Investigating Learning Strategies and Course Design in First Year Biology

By

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ABSTRACT

Higher education faces the challenge of high student attrition, which is especially disconcerting if associated with low participation rates, as is the case in South Africa. Recently, the use of learning analytics has increased, enabling institutions to make data-informed decisions to improve teaching, learning, and student success. The aim of this study is to improve student performance in the first year by probing students' learning strategies and by examining the effectiveness and efficiency of a blended course design. To date, most student success studies has focused on the at-risk students. This study takes a difference approach to student success by focusing on a group of students termed the "murky middle' (MM).

The first part of this study used demographic and prior learning data to define three subgroups of students, those at-risk of failing without substantial intervention, the MM, and the students that are likely to pass. Subsequent to the identification of the MM students, self-report learning strategies were analyzed to examine the strategies of successful students. The second part of this study focused on evaluation of the blended course design by investigating patterns of student engagement with the learning opportunities in the course. This was followed by an analysis of which of the learning opportunities contributed most to success of the subgroups of students.

The results of this study showed that it is possible to identify the MM using data available at the start of their academic career. The analysis of learning strategies provided useful information to guide the design of interventions aimed at improving the prospect of success for all students but specifically for the MM. Results from the analysis of the course design validated the use of blended learning, as we could show that face-to-face tutorial classes and online formative assessments contributed the most to student success. We also showed that the at-risk and MM students' engagement with compulsory learning opportunities declined during the semester. The information generated in this study is useful for course design, classroom practice and student advising and could potentially contribute to student success.

Declaration

I, Angelique Kritzinger declare that the thesis which I hereby submit for the degree Doctor of Philosophy (Mathematics and Science Education) at the University of Pretoria, is my own work and has not previously been submitted by me for a degree at this or any other tertiary institution

Signature

Date

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The Lord, for giving me strength and perseverance to do this.

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LIST OF ABBREVIATIONS

CHAID – Chi-square Automatic Interaction Detector

CHE – Council on Higher Education

EAB – Education Advisory Board

LA – Learning analytics

LTP – Likely-to-pass

MM – Murky Middle

MSLQ – Motivated Strategies for Learning Questionnaire

NBT – The National Benchmark Tests

SRL – Self-regulated Learning

SSC- Student Success Collaborative

STEM – Science, technology, engineering and mathematics

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CHAPTER 1: INTRODUCTION AND RATIONALE

INTRODUCTION

This chapter orientates the reader to the study topic. This study sets out to investigate student success in a specific course by means of a comprehensive analysis of student behavior[1] and course design. This chapter provides an introduction to the research problem, the main aim of the study and the research goals. The purpose of this chapter is to sketch a brief background and rationale for the study and to highlight the importance and possible contributions of the research.

BACKGROUND OF THE STUDY

Poor academic performance and high dropout rates in higher education institutions are of concern nationally and internationally. Gumede (2017) reports that 47.9% of university students in South Africa did not complete their degrees in 2017. A report by the Council on Higher Education (CHE) (2018) shows that only 29% of the students from the 2011 cohort graduated within three years and 58% graduated after six years. Success rates in the sciences are even lower, with only 21% of students graduating within three years and 51% graduating after six years. The success rates of South African students are comparable to those in the USA where only 59% of full-time students who had enrolled for the first time in 2006 to study toward a bachelor's degree, had graduated by 2012 (Barton, 2015). However, the major difference is that the participation rate in South Africa is about one-third of the USA rate and has remained at 18% (Council on Higher Education, 2018). It is widely acknowledged that higher education worldwide is characterized by growing student numbers, increased diversity of students and

[1] Articles were published in, or submitted to journals that requires U.S. English as the editing language. This document will therefore use the U.S. English spelling convention.

reduced resources (Cash, Letargo, Graether, & Jacobs, 2017). The challenge, however, is particularly acute in South Africa where students numbers have almost doubled since 1994, although the per capita funding for students has decreased (Education, 2016).

In conjunction with the increase in student numbers and reduced resources, the diversity and academic preparedness of students entering the tertiary education system has changed due to the many challenges faced by the South Africa schooling system (Ramdas, 2009; Roodt, 2018). There are a myriad root causes for the problems faced by the school system. Among these problems are the inequalities in school infrastructure, the lack of financial and educational resources, the discrepancies in the quality of teaching, the disadvantageous socio-economic levels of learners, and the poor literacy and mathematical skills of learners, among others (Maarman & Lamont-Mbawuli, 2017; Ramdas, 2009; Roodt, 2018). Many international assessments of Mathematics, Science and Literacy also indicate that South African children are trailing behind their counterparts in the rest of world (Roodt, 2018). Spaull (2018) points out that the expenditure per capita in South Africa has declined dramatically over the last decade and that austerity measures may have influenced poor performance on these international assessments. Although per capita expenditure decreased, the proportion of educational expenditure relative to the GDP in 2012 and 2016 was 5.9%. This places South Africa among the top ten countries of the world in respect of expenditure on education (Organisation for Economic Co-operation and Development, 2015; Roodt, 2018; The World Bank, 2018). The challenges faced by the schooling system directly influence the preparedness of students, which has created a knock-on effect in higher education performance outcomes (Bunting, 2004; Govender, 2017; Rantsi, 2016). This increase in diversity and decrease in academic preparedness raises the question of how to support students who may not have the necessary skills, on a personal or academic level, to do well, despite having the inherent ability to succeed. It is a challenge to create an environment where increasingly diverse and academically underprepared students can thrive, while testing and stimulating high achieving students. Limited resources and increasing reliance on outside funding to increase student success and retention also exacerbate this problem. This is a challenge that many countries share (Heath & Leinonen, 2016).

Many tertiary institutions are using technology to enhance teaching and learning and to extend access to a new population of students (Twigg, 2003). Blended learning has become commonplace in higher education institutions (Bonk & Graham, 2012; Means, Toyama, Murphy, & Baki, 2013). However, there is a danger that new technologies could become a "black hole" of additional expenses (Twigg, 2003, 2015) if the technologies are just added onto existing courses and facilities. Redesigning initiatives to improve learning and reduce costs has had mixed results with almost all courses reducing their costs. However, only 50% of the studies have shown improved learning outcomes (Twigg, 2015). In a meta-analysis Vo, Zhu, & Diep (2017) analyzed many studies, comparing traditional classes with blended learning classes and concluded that in science, technology, engineering and mathematics (STEM) education, blended learning has a significant association with positive performance. Blended learning has been used frequently in science education but its impact has not been rigorously evaluated (Stockwell, Stockwell, Cennamo, & Jiang, 2015). Holistic research into the effectiveness and efficiency of blended learning, especially in sciences courses, has not been routinely conducted. However, while there are some studies that have attempted to determine the effectiveness of blended learning, these studies were typically conducted by means of randomized controlled trials designed to determine the effect of a single variable, such as the online component of a course. Examples of studies such as these in the sciences can be found in Adams, Randall, & Traustadottir (2015) and Riffell & Sibley (2005).Very rarely has the course as a whole been evaluated.

When redesigning a course to incorporate technology, it is important to carefully consider the purpose of the technology within the course. Technology should contribute to the effectiveness and efficiency of courses while supporting the learning of the largest group of students, making it economical in terms of time, cost and learning outcomes for both the students and institutions.

In a resource-constrained environment, it is essential that each learning opportunity in the course design should contribute optimally to student success. The effectiveness and efficiency of a course design should be investigated and purposefully planned. Effective courses are underpinned by good pedagogical practices (Chickering & Gamson, 1987). Efficient courses are those in which each learning opportunity in the course design is essential in contributing to learning while avoiding unnecessary duplication. Technology can be used to advance good practice principles in undergraduate teaching (Babb, Stewart, & Johnson, 2014; Chickering & Ehrmann, 1996; Kocaman Karoglu, Kiraz, & Ozden, 2014) but it is important to redesign and evaluate the course to assess both its effectiveness and efficiency.

Students' behavior, and particularly the learning strategies that they use, has an influence on their success. Effective learning strategies are not static, but change together with rapid changes in the tertiary environment and the needs and demands of new generations of students. Lecturers and advisors must understand which strategies are associated with success to enable them to recommend appropriate learning strategies. Studies show successful strategies, such as self-testing, re-reading and scheduling (Hartwig & Dunlosky, 2012) and behaviors such as self-regulation are associated with success (Boekaerts, Pintrich, & Zeidner, 2000; Zimmerman & Schunk, 2001). However, it has been found that although these strategies have proved to be effective, most students do not use them (Karpicke, Butler, & Roediger III, 2009). Based on the findings, researchers suggest that it would be beneficial to inculcate advantageous academic behavior using different platforms, such as classroom instruction and academic advising and by imbedding these practices into course design.

Higher education institutions have recognized that the analysis and interpretation of information from various university data sources could assist in the improvement of course delivery (Siemens & Long, 2011). 'Analytics' is a blanket term for the use of data and statistical analysis to build explanatory and predictive models. Under the collective term of 'analytics', 'learning analytics' (LA) refers to the use of methods of analytics to improve student learning and student success. LA can be used in a variety of ways, amongst others, providing input for continuous improvement in course design and delivery. With the abundant availability of large datasets, researchers in the field of learning analytics can explore data gathered from various platforms, such as university enrolment systems and Learning Management Systems (LMS). The data can be used to track students and build theoretical models to predict student success (Dietz-Uhler & Hurn, 2013; Jayaprakash, Moody, Lauría, Regan, & Baron, 2014; Kotsiantis, Tselios, Filippidi, & Komis, 2013; Mwalumbwe & Mtebe, 2017; Sclater, Peasgood, & Mullan, 2016; Seidel & Kutieleh, 2017; Van Zyl, Gravett, & De Bruin, 2012). It can also be applied to enhance teaching and learning (Manzoor, 2016) and to understand how learning takes place, especially in the online environment (Halimat, 2016). In many of the studies this is achieved by analyzing usage patterns (Halimat, 2016) or student perceptions (Kotsiantis et al., 2013; Sclater et al., 2016) in conjunction with final course grades to draw conclusions.

RATIONALE

Higher Education in South Africa is plagued by poor student performance, low throughput (as elsewhere in the world) and low participation rates. Poor academic performance coupled with low participation rates in a country with limited resources, such as South Africa, has a widespread economic impact. Investigations to understand the reasons for poor performance should include both the effectiveness and efficiency of academic provisioning (course design and student support) as well as student behaviors (learning strategies).

Traditionally, higher education in South Africa was characterized by face-to-face contact at residential universities and blended learning courses were only introduced recently. Due to a lack of understanding, blended courses often lack sound pedagogical design and quality assurance. Holistic investigation of blended learning courses has been reported to a limited extent in the subject literature. This study aims to investigate student academic behavior and academic provisioning in first-year biology. This study focuses on the blended learning, entry level course, Molecular and Cell Biology (MLB 111), using learning analytics as the tool for the investigation. This study takes a different approach to student success by focusing on a unique group of students, namely, those who are borderline in terms of their prospects for success. These students are not labelled by traditional 'at-risk' profiles and their academic success is difficult to predict.

