





Data-driven decisions with Bayesian networks and data visualisation





the Witwatersrand Workshop & University of





Southern African Association for Institutional Research

Welcome





SAHELA 2017 Workshop the Witwatersrand Jniversity of Pretoria & University of

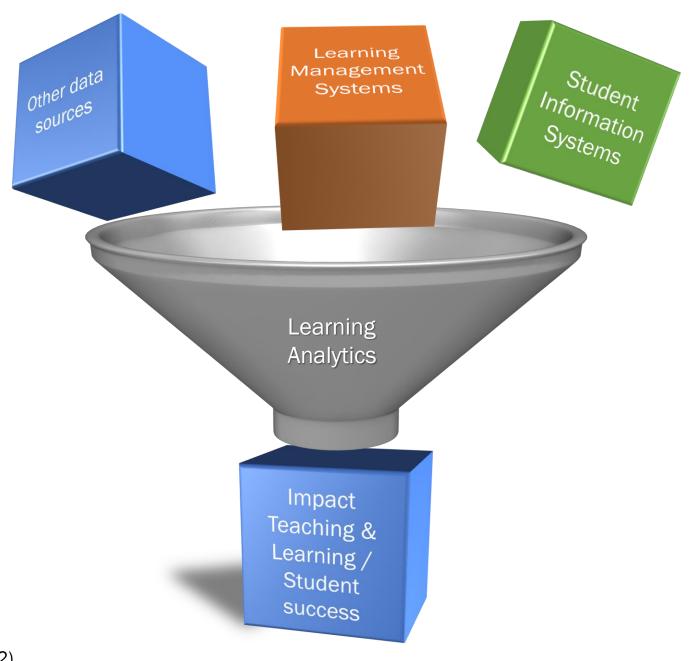




Institutionalise Learning Analytics







1. Other data sources and...

2. Adoption of LMS and use of clickstream data combined with...

3. Transactional- and biographical data from Student Information Systems (SIS) = drivers for LA

Allow stakeholders to identify patterns in student activity.

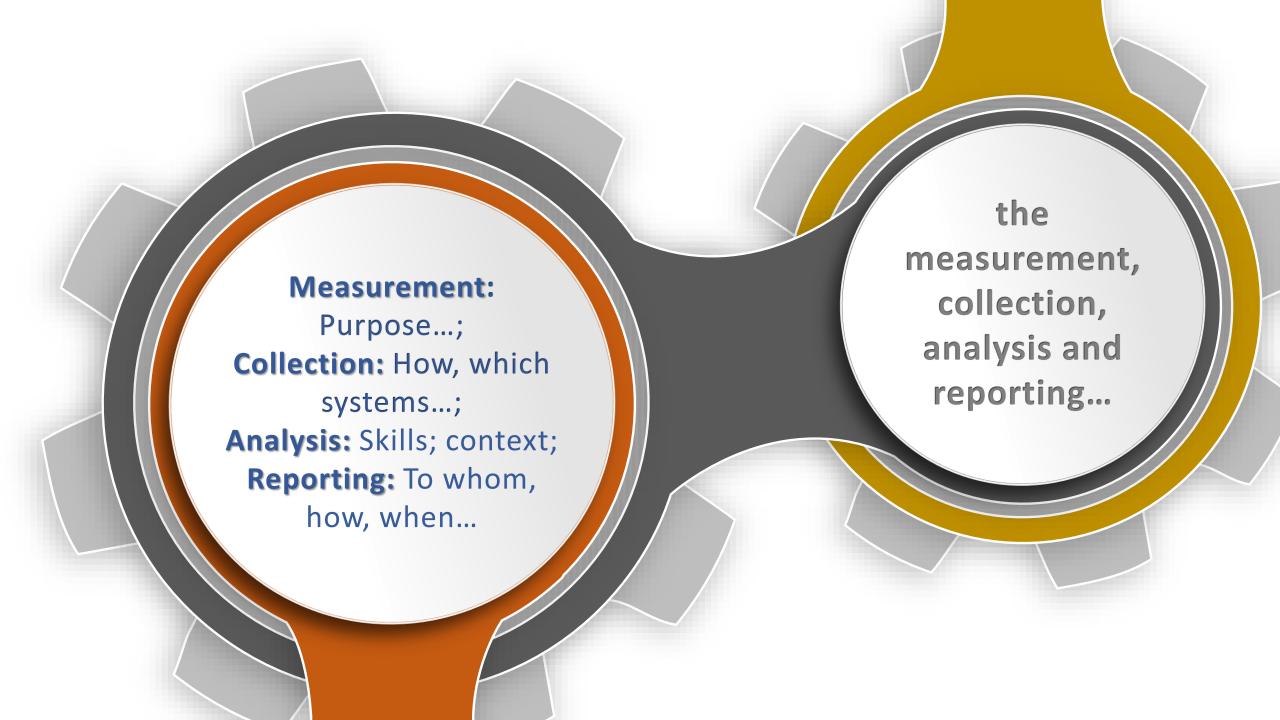
Challenge remains to extract value and to Institutionalise LA

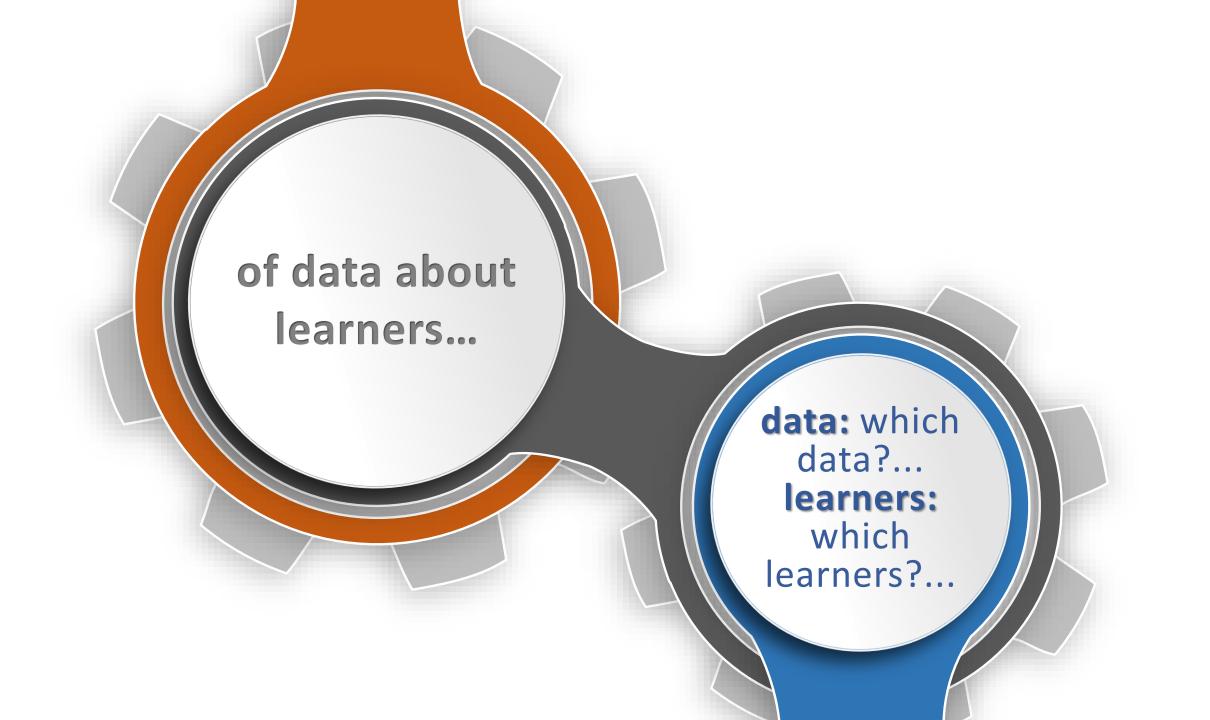
(Beer et al., 2012; Ferguson, 2012)

Learning Analytics Definition

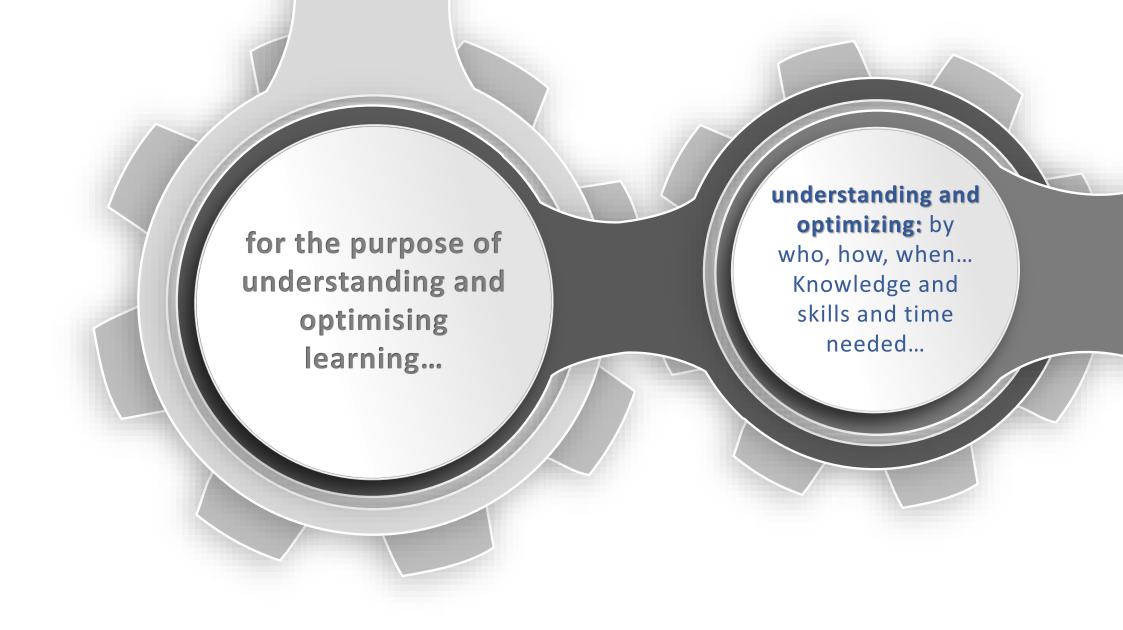
"Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for the purpose of understanding and optimising learning and the environments in which it occurs."

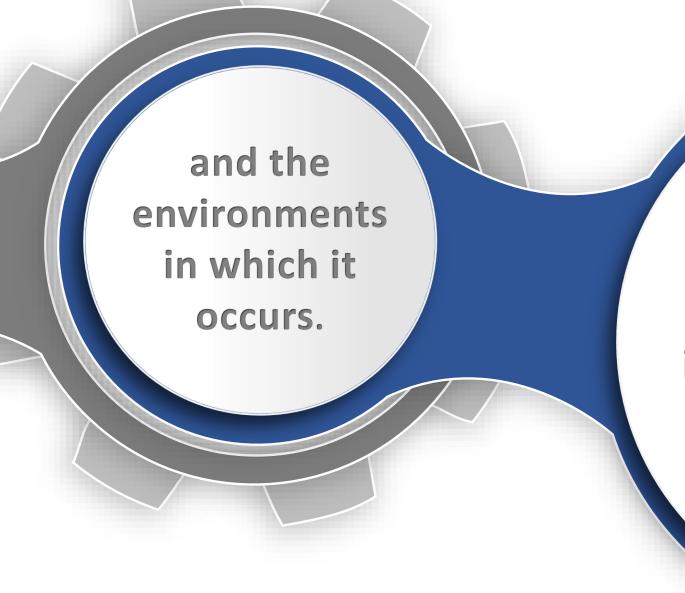












environments: Online,
Face-to-face, offcampus...

in which it occurs: real time, measurement of changes, willingness...

