Learning strategies to move the "murky middle" of students in first-year biology

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Make today matter

Education Advisory Board (USA) collected data from 73 diverse American tertiary institutions (740 000 student records)

- And at most colleges and universities, academic support goes disproportionately to the students who are thriving, because they seek it out, and to the students at risk of failing, because the college sees they're at risk.
- The middle group has characteristics of both the strong and weak groups = "murky"
- Small academic improvements within the middle group correlate with greatly heightened chances of graduation. Thus the "murky middle" offers colleges a powerful "return on investment".

The "murky middle" (MM)

EAB defined the MM as students at risk of dropping out of university later than the first year (Student Success Collaborative 2014)

Three findings are important for the MM:

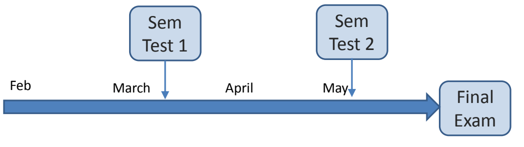
1. They do not conform to the characteristics that are used to flag at-risk students.
2. The leading indicator before drop out is not a decrease in GPA but an increase in the number of courses that they fail.
3. Outcomes improve dramatically when the downward trends in grades are reversed.

Need for early detection and intervention.

Context

- First year, first semester biology module, MLB 111
- Enrolment in 2015: 1587 students
- Sample (no repeaters or transfer students): 1084 students

  730 females (67%) and 354 males, 73% chose English as preferred medium of instruction



Research questions

1. Which characteristics differentiate effectively between students that are likely-to-pass, the murky middle (MM) and students at-risk of failing? (limited to pre-entry data)
2. Which learning strategies in first year biology are associated more strongly with good performance than with marginal or poor performance?

Theoretical underpinnings

- Self-regulated learning (Pintrich, Zimmerman, Boekarts)
- College readiness framework (Conley)

Data for categorisation (RQ1) - possible predictor variables

Demographic data

- Race
- Gender
- Home language
- Preferred language of instruction (LOI)
- Match between home language and LOI (Y/N)

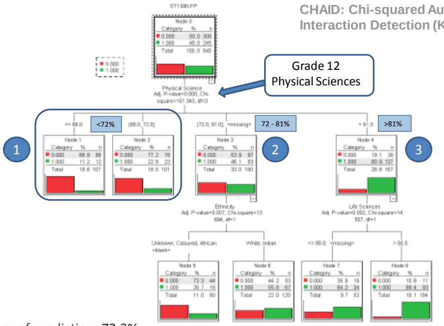
Prior performance data

- Grade 12 results (maths, science, biology, English)
- APS score
- NBT results
- Computer literacy (placement tests)

Outcome variable: Semester Test 1 results

Categorisation by means of CHAID analysis

CHAID: Chi-squared Automatic Interaction Detection (Kass 1980)



Power of prediction: 72.3%

Validation of construct: MM

	2015				2016		
	Number at start of 2015	MLB 111: Students passed (%)	Mean GPA (2015)	Mean Credit Pass Ratio (2015)	Number at end of 2016	Mean GPA (2016)	Mean Credit Pass Ratio (2016)
At-risk	426				332 (-94)		
Murky middle	315				254 (-61)		
Likely-to-pass	343				301 (-42)		

Validation of construct: MM

	2015				2016		
	Number at start of 2015	MLB 111: Students passed (%)	Mean GPA (2015)	Mean Credit Pass Ratio (2015)	Number at end of 2016	Mean GPA (2016)	Mean Credit Pass Ratio (2016)
At-risk	426	49%	54	0.78 (SD 0.26)	332 (-94)	54	0.83 (SD 0.20)
Murky middle	315	68%	60	0.88 (SD 0.20)	254 (-61)	60	0.90 (SD 0.16)
Likely-to-pass	343	93%	71	0.98 (SD 0.06)	301 (-42)	71	0.98 (SD 0.06)

RQ2: Which learning strategies are associated more strongly with good performance than with marginal or poor performance?

Data collection: Motivated strategies for Learning Questionnaire (MSLQ) (Pintrich 1990)

Two sections: Motivation (31 items) & **Learning strategies** (50 items, 9 subscales)

Cognitive and metacognitive strategies (31 items)
- Rehearsal
- Elaboration
- Organisation
- Critical thinking
- Metacognitive self-regulation

Resource management strategies (19 items)
- Time and study environment
- Effort regulation
- Peer learning
- Help seeking

MSLQ data

- Data captured before final exam: 715 data records (66% response rate)
- 4-point Likert scale: Very true of me (scored 3), Mostly true of me (2), Seldom true of me (1) and Not at all true of me (0).
- Composite scores for subscales: One-way ANOVA followed by *Tukey post hoc* tests to locate the difference

Results: Comparison of subscales

Cognitive and metacognitive strategies (31 items)
- Rehearsal (p=0.005)
- Elaboration (p=0.013)
- Organisation (p=0.053)
- Critical thinking (p=0.021)
- **Metacognitive self-regulation (p=0.002)**

Resource management strategies (19 items)
- Time and study environment (p=0.013)
- **Effort regulation** (p<0.001)
- Peer learning (p=0.015)
- ~~Help seeking~~

Findings: Productive learning strategies of likely-to-pass students

A1. Work with other students to complete assignments and clarify concepts (items 34 and 45) Peer learning

A2. Apply deep learning by relating ideas to other courses and connecting concepts within a course (items 62 and 81) Study skills for Long term memory

B1. Sort out any confusion in a timely manner (Items 41 and 79) Metacognitive monitoring & management of learning

B2. Persist even when work is difficult or not of interest (items 37, 48 and 60) Effort regulation (self-discipline and persistence)

Findings: Productive learning strategies of likely-to-pass students

C1. Choose suitable spaces to study (item 35) Study skills

C2. Apply good time management and thus have time for revision and rehearsal (item 46) Time management

C3. Employ appropriate study methods that include memorisation and organization (item 49 and 59) Study skills

C4. Plan study activities and set goals to direct these study activities (Items 78 and 61) Study skills

Summary and conclusions

- It was possible to categorise students and validate the categorisation using prior learning data (Grade 12 performance in Physical Sciences).
- MM consistently failed to pass all modules that they registered for (on average one module per year) – vulnerable in the long run.
- Identified productive learning strategies used by the likely-to-pass group more so than by the other two groups.
- The findings can be used to inform classroom practice and academic advising.

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