eleven non-cognitive factors of learning included in the study. Questionnaire items were primarily taken from validated instruments in the public domain and administered during first year student induction using an online tool developed for this study (www.howilearn.ie). Questionnaire length can affect the quality of response (Burisch, 1997; Galesic & Bosnjak, 2009). Consequently, the number of items was

[5] Details of subject groups can be found at the Department of Education's website: www.careersportal.ie.

reduced for some scales. Internal reliability was assessed using Cronbach's alpha. All factors had acceptable reliability (>0.7) given the small number of questions per scale[6] (between 3 and 6).

The personality factors included were *conscientiousness* (e.g., *I like to do things according to a plan or schedule*) and *openness* (e.g., *I like art and creativity).* The six items for each scale were taken from the International Personality Item Pool (IPIP) scales (Goldberg et al., 2006). Motivation was assessed based on *self-efficacy* (e.g., *I believe I can do well*). The three items used were from the self-efficacy scale in the Motivation Strategies for Learning Questionnaire (MSLQ) (Pintrich, Smith, Garcia & McKeachie, 1991). Two factors of self-regulation from MSLQ were also included: metacognitive *self-regulation* (e.g., *I set goals for each study period in order to direct my activities*) and effort regulation (*study effort*, e.g., *I would work hard to do well even if I don't like what I am doing*). To facilitate administration during student induction, items were selected based on their relevance to prior academic experiences.

Learning approach was assessed based on the Revised Two-Factor Study Process Questionnaire (R-SPQ-2F) published by Biggs et al. (2001). The published questionnaire provided separate scales for *shallow* and *deep learning approaches*. The question style was changed for this study forcing participants to choose between a *deep*, *strategic* or *shallow learning approach*. Each item on a four-item scale asked participants to pick one of three statements: two statements, relating to *deep* and *shallow learning approach*, were taken from R-SPQ-2F; the third statement, relating to a *strategic learning approach*, was compiled in collaboration with the National Learning Network Assessment Service[7] (NLN).

In agreement with NLN, scales from their learning styles questionnaire were also included, covering *learner modality* (*Visual, Auditory* and/or *Kinaesthetic* (VAK) (Fleming,

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[6] Cronbach alpha close to 0.7 can be regarded as acceptable for scales with fewer items (Tavakol, 2011).
[7] The National Learning Network Assessment Service provides functional strategies and support for children, adolescents and adults with specific learning difficulties. They are located on campus at ITB (www.nln.ie).

1995)). This was scored from six questions, each offering two choices of modality, resulting in four items per modality across the six questions.

Year 1 Academic Performance

First year academic performance was measured as Grade Point Average (GPA), an aggregate score from between 10 and 12 first year modules, range [0,4]. GPA is calculated from module grade achieved multiplied by module weighting (credits). A GPA<2.0, or a result of *fail* in any individual module, results in an award of *Fail* overall. Otherwise a student is awarded a *Pass* result and may progress to the next academic stage. Table 3 shows the academic profile of study participants across GPA bands. Of the students with GPA≥2.5 (n=558, 46%), 92% passed all modules indicating a low risk group that can progress to year two. Of the students with GPA<2 (n=432, 36%), 91% failed three or more modules, indicating a high risk group falling well short of progression requirements. For the remaining students in the GPA band [2.0, 2.5) (n=217, 18%), 35% passed all modules, 36% failed one module, 20% failed two modules, and 8% failed more than two modules. This is a less homogenous group in terms of academic results, but could be regarded as struggling academically (medium risk), either passing all modules with low grades or required to repeat one or two modules to progress. Repeat examination results were not considered in GPA calculations for this study.

Both two and three GPA bins were considered for classification models, and evaluated using Naïve Bayes (NB) with 10-fold cross validation. Optimal accuracy was achieved with a binary class label using a boundary of GPA=2.0 (accuracy: 68.5%, recall on fail: 71%). Models predicting three GPA bins of high-risk, medium-risk and low-risk were less successful (accuracy: 53.5%, recall on fail: 64%). Therefore, two GPA bins were used for classification models in this study, GPA<2.0 (class=*fail*) and GPA≥2 (class=*pass*). This distinguished high-risk students from other students.