Large Scale Adoption



Challenges

Summary of challenges documented and experrienced



Case studies

Examples of successful institutional adoption



Models

Overview of existing institutional adoption models for LA implementation



Case studies

Adoption models

Dimension



Evaluating a single adoption capacity area

Challenges

Data

Resources & Skills

Policies & Processes

Culture

Quantity

Governance

Adoption

Organisational change



Data

Management, access, standardisation, interpretation, access, accuracy...



Resources & Skills

Access to HR, IT & Financial resources to sustain LA; new skill set. Stakeholders...



Policy & Process

Adoption of new & evaluation of related policies. Institutional processes



Culture

Resistance to change, Institutional priorities, Evidence of data-driven decision making

Large Scale Adoption: Case Studies

Purdue Signals

Pioneering work at the University of Purdue through the Course Signals systems (Arnold and Pistilli, 2012)

Nottingham Trent University

Providing students, tutors and support staff access to a student progress dashboard using data from various data sets (Day, 2015;Foster, 2015)

Maryland, Baltimore County

Student facing notification dashboard which allowed students to 'Check my Activity" (Fritz, 2011)

Open University UK

Experience in managing student data supported throug considerable research informed the institutional adoption of evidence based decision-making (Ferguso



Purdue Signals

It uses descriptive data from the SIS, LMS and gradebook to provide a student facing report with an interface simulating a traffic light

Nottingham Trent University

Student dashboard at NTU received positive feedback from tutors and students and resulted in an institutional culture of data-driven decision making.

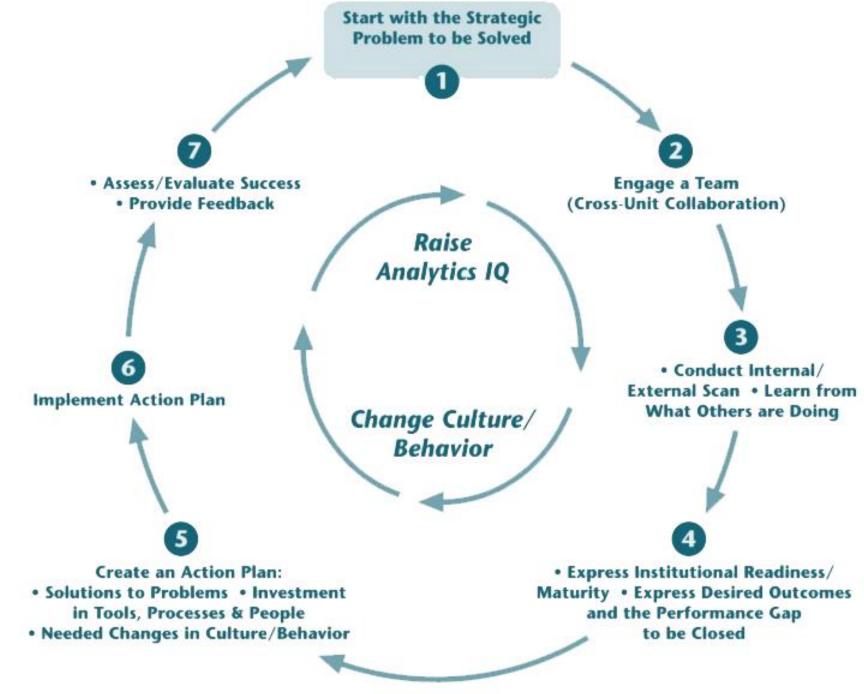
Maryland, Baltimore County

Provides students with real-time feedback about their own performance to enhance student responsibility for learning.

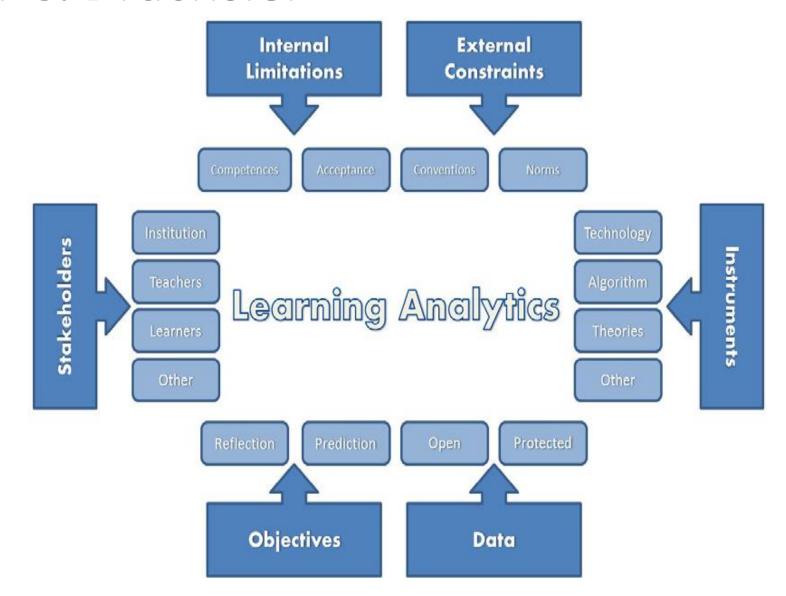
Open University UK

Senior management act as sponsor for the project and provided the vision and took ownership for implementation of the ROMA Framework to institutionalise learning analytics

Action Plan for Analytics

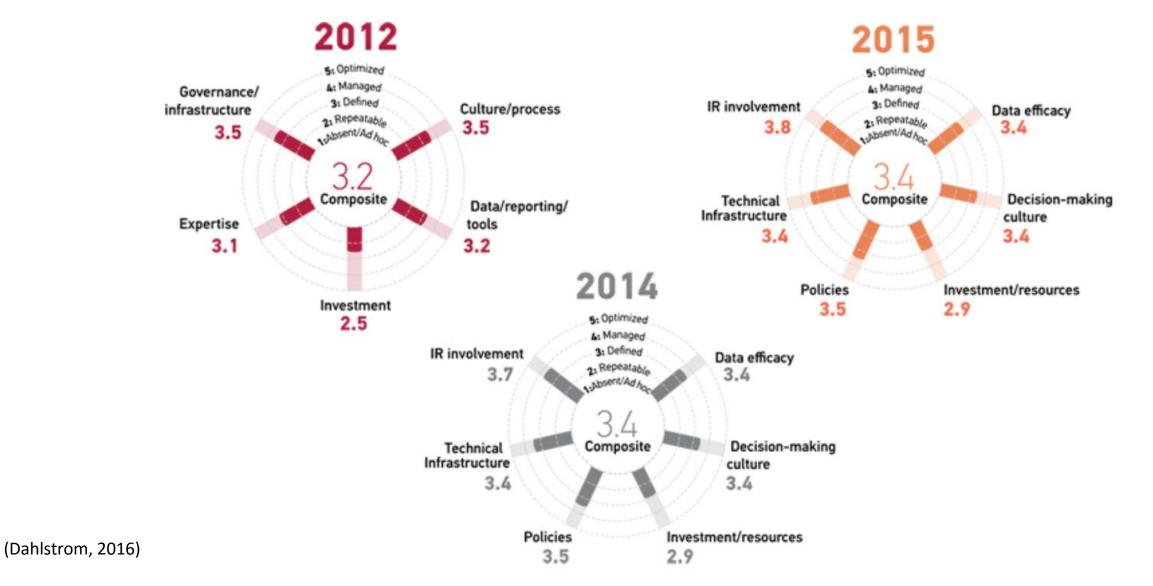


Greller & Drachsler

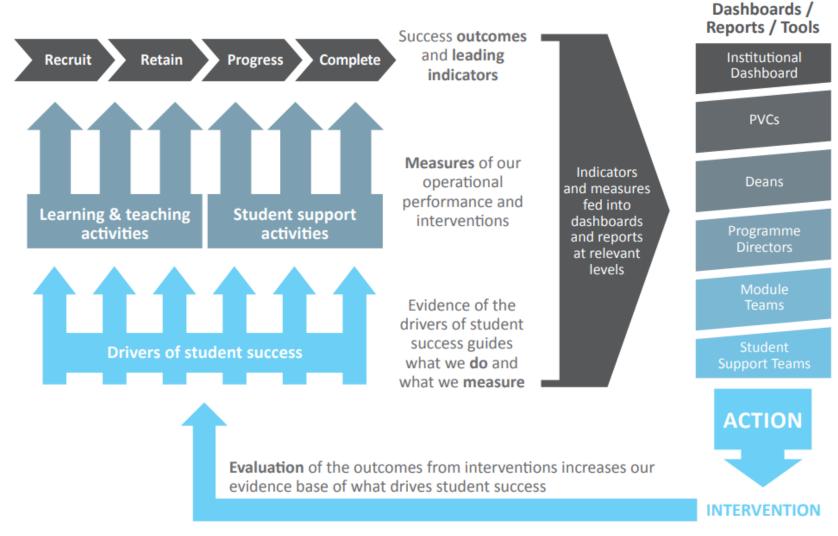


(Greller and Drachsler, 2012)