Unlike at-risk students whose reasons for failure are well described, the reasons for failure of this group of borderline students are not well understood (Student Success Collaborative, 2014). These students also drop out after the first year. Ideally, institutions would like to identify these students at an early stage in their academic careers, as early identification and interventions in the case of borderline students could offer them the opportunity of improving their success rate. It also has the potential of a high return on investment for tertiary institutions.

THEORETICAL FRAMEWORK(s)

The theoretical frameworks that informed this study are discussed in detail in the chapters that follow. In brief, the theories of self-regulated learning (SRL) as formulated by Boekaearts, Niemivirta and Pintrich (2005), Panadero (2017) and Pintrich (1995) in together with Conley's (2007a) definition of student college readiness describe the skills that students need to be successful in their academic careers. These two theories are presented in more detail in Chapter 2 as the underpinning of the student learning strategies that are measured by the self-report instrument, namely, the Motivated Strategies for Learning Questionnaire (MSLQ). In chapter 3, good pedagogical practice as first described by Chickering and Gamson (1987) and later applied to technology in the classroom by Chickering and Ehrmann (1996) is described and elaborated on as being related to the effectiveness and efficiency of blended learning courses.

CONCEPTUAL FRAMEWORK

The unit of analysis for this study is a single course, with the aim of examining student learning strategies and course design. The learning strategies of successful students need to be investigated and compared to the strategies of less successful students to enable researchers to design tangible interventions for teaching and advising. In addition, an investigation of the course design could give insight into the learning opportunities that contribute most to the success of students in different performance categories, but with the focus on borderline students. In principle, statistical information can be used to divide students into three distinct groups. The first group are those at risk of failing without substantial intervention. In the subject literature they are referred to as ‘at-risk students’. The results of research on these students has identified the particular variables that predict whether a student could be at-risk. The second group of students are those who would probably pass without any intervention, that is, those students who are likely-to-pass (LTP). The last group are those students for whom academic success is difficult to predict. These students are termed the murky middle (MM). The use of self-report learning strategies surveys, such as the MSLQ, could enable researchers to potentially pinpoint the learning strategies of successful students and to use the data to design tangible interventions to support student learning. Course design and academic advising could contribute to student self-regulation and promote successful academic learning strategies. Academic provisioning must also be evaluated and each learning opportunity should ideally contribute to the success of the students. The learning opportunities should be structured to promote the principles of good pedagogical practice and contribute to the effectiveness and efficiency of the course.

RESEARCH AIM

This study has the aim of generating actionable data on productive learning strategies and student engagement with learning opportunities in the course to guide those involved in advising students and academic provisioning (course design). This could be accomplished by using a two-pronged approach. Firstly, evidence-based student advising by lecturers and faculty student advisors to promote productive learning strategies could potentially address the non-cognitive aspects of student learning. Secondly, appropriate learning opportunities through optimal course design may address the cognitive aspects of student learning in this specific course.

Specifically, this thesis sets out to answer the following research questions:

The following research objectives are addressed in chapter 2:

> RQ1. Which pre-entry characteristics differentiate effectively between students who are likely-to-pass (LTP), borderline students, and students at-risk of failing?

RQ2. Which learning strategies in first-year Biology are associated with good academic performance?

The following research questions are dealt with in chapter 3:

The overall aim of this study is to evaluate the effectiveness of the blended learning environment by addressing the following research questions:

RQ 1. What are the differences between the likely-to-pass, borderline and at-risk groups of students in their engagement with learning opportunities?

RQ 2. Which of the activities in the blended learning environment are associated most strongly with success for the borderline students?

CONTEXT AND STUDY POPULATION

The focus of this study is Molecular and Cell Biology (MLB 111), which is a first-year course at the Faculty of Natural and Agricultural Sciences at the University of Pretoria, South Africa. It is a service course for first-year students enrolled for biological sciences, medical or veterinary sciences. The course has an average annual enrolment of 1500 students and is offered in the first semester of the academic year. This course is also a gateway course and failure in this course will have a significant impact on progress in any biologically-based discipline. MLB 111 is presented in a blended learning format with both face-to-face and online components. Some of the activities are compulsory and others are optional. A more in-depth description is given in chapter three in the thesis. The 2015 student cohort was used for this study. The students were tracked in terms of their academic performance until the end of 2016. A total of 1084 students were included in the analysis. The researcher for this project was one of the lecturers responsible for the MLB 111 course at the time when data capturing took place.

METHODOLOGY

A brief overview of the methodology is presented here. More detailed descriptions are provided in the applicable chapters. A quantitative methodological approach was used to analyze three sets of data. The first objective of the study (Chapter 2, RQ1) was to categorize students into three subgroups based on their prospects of success in the course. The possible predictors for the categorization were limited to pre-entry data in respect of the student cohort that are readily available at the start of the academic year. Therefore, only demographic and prior achievement data were used.

After categorization of the students based on the pre-entry data, the second objective of this study was to determine the learning strategies associated with good academic performance (Chapter 2, RQ2). The MSLQ was selected as the most suitable instrument to measure students' self-reports of learning strategies based on the MSLQ's record of accomplishment and level of acceptance in the field of educational psychology. The second part of the study involved an evaluation of the course design based on student engagement (Chapter 3, RQ 1 and RQ2). Data was collected on students' interaction with the full range of learning opportunities and this was captured in various ways and logged into the LMS system. This constituted the engagement data that was used for the second part of the study.

A quantitative approach was adopted to (1) divide students into three groups based on demographic and prior achievement data (chapter 2); (2) to determine which of the reported learning strategies were associated with success (chapter 2); and (3) to determine which of the learning opportunities available in the blended learning environment has the biggest impact on success (chapter 3). Figure 1 gives a brief outline of the sequence of data analysis of this project.

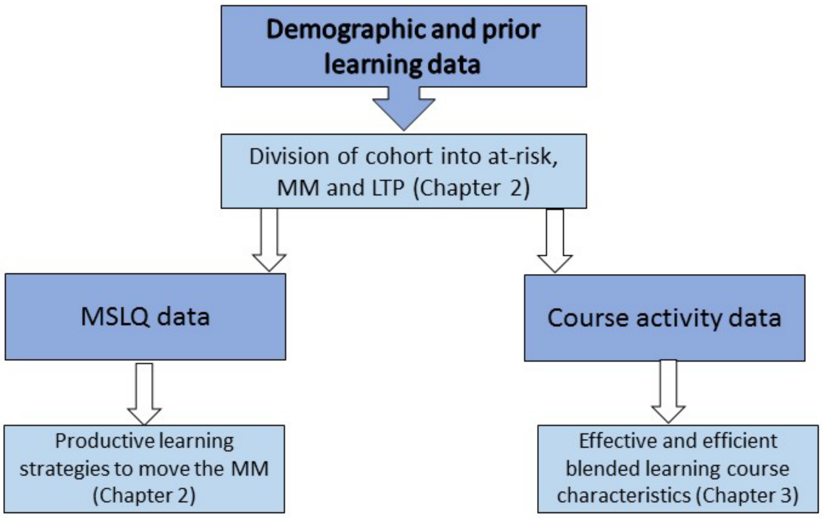

Figure 1: Sequence of data-analysis.

Data analysis required a statistical technique that would be suitable for the non-parametric nature of the data. Chi-square Automatic Interaction Detector (CHAID) (Kass, 1980) was chosen as the method of analysis to detect interactions amongst variables for the division of students into groups and to determine the contribution to success of the different learning opportunities. CHAID analysis is a non-parametric test. Non-parametric decision tree algorithms, such as the chi-squared automatic iterative detection (CHAID) decision-tree model, have been used to predict customer attrition in the commercial sector, and have been shown to surpass parametric predictive models (Au, Li, & Ma, 2003; Seidel & Kutieleh, 2017). Au, Li and Ma (2003) state that in addition to precision and accuracy, the benefits of a decision-tree method include model parsimony, robustness, handling of missing data, and enabling the inclusion of customers with missing data in retention activities. CHAID models are relatively simple to interpret, validate and implement and thus suitable as a tool to use to study student-related data.

VALIDITY AND RELIABILITY

These indicators will be dealt with in chapters two and three.

ETHICAL CONSIDERATIONS

Permission to conduct this study was obtained from the Ethics Committee of the Faculty of Natural and Agricultural Sciences at the University of Pretoria (see approval letter in Appendix C). Students signed an informed consent form indicating their willingness to participate in the study. They were informed of the right to withdraw from the study at any time without negative consequences (see informed consent letter in Appendix C).

CONCEPT CLARIFICATION

At-risk – The concept of "at-risk" refers to students who are at risk of failing or dropping out without substantial academic and, or psychosocial interventions.

Blended learning – In the literature blended learning are defined as combining different instructional modalities within a course (Graham, 2005)

Chi-square automatic interaction detection (CHAID) - The CHAID analysis builds a predictive model, or tree, to help determine how variables best interact to explain the outcome in the given dependent variable (Kass, 1980).

Effectiveness – In this thesis, effectiveness is defined as an outcome of good pedagogical practices in a classroom.

Efficiency – In this thesis, efficiency is defined as related to a course where each learning opportunity should be essential in their contribution to learning to ensure that resources are used optimally.

Higher education – In this thesis, the term 'higher education' refers to institutions that offer programs equivalent to a Bachelor's degree and where students can continue to post-graduate studies.

Learning analytics - Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs (Sclater, Peasgood and Mullan, 2016).

Murky middle – In this thesis the murky middle students are a group of borderline students whose probability of success is difficult to predict.

POSSIBLE CONTRIBUTION OF THE STUDY

On a theoretical level, this study could contribute to the field of modelling of student success. Almost all studies on student success have focused on at-risk students. This study should add a new dimension to the discourse on student success by defining a group known as the "murky middle". This group of students is often equal in number to the at-risk students but they tend to drop out after the first year of study. This thesis attempts to provide guidelines for identifying these students early in their academic careers and suggests ways to structure interventions to improve their chances of success. This study could contribute to the field by focusing on a single course as the unit of analysis, namely that of first-year biology. This course was selected because it could hamper students' progress through their undergraduate studies. The nuanced analysis of the academic behavior of a particular category of student, namely, the borderline group, should also contribute to the existing knowledge of contributors to student success, specifically productive learning strategies for first-year biology.

This study could make a positive contribution to teaching practice, course design and student advising. The examination of three different subgroups of students should give a better insight into the learning strategies that successful students use and how they differ from the at-risk and MM students. The results could assist student advisors to structure well-designed interventions to help struggling students. In addition, the results would add to the body of knowledge on methods of intervention in teaching practice to promote productive learning strategies. Secondly, the analysis could provide a holistic insight into student engagement within a blended learning course and identify the learning opportunities that contribute to success. These results should provide lecturers with useful pointers to design effective and efficient courses that could support a large group of students on the road towards academic success.