Table 1

Leaving certificate points by subject category (m ± s)

Subject	**Average Points**	**Subject Category**	**Average Points**
CAO points	259.5±78.1 (n=1,018)	Applied Average	48.5±19.5 (n=647)
English	46.4±18.5 (n=1,015)	Humanities Average	40.0±14 (n=1,016)
Mathematics	23.8±13.9 (n=1,008)	Methodical Average	32.1±15.5 (n=1,016)

Valid range for CAO points is [0,600]. Range for subjects and subject categories is [0,100]. Means (m) and standard deviations (s) were calculated based on the number of participants who had results in each category, as indicated by "n" above.

Table 2

Non-cognitive factors of learning

Category & Instrument	Factor	m ± s	95% CI
Personality, Goldbergs IPIP scales (http://ipip.ori.org)	Conscientiousness	5.95 ± 1.53	[5.86, 6.03]
	Openness	6.07 ± 1.29	[5.99, 6.14]
Motivation and self-regulated learning, based on MSLQ (Pintrich et al., 1991)	Self-efficacy	6.85 ± 1.42	[6.77, 6.93]
	Self-regulation	5.88 ± 1.36	[5.80, 5.95]
	Study effort	5.93 ± 1.77	[5.83, 6.03]
Learning style, based on R-SPQ-2F (Biggs et al., 2001)	Deep learner	5.36 ± 2.91	[5.20, 5.53]
	Shallow learner	1.33 ± 1.95	[1.22, 1.44]
	Strategic learner	3.41 ± 2.48	[3.27, 3.55]
Preferred learning channel, NLN Learning Styles Questionnaire.	Visual	7.17 ± 2.06	[7.05, 7.28]
	Auditory	3.13 ± 2.17	[3.04, 3.29]
	Kinaesthetic	4.67 ± 2.42	[4.53, 4.80]

Valid range for each factor is [0,10]. m:mean; s:standard deviation.

Table 3
Number of modules passed, by GPA band

GPA band	n	Failed > 6 modules	Failed 3 to 6 modules	Failed 1 to 2 modules	Passed all modules
$0.0 \leq GPA < 2.0$	432	245 (57%)	146 (34%)	39 (9%)	1 (0.2%)
$2.0 \leq GPA < 2.5$	217	0 (0%)	18 (8%)	122 (56%)	77 (35%)
$2.5 \leq GPA \leq 4.0$	558	0 (0%)	5 (1%)	38 (7%)	515 (92%)

Analysis Methods Used

Correlation

Pearson product-moment correlation coefficients (r) were calculated between all study factors and GPA. An assumption of calculating the significance of a Pearson's correlation is that attributes are normally distributed. However, all study attributes failed a Shapiro-Wilk normality test ($p > 0.05$). This is common in data relating to education and psychology (Kang & Harring, 2015; Micceri, 1989; Smith & Wells, 2006). Therefore significance was verified using 1,999 bootstrap confidence intervals (B-CI) using the bias corrected and accelerated method as implemented in R version 3.0.2.

Regression

Linear regression models predicting GPA were run using Rapidminer Studio V7.1. Two model fits are reported, adjusted coefficient of determination ($\overline{R^2}$) and mean squared error (MSE). $\overline{R^2}$ is reported to facilitate comparison with other studies. However, $\overline{R^2}$ is influenced by variability in underlying independent variables. Consequently, Achen (1982, p. 58-61) argued prediction error is a more appropriate fitness measure for psychometric data. Therefore, MSE mean (m) and standard deviation (s) is also reported, as recommended by Pelánek (2015) for student models.