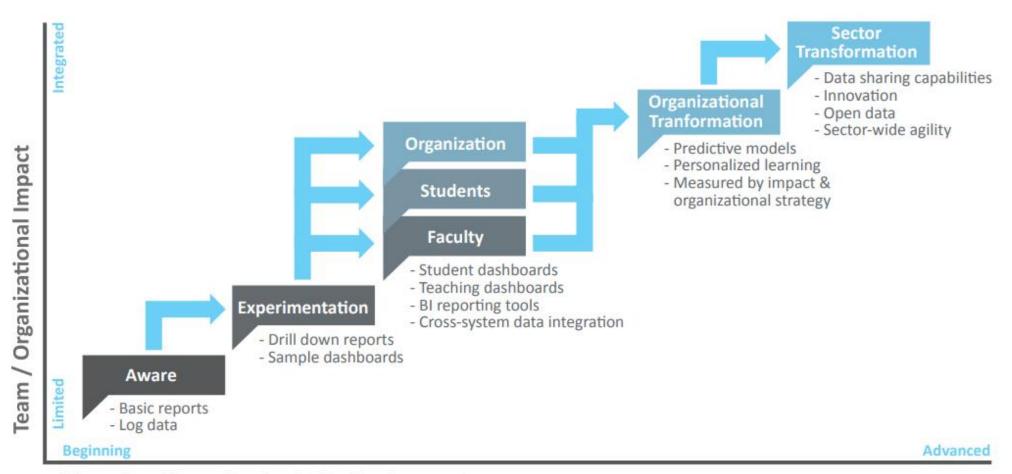
EDUCAUSE: LA Maturity index



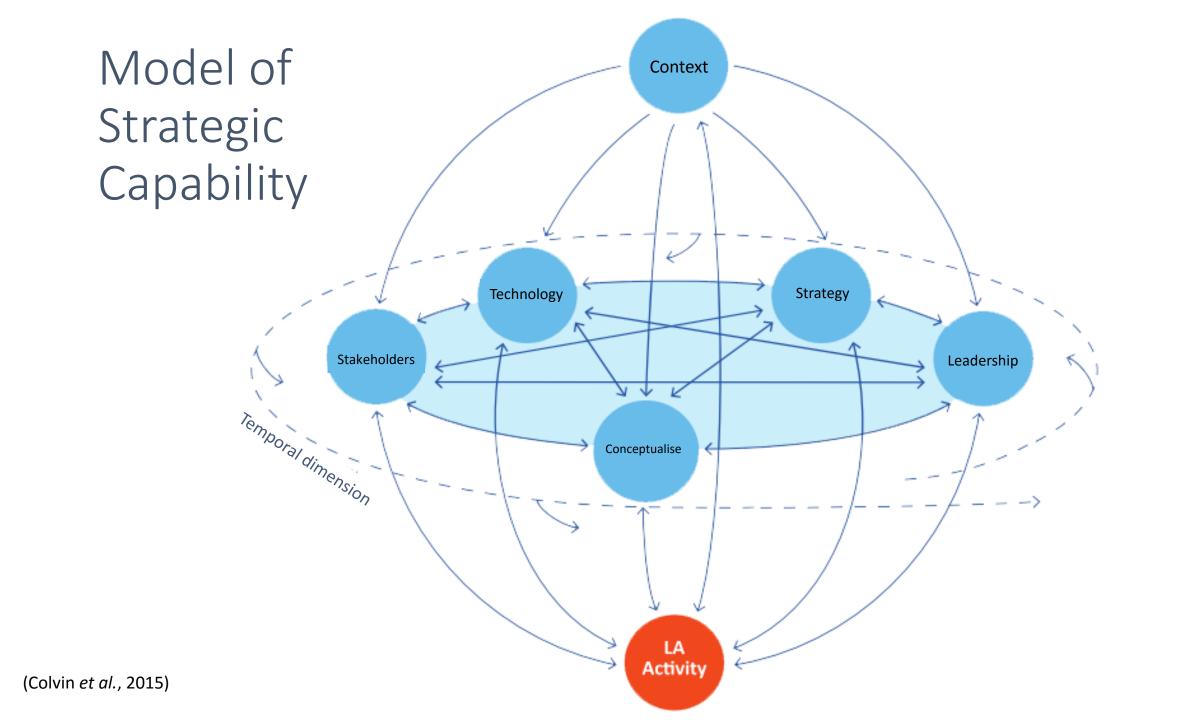
Systemic LA at the OU in the UK



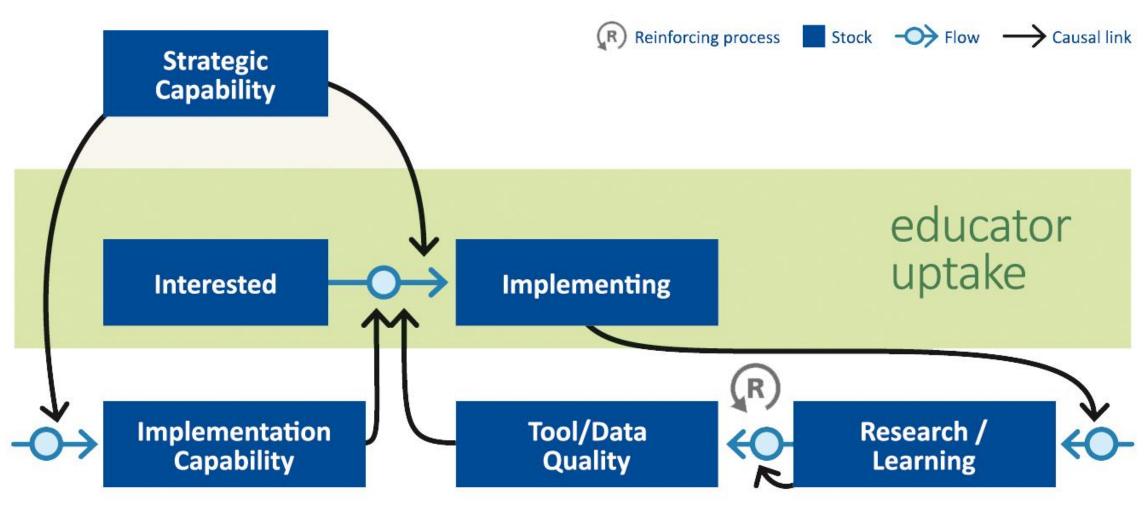
LA Sophistication Model



Maturity of Learning Analytics Deployment



Model of system conditions for sustainable uptake of LA



Learning Analytics Drivers

| Institutional | Name of Institution |
|------------------------------------|---------------------|
| Retention | |
| Course level performance | |
| Demonstrate effectiveness in T&L | |
| Understand student characteristics | |
| Improve course design / quality | |
| Improve service delivery | |
| Faculty productivity | |
| Reduce costs | |
| Cohort analysis | |
| Other | |

Mapping of institutional adoption capacity areas

| LARI (Arnold, Lonn & Pistilli) | EDUCAUSE: Maturity Index 2015 | Jisc |
|--------------------------------|-------------------------------|--------------------------|
| Culture & Processes | IR involvement | Culture & Vision |
| Data management expertise | Technical infrastructure | Ethics & Legal issues |
| Data Analysis Expertise | Policies | Strategy & Investment |
| Governance / Infrastructure | Investment / resources | Structure & Governance |
| Readiness perception | Decision-making culture | Technology & Data |
| | Data efficacy | |
| Ş | ? | , |

Capacity activity

List Indicate Evaluate State Plan

- List the critical institutional adoption dimensions
- Indicate
 institutional
 stakeholders
 involved and
 their role /
 needs
- Evaluate
 existing- and
 required
 skills and
 resources
- State impact the dimension may have on student success interventions
- Plan action steps in order of feasibility and priority

References

- Arnold, K.E. & Pistilli, M.D., Course signals at Purdue: Using learning analytics to increase student success. In: Proceedings of the 2nd international conference on learning analytics and knowledge, 2012. ACM, pp. 267-270.
- Ali, L., Asadi, M., Gašević, D., Jovanović, J. & Hatala, M., 2013. Factors influencing beliefs for adoption of a learning analytics tool: An empirical study. *Computers & Education*, 62, pp. 130-148.
- Altbach, P.G. & Knight, J., 2007. The internationalization of higher education: Motivations and realities. *Journal of studies in international education*, 11(3-4), pp. 290-305.
- Arnold, K.E., Lonn, S. & Pistilli, M.D., 2014. An exercise in institutional reflection: the learning analytics readiness instrument (LARI).
 Proceedings of the Fourth International Conference on Learning Analytics And Knowledge. Indianapolis, Indiana, USA: ACM, pp. 163-167.
- Beer, C., Jones, D. & Clark, D., Analytics and complexity: Learning and leading for the future. In: Proceedings of the 29th Annual Conference of the Australasian Society for Computers in Learning in Tertiary Education, 2012. pp. 78-87.
- Colvin, C., Rogers, T., Wade, A., Dawson, S., Gašević, D., Buckingham Shum, S. & Fisher, J., 2015. Student retention and learning analytics: A snapshot of Australian practices and a framework for advancement. Sydney, NSW: Australian Office for Learning and Teaching.
- Dahlstrom, E., 2016. Moving the Red Queen Forward: Maturing Analytics Capabilities in Higher Education. EDUCAUSE Review, 51(5), pp. 36-54.
- Day, M., 2015. NTU Dashboard. *Learning Analytics Network*. University of East London: https://analytics.jiscinvolve.org/wp/files/2015/02/Jisc-LA-Network-Mike-Day.pdf.
- Dietz-Uhler, B. & Hurn, J.E., 2013. Using learning analytics to predict (and improve) student success: A faculty perspective. *Journal of Interactive Online Learning*, 12(1), pp. 17-26.

References

- Dietz-Uhler, B. & Hurn, J.E., 2013. Using learning analytics to predict (and improve) student success: A faculty perspective. *Journal of Interactive Online Learning*, 12(1), pp. 17-26.
- Ferguson, R., 2012. Learning analytics: drivers, developments and challenges. *International Journal of Technology Enhanced Learning*, 4(5/6), p. 304.
- Ferguson, R., Clow, D., Macfadyen, L., Essa, A., Dawson, S. & Alexander, S., Setting learning analytics in context: overcoming the barriers to large-scale adoption. In: Proceedings of the Fourth International Conference on Learning Analytics And Knowledge, 2014. ACM, pp. 251-253.
- Friedman, T.L., 2006. The world is flat: the globalized world in the twenty-first century. Updated and expanded [ed.]. ed. London: London: Penguin.
- Ali, L., Asadi, M., Gašević, D., Jovanović, J. & Hatala, M., 2013. Factors influencing beliefs for adoption of a learning analytics tool: An empirical study. *Computers & Education*, 62, pp. 130-148.
- Fritz, J., 2011. Classroom walls that talk: Using online course activity data of successful students to raise self-awareness of underperforming peers. *The Internet and Higher Education*, 14(2), pp. 89-97.
- Fritz, J., 2016. *Using analytics to encourage student responsibility for learning and identify course designs that help.* University of Maryland, Baltimore County.
- Drachsler, H. & Greller, W., Privacy and analytics: it's a DELICATE issue a checklist for trusted learning analytics. In: Proceedings of the sixth international conference on learning analytics & knowledge, 2016. ACM, pp. 89-98.
- Macfadyen, L.P. & 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), p. 149.

References

- Maringe, F. & Foskett, N., 2010. Introduction: Globalization and Universities. Et Nick Foskett, dir. (2010), Globalization and Internationalization in Higher Education, New York: Continuum International Publishing, pp. 1-13.
- Norris, D.M. & Baer, L.L., 2013. Building organizational capacity for analytics. Boulder, CO: Educause. Retrieved May, 10, p. 2015.
- Picciano, A.G., 2014. Big Data and Learning Analytics in Blended Learning Environments: Benefits and Concerns. *International Journal of Interactive Multimedia and Artificial Intelligence*, 2(7), pp. 35-43.
- Porter, P. & Vidovich, L., 2000. Globalization and higher education policy. *Educational Theory*, 50(4), pp. 449-465.
- Shacklock, X., 2016. From Bricks to Clicks: The Potential of Data and Analytics in Higher Education. Higher Education Commission.
- Siemens, G. & Long, P., 2011. Penetrating the fog: Analytics in learning and education. EDUCAUSE review, 46(5), p. 30.
- Van Barneveld, A., Arnold, K.E. & Campbell, J.P., 2012. Analytics in higher education: Establishing a common language. *EDUCAUSE learning initiative*, 1(1), pp. I-II.
- Yanosky, R. & Arroway, P., 2015. The Analytics Landscape in Higher Education. ECAR.



THANK YOU!

Dolf Jordaan dolf@up.ac.za







Bayesian logic and Data visualisation





the Witwatersrand of Pretoria & University of Workshop

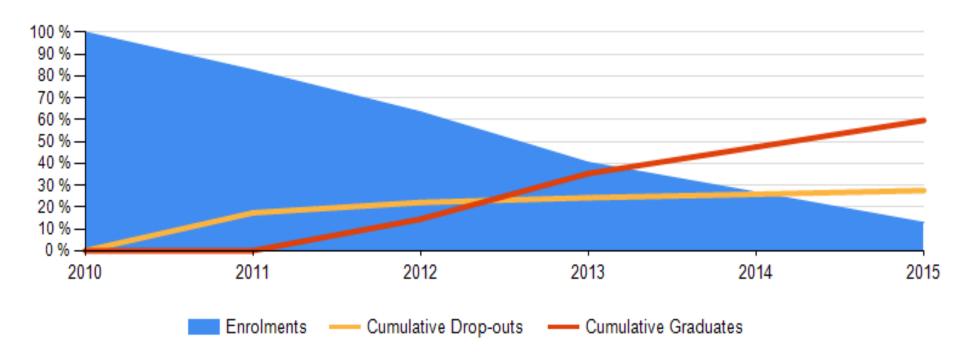
Objectives

- Analyse student throughput
- Answer questions such as
 - % students completing studies in
 - min time
 - min + 1 time
 - min + 2 time
 - % students still active in system
 - Per faculty
 - Demographics

Descriptive Statistics

Heda System

2010 Baseline Enrolment



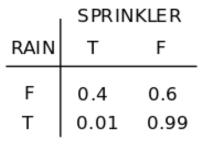
Alternative Approach

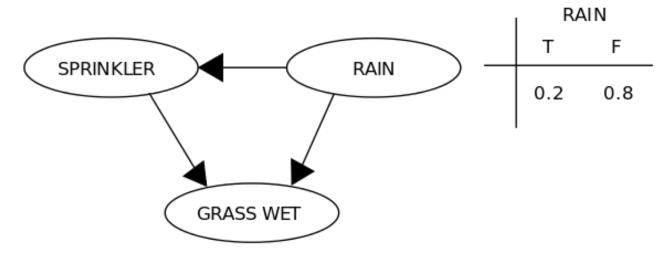
- Knowledge base system (KBS)
 - Knowledge base contains information about the system
 - Inference engine contains logical rules about the system
- Main output
 - Reason about the system

Bayesian networks

- Graphical structure
 - Nodes
 - A set of random variables
 - Directed Arcs
 - Connect nodes, representing the direct dependencies between variables
 - Strength of dependencies is quantified by conditional probability distribution associated with each node.