STRUCTURE OF THESIS

This thesis consists of four chapters – an introduction, two chapters written in journal article format, and a final chapter as conclusion. The two article chapters are coherent units, each with a literature review, methodology section, results and discussion. At the time of submission of this document, Chapter 2, Learning Strategies for First-Year Biology: Toward Moving the "murky middle" was published in the Journal CBE Life Sciences Education (DOI:10.1187/cbe.17-10-0211 see Appendix D). Chapter 3, Investigating the effectiveness of a blended first-year biology course, was submitted for review on 16 August 2018. To avoid unnecessary repetition, the introduction chapter serves as a brief, holistic overview of the study to provide a general background and rationale for the study. Literature, theoretical frameworks and methodology pertaining to each chapter are included in the specific chapter itself. The references were combined and are placed after the last chapter. As the articles were published in, or submitted to journals that requires U.S. English as the editing language, this document will, for consistency, use the U.S. English spelling convention. The structure of the thesis is as follows:

Chapter 1 consists of an introduction to the study and describes the context in which this study took place.

Chapter 2 focuses on the division of students into different academic performance groups and the validation of that division. In addition, the learning strategies of the different performance groups will be analyzed.

Chapter 3 focuses on the design of a blended learning course, its effectiveness and efficiency, and the contribution that the relevant learning opportunities make toward student success. In addition, the research findings provide a nuanced picture of student engagement with course activities.

Chapter 4 presents an overview of the study, a critical appraisal of its contribution to knowledge in this domain and the implications for teaching and learning.

CHAPTER 2: LEARNING STRATEGIES FOR FIRST-YEAR BIOLOGY: TOWARD MOVING THE "MURKY MIDDLE"

ABSTRACT

Higher education faces the challenge of high student attrition, which is especially disconcerting if associated with low participation rates, as is the case in South Africa. Recently, the use of learning analytics has increased, enabling institutions to make data-informed decisions to improve teaching, learning, and student success. Most of the literature thus far has focused on "at-risk" students. The aim of this paper is twofold: to use learning analytics to define a different group of students, termed the "murky middle" (MM), early enough in the academic year to provide scope for targeted interventions; and to describe the learning strategies of successful students to guide the design of interventions aimed at improving the prospects of success for all students, especially those of the MM. We found that it was possible to identify the MM using demographic data that are available at the start of the academic year. The students in the subgroup were cleanly defined by their grade 12 results for physical sciences. We were also able to describe the learning strategies that are associated with success in first-year biology. This information is useful for curricular design, classroom practice, and student advising and should be incorporated in professional development programs for lecturers and student advisors.

INTRODUCTION

Researchers in the United States who have studied retention over a number of decades have aptly noted that student success is a complex puzzle (Baird, 2000; Bean and Eaton, 2000; Braxton, 2000; Kuh et al., 2007). Despite many research studies, models, frameworks, and interventions based on the findings from this research, U.S. institutions have experienced slow growth in graduation rates. One notable way in which the college system in the United States has approached the student retention and success puzzle is the use of analytics to transform data into actionable information that could be used to move the needle on student success indicators.

It is widely acknowledged that, across the higher education sector in South Africa, the level of attrition at first-year level is high, overall completion rates are low, and the majority of students do not complete their degrees in regulation time (Scott, Yeld, Hendry, 2007). In South Africa, the higher education system comprises universities and universities of technology where students can study for a bachelor's degree and continue to postgraduate level. According to the Council on Higher Education in South Africa, only 25% of the 2008 student intake in the sciences completed their degrees in the minimum regulation time of 3 years; after 6 years, only 58% of the students had completed their degrees (Council on Higher Education, 2014). Developed countries have similar attrition rates but are able to compensate to some extent for the losses with high participation rates in higher education. However, in developing countries where participation in higher education is low, a poor success rate leading to high attrition is problematic.

With the objective of identifying students at risk of failing, a fair amount of institutional research over the past few years has been done to describe the student population in South Africa in terms of demographic characteristics, including prior learning, student readiness, the impact of financial aid, race, and gender, (Van der Merwe and Pina, 2008; Lemmens, 2010; Van Zyl et al., 2012; Van Zyl, 2013). The purpose of these descriptive studies was to identify factors that affect student retention and success by describing the characteristics of the students who are successful compared with those who are not.

In South Africa, as in other countries, the focus of many of these studies is to provide an early alert of high-risk student groups through the prediction of poor academic performance and attrition, mainly in the first year. Lacking from these research studies is evidence of the impact of interventions on student success, and from a learning analytics perspective, the impact on making learning more effective and efficient (Vuorikari et al., 2016). Vuorikari et al. (2016) point out that a reason for limited evidence on impact is the short time frame of many of the studies, specifically in Europe, and in the case of North America, the possible inefficient use of data by focusing on annual and retrospective reporting practices of student data, which are more associated with academic analytics (DeBerard, Speilmans and Julka, 2004; Siemens and Long, 2011). Another possible reason, albeit not as obvious, is the perpetual focus on identifying and supporting the "at-risk" students in many of the early-alert models currently used, in order to improve the retention and success rates of institutions (Siemens and Long, 2011; Sclater et al., 2016). The question thus emerges whether the primary support of the at-risk student group should not be expanded to include students whose chances of success are also dubious but, due to unknown reasons, are not flagged as being at risk through conventional early warning models. A relatively small investment of resources for the support of these students could potentially make a big difference in their prospects of success.

In 2014, the Education Advisory Board (EAB) of the United States defined the "murky middle" (MM) as students who are at risk of dropping out of university later than their first year (Student Success Collaborative, 2014). These students are not included in the category of at-risk students who are flagged for possible drop out in the first year; they are part of a student population with a grade point average (GPA) of between 2.0 and 2.99 who progressed to the second year of study; yet a significant proportion of them drop out later in their studies. The EAB collected data from a large number of diverse American higher education institutions (740,000 unique student records from 73 institutions) and analyzed those data for trends and patterns that can inform the design of effective intervention strategies. Three findings are important for the MM; first, these students do not conform to the characteristics that are used to flag at-risk students. Second, the leading indicator before some of the students drop out is not a general decrease in GPA but an increase in the number of courses failed. The MM dropouts earn roughly the same number of "A's" per term, fewer "B's" and "C's", but the number of "F" increases shortly before they terminate their studies. The distribution of grades in successive semesters thus shows an increase in the number of courses failed while still maintaining a GPA that will not point to the student being at risk of dropping out. The third important finding is that outcomes improve dramatically when the downward trends in grades are reversed (Student Success Collaborative, 2014). Very little is known about this group of students other than the characteristics just described. However, the possibility that interventions targeted at these students will have a high return on investment is an attractive prospect.

While the concept of the MM was defined in the context of a very large student group at a large number of institutions, we propose that it can also be applied within a single course to facilitate analysis of student characteristics and the relation of this analysis to student performance. In principle, students enrolled for a specific course can also be divided into three groups: those who are at risk of failing, those who are likely to pass with relative ease, and those students for whom the outcomes are uncertain (whom we also label the MM). In learning analytics and prediction studies, characteristics such as prior learning, demographics, gender, race, and financial status are usually used to predict performance; however, very few studies try to characterize students in terms of other factors, such how well students can regulate their learning and which learning strategies good students use to be successful.

Self-regulated Learning

Self-regulated learning (SRL) is a learning theory that describes the self-directed processes learners use to "transform their mental abilities into task-related academic skills" (Zimmerman and Schunk, 2001). Although there are many theoretical perspectives concerning SRL (Boekaerts, 1999; Boekaerts et al., 2000; Butler and Winne, 1995; Winne, 1995; Pintrich, 1995; Greene and Azevedo, 2007), most come to the same conclusion—that the most effective learners are skillful self-regulators. According to Pintrich and de Groot (1990), there are a variety of definitions of self-regulated learning. In all of them, three components seem to be important in classroom performance. The first, metacognition, includes students' strategies for planning, modifying, and monitoring their cognitions. The second is students' management and control of their effort in classroom academic tasks (behavior); and the third is the actual cognitive strategies that students use to learn, remember, and understand material. Goals have been shown to play an important role in SRL, and Zimmerman (2002) states that the skills inherent to SRL include setting specific goals, adopting strategies for attaining goals, using time management skills, monitoring performance, and managing physical and social contexts. In a recent study, Sebesta and Bray Speth (2017) show that various self-regulation strategies such as self-evaluation, goal setting and planning, and information seeking were associated with improved grades in a large biology class. Very few studies in biology education focus on SRL as a construct in itself, they rather focus on aspects of SRL such as metacognition and metacognitive regulation.

With the SRL theory as a basis, Pintrich, Smith, Garcia and McKeachie (1991) developed the Motivated Strategies for Learning Questionnaire (MSLQ) to assess students' motivational orientations and their use of different learning strategies. The final version of the MSLQ was completed in 1990 and was presented formally for the first time in the Journal of Educational and Psychological Measurement in 1991 (Pintrich et al., 1991). The MSLQ has two sections: the Motivation section consists of 31 items that assess a student's goals and value beliefs for a course; and the Learning Strategies section includes 50 items related to a students' use of different cognitive and metacognitive strategies and resource management. The different subscales will be discussed in more detail later in the paper. The MSLQ has a modular design, enabling researchers to use each section separately. The MSLQ was developed to be course specific; however, according to Conley (2007), cognitive and metacognitive strategies are transferable. This means that successful learning strategies documented for one course in biology could also be effective in other biology courses, but there might be some course-specific requirements.

The MSLQ was chosen as the self-report instrument to measure learning strategies in our study. The MSLQ has been widely used in research, and a meta-analysis of these studies was recently published by Credé and Phillips (2011). Credé and Phillips (2011) indicate that total scores on the MSLQ were better correlated with single-course grades than with GPA. Research by Hilpert, Stempien, van der Hoeven Kraft and Husmann (2013), Credé and Phillips (2011), and Dunn, Mulvenon and Sutcliffe (2012), suggests that the effort regulation and metacognitive regulation subscales should be combined, as they operate at the same level of analysis (executive function). The researchers also point out that these two subscales mediate motivation and academic performance. However, the other subscales that measure "strategy use" are not good predictors of academic outcomes. The relationships between MSLQ subscale scores and academic performance were generally weak to moderate, with "effort regulation," "self-efficacy," and "time and study environment" for individual classes showing the highest validity. They also showed that specific learning approaches such as rehearsal, organization, and peer learning were largely unrelated to academic performance, while the less contextual abilities, such as metacognitive self-regulation and effort regulation were most strongly related to academic performance. In addition, the relationship between peer learning and GPA was not in the expected direction. That being said, the MSLQ in this study was not specifically used for prediction of academic performance but used as a way to describe students in terms of their enacted learning strategies and to pinpoint possible opportunities for interventions. The MSLQ has also been used in first-year biology classes to determine the effect of the flipped classroom approach as reported by van Vliet et al. (2015). They found that the flipped classroom approach changed the learning strategies of students and enhanced learning strategies such as critical thinking, task value, and peer instruction (as measured by the MSLQ) but that the effect of change in learning strategies was not long-lasting. According to Zeegers (2004), researchers found that there was a consistent correlation ($r = 0.30$) between academic achievement and measures of self-regulation.

In line with the SRL theory, Conley (2007) defines academic preparedness as the single most important determining factor for success in higher education. Conley (2007) defined college readiness operationally as the level of preparation a student needs to enroll and succeed—without remediation—in a credit-bearing general education course at a postsecondary institution. The Conley framework foregrounds and repackages most of the elements of SRL as operationalized by the MSLQ. Conley identifies four key components that form the foundation of academic readiness. These components are multifaceted and include factors both internal and external to the university environment. In the current study, key cognitive strategies, key content, and academic behaviors are the facets of interest. Contextual skills and awareness, the fourth facet of the model, refers to the systemic understanding on how higher education institutions operate as a system and as a culture (Conley, 2007). This facet was beyond the scope of the study. The most central of the facets of readiness, key cognitive strategies, is important in the broader context of higher education. It focuses on learning skills that are not content specific, such as critical thinking and problem solving. These skills enable students to learn content from a range of disciplines (Conley, 2007).

The second element of the framework is key content, which refers to general academic knowledge and overarching academic skills such as writing and research. Although some discipline-specific knowledge is essential, overarching academic skills that are not content specific are needed for students to be ready for the demands of university. An example of these academic skills is areas in which science studies instill the knowledge of how to use all the steps in the scientific method, how to communicate science, and to appreciate that scientists think in terms of models and systems to interpret complex phenomena.

Academic behaviors refer to a range of behaviors that reflect self-awareness, self-monitoring, and self-control and are independent of specific content areas. Key academic behaviors consist largely of self-monitoring skills and study skills. Self-monitoring skills are a form of metacognition that requires students to be aware of their understanding of a subject, to reflect on task effectiveness, and to adjust learning strategies by transferring skills from familiar settings to new settings.

Present Study

To enhance student success and throughput, we need to take a different approach to the analysis of student performance by going beyond prediction and description of at-risk students. In this study, we chose to focus instead on a group of students who are typically not flagged as at risk for possible drop out in the first year of study. However, many of these students drop out later during their undergraduate studies without triggering any alerts within normal systems. We have also labeled them the "murky middle," because their graduation outcomes are difficult to predict. Thus, the aim of this paper is to investigate whether it is possible to categorize students in a single course (microlevel) similar to what was done by the Student Success Collaborative on the macrolevel and derive meaningful information about student success from the difference in the resultant subsets of student characteristics in which categorization is based only on demographics and prior learning achievements. In essence, we designed this study to explore the potential of learning analytics applied to a single course as the unit of analysis, in combination with strong learning theories such as SRL and college readiness, to generate useful pointers about effective learning strategies that can inform course design and advisory practices. Specifically, we set out to answer the following research questions:

RQ1. Which pre-entry characteristics differentiate effectively between students who are likely to pass (LTP), the murky middle (MM), and students at risk of failing?

RQ2. Which learning strategies in first-year biology are associated more strongly with good performance than with marginal or poor performance?

Our approach was to compare the self-reported learning strategies of the strong and weak groups to identify those strategies that are significantly different to inform the design of activities that could move the MM toward behaviors associated with success rather than failure.

METHODOLOGY: PARTICIPANTS AND CONTEXT

Molecular and Cell Biology (MLB 111) is a first-year course in the Faculty of Natural and Agricultural Sciences at the University of Pretoria (UP), South Africa. It is a service course for students in the biological sciences program and other programs such as medicine and veterinary science. Only 27% of the students enrolled in the Faculty of Natural and Agricultural Sciences, the faculty where this course is housed, chose the program that they are registered for as a first choice of study. The fact that the majority of the MLB 111 students are not enrolled in their preferred program influences the level of motivation for this course as well as the "expectancy value" (Ambrose et al., 2010) for the course. A further complicating factor is the wide range in academic preparedness of the students upon entry, with the majority of them being underprepared for the demands of higher education (Scott et al., 2007). Generally, a small number of those students enrolled for MLB 111 succeed in their objective to transfer to their program of choice; the rest either drop out or continue to complete their studies in biological sciences.

The course has an average enrollment of 1500 students and is presented during the first semester of each academic year. A team of three lecturers is involved; each teaches a specific component of the course and repeats the same lecture for three groups of ~500 students. In the interest of consistency, the instructors use the same assessment approaches throughout the semester (e.g., formative assessment by means of clickers (Miller and Tanner, 2015) during class and in tutorial classes, online tests via the learning management systems, and two high-stakes summative assessments during the course of the semester).

DESCRIPTION OF THE DATA SET

Data for this study were obtained from a convenience sample of students enrolled during the first semester of 2015 for MLB 111. The data set comprised biographical data, prior achievement data, longitudinal data, and MSLQ survey data.

Biographical Data

Biographical data were obtained from the university student information system. Only students entering higher education for the first time were included. A total of 1084 student records were used for the study. This number represented 68.3% of the total population of students registered for this course. The remainder (31.7%) were either students repeating the course or students who transferred from another university. The decision was made to use only first-time entering first-year students in this study. The rationale for delimiting the sample was to allow the research team to focus on students who are new to the academic environment, as repeating or transfer students had exposure to the course content and the demands of the higher education environment. The experiences that repeating and transferring students bring with them are confounding factors and would lead to spurious associations. The students excluded from the study might also benefit from the actionable interventions emanating from the findings of this study. The sample comprised 730 females (67%) and 354 males (33%), and the ages of the students ranged between 17 and 31, with an average age of 18.3 years. Field of study was determined by the faculty in which the students were enrolled; 801 students majored in science (74%), 174 in medical sciences (16%), 77 in veterinary sciences (7%), and 32 in a non–science major (3%). The racial division of the students was 58% white, 29% Black, and 13% racial minorities.

Prior Achievement Data

High School Achievement Data. High school achievement data such as GPA have been used in nearly all retention and prediction studies and appear to be consistently significant predictors of student success internationally (Kokaua et al., 2014) and in South Africa (Lourens and Smit, 2003; Baard et al., 2010; Van Zyl et al., 2012; Kirby and

Dempster, 2015a). Performance scores achieved in the grade 12 school leaving examination (National Senior Certificate, NSC) that were deemed relevant to this study are those for mathematics, physical sciences (chemistry and physics), biology, and English as first language or as first additional language. In the South African secondary school system, the subject of physical sciences consists of roughly equal amounts of chemistry and physics content.

National Benchmark Tests (NBTs). The National Benchmark Tests (NBTs) are designed to support decision making in South African universities about the academic readiness of first-year students, university placement, course development, and program planning. In a recent study, Rankin et al. (2012) found that both the school leaving examination (NSC) and the NBTs were useful predictors of academic performance in higher education in South Africa. However, research at the institution where the study of this article was completed found that high school results were better predictors of university success than proficiency tests such as the NBT (unpublished technical reports by Lemmens [2011, 2014] and Lemmens and Schaap [2012]). According to Conley (2007), admission tests have been reasonably effective methods of identifying students who are potentially college ready in the United States. NBT test scores were obtained from the university's enrollment system.

Computer Literacy. The MLB 111 course has an online component in which students are required to complete weekly online assignments. Van Zyl et al. (2012) found that self-reported computer skills were a significant predictor of student success in the first semester of higher education studies at another South African University. Students at the UP take a computer literacy placement test upon entry, and the performance results for this test are included in the analysis.

Longitudinal Data

Student academic standing and GPAs were obtained at the end of 2015 and 2016 with the aim of validating the categorization of students.

Data on Learning Strategies

The MSLQ has two sections: Motivation and Learning Strategies. Learning strategies have been shown to be strongly predictive of grades (Credé and Kuncel, 2008), but motivation is more difficult to influence than learning strategies, and its association with performance is complex. As previously mentioned, research by Hilpert et al. (2013), Credé and Phillips (2011), and Dunn et al. (2012) points out that effort regulation and metacognitive regulation, traits represented in the Learning Strategies section of the MSLQ, mediate motivation and academic performance. We have therefore decided to use only the Learning Strategies section of the MSLQ for data collection. The Learning Strategies section has nine subscales, broadly divided into cognitive and metacognitive strategies and resource management strategies. Rehearsal, organization, metacognitive self-regulation, elaboration, and critical thinking are all part of the cognitive and metacognitive self-regulation strategies, whereas time and study environment, effort regulation, help seeking, and peer learning are part of the resource management strategies. The wording of the MSLQ items was slightly adapted to fit South African colloquial use (Appendix A in the Supplemental Material), without making changes to the psychometric properties of the survey. The seven-point Likert scale was changed to a four-point 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). We reduced the number of response categories to lower the cognitive load (Revilla et al., 2014) and opted for an even number of categories to avoid distortions often associated with the middle category of Likert scales (Nadler et al., 2015). The questionnaire was administered electronically in the last 2 weeks of the semester, directly before the examination, via the university's learning management system. Negatively worded items were reverse scored. Reverse-scored items are indicated as such in Appendix A in the Supplemental Material and Table 2. Of the sample of 1084 students, 715 students completed the questionnaire, representing a response rate of 66%. Only 528 (49%) of the 715 responses were usable after correcting for incomplete response sets. This subgroup consisted of 380 females (72%) and 148 males registered for the following programs: 80% science, 10% medical sciences, 8% veterinary sciences, and 2% from non–science majors. The racial division of the students was 59% white, 29% Black, and 12% racial minorities. Thus, the subgroup of students who completed the questionnaire was comparable to the bigger sample of students used for classification.

The first objective of this study was to define and describe the MM group of students within the first-year biology course. The first year is the time with the highest attrition in higher education. The second objective of this study was to identify the particular learning strategies that seem to be most effective for the disciplinary context. Effective learning strategies are essential for being successful in college (Tuckman and Kennedy, 2011), and the use of inappropriate learning strategies is one of many reasons for students dropping out, but one that can be addressed with well-designed interventions.

The research commenced with an inductive analytical approach to explore the relationship between an outcome variable and possible predictor variables. The possible predictor variables were limited to pre-entry data that are readily available at the start of the academic year. These include demographic and prior achievement data. The outcome variables were summative assessments conducted during the semester, namely, two semester tests and the exam marks for the module.

The research questions dictated the use of a statistical method that allows for the investigation of the patterns of relationship as well as the interaction effects among variables. Many of the variables do not have a linear relationship and, arguably, many of the academic-related variables are not at an interval level, hence the need for nonparametric statistical techniques. CHAID (chi-squared automatic interaction detection) analysis was chosen as the preferred method of analysis to answer the first research question, largely due to the nonparametric nature of the data, the need to segment students according to their academic outcomes, and the need to understand the interaction effects of the predictor variable and for its ability to generate a simple, yet powerful display that supports the interpretation of the results. The CHAID technique, which is similar to a classification and regression tree analysis, was developed by Kass (1980), and is a model often used in data mining, such as prediction modeling and segmentation (Nisbet et al., 2009). The technique has been used recently by various authors for performance analysis of student populations (Kirby and Dempster, 2014, 2015b; Baran and Kilic, 2015). The CHAID model creates a tree diagram by identifying the most important predictor variables associated with the outcome variable and then splits the first predictor variable into groups that are significantly different from one another. After the first split is made, based on the chi-square test to determine the best split at each step, the model proceeds to the remainder of the predictor variables (see Figure 1). The model repeats this process until there are no significant contributions left (Nisbet et al., 2009). When using educational data, we frequently use two states: pass versus fail. The outcome variables (i.e., summative assessments) were transformed into these two states for the CHAID analysis. However, school performance data were left as continuous data and not transformed. The IBM SPSS Statistical package, v. 23, was used for the CHAID analysis, and the Bonferroni adjustment was applied to limit the type I error.

The term "MM," as described by the EAB, can only be claimed if the group identified as the MM had similar medium-term success prospects as defined in the larger-scale study (Student Success Collaborative, 2014). Thus, the results of the CHAID division have to be validated using different strategies; first, a cross-tabulation was constructed, and the associated Goodman and Kruskal's coefficient was calculated to describe the correlation between the strongest predictor variable and the first summative assessment of the course. Second, the three groups of students had to be tracked in terms of their GPAs and academic standings at the end of successive years to verify performance patterns relative to their classification (Table 1). In South Africa, GPA is a number that expresses student performance as a percentage point (%). The students can achieve a maximum of a 100%, with 50% representing a pass and 75% a distinction.

The second objective of this study was to formulate a rich description of effective learning strategies to guide the design of suitable interventions aimed at improving the prospects of success of all students. To answer the second research question, we divided the MSLQ data into three subsets for the at-risk, MM, and LTP students. Of the 528 complete questionnaires, 199 students were of the at-risk group, 166 from the MM, and

163 from the LTP. The results were analyzed for significant differences between the composite scores for each subscale in the Learning Strategies section of the instrument. To test the validity of the instrument, which was changed from a seven-point Likert to a four-point Likert, we performed a Cronbach alpha analysis ($\alpha = 0.92$), which compares favorably with the Cronbach alpha values reported in the MSLQ manual for the Learning Strategies subscales ($\alpha = 0.52–0.79$). One-way analysis of variance (ANOVA) tests were performed on these composite scores to detect any statistically significantly differences between groups. Significant differences on the ANOVA were further evaluated with Tukey post hoc tests to see which groups were significantly different (a summary of the means of the subscale scores is presented in Appendix B in the Supplemental Material). This was then followed by a Kruskal-Wallis H analysis of item responses to identify items with significantly different response patterns. The "between-group" differences for individual items were determined by means of a Mann-Whitney U test. These results are reported in Table 2 and are discussed in the next section.

RESULTS

Categorization and Validation

To divide the students into at-risk, MM, and likely-to-pass students, we performed a CHAID analysis to determine the prior learning factor that best predicted the outcome of the first summative assessment. The CHAID analysis showed that grade 12 performance in physical sciences was the best predictor of success in the first semester test of MLB 111. The results for the test sample are represented in the tree diagram shown in Figure 1.

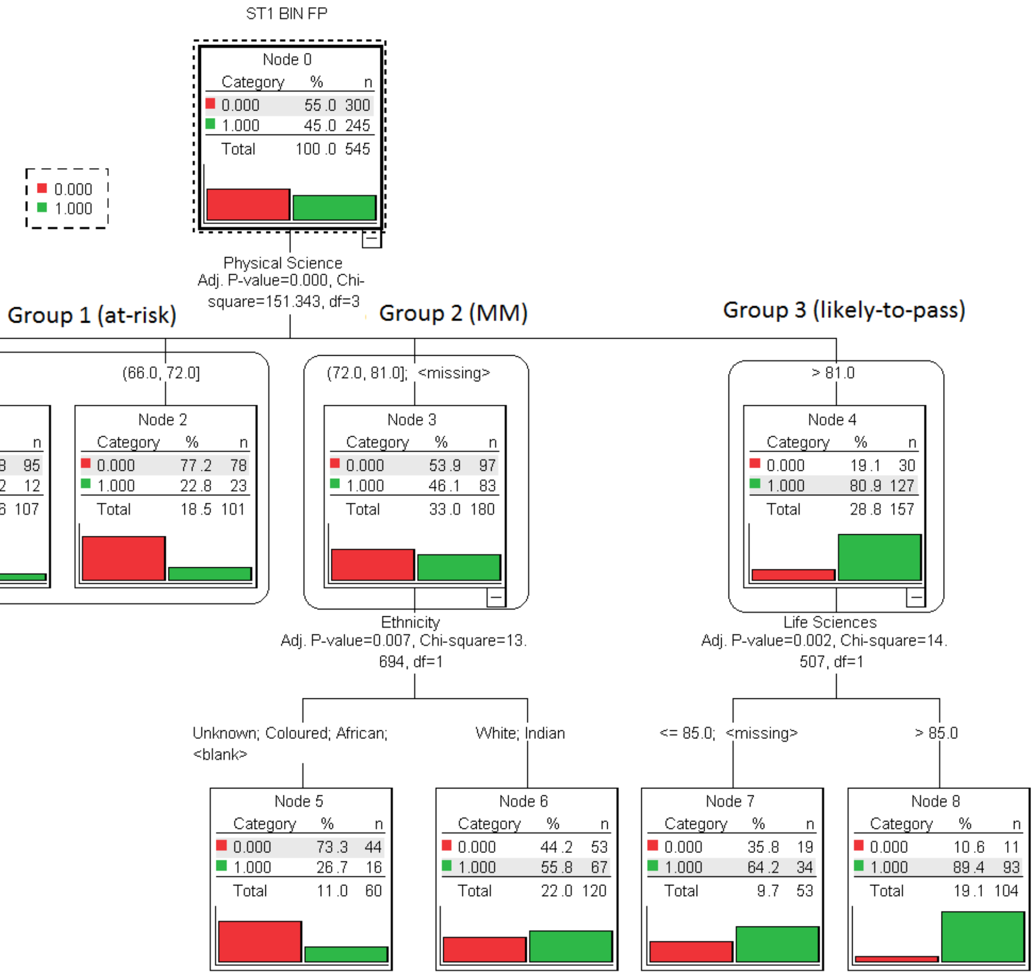

Figure 1: CHAID analysis with semester test 1 as the outcome variable.

The green bars indicate the students who passed the first semester test and the red bars the students who failed, with the relative height of the bars representing proportions of the subset. In each box, the total number of cases is reported as well as its proportion of the test sample. Figure 1 indicates that the student group was divided into four subgroups or nodes based on performance in grade 12 physical sciences (chi-square 151.34, df 3, p < 0.001). However, upon inspection, it was clear that both nodes 1 and 2 represent subgroups of students with a poor chance of success: 11.2% and 22.8%, respectively. These two nodes can therefore be combined to generate three distinct subgroups of comparable sizes, namely, 208, 180, and 157 students. Thus, students with a grade 12 physical sciences mark below 72% were designated as at risk (group 1). Students with a mark between 72 and 81% were designated the MM (group 2), and students with a mark higher than 81% were designated as LTP (group 3). Those students for whom no physical sciences marks (6%) were captured in the system (missing) were grouped with the MM (group 2). All subsequent analyses were performed in SPSS with the student sample split into these three groups (426 at risk, 315 MM, and 343 LTP). Although the CHAID indicated that ethnicity and life science marks were contributing factors that were also predictive within the model, a decision was made not to include the second level of analysis to determine the categorization of students. Ethnicity was shown to be a predictor for success in higher education in other studies (Kuh et al., 2008; Van Zyl et al., 2012; Tejada et al., 2016), but in our case, physical sciences marks proved to be the stronger predictor, thereby allowing us to categorize on neutral grounds. The results indicate that the model has good overall precision; it is able to correctly classify 75% of the cases, and detection of false positives is also 75%. The exclusion of the second level of the CHAID from the classification reduced the model accuracy by only 2% (72.8%). Research by Lemmens (Lemmens, 2015; Lemmens and Kebalepile, 2017) on the grade 12 high school results, notably physical sciences and Mathematics, tend to have weak Spearman's rank-order correlations with the first year academic performance when the unit of analysis is at the department or faculty level. This correlation improves significantly when the unit of analysis is at the course level. This finding could be due to less spurious relationships at the course level. Thus, the ability of the CHAID model to classify students with a 75% accuracy with only physical sciences marks is regarded as very promising in this instance. It is important to note that the 25% level of classification inaccuracy does not present a threat to the overarching aim of the project, because the purpose of classification was to enable a more nuanced understanding of student behavior. No student would be excluded from the opportunity to benefit from the interventions that would result from it. The ability of the CHAID classification model to classify students correctly with 75% accuracy is regarded as acceptable to classify students into the three performance categories. Using the categories created by the CHAID, a Spearman's rank-order correlation was calculated between physical sciences marks and the first summative assessment, namely, semester test 1. There was a strong, positive correlation that was statistically significant ($G = 0.621$, $p < 0.001$). By comparison, the precision of the models wherein the second semester test or the final marks for the course were used as the outcome variable were 52% and 56%, respectively. The first summative assessment was chosen as the outcome variable of choice for the following reasons: the predictive power of prior learning and demographic data is the highest for summative assessments done early in the semester; and early identification of students at risk and, in this case, the MM, creates opportunities for student support to prevent failure or drop out.

The validity of the categorization of the sample into three subsets based on performance in grade 12 physical sciences was checked in terms of its correlation with the other prior learning variables. An ANOVA was performed to determine individual correlation between the physical sciences performance categories and performance on the other variables. A significant difference at the 5% level was found between the three groups for all other predictor variables. All the variables, with the exception of computer literacy (CompLit), had significance levels of $p < 0.001$. Where between-group values were significant, Tukey post hoc tests were performed to see which groups showed significant differences. The results are shown in Figure 2 with red, yellow, and green bars for the at-risk, MM, and LTP groups, respectively.

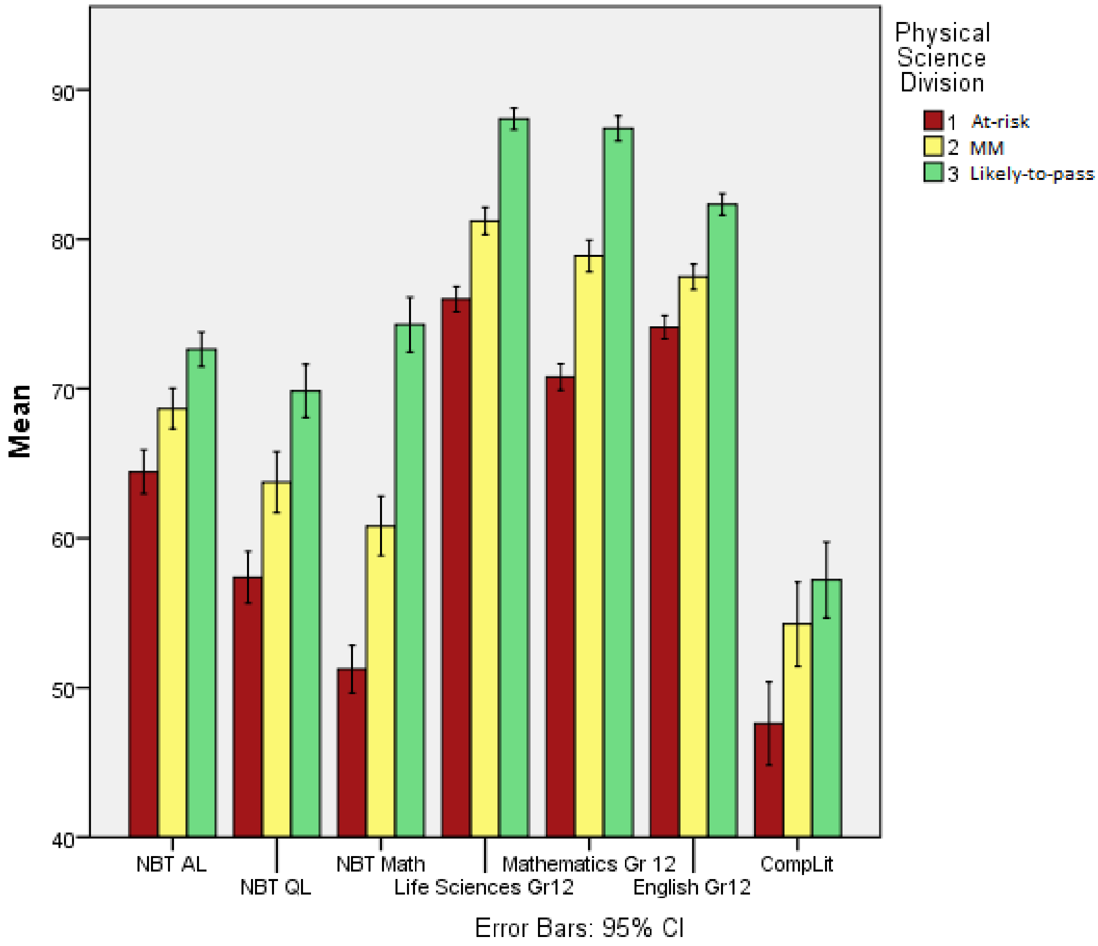

Figure 2: Summary of all prior achievement scores showing statistically significant differences in the means of the scores for the at-risk, MM, and LTP groups.