Classification

A comparison of eight classification algorithms reported in Gray et al. (2016) found that a non-linear learner, *k*-Nearest Neighbour (*k*-NN), gave the best model accuracy when modelling a similar dataset. Therefore *k*-NN model accuracies are reported here. A test of values for *k* in the range [1, 40] found *k*=15 gave best model accuracy. Models were trained on the 2010 and 2011 student cohort, and tested on the 2012 student cohort.

A total of 38% of participants were in class *fail* and 62% were in class *pass* resulting in a class imbalance. Therefore, classes were balanced by oversampling the minority class using bootstrap sampling. Training and test datasets were balanced separately, i.e., instances from the training dataset were not available when resampling test instances, and vice versa. Attribute subset selection techniques can improve model performance and identify relevant attributes (Hall & Homes, 2003). Forward subset selection was used to identify the subset of attributes most predictive of the class label (Hall & Homes, 2003). In addition, all attributes were scaled to mean of 0 and standard deviation of 1.

Three classification model results are reported, accuracy, recall on class *fail*, and geometric mean (GM). GM is more appropriate than accuracy for unbalanced datasets; it combines the precision and recall of each class and so compensates for the greater influence of the majority class in accuracy calculations (Romero et al., 2008). Accuracy was calculated from the confusion matrix of the balanced test dataset. GM and recall were calculated from the confusion matrix of the original, unbalanced, test dataset, i.e. after removal of bootstrap replicates. Model predictions were compared using McNemar's chi squared (χ^2) test (Dietterich, 1998) implemented in R.

Results

Correlations

All factors of prior academic performance had significant correlations with GPA ($p<0.05$) as illustrated in Table 4. Methodical subjects (r=0.302), CAO Points (r=0.285) and Mathematics (r=0.274) had highest correlations with GPA. Similar correlations were cited in other studies that included mature students (Conrad, 2006; Kaufman, Agars, & Lopez-Wagner, 2008). With the exception of *learner modality*, all non-cognitive factors of learning were also significantly correlated with GPA ($p<0.05$). *Age* (r=0.25), a *deep learning approach* (r=0.234) and *study effort* (r=0.187) had highest correlations with GPA. *Openness* (r=0.084) had the weakest statistically significant correlation with GPA. Correlations were comparable with other studies of diverse student populations with the exception of *self-efficacy* (r=0.12, 95% B-CI [0.06, 0.18]), which was lower than expected (Cassidy, 2011: r=0.397; Diseth, 2011: r=0.44).

Regression Models Predicting Year 1 Academic Performance

The best regression model predicting GPA for all participants ($\overline{R^2}$ = 0.196, MSE = 0.819 ± 1.068) was based on eight factors, namely *age*, *methodical average*, *humanities average, study effort, deep, strategic and shallow learning approach* and *gender*. Model fit and standardised coefficients are given in Table 5. Model fit improved when mature students were excluded, concurring with other studies (Chamorro-Premuzic & Furnham, 2008; Robbins et al., 2004). For example, a model of participants aged [18, 22] (n=852) had $\overline{R^2}$ = 0.251, however improvement in MSE (0.748 ± 0.985) was not significant (t(1919)=1.51, p=0.13).

Age was statistically significant in both regression models. Factors of prior academic performance were also statistically significant. Overall performance aggregates were significant for younger students, whereas subject area aggregates were more significant when mature students were included in the model. Of the non-cognitive attributes, the three attributes with the highest correlations with GPA were also the most significant in regression models, namely a *deep learning approach, study effort* and *conscientiousness*.

Classification Models Predicting Students at Risk of Failing

Classification model accuracy distinguishing between a failing (GPA < 2.0) and passing (GPA ≥ 2.0) GPA achieved overall model accuracy of 73.1% when applied to a different student cohort. Recall on class fail was 74%, the geometric mean was 68.4%. In total, nine attributes were used, *methodical average, age, study effort, CAO points, self-efficacy, visual* and *kinaesthetic modality, applied average* and *humanities average*. Table 6 shows the improvement in model accuracy at each step of forward selection as attributes were added to the model. *Methodical average* was the best predictor of at-risk students. A model trained on *methodical average* only achieved classification accuracy of 59.9%. Adding *age* increased model accuracy to 64.7%. Adding a third attribute, *study effort* increased model accuracy to 67.2%. The addition of each of the remaining attributes resulted in smaller increases in model accuracy, although some differences were statistically significant. For example, a McNemar test comparing predictions from a model based on the first four attributes (68.9%) with a model based on all nine attributes (73.1%) found the difference was marginally significant ($\chi^2(1, N = 436) = 4.65$, $p = 0.03$).