Example





| | | GRASS WET | |
|-----------|------|-----------|------|
| SPRINKLER | RAIN | Т | F |
| F | F | 0.0 | 1.0 |
| F | Т | 0.8 | 0.2 |
| Т | F | 0.9 | 0.1 |
| Т | Т | 0.99 | 0.01 |
| | | | |

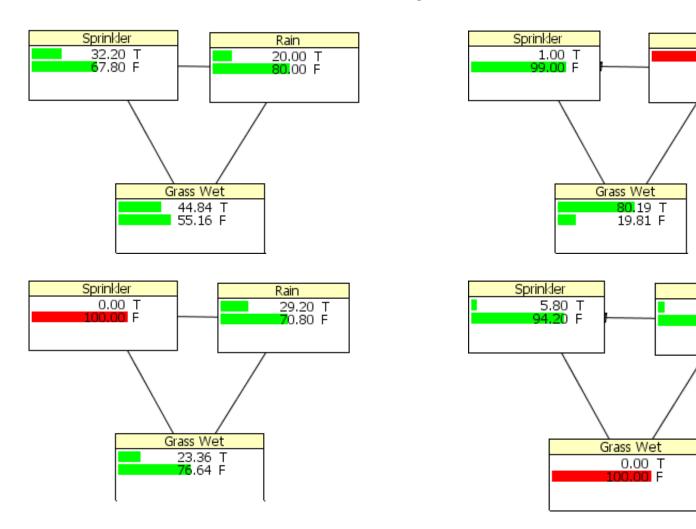
Inference (What-if Analysis)

Rain

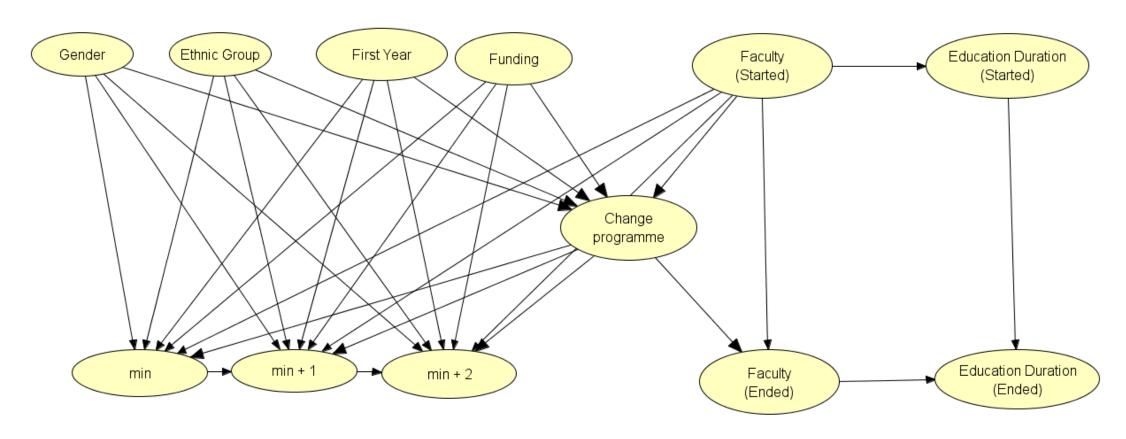
0.00 F

Rain

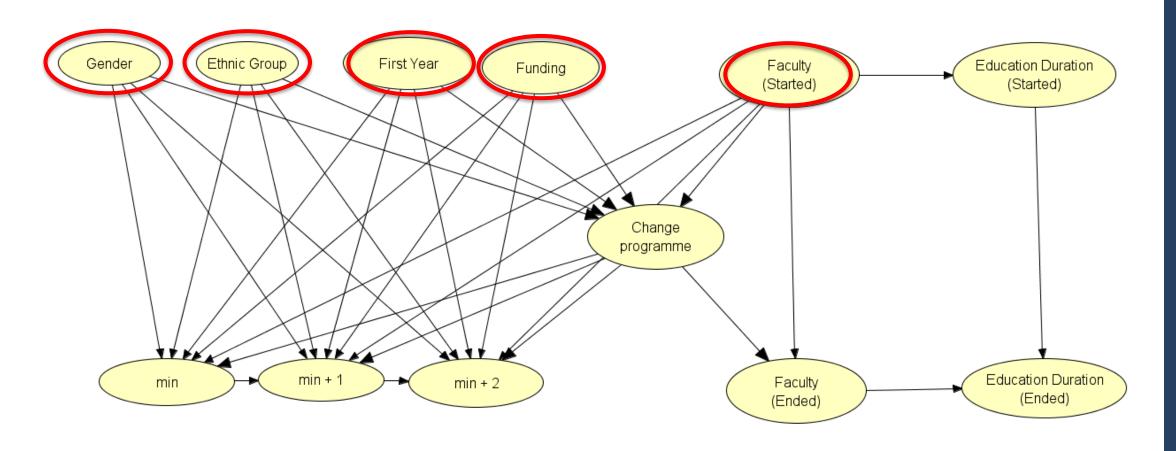
7.18 T **92.8**2 F



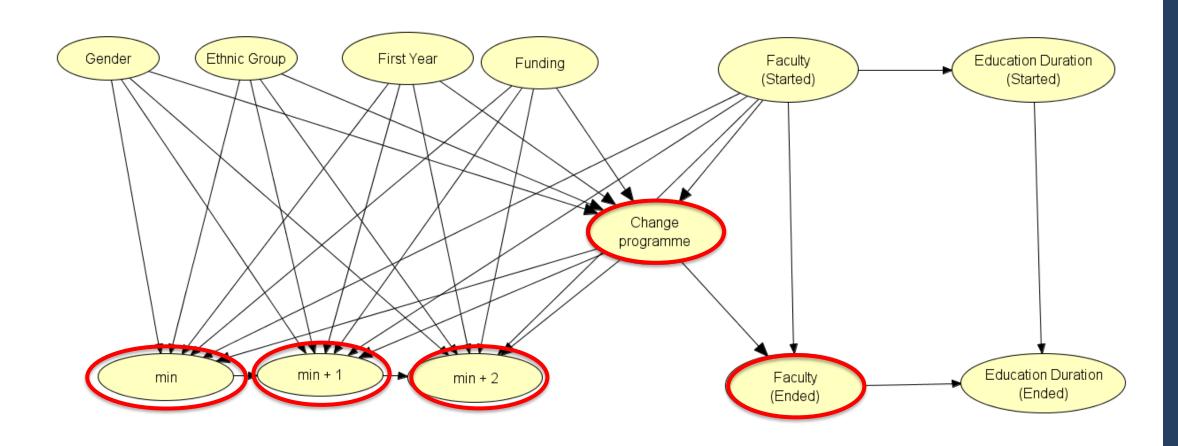
Leitlho* A KBS for Student Throughput Analysis



"Independent" Variables



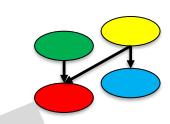
"Dependent" Variables



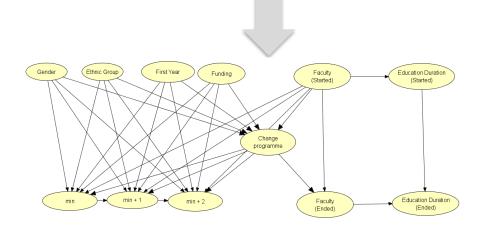
Components of model

- Data
 - Preprocessing (Python)
 - One line per student (csv format)
- Graphical structure
 - Variables
 - States of variables
 - Structure
- Parameterise
 - EM Algorithm





EM Algorithm (Parameterise)







Southern African Association for Institutional Research

The Wits Biographic Questionnaire





the Witwatersrand of Pretoria Workshop & University of

The Wits Biographic Questionnaire

- Comprehensive school and student background questionnaire, administered to <u>first-time</u>, <u>first year students</u>
- Aimed at better understanding how a student's background influences theirs success the University
- Using the BQ, the University will be in a better position to implement appropriate programmes that support the high school/ university transition

The Biographic Questionnaire

- The Biographic Questionnaire is currently funded by the Kresge
 Foundation (Siyaphumelela 'We Succeed' Project)
- One of the main objectives of the Wits Siyaphumelela Project is to 'Understand university readiness among undergraduate students'

BQ Progress

- The student Biographic Questionnaire is fully online and has been integrated into the Wits administration process (compulsory)
- Data collected in 2016 & 2017

BQ Structure

Home background

• Facilities at home; Location; 1st Generation status; Family support structure; Financial income; Educational background, etc.

School background

• Location; Classification; Infrastructure; Language of instruction; etc.

Additional Information

• Payment of tuition fees; Part-time employment; Accommodation; How far is student stay from campus; Mode of transport, etc.

BQ- Role players

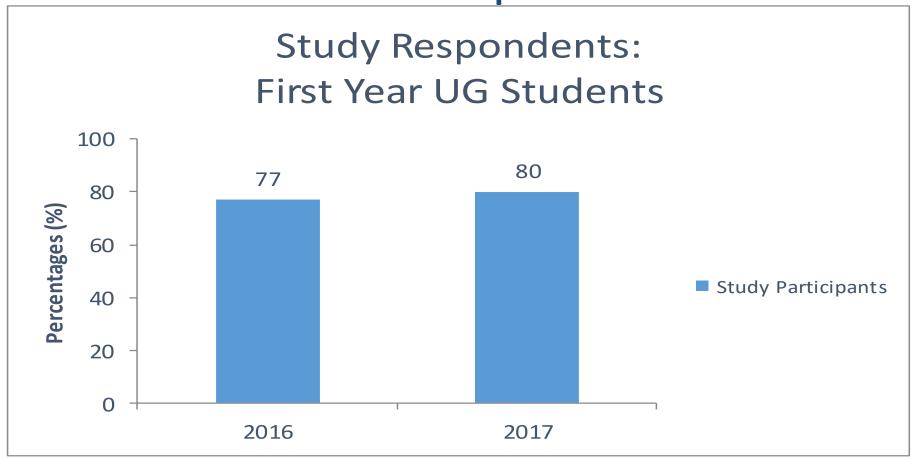
- 1. Support from the Registrar and DVC Academic
- 2. Independent developer and the Wits Academic Information Systems Unit (AISU)
- 3. First year experience (FYE) office
- 4. Wits call center
- 5. Wits student enrolment center
- 6. Faculty Program coordinators

BQ Coordination

- BQ planning takes place during the last quarter of the year
 - Reviewing questionnaire
 - Initial meeting with role-players

- January
 - Training to temp call center agents and FYE student assistants
 - Reminders sent to role-players
 - Weekly progress emails during course of registration

BQ Response rate



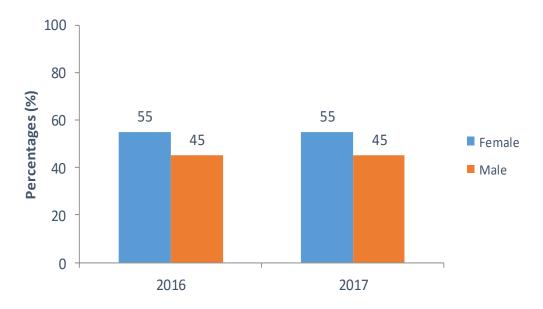
Why not 100%?