The final test for the categorization of students into groups based on grade 12 physical sciences marks was whether a significant difference between the prospects of success of the three groups could be found in the short and medium term of higher education studies. The pass rate for MLB 111 and the credit pass ratios for 2015 and 2016 were compared for the three subgroups, where the mean credit pass ratio reflects the percentage of credits passed compared with the total number of credits enrolled for. The results are reported in Table 1.

Table 1. Overall performance of students at the end of the first and second year

		Group 1 At-risk	Group 2 Murky Middle	Group 3 Likely-to-pass
2015	**N at start of 2015**	426	315	343
	% of group that passed MLB 111	49.1	67.9	93
	Average % of final mark per group	49.9	55.7	67.4
	Dismissed due to poor academic performance	27	6	1
	Mean GPA (2015)	54	60	71
	Mean Credit Pass Ratio	0.78 +/-0.26	0.88 +/-0.20	0.98 +/- 0.67
2016	**Active students at end of 2016**	332	254	301
	Mean GPA (2016)	54	60	71
	Mean Credit Pass Ratio (2016)	0.83 +/-0.20	0.90 +/-0.16	0.98 +/-.06

There was a significant difference between the "mean GPA" for the different groups ($F = 40.42$, $df = 2$, $p < 0.001$). At the end of 2015, the at-risk group passed, on average, 78% of credits enrolled for, the MM 88%, and the LTP group 98%. The mean GPA for the at-risk group was 54, the MM 60, and the LTP group 71 (expressed as a percentage). This means that, in 2015, the at-risk group failed on average two 16-credit courses, while the MM group failed one 16-credit course out of the first-year total of 144 credits. In 2016, the picture stayed mostly the same. While the prospects of success for the MM are significantly higher than those of the at-risk group (88 vs. 78%), it still means that the MM group will have to repeat courses that they failed, which will extend their study duration and increase their risk of dropping out during later years.

Difference in Learning Strategies between the Three Defined Groups

The analysis of the MSLQ Learning Strategies subscales indicates distinctly different response patterns for the three subgroups of students for eight of the nine subscales at the 5% level of significance. The means for all the groups were always with the at-risk group the lowest mean and the LTP the highest mean (Appendix B in the Supplemental Material). The results of the statistical analyses (for the different subscales) are reported in Table 2. In all but one of these subscales (help seeking), there is a difference between the at-risk and LTP groups; in addition, one subscale differentiated between the at-risk and MM groups (rehearsal) and one subscale differentiated between the MM and LTP students (effort regulation). Three of the scales (rehearsal, metacognitive self-regulation, and effort regulation) provided strong evidence of differences between groups (see Appendix B in the Supplemental Material for p-values showing statistical differences between groups).

Table 2. Subscales of the MSLQ and items showing significant difference between groups

Scale name	Number of items	Significance of ANOVA[a]	Items with significance (5% level)[b]	Kruskal-Wallis Asymp. Sig.
		Cognitive and metacognitive strategies		
Rehearsal	4	**0.005** (at-risk & LTP) At-risk and MM p=0.037	46. (Group 1&2 and 2&3) When studying for this course, I work through my class notes and the course materials a number of times 59. Group (1&2) I memorise key words to remind myself of important concepts in this course.	0.000 0.026
Organisation	4	0.053	49. I make simple charts, diagrams, or tables to help me organise course material.	0.036
Metacognitive self-regulation	12	**0.002**	41. When I become confused about something I'm reading for this course, I go back and try to figure it out 61. (Group 2&3) I determine what I am supposed to learn from the material before I start studying 78. (Groups 1&2) When I study for this course, I set goals for myself in order to direct my activities in each study session. 79. (Group 1&2) If I get confused taking notes in this course, I make sure I sort it out afterwards.	0.023 0.009 0.001 0.001
Elaboration	6	0.013	62. (Group 2&3) I try to relate ideas in this subject to those in other courses whenever possible. 81. (Group 2&3) I try to apply ideas from course material in other course activities such as lectures and discussions	0.032 0.000
Critical thinking	5	0.021		

Resource management strategies				
Time and Study environment	8	0.013	35. (Group 1&2) I study in a place where I can concentrate on my course work.	0.000
Effort Regulation	4	**0.000** (at-risk & LTP) **MM and LTP** **p= 0.010**	37. (Group 1&2 and 2&3) I feel so lazy or bored when I study for this course that I give up before I finish what I planned to do. (reverse coded) 48. (Group 1&2 and 2&3) I work hard to do well in this course even if I don't like what we are doing. 60. When course work is difficult, I either give up or only study the easy parts. (reverse coded)	0.000 0.000 0.005
Peer learning	3	0.015	34. (Group 2&3) When studying for this course, I try to explain the material to a classmate or friend. 45. (Group 2&3) I try to work with other students from this course to complete the course assignments.	0.003 0.032

[a]All significant differences indicated are between the at-risk and LTP group unless otherwise indicated.

[b]Scales indicated in bold are scales that show “convincing” evidence ($p<0.01$) of differences between the two extreme groups.

The results of item analyses presented in Table 2 will be discussed next with reference to the findings of the meta-analysis of other studies by Credé and Phillips (2011). They found that some of the constructs in the MSLQ exhibit meaningful relationships with academic performance. Their study showed the effort regulation subscale to have the highest correlation with academic performance ($\rho = 0.41$), which is on par with more traditional predictors of academic performance such as admission tests, prior learning, and study skills (Credé and Phillips, 2011). In the present study, effort regulation distinguished strongly between two pairs of groups, with two items (37 and 48) differentiating between all three groups. The effort regulation subscale probes students' ability to apply sustained effort and persist even when the work is difficult, there are distractions, or tasks are boring.

Credé and Phillips (2011) have shown that the meta-analysis is broadly supportive of the basic assumptions that underpin the theory of self-regulated learning: those students who can engage metacognitively, regulate their effort, and have appropriate learning strategies have higher average grades than students who cannot do so. This is in agreement with our results, in which the subscale of metacognitive self-regulation strongly differentiated between the at-risk and LTP groups ($p = 0.002$), with two items (78 and 79) also differentiating between the at-risk and MM and one item (61) between the MM and LTP groups. Item 61 provided strong evidence that the LTP group members had better planning capabilities and were more skilled in the selection of important learning material. The results for item 78 suggest that the at-risk students were less adept at setting goals before each study session and monitoring their progress. Items 79 and 41 point to the importance of students taking control of their own learning.

Credé and Phillips (2011) found that many of the specific learning strategies, such as rehearsal, elaboration, organization, critical thinking, peer learning, and help seeking, appeared to be unrelated to academic performance as operationalized in the MSLQ, but that less-contextual abilities, such as metacognitive self-regulation and effort regulation, were most strongly related to academic performance. In this study, scales such as rehearsal, peer learning, organization, and elaboration distinguished, at least, between the two extreme groups. Help seeking did not distinguish between any of the groups, and the reason might be related to the explanation provided by Credé and Phillips (2011). Good students might not need help or may not report on their help-seeking behavior, and low-performing students might not realize they need help and would therefore also not report any help-seeking behavior. Rehearsal strategies differentiated between the at-risk and MM students ($p = 0.037$) and between the at-risk and LTP students ($p = 0.005$). Of specific importance is item 46, which distinguished significantly between all groups, thereby providing evidence for the importance of repetition for mastering biology.

The fact that peer learning showed a significant difference ($p = 0.015$) between groups in our study is noteworthy. Two items differed significantly between the MM and LTP groups as well as between the two extreme groups, which indicates that the need to work with fellow students was recognized more strongly by the LTP group than the others. Conley (2007) states that academic behaviors such as the ability to participate successfully in study groups are critical for success in certain disciplines. It would therefore be advisable to intentionally build peer-learning activities into course design for first-year biology.

Elaboration strategies help students store information in long-term memory by building connections to related concepts. Elaboration strategies are considered deep processing strategies and are important for higher education (Weinstein and Mayer, 1986). The difference in the response patterns of the three groups was significant ($p = 0.013$). The two items (item 62 and 81) that differentiated did so between the at-risk and LTP but also between the MM and the LTP groups. These items probed whether students made an effort to connect concepts within the course and also relate it to other courses. The MLB 111 course that was the focus of this study includes material from other disciplines such as chemistry, biochemistry, physics, and plant science, and the awareness of alignment with other disciplines is thus important for success.

The previous discussion focused on the differences between the three groups of students that manifested most prominently between the at-risk and likely to pass students. The at-risk students need substantial academic and psychosocial support to be successful, while the LTP students will probably be successful without a lot of intervention. However, as this paper aims to describe the MM and generate actionable data regarding this group, it is important to look more closely at this group of students. By definition, MM students displayed characteristics of both the at-risk and LTP students. This is evident in the distribution of questionnaire responses; the average scores for the MM falls roughly in the middle of the subscale (Appendix B in the Supplemental Material). The subscales for which this is not the case are therefore of interest, particularly if their responses resemble those of the at-risk subgroup rather than those of the LTP. One scale for which the MM clearly tended more toward the at-risk group was effort regulation (see Appendix B in the Supplemental Material). Duckworth (2016) eloquently explains in her recent book that "effort counts twice," because effort improves skills, and skills combined with effort equals achievement. Admittedly, many other factors might influence the success of the MM students, but this study highlights the importance of the students putting effort into their academic work, even when it is a boring or difficult, a skill that in this study seems to be not as strongly developed in the MM. Building a culture in class that promotes perseverance (or grit) by demonstrating the value and relevance of the content and advocating for increased effort. This is a low-cost intervention that, for the MM, may have a large impact and high return on investment.

DISCUSSION

We have shown in this study that it was possible to identify indicator(s) that would differentiate between three groups of students: those who are likely to pass (LTP), the murky middle (MM), and those who are at risk of failing. Our analysis has identified grade 12 performance in physical sciences as the most powerful predictor for the first 2 years of study, and it defined the MM as students within the performance band of 72–81% for this subject. The findings suggest that students seem to be confined to a specific performance band and will find it hard to break free from that group without interventions and additional effort. The categorization of students was confirmed by various outcomes such as the mean GPA and mean credit pass ratio. At the UP, all the prior learning variables analyzed in this study showed significant differences between the three groups ($p < 0.05$), indicating that these students enter the university system with distinctly different academic competencies and prospects of success. This finding is noteworthy and could be useful on an administrative level with regard to admission of students and subsequent support of students admitted into the first year of a science degree. Students who are in the at-risk category should not be admitted unless extensive support is provided and embedded in their programs. The UP offers an academic development program (ADP) with a lower entrance requirement, which is specifically designed for this purpose. However, our results suggest that careful consideration should be given to raising the entrance requirements for MLB 111–70% for physical sciences, which would channel at-risk students into the ADP rather than the mainstream.

After categorization of the students, the self-reported learning strategies of the three groups were compared to identify strategies that are associated with success, information that will guide the design of future teaching and learning interventions. The results of the MSLQ analysis indicate distinct differences between learning strategies of the at-risk and LTP students. Metacognitive self-regulation, rehearsal, and effort regulation were the subscales that differentiated most convincingly between the groups. In addition, the ability to relate course material to other courses and the ability to manage the resources well were linked to good performance. Thus, a profile of learning strategies associated with good academic outcomes can be derived from the items that differentiated most convincingly between students who were LTP (group 3) or at risk (group 1).

The productive strategies of the LTP students can be summarized as follows:

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

2. Apply deep learning by relating ideas to other courses and connecting concepts within a course (items 62 and 81)

3. Sort out any confusion in a timely manner (items 41 and 79)

4. Persist even when work is difficult or not of interest (items 37, 48, and 60)

5. Choose suitable spaces to study (item 35)

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

7. Employ appropriate study methods that include memorization and organization (items 49 and 59) 8. Plan study activities and set goals to direct these study activities (items 78 and 61)

The list of effective learning strategies for MLB 111 resonates well with the literature on student success in science. Multiple studies have been reported of teaching practices that incorporate these pointers and deliver improved student outcomes. This confirms the credibility and usefulness of these results. For example, active-learning strategies such as peer instruction (Crouch and Mazur, 2001; Lasry et al., 2008) and think–pair–share (Miller and Tanner, 2015) encourage students to work with peers to solve problems (items 34 and 45). Clickers (Miller and Tanner, 2015) are widely used during lectures as a form of formative assessment to provide immediate feedback and encourage students to sort out confusing work in a timely manner (item 41 and 79). Research has also shown that group work in and out of class can transform course experiences for the better and help students to become actively engaged with the work (Wood, 2009). These strategies are suitable for large lecture halls and in smaller tutorial classes and can be taught by student advisors. Making connections (items 62 and 81) between new information and what is already known or understood is an essential part of the learning process and something that can be explicitly taught in class. Knowing in advance what the big ideas are and how they relate to one another helps learners make sense of information (Hammond et al., 2001). Items 37, 48, and 60 clearly distinguish between the three different groups and point to effort regulation and the willingness to persevere even when the work is not of interest or difficult. This was also the subscale for which the MM were statistically much closer to the at-risk than to the LTP, indicating the need to focus efforts to improve these skills for the MM specifically. Grit (Duckworth, 2016) has been shown to be predictive of academic success and is a teachable skill (Duckworth et al., 2007).

The challenge is to ensure that first-year biology students, especially MM and at-risk students, develop these strategies in time to help them to be successful. In our view, this is the joint responsibility of lecturers and student advisors. Lecturers should be guided to adjust the course design of their courses to purposefully incorporate SRL skills during lectures or in the online environment. Recent research has shown that changing course design to be more student centered increases learning gains in biology classes (Connell et al., 2016). This, coupled with the research by Owens et al. (2018), who showed that professional development for faculty helped them make significant changes in their course design, makes the case for developing professional development courses for lecturers and student advisors to facilitate the explicit teaching and demonstration of SRL skills inside and outside the classroom.

Student advisors, on the other hand, should take responsibility for assisting students in the learning process by teaching "soft skills" that students can adapt as needed. According to Simpson et al. (1997), learning to learn programs that are focused on assisting students to become self-regulated learners and that are based in conceptual work in psychology are the most successful interventions for teaching students learning strategies. These courses focus on developing a repertoire of learning strategies such as time management (item 46) and study methods (item 49 and 59) that students can adapt as necessary. These courses have been shown to increase GPA, retention, and graduation rates (Weinstein et al., 2000). On the basis of these results, we propose that large introductory courses should be supported by a learning to learn intervention, which is designed in conjunction with student advisors and incorporates these findings.

CONCLUSION

The first aim of this study was to determine whether the concept of the MM, as defined by the EAB (Student Success Collaborative, 2014), was applicable in our context of a single course within a program (microscale) to generate useful insights similar to its application to programs within institutions (macroscale). Our results indicate that it is possible to define the MM students in a specific course using only prior achievement data. Furthermore, the validity of the categorization was confirmed for subsequent performance and longitudinal data for academic standing. The MM students were consistently unsuccessful in passing all courses that they registered for as indicated by the mean credit pass ratio for the group in 2015 and 2016. This means that they were falling behind because of having to repeat courses, which would hamper progression and prolong their study time. This situation makes them more vulnerable to drop out in later years due to financial constraints and discouragement. The middle group can therefore be labeled the MM, in line with the findings of the Student Success Collaborative, which first coined the term. In our context, more than half of attrition of students happens after the first year. However, most efforts are currently focused on the first year, with limited resources allocated to subsequent years. The development of focused interventions for students who persist beyond the first year but continue to fall behind is thus an important area for investigation.

Related to our second research question, the study identified productive learning strategies that were used by the LTP group more than the other two groups. In addition, the study identified that effort regulation was the learning strategy for which intervention could make a meaningful contribution toward the prospect of success for the MM. These findings can be used to inform classroom practice and student advising. We argue that identifying the MM early and providing interventions with a focus on this group of students can significantly increase throughput rates. Well-designed interventions aimed at the development of effective learning strategies at the start of an academic career will have an impact beyond the first year. The MM falls just short of success by failing on average one course per year, but this shortfall accumulates over time with possible disastrous effects. By “moving the middle” toward success, these effects can be mitigated. Finally, within an environment of resource constraints, well-designed interventions aimed at the MM are expected to have a higher return on investment than those aimed at the at-risk group, which requires much more comprehensive support to achieve success.

Lecturers may have limited control over the admission of students into their programs, but they do have an obligation to teach the students admitted into the system. Typically, lecturers do not take responsibility for the development of soft skills, presumably because they are unaware of the specific needs of students, or because they see that as the task of student advisors. Learning strategies such as effort regulation, setting study goals, and having good time management skills are all skills that can be developed within a classroom setting, and it would be of great benefit to the students if lecturers were aware of the contribution that they can make in this regard. Course design that incorporates the principles of deep learning (making connections), peer learning, and metacognitive monitoring will benefit all students, especially the MM and at-risk students. On the basis of our results, we advocate for the inclusion of research-based material on effective learning strategies in staff development programs to empower faculty to actively promote or incentivize these learning strategies. In conclusion, we propose that our definition of the murky middle at course level and our study of the learning strategies of groups with different prospects of success have delivered actionable information that will be of interest for university management, curriculum designers, lecturers, and student advisors in the quest to improve retention and student success.

CHAPTER 3: INVESTIGATING THE EFFECTIVENESS OF A BLENDED FIRST-YEAR BIOLOGY COURSE

ABSTRACT

Increased class sizes and the rapid advancement of information technology have prompted institutions to move toward blended learning. The effectiveness of the instructional design of blended learning courses for large classes has not been studied extensively. This study aimed to interrogate the effectiveness and efficiency of the course design of a large first-year biology class with the aim of optimizing the blend to benefit all students, but specifically the at-risk and "murky middle" (MM) students. This was achieved by investigating patterns of student engagement over time with the learning opportunities in the course, followed by analyzing which of the different learning opportunities contributed most to the success of the subgroups of students. The results show that face-to-face tutorial classes and online formative assessments contributed the most to student success. Students did not engage meaningfully with optional activities, such as virtual classrooms and pre-reading for lectures. The at-risk and MM students' engagement with compulsory learning opportunities declined during the semester. We can conclude that these students need carefully chosen compulsory activities that are complementary in design and purpose, while optional activities are best suited for enrichment of students that are likely to pass.

Keywords: Learning analytics, blended learning, first-year biology, course design

INTRODUCTION

For teaching and learning, advances in technology for teaching and learning, with the promise of increased student participation and improved learning outcomes, have encouraged experimentation with alternative instructional approaches. We revised the instructional model of a first-year, first semester course in biology to include a wide range of learning opportunities. These opportunities comprised both face-to-face and online activities, for which participation was either voluntary or compulsory. The need arose to investigate the *effectiveness* of this blended learning course. In this study, we define effectiveness in terms of the quality of pedagogical practices and their efficiency in supporting student success. By defining effectiveness in this way, we added an economic consideration, which is an imperative in the resource-restricted context of a developing country. Our definition of course effectiveness resonates with that proposed recently by Renner, Laumer, and Weitzel (2014).They define and conceptualize *learning effectiveness* as a function of effective pedagogical practices, and *learning efficiency* as knowledge gain in relation to learning time. Renner et al., (2014) argue that learning efficiency and learning effectiveness should both be considered in evaluations of courses. While there is a body of knowledge on learning effectiveness, i.e. what constitutes good pedagogical practice in undergraduate education, the same is not true for learning efficiency. In our view, *learning efficiency* requires that each learning opportunity is essential and unique in its contribution to learning, and that the blend of learning opportunities is optimized to benefit all students, but specifically for the at-risk and borderline students. In essence, the blend must offer learning opportunities from which the largest group of students can benefit while being cost effective for the students as well as the institution.

We have used a unique lens through which to study the effectiveness of the blend, which is that of stratifying the sample group into three distinct performance groups. This will enable a more nuanced understanding of the engagement of different subgroups in the sample with specific learning opportunities and their contribution to student performance. The study is a quantitative study using learning analytics to evaluate learner activity in order to generate actionable data for improving the design of the blended learning course.

LITERATURE REVIEW

The literature review will commence with a brief discussion of the research on blended learning. The review will then explore the principles of good undergraduate teaching and will conclude with a discussion of the use of learning analytics to study learner interaction in blended learning courses.

Research on Blended Learning

At the start of this century, the American Society for Training and Development identified blended learning as one of the top emerging trends in the knowledge delivery industry (Finn, 2002 as cited by Halverson, Graham, Spring, & Drysdale, 2012). Since then, there has been a rapid growth in adopting and implementing blended learning by individual lecturers and institutions.

Blended learning has been studied for its transformative potential in education (Amaral & Shank, 2010; Garrison & Kanuka, 2004; Graham, 2005). Drysdale, Graham, Spring, and Halverson (2013) and Halverson et al., (2012) analyzed high impact scholarship, research and publication trends in blended learning by examining the most frequently cited authors, articles and books, as well as the research trends in dissertations and theses. They concluded that there is little coherence in blended learning research. Many studies are published under the banner of online learning while actually studying the online elements of blended learning. A holistic evaluation of the blended learning design with all course components included is rarely done (Bliuc, Goodyear, & Ellis, 2007). Halverson et al., (2012) also noted that most seminal work focused on definitions and the potential of blended learning. They emphasized that the time has come for researchers to devote their attention to research on which blended learning strategies are more effective in a particular context. Research on trends also show that the majority of manuscripts (dissertations and theses) focus on the relationship between course-level blends and student performance. Only one third of the research is focused on instructional design (Drysdale et al., 2013). They also showed that only 5.4% of the most cited papers addressed the issue of effectiveness.

Principles of Good Practice

Three decades ago Chickering and Gamson (1987) formulated the seven principles of good undergraduate education. In short, these are contact between students and lecturers, reciprocity and cooperation amongst students, active learning, timely feedback, time on task, communication of high expectations and respecting diverse talents and ways of learning. Chickering and Ehrmann (1996) later described cost-effective and appropriate ways to use technology to advance these seven principles. This framework for good practice has been widely accepted and has been applied to different contexts, such as the online environment (Alvarez, 2005; Dreon, 2013; Tirrell & Quick, 2012), blended learning environments of institutions (Aspden & Helm, 2004; Babb, Stewart, & Johnson, 2010; Babb et al., 2014) and to a lesser extent at the course level (Kocaman, Karoglu, Kiraz, & Ozden, 2014). The manner in which these principles can be applied in a blended learning course is considered next.

Face-to-face classes provide an opportunity for contact between students and lecturers, and can provide the platform for reciprocity and cooperation between students, communication of high expectations and timely feedback. Class attendance and participation in class have been shown to correlate well with achievement as reported in the meta-analysis by Credé, Roch, and Kieszczynka (2010). In class, active learning strategies such as peer instruction (Crouch & Mazur, 2001; Vickrey, Rosploch, Rahmanian, Pilarz, & Stains, 2015) and the teaching method, think-pair-share pioneered by Lyman (1981), facilitate the implementation of the previously mentioned principles.

Just like the face-to-face part of the blended course, the online component can also be structured to promote the principles of good undergraduate education. Time on task, timely feedback and respecting diverse talents and ways of learning can all be promoted successfully in the online environment. There are a wide variety of methods that can be used for this purpose, including synchronous and asynchronous modalities, of which only a few will be discussed here. Virtual classrooms have been used synchronously in the online and blended learning environments to promote interactivity, develop community, and reach students at different locations (Martin & Parker, 2014). In a blended learning environment, virtual classrooms have the advantage of providing extra synchronous class time outside of scheduled face-to-face classes, thereby increasing contact between lecturers and students.

Online testing has become commonplace in higher education in the Twenty First Century. A review of the literature by Gikandi, Morrow and Davis (2011) shows that it is mostly used for immediate feedback, engagement with critical learning processes and promoting equitable education by addressing diverse student needs. Research by Angus and Watson (2009) shows that frequent, low stakes, online tests have a positive effect on learning by helping students study effectively throughout the course. The automation of assessment facilitates repeated practice with prompt feedback, pedagogical practices that are known to enhance learning (Twigg, 2015).

The use of technology has also become increasingly common, and it is used in various forms, both in face-to-face classes (e.g. clickers) and the online environment. Blended instruction combines the benefits of face-to-face instruction and online learning and is becoming increasingly popular (Adams et al., 2015). The effectiveness of blended courses when compared to the face-to-face instruction has been investigated in a number of recent studies (Adams et al., 2015; Amaral & Shank, 2010; Joyce, Crockett, Jaeger, Altindag, & O'Connell, 2014). The findings from the research suggest that the outcomes of these courses are on par with traditional face-to-face courses or sometimes slightly better. All these studies attempted to determine the effect of a single variable, such as the mode of delivery or the time students spent in the classroom but did not incorporate all activities provided in the course into the analysis. In many cases experiments with randomized controlled trials (RCT), where a "treatment" group was compared to an "experiment" group, were applied. All of these studies were completed in response to radical course redesign in an attempt to determine the effect of an intervention, either positive or negative. In these kinds of studies, it is impossible to control for all possible variables that might influence the experiences of the students or the outcomes of the course. When studying blended course designs it is difficult to determine which factors lead to increased success. More often than not success (or lack thereof) is attributed to one factor while controlling for all other factors. Although blended learning has been investigated in many studies (Gleadow, Macfarlan, & Honeydew, 2015; Pereira et al., 2007; Stockwell et al., 2015) the effectiveness of the blend, especially in large classes, has not been studied extensively. These studies also use traditional metrics such as gender, GPA, course marks and other factors to measure the effect of interventions.

Learning Analytics

Learning analytics (LA) has been used in the recent past to study large datasets of how learners are interacting with learning resources in real time (Lockyer, Heathcote, & Dawson, 2013). Siemens and Long (2011) define learning analytics as the use of learner produced intelligent data and analysis models to uncover information, to predict, and to advise on learning. Recently the widespread adoption of learning management systems (LMS) has generated different sets of learning data in addition to the usual surveys and focus group interviews. According to Lockyer et al., (2013), this digital footprint generated by LMS interaction can be analyzed to provide assessments of student learning and engagement and to evaluate teaching practice. These analyses can be used to inform course design (Lockyer et al., 2013). The challenge posed to learning analytics is interpreting the resulting data against pedagogical intent and the context (Dawson, Bakharia, Lockyer, & Heathcote, 2011). LA can be used to assess resource use such as the uptake of tutorials and online work (Atherton et al., 2017) and to evaluate the success of a learning activity or learning design (Dawson et al., 2011). Data from the LMS can provide significant predictions of student outcomes. Analysis of LMS data can therefore help researchers detect interaction with learning opportunities and assist with the design of interventions to improve student outcomes.

RESEARCH DESIGN

The aim of this paper is to assess the overall effectiveness of a large enrollment, undergraduate biology course that is presented in a blended learning format. Not all students will utilize the learning opportunities that are available in the same way, or will benefit equally from these opportunities. Because of the diversity within a class (especially a large enrollment class), the assumption can be made that some learning opportunities will have a bigger impact on certain groups of students than others. In this study, the academic diversity inherent to the class is conceptualized as outlined hereafter.

In principle each cohort of students can be divided into three groups; students that are likely to pass with relative ease (termed the likely-to-pass or LTP), students that are likely to fail the course in the absence of substantial interventions (termed at-risk) and students for whom the prediction of outcomes is difficult. The Student Success Collaborative in the USA (Student Success Collaborative, 2014b) coined the term the "murky middle" (MM) for these students for whom the academic outcome is difficult to predict. The Education Advisory Board (EAB) analyzed 740 000 student records from 73 higher education institutions in America and demonstrated that a lot of resources are typically allocated to the at-risk group and comparatively little to the MM students, while an investment of resources to support this group of students is likely to deliver a higher return on the investment. It is clear that the MM deserves significantly more attention than it normally receives.

While the concept of the MM was defined in the context of a very large student group at a large number of institutions, we propose that it can also be applied within a single course to enrich analysis of student engagement patterns and their relationship to student performance. The aim of this paper, as stated earlier, is to assess the effectiveness of the blend. Framing effectiveness in terms of how well it caters for the broadest number of students, but specifically for the MM, could achieve this aim. While it is desirable to cater generously for the needs of all the students enrolled for the course, this is seldom possible. Decisions have to be made about the targeting of learning opportunities and such decisions become especially difficult when resources are constrained. While students that are at risk of failing usually receive special attention, we argue that the focus should be broadened to include the MM as well. At-risk students require extensive scaffolding and support but we argue that the MM students could potentially benefit more from well-designed, low cost learning opportunities and a lesser degree of scaffolding.

With the overall aim (to assess to effectiveness of the blend) and the premise of the MM to guide the study the following research questions are posed:

> RQ 1. What are the differences in engagement with learning opportunities by the likely-to-pass, murky middle and at-risk groups of students?
>
> RQ 2. Which of the activities in the blended learning environment are associated most strongly with success for the MM?

The first research question probes patterns of engagement with compulsory and voluntary learning opportunities and their variation both between groups and within a specific group over time. In this paper, the term "engagement" refers to an interaction with a learning opportunity as a proxy for learning; it does not attempt to evaluate the quality of the interaction. The second research question focuses specifically on one subgroup for the reasons of effectiveness and efficiency as explained earlier. Our expectation is that the findings from these two questions will enable us to better accommodate the diverse learning needs of all the students enrolled for first-year biology at our institution.

CONTEXT OF COURSE AND DESCRIPTION OF THE BLEND

Molecular and cell biology (MLB 111) is a first-year course in the Faculty of Natural and Agricultural Sciences at the University of Pretoria, South Africa. A large number of students annually enroll for this course (ca. 1500 students). The course has a blended learning design with both face-to-face and online components, with either compulsory or voluntary participation. Data for this study were obtained from the students enrolled for MLB 111 during the first semester of 2015. A total of 1084 student records were used for the study. This number represented 68.3% of the total population of students registered for this course. The remainder (31.7%) were either students repeating the course or students that transferred from another university. Their records were removed from the sample to ensure that the findings represented the patterns for first-time, first-year students only. The sample comprised 730 females (67%) and 354 males. The engagement data for the study were obtained from the Grade Centre of the Learning Management System (Blackboard). All activities, both face-to-face and online were logged into the Grade Centre during the course of the semester.

Molecular and cell biology is a 16 credit course (160 credit hours) in the first semester of the first year. The lectures for this course start with introductory biochemistry, including the nature of water, acids and bases and general chemistry of the cell. Following the biochemistry section, the course then covers introductory cell biology with topics on cell structure and membranes. The cell biology is followed by an introduction to metabolism in the form of respiration and photosynthesis and the course concludes with introductory molecular genetics that includes DNA replication, transcription and translation. Each of the topics are allocated a quarter of the time for the course. The researcher was involved in the teaching of a third of the course material. The summative assessments for the course, two semester tests and a final exam, consisted of a mixture of multiple choice questions (20% of the paper), short answer questions such as definitions (25% of the paper) and questions requiring longer answers to test content knowledge and the ability of the student to apply the knowledge.

The learning design of the course was informed by literature reports on interventions that were proven to be effective. Some of the activities (e.g. tutorials) have been part of the course structure for a number of years, whereas others were introduced recently as part of the move to blended learning. The following describes the different learning opportunities in the course.

Compulsory activities

Students were required to complete a certain percentage of compulsory activities in the course to gain access to the final examination. There were three types of compulsory activities namely, *class participation, tutorials* and *Connect quizzes*. All compulsory activities were graded and contributed to the semester mark of the course, thus, students who did not participate or complete compulsory activities lost the marks for the activity. Students have access to computer labs on campus and could access online material from these labs at any time during the semester.

Theory classes were based on peer instruction (Lasry, Mazur, & Watkins, 2008) and participation in class was recorded using clickers in each lecture. Participation in class counted towards the semester mark. Class participation marks were awarded regardless of the correctness of the responses.

The second face-to-face activity included in the course design was tutorial classes during which students met in smaller groups