Table 4
Heat map of correlations between study factors and GPA

Study factor	Correlation	Study factor	Correlation
Methodical Average	0.302 [0.24, 0.36]	Self regulation	0.130 [0.08, 0.18]
CAO Points	0.285 [0.22, 0.34]	Self efficacy	0.120 [0.06, 0.18]
Mathematics	0.274 [0.21, 0.33]	Gender	0.100 [0.05, 0.15]
Age	0.250 [0.20, 0.30]	Openness	0.084 [0.03, 0.14]
Deep learner	0.234 [0.18, 0.29]	Visual	0.005 [-0.01, 0.11]
Humanities Average	0.228 [0.17, 0.29]	Auditory	0.002 [-0.04, 0.08]
Study effort	0.187 [0.14, 0.24]	Kinaesthetic	-0.059 [-0.11, 0.00]
Applied Average	0.172 [0.10, 0.24]	Shallow learner	-0.146 [-0.21, -0.09]
English	0.169 [0.11, 0.23]	Strategic learner	-0.158 [-0.22, -0.1]
Conscientiousness	0.150 [0.09, 0.21]		

Intervals are 95% Confidence Intervals based on 1,999 bootstrap samples. Only students with school leaving certificate results were included in calculations for prior academic performance (n=1,018). Applied average results are based on a subset of students who did applied subjects (n=647, 64%).

Table 5
Regression model results

	All (n=1207)	Age < 23 (n=852)
R^2	0.196	0.251
MSE	0.819 ± 1.068	0.748 ± 0.985
	Standardised model co-efficients	
Age	0.388***	0.149***
Methodical Average	0.218***	
Humanities Average	0.143***	
Average leaving certificate		0.356***
Maths		0.105**
Conscientiousness		0.120***
Study effort	0.097***	
Deep learner	0.816**	0.090**
Strategic learner	0.581*	
Shallow learner	0.420*	
Gender	0.055	0.102***

Intercept was 0 in both models. *p<0.05; **p<0.01; ***p<0.001

Discussion

Results from both correlation and regression analysis in this study concur with results reported in other studies from tertiary education, supporting the validity of early measurement of non-cognitive factors of learning (e.g., Cassidy, 2011; Conrad, 2006; Chamorro-Premuzic & Furnham, 2008; Diseth, 2011; Kaufman et al., 2008). Both correlation and regression analysed linear relationships between study factors and GPA. Therefore, it was unsurprising that significant factors in regression models also had higher correlations with GPA.

Table 6

Improvement in classification model accuracy as attributes were added to the model

Order that attributes were added to the model	Model accuracy(%)	Increase in model accuracy
Methodical average	59.9	
Age	64.7	4.8**
Study effort	67.2	2.6***
CAO Points	68.9	1.6
Self efficacy	69.4	0.5
Visual	71.8	2.4
Kinaesthetic	72.9	1.1
Applied average	71.1	-1.8
Humanities average	73.1	2.0

**p<0.01; ***p<0.001, based on McNemar χ^2test

This study included a diverse student population in terms of age, academic discipline, and assessment methods used. Nonetheless, a classification model predicting students at risk of failing in first year of study, trained on data available during first year student induction, achieved good predictive accuracy when applied to a different student cohort (73%). Poor prior academic performance in science and/or business related subjects was more indicative of at risk students than prior academic performance in other subject areas. Of the non-cognitive study factors *study effort* facilitated the best improvement in model accuracy. A *deep learning* *approach* was not significant in the non-linear classification model in spite of its relatively strong correlation with GPA (Table 4). In addition, there is no evidence to date to suggest that learner modality is predictive of academic performance (Gilakjani, 2012; Kablan, 2016). Correlation results (Table 4) concurred with this observation. Therefore, it was surprising that the inclusion of learner modality, in particular a visual modality, improved classification model accuracy when using *k*-NN. Further work is needed to determine if this result generalises to other student cohorts, or is a result of some confounded factor.