BQ Challenges

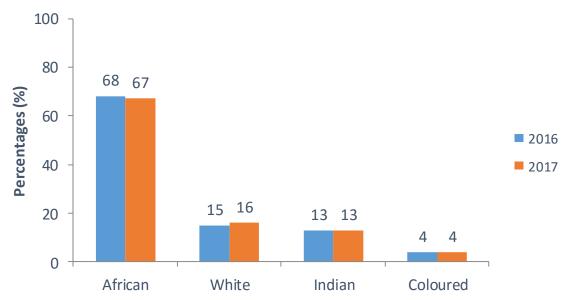
- Mostly technical in nature
 - Students 'not seeing' the BQ
 - Internet browser version
 - Reminder emails
 - Tracking progress
- Computer proficiency not a challenge

Gender and Race (from University data)

Gender: 1st Year UG Students

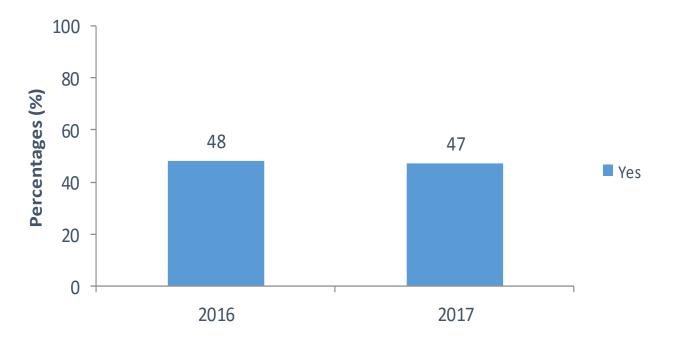


Race: 1st Year UG Students



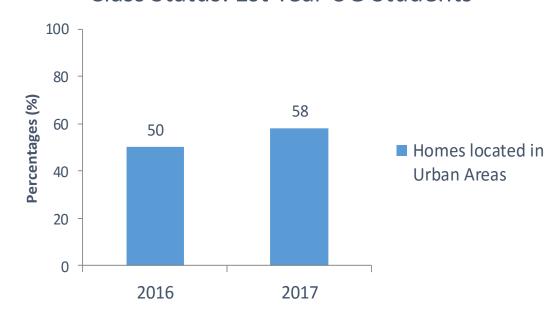
First generation status

First Generation Status:
1st Year UG Students



Home information



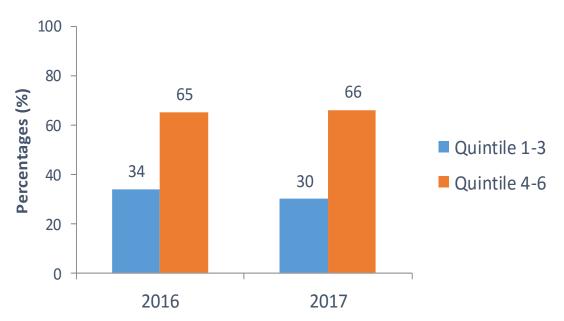


Taught in Home Langauge: 1st Year UG Students

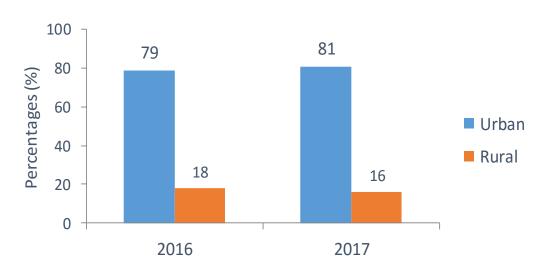


School information

School Quintiles: 1st Year UG Students



School Location (Urban/Rural): 1st Year UG Students

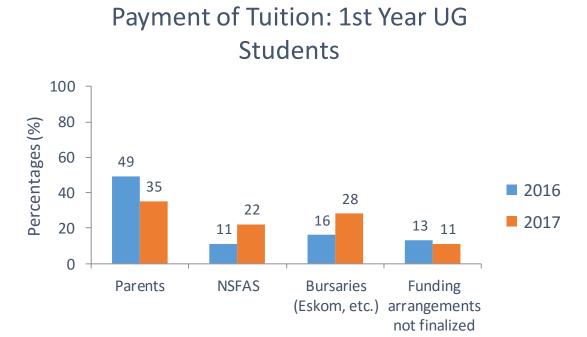


School information

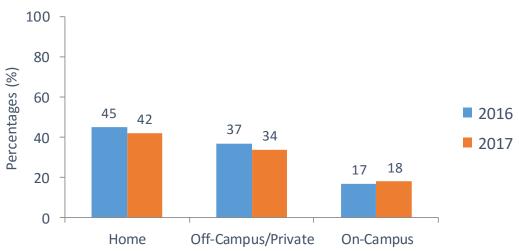
School Infrastructure:

| | 2016 | 2017 |
|--------------|-----------|-----------|
| Science Labs | 77% (65%) | 75% (66%) |
| Library | 68% (58%) | 70% (59%) |
| Computers | 78% (62%) | 78% (61%) |

Tuition and accommodation



Accommodation During Studies: 1st Year UG Students



BQ Reporting

- Preliminary data analysis February
- Present prelim data to University Forum late March
- Data triangulation/ validation April/ May
- Final report June

The BQ moving forward

- Data collection will continue in 2018
- Partner with other Universities
- Conducting analysis looking at student performance
- Longitudinal potential
 - following progress of student cohorts over time

Thank You

Fezile Mdluli Institutional Researcher

Fezile.Mdluli@wits.ac.za





Southern African Association for Institutional Research

The case of Wits: Discussion





the Witwatersrand of Pretoria Workshop & University of





Presentation on Bayesian models (The case of UP and Wits)





the Witwatersrand Workshop & University of





Southern African Association for Institutional Research

Student throughput analysis using a Bayesian Model: The case of UP





Roadmap



- Main objective
- Research questions
- Model
- Results
 - Institutional level (UP)
- Impact

Main objective and research questions

- Main objective
 - To analyse student throughput using a Bayesian Model
- Research questions
 - From which Faculty/Gender/Ethnicity students graduate in minimum time?
 - Which demographic profiling of students are more likely to be active after minimum graduation time plus 2 years?
 - Does funding have an impact on the profiling of UP students?
 - Are students who change programmes more likely to droput?
 - What variables are most likely to impact on students academic performance?

Processed variables

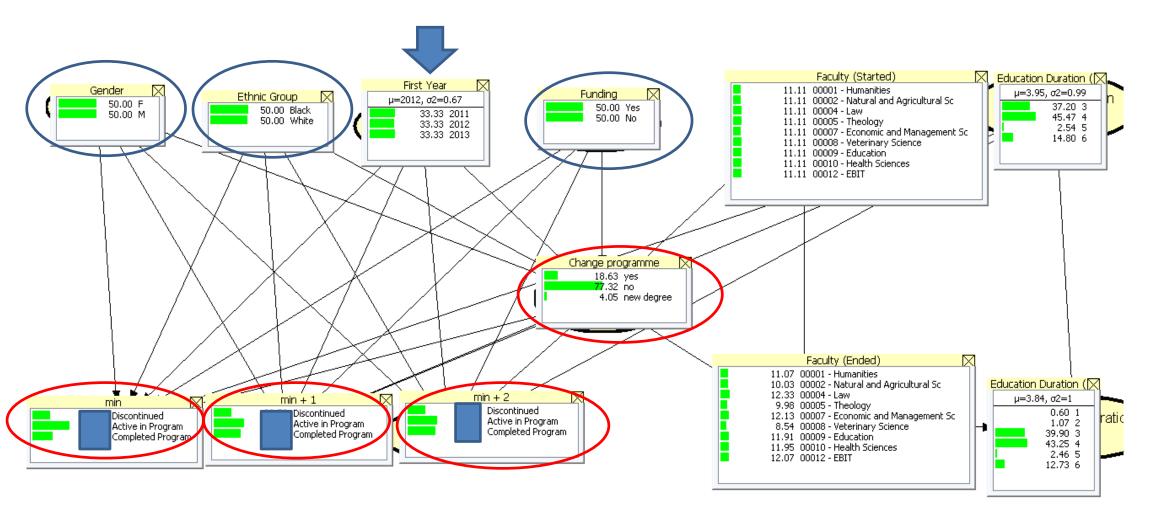
Independent variables

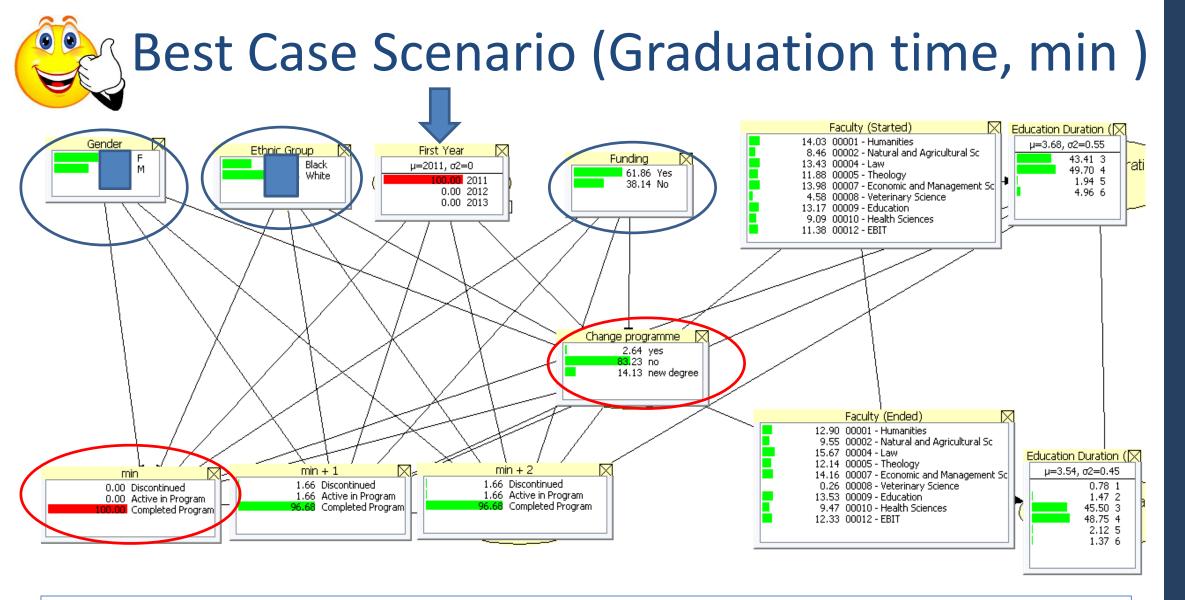
- Gender: Gender description of the student.
- Ethnic group: Ethnic group of the Students according to Hemis.
- First year: First term of the student at the institution (2011,2012, and 2013 Cohort).
- Funding: Yes/No, the status indicate whether a student has a sponsor such as a bursary, loan etc.

Dependent variables

- Change study programmes?: Yes/No
- Min: the minimum number of years of study required for the completion of the qualification.
- Min + 1: the minimum number of years of study required for the completion of the qualification plus 1 year.
- Min + 2: the minimum number of years of study required for the completion of the qualification plus 2 years.

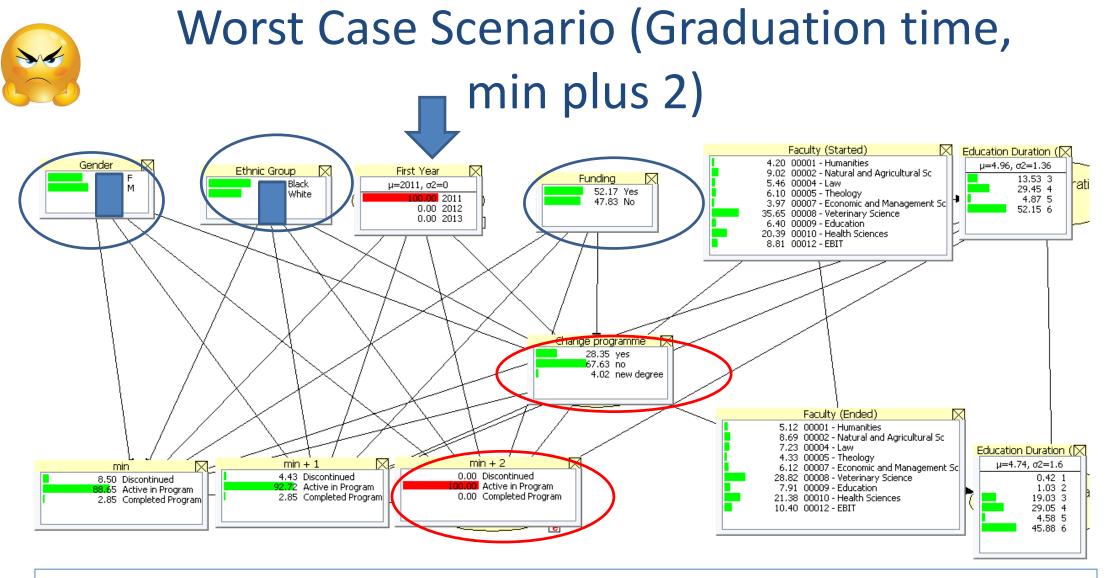
Model (Institutional Level): Student throughput analysis





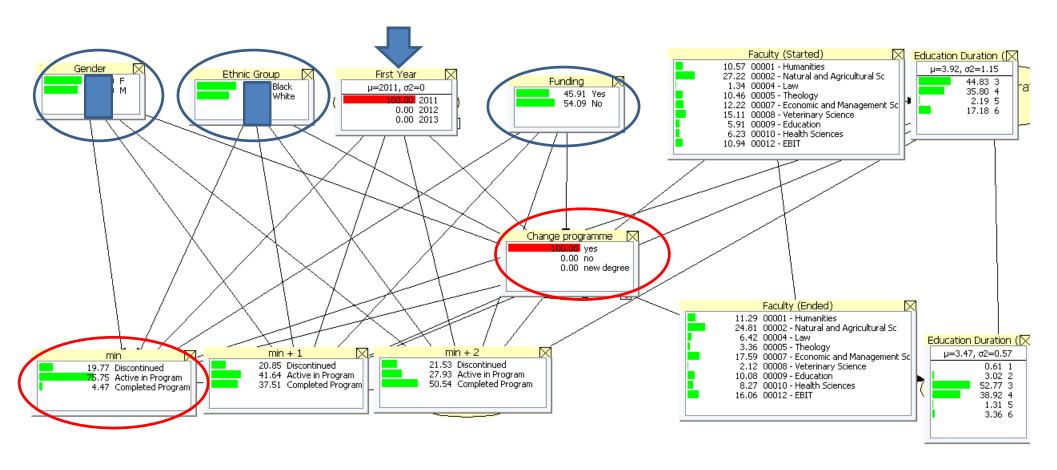
Control variables: Completed in min time and cohort = 2011

Associated student profile: White female students with financial support that do not change programme



Control variables: Still active in min time plus 2 years and cohort = 2011
Associated student profile: More likely to be black male students with or without funding support that do not change programmes

Change programme: Yes



Control variables: Change program YES and cohort = 2011

Associated student profile: They are more likely to be still active after minimum time

Thank you!

ben.ntshabele@up.ac.za





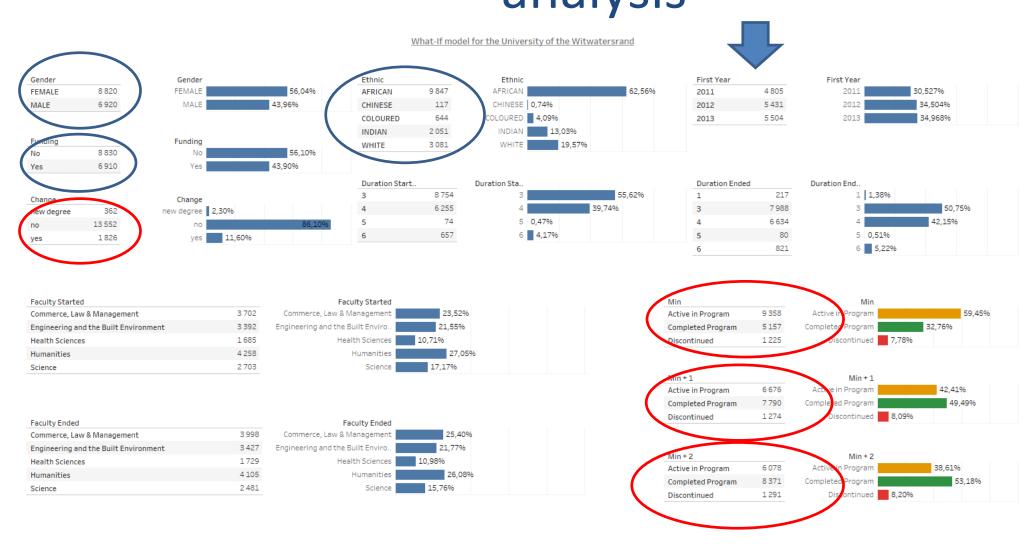


Student throughput analysis using a Bayesian Model: The case of Wits



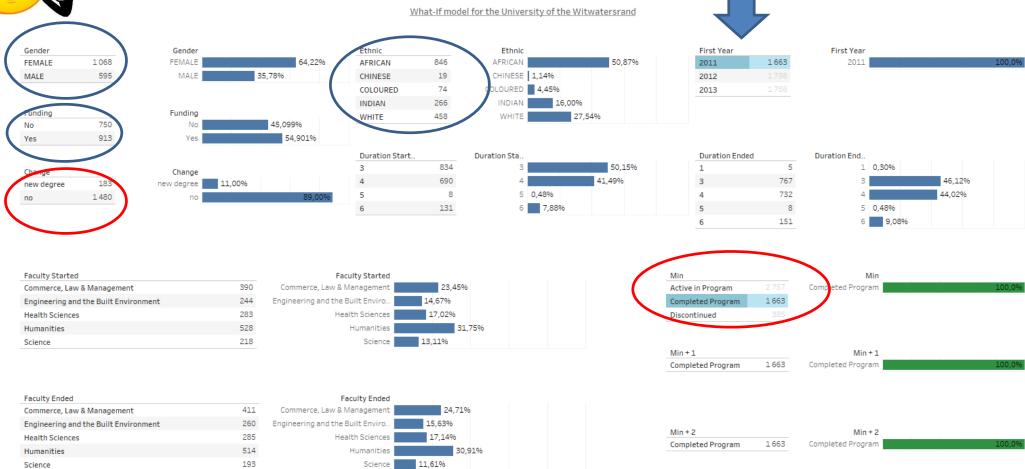


Model (Institutional Level): Student throughput analysis





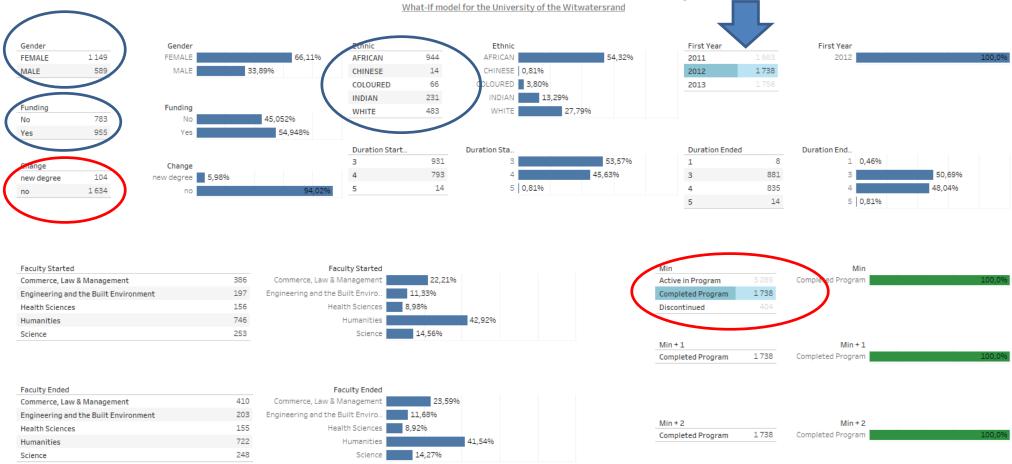
Best Case Scenario (Graduation time, min)



Control variables: Completed in min time and cohort = 2011

Associated student profile: African female students with financial support that do not change programme

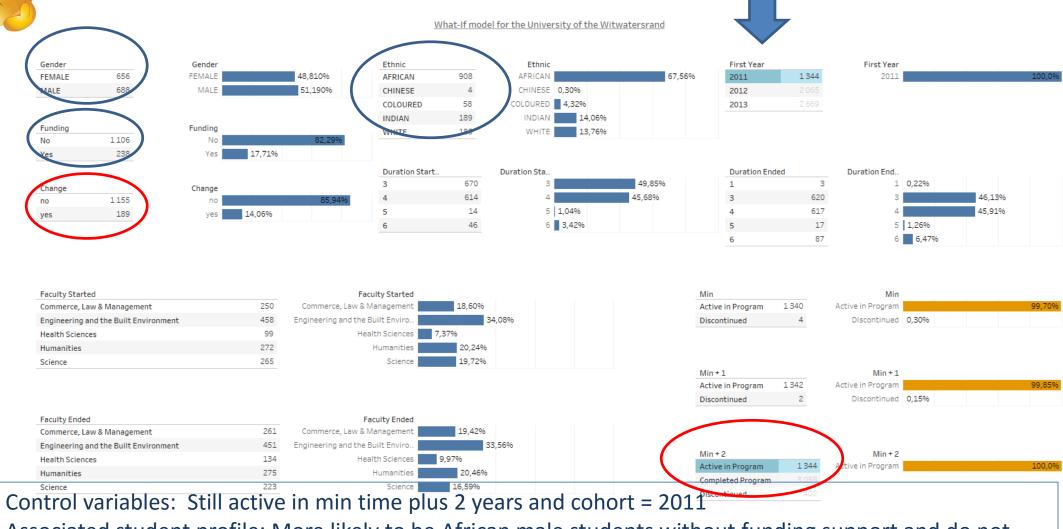
2012 Cohort: Graduation time, minimum time



Control variables: Completed in min time and cohort = 2012

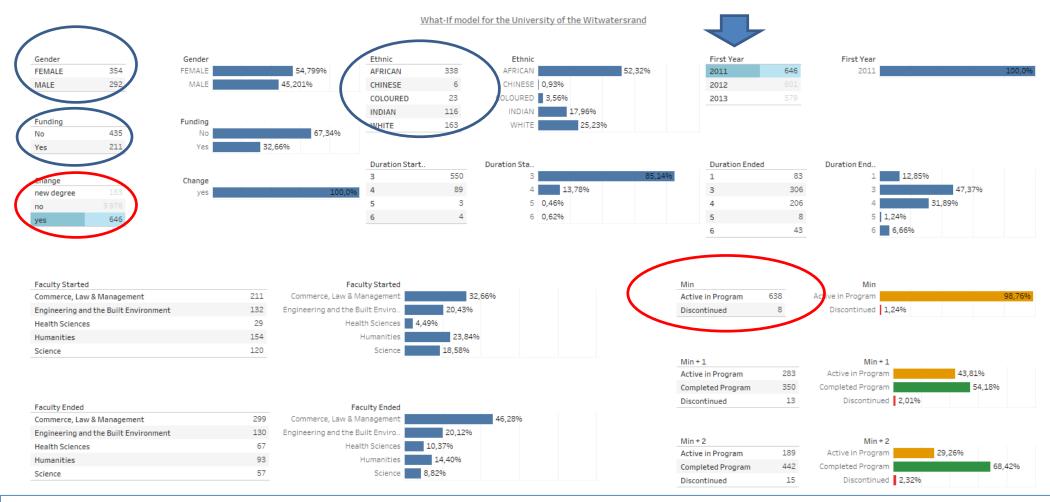
Associated student profile: African female students with financial support that do not change programme

Worst Case Scenario (Graduation time, min plus 2)



Associated student profile: More likely to be African male students without funding support and do not change programmes

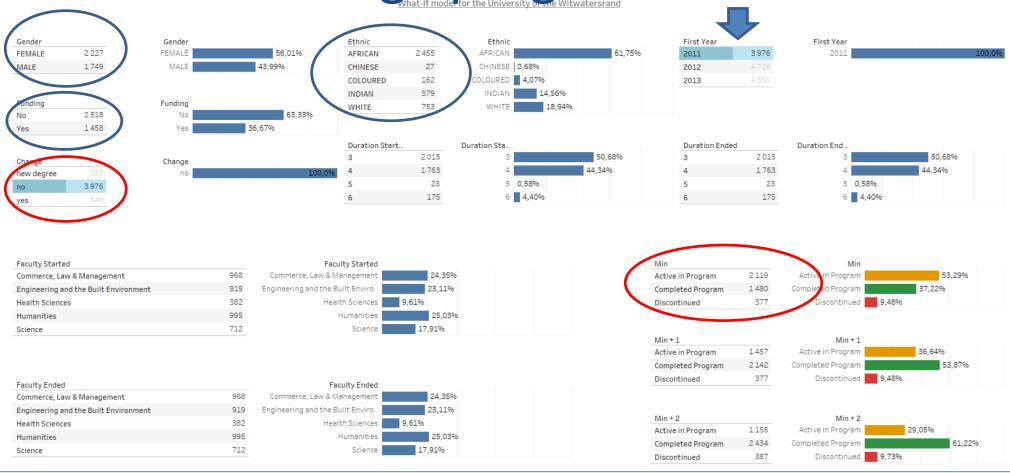
Change programme: Yes



Control variables: Change program YES and cohort = 2011

Associated student profile: They are more likely to be still active after minimum time

Change programme: No



Control variables: Change program No and cohort = 2011

Associated student profile: They have a lower probability of completing in minimum time

In conclusions

Findings

- African females at the University of the Witwatersrand are more likely to complete in minimum time.
- Funding is interlinked with graduation in minimum time.
- Students who complete their programmes in minimum time, are more likely to have funding and less likely to change a programme.
- Students who change programmes are more likely to be still active after minimum plus 2 graduation time.
- Based on the model, funding and changing programme are variables that are most likely to impact on student's completion time.

[Hence] Impact

- Gain insight in institutional profiles for student success.
- Motivate faculties to focus more closely on initiatives to improve throughput rates.
- The university should focus on making student funding more available.

Thank you!

ali.denewade@wits.ac.za







Southern African Association for Institutional Research

Theory of Change



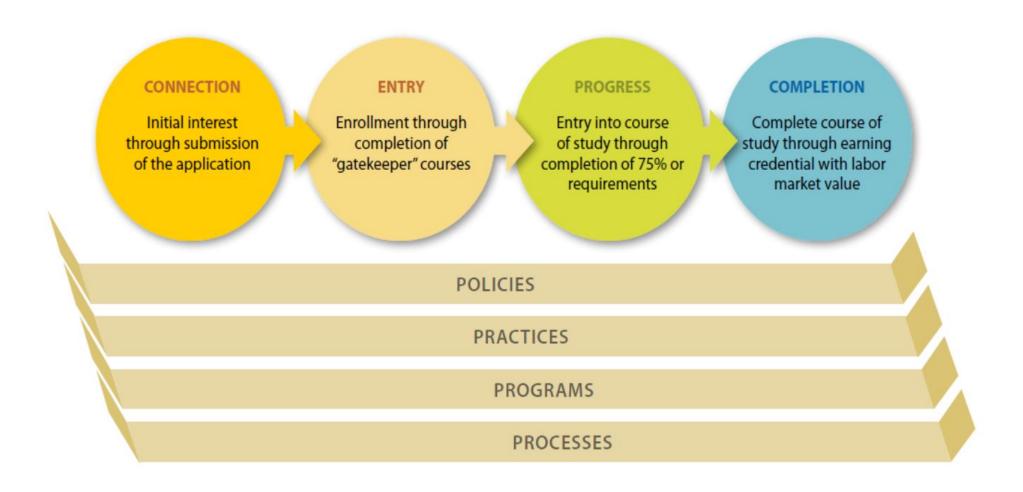


the Witwatersrand niversity of Pretoria Workshop & University of

SA institutions are data rich but information poor?

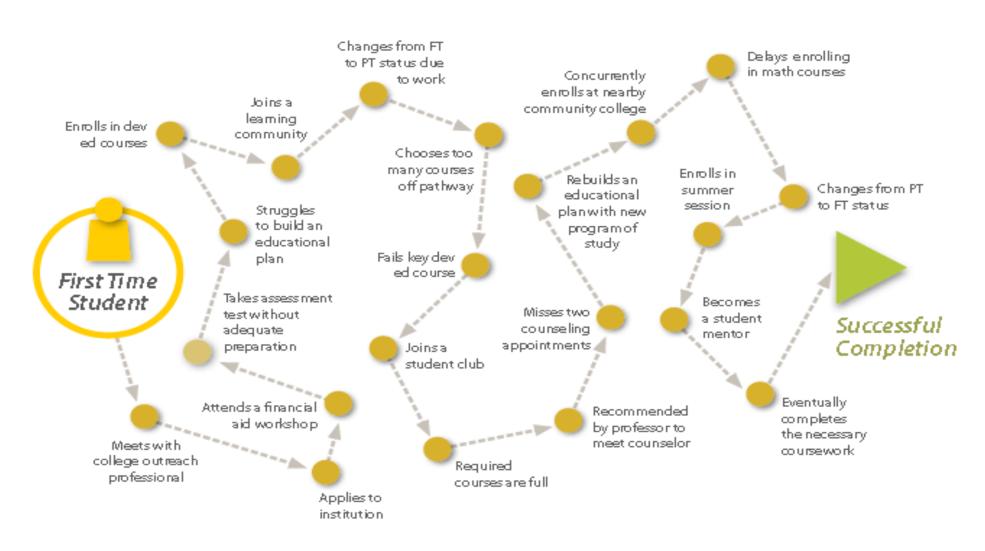
- Strategic planning: objectives and indicators/ scorecards
 - Success rates
 - Graduation rates
- Faculty plans
- Support departments objectives and indicators
- DHET reporting function
- Other: surveys, intervention evaluation, quality assurance activities, programme reviews

Integrated student experience?



Understanding The Student Experience Through The Loss/Momentum Framework: Clearing the Path to Completion

Student experience pathway



Understanding The Student Experience Through The Loss/Momentum Framework: Clearing the Path to Completion

Evaluation Frameworks

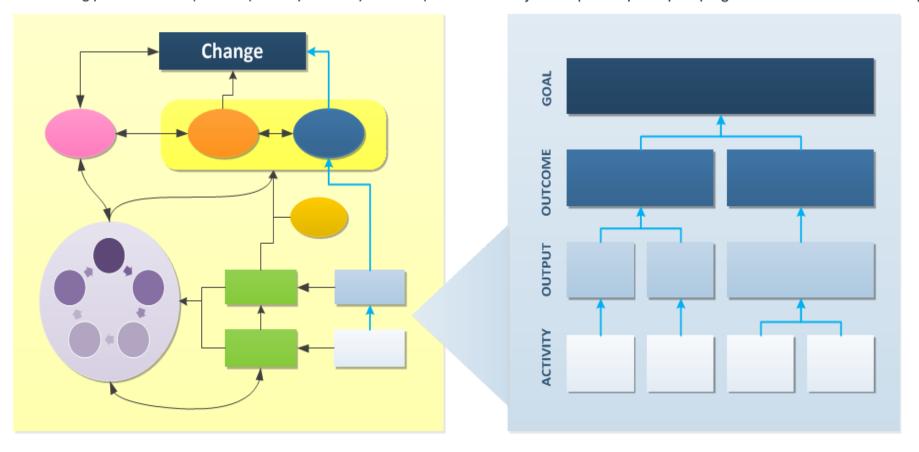
http://www.tools4dev.org/resources/theory-of-change-vs-logical-framework-whats-the-difference-in-practice/

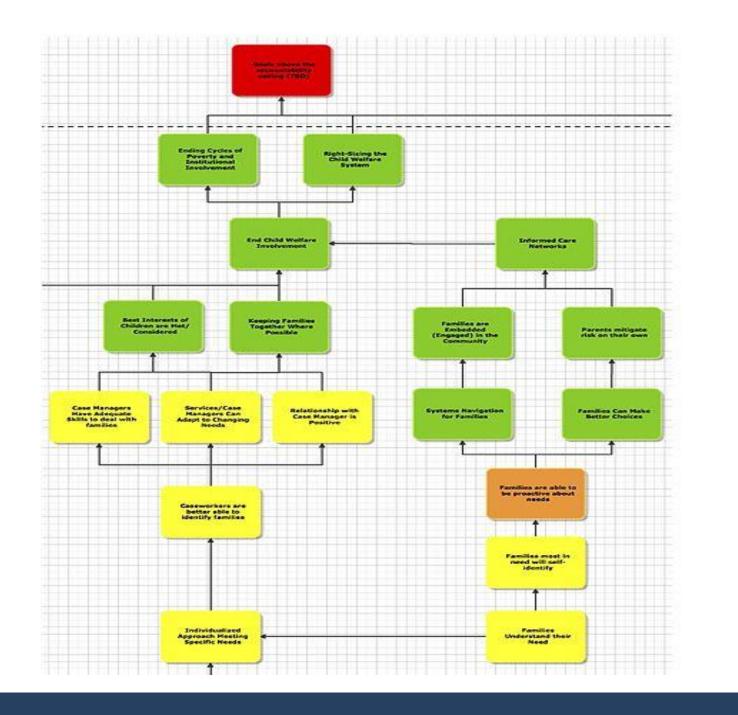
Theory of Change

Shows the big picture with all possible pathways – messy and complex

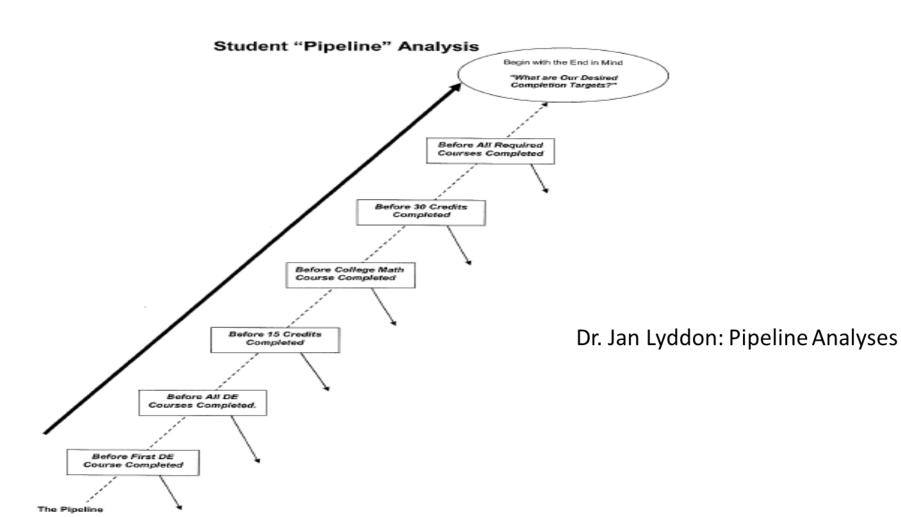
Logical Framework

Shows just the pathway that your program deals with – neat and tidy

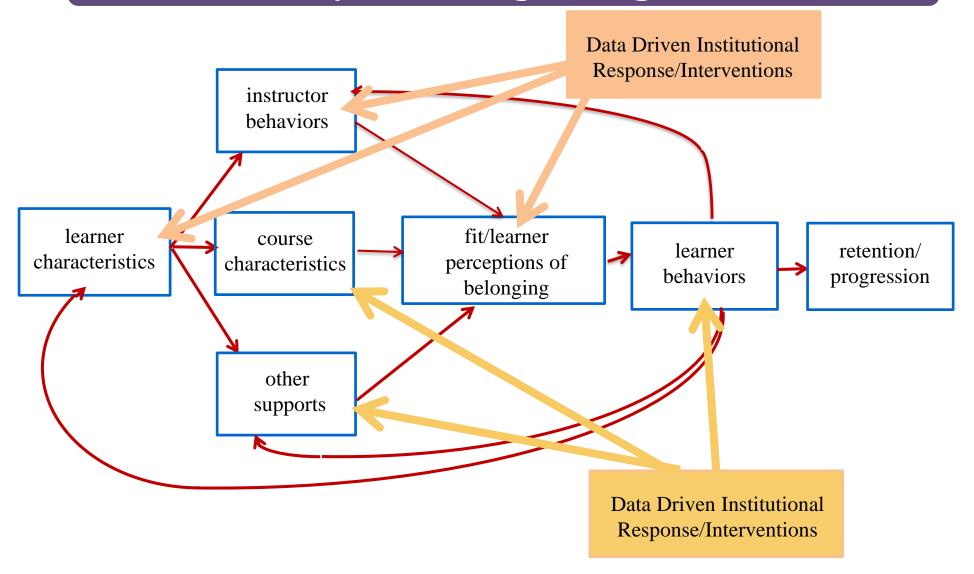




Student experience pathway



Theory of Change/ Log Frame



Theory of Change

- Identifying long-term goals and the assumptions behind them
- Backwards mapping from the outcome variable by working out the preconditions or requirements necessary to achieve that goal and explaining why.
- Voicing your assumptions about what exists in the system without which your theory won't work, and articulating your rationales for why intermediate outcomes are necessary preconditions to other outcomes.
- Weighing and choosing the most strategic interventions to bring about your desired change.
- Developing indicators to measure progress on your desired outcomes and assess the performance of your initiative.
- Quality review should answer three basic questions: Is your theory 1)
 plausible, 2) "doable" (or feasible), and 3) testable?
- Writing a narrative to explain the summary logic of your initiative.

Activity

- Create a process map to visualise the student experience: explore how students move through your institution/ faculty and experience student services
- Include the four phases of the student pathway (Connect, Entry, Progress, Completion)
- Include the underlying factors that have an impact on the institution and the students (Policies, Practices, Programs, Processes)
- The outcome variable is the graduation rate (min, +1, +2) at the Faculty of Natural Sciences (Set the baseline and determine goals)
- Use a Theory of Change Process (start from the end and work backwards)

Activity

- Process map (ToC process)
- Determine 'leakage points' (entry at 100%)
 - Student characteristics, support services, policies, practices, etc.
 - What interventions are in place (any data to show impact?)
 - What educational practices are involved?
- Determine at each of the four phases
 - What technology is used
 - Who are the key role-players
 - What technology is used
 - What are the 'disconnects' (things that go wrong)
- What should change in order to meet the Goal?

References

- https://focusedunow.com/process-mapping-for-enrollment-and-retention-success/
- https://www.insidehighered.com/views/2016/09/27/redesigning-college-processes-student-mind-essay
- http://www.higher-education-marketing.com/blog/student-journey-mapping-personalize optimize-conversion
- https://en.wikipedia.org/wiki/Theory of change
- http://www.bredeschool.org/sites/default/files/theoryofchangeguide%282%29.pdf
- https://er.educause.edu/articles/2013/12/the-predictive-analytics-reporting-par-framework-wcet
- http://www.parframework.org/
- https://powerofcommunity.force.com/education/s/cbd-home





Moving the needle (Institutional and National)





the Witwatersrand Pretoria Workshop & University of

Effectiveness of Learning Analytics (LA) Initiatives

- There is a growing literature on the effectiveness of LA:
 - Student retention
 - Students grades
 - Other Student success indicators
- Challenge is the difficulty in isolating & identifying the direct influence of the use of LA
 - often part of wider initiatives aimed at improving academic achievement & student success

Effectiveness of Learning Analytics (LA) Initiatives

- LA systems enable universities to:
 - track individual student engagement, attainment & progression
 - flag any potential issues (tutors & support staff)
- This allows the earliest identification of the students at risk of droppingout or under-achieving
- Predictive models (used by LA systems) are developed using historical data from previous cohorts of students
 - examining their patterns of activity & how these correlate with subsequent academic achievement

Effectiveness of Learning Analytics (LA) Initiatives

Example:

Civitas Learning:

- Study on 23 institutions showed that student engagement with Virtual Learning Environment (VLE) was high predictor of student success
 - the most significant predictor of student success was the percentage of days that they logged onto the VLE during the first 14 days of the term

- The true value of LA becomes clear only when actions are taken with students on the basis of the data
- Various studies have been carried out involving control groups
 - demonstrating some of the most convincing evidence for LA in influencing student success

Example:

University of South Australia

- 730 students across a range of courses identified as at risk
- Of the 549 who were contacted, 66% passed with an avg Grade Point Average (GPA) of 4.29
- 52% of at risk students who were not contacted passed with an avg GPA of
 3.14

- This shows the importance of intervention programmes in universities
 - if a student has been identified as at risk and they are left alone, they are more likely to fail
- Once a student has been flagged as being at risk, LA can help universities to understand which interventions work best
- By using proxies to measure student engagement, universities can examine how effective an intervention is

- Currently, there is increasing focus on the efficacy of spending on access and student success
 - LA can help institutions to review & demonstrate the effectiveness of their student support
- Other studies suggest that by simply making the students to be aware that they are at risk, may be enough

Examples:

Marist College case study

 There was a positive impact on grades for those students who were able to view comparative data on their engagement and progress

Nottingham Trent University

• A survey of the first year students showed that 27% of the students changed their behaviour in response to data on their LA dashboards

South African Learning Analytics Initiatives

SAHELA

- Launch of the SAHELA (South African Higher Education Learning Analytics)
 in 2013 by UP (in collaboration with Learning Analytics Summer Institute)
 - since then a number of workshops have been organised as part of the SAAIR

Proposed Way forward:

- SAHELA to be incorporated as part of the SAAIR
- Have more universities participating in the workshops

South African Learning Analytics Initiatives

Siyaphumelela – 'We Succeed' Initiative

- Launched in 2015
- Initiative funded by the Kresge Foundation

Overall aim:

'to help SA universities by strengthening their internal capacity to collect student data & address student success issues on their campus'

Specific objectives:

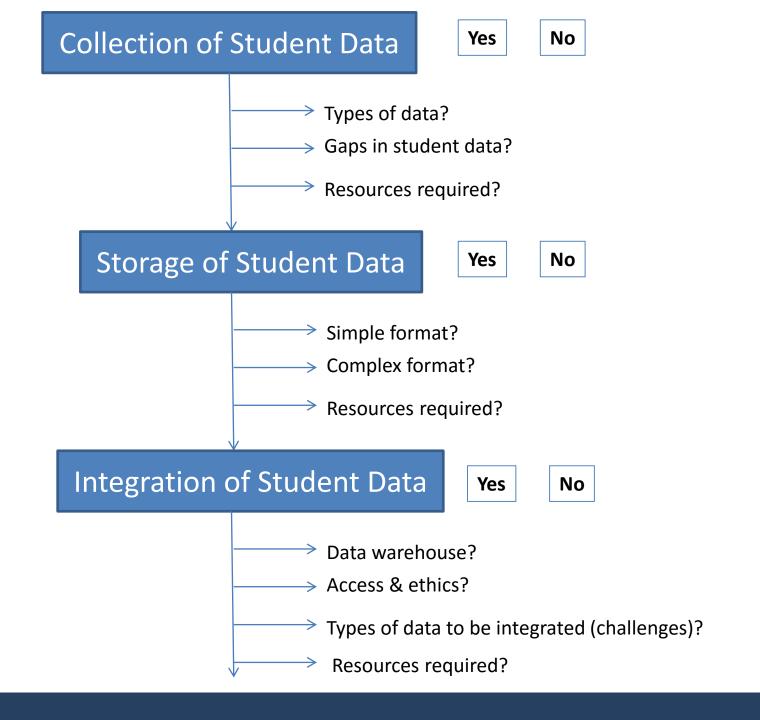
- create SA models of universities using successful data analytics to improve student outcomes

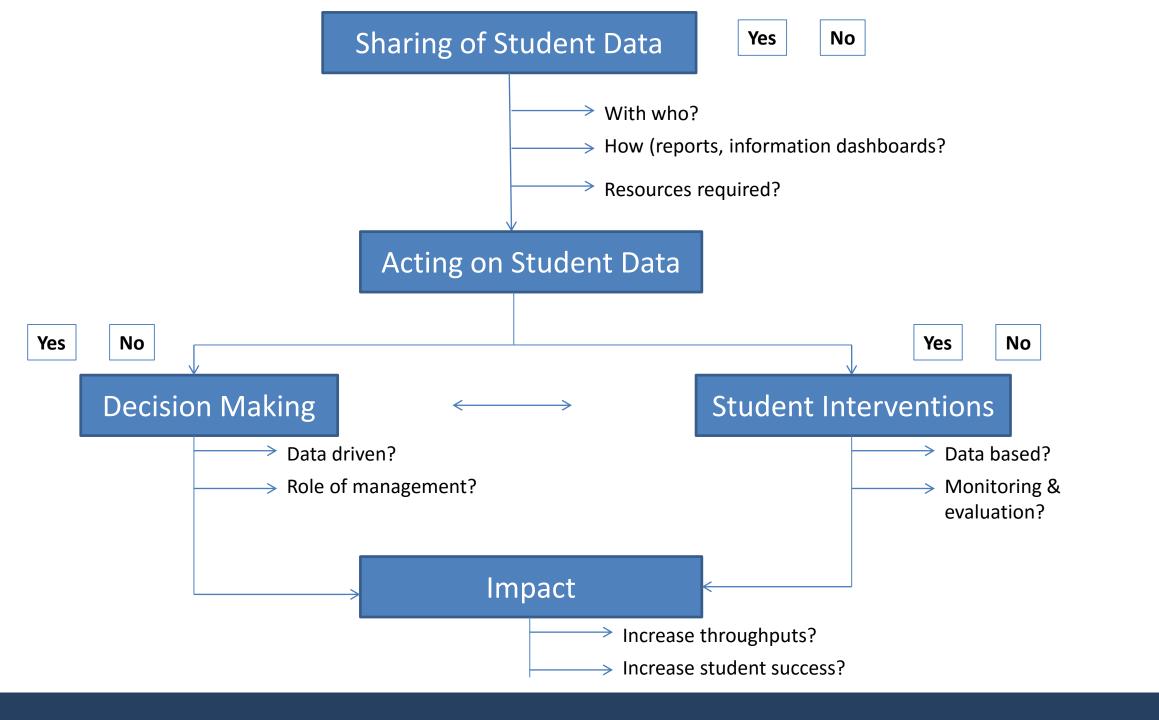
South African Learning Analytics Examples

Impact of initiative so far:

- sharing of data among the 5 partner universities (*DUT, UP, Wits, NMMU, UFS*)
- focused tackling of student success issues (student advising, data handling, ethics, etc.)

Open Discussion





Thank you!

mxolisi.masango@wits.ac.za







Closure and conclusion





SAHELA 2017 Workshop the Witwatersrand of Pretoria & University of

Facilitator contact details

- Dolf Jordaan dolf@up.ac.za
- Ali Denewade <u>ali.denewade@wits.ac.za</u>
- Ben Nsthabele ben.nsthabele@up.ac.za
- Mxolisi Masango
 Mxolisi.masango@wits.ac.za
- Alta de Waal <u>alta.dewaal@up.ac.za</u>
- Fezile Mdluli Fezile.mdluli@wits.ac.za
- Juan-Claude Lemmens jlemmens@up.ac.za