The results cited here evidenced that prior academic performance is more predictive of future academic performance than measurements of learner disposition. However, the value of measuring learner disposition warrants discussion. There is an interest value in measurement of learner disposition. A survey of first year students in ITB who received online feedback on their learning disposition in 2015 found 82% of respondents would like to know more about factors relevant to an effective learning disposition (n=52). Interestingly, Duffin and Gray (2009) found that 56% of students understood online feedback on learning disposition, and this rose to 83% when online feedback was followed up by explanatory workshops. In addition, interventions to improve learner disposition evidence that effective learner dispositions are malleable. For example, a meta-analysis of studies on self-regulation reported improvements in self-regulation following self-regulation training and support (Winters, Greene & Costich, 2008). Similarly, Miller-Reilly (2006) evidenced that teaching approaches had changed adult learners' self-efficacy in mathematics. Arnold and Pistilli (2012) reported a 6.4 percentage point decrease in grades D, F and withdrawals amongst users of their Course Signals tool that provided both early warnings and suggested improvement strategies to at risk students. On the other hand, Jayaprakash et al. (2014) found that simply making students aware that they may be at risk of failing significantly increased numbers passing and number of withdrawals, but providing further supports did not effect additional change in either measure. Therefore, further work is needed to assess the impact of timely feedback on learner disposition, specifically on subsequent optimal use of that feedback.

Conclusion

Models developed in this study to predict students at risk of failing based on data gathered prior to or during first year enrolment achieved good model accuracy (73%). The dataset was diverse in terms of age, academic discipline and assessment strategies used (n=1,207). Informed by a review of factors predictive of academic performance in tertiary education, study factors related to prior academic performance, personality, motivation, learning strategies, learner modality, age and gender. The twenty-one study factors were measured prior to commencement of first year of study. Correlation and regression results were similar to results reported in other studies with the exception of self-efficacy which had a lower correlation with GPA compared with other studies.

Attributes that were significant for accurate prediction of students at risk of failing across a range of courses included:

- Age: The study sample had an age range of [18,60]. Younger students had a greater risk of failing in first year of study.
- Aggregates of prior academic performance: In particular, an aggregate of mathematics, science and business related subjects was found to be a stronger predictor of year 1 students at risk of failing compared to other prior academic performance aggregates.
- Self-regulation, specifically study effort: low study effort was more indicative of an at-risk student than other factors relating to an effective learning disposition.
- A visual modality was indicative of potential to achieve a passing grade.

A deep learning approach had relatively good correlations with GPA, and was significant in a regression model predicting GPA, but was not significant in a *k*-NN (non-linear) classification model. On the other hand, inclusions of learner modalities did improve model accuracy in a *k*-

NN classification model in spite of relatively weak correlations with GPA. Conclusions from this study that learner modality improved model accuracy was not widely observed in other studies. Therefore, further work is needed to determine if its importance in models of learning, as reported in this study, generalises to other student cohorts.

It has been argued that non-cognitive factors of motivation, self-regulation and approaches to learning are malleable, and key to an effective learning disposition, which in turn should be a valued learning outcome of courses in tertiary education. In addition, measurement of factors relating to effective learner disposition provides interesting feedback to students and faculty. However the usefulness of such feedback is less clear. While studies have shown that additional supports and interventions can improve learner disposition, there is also some evidence to show that such interventions do not improve student progression over and above simply informing a student that they are at-risk of failing. Further work is needed to evaluate subsequent benefits of profiling non-cognitive factors of learning during student induction, both for the student, and for first year mentoring and support programmes.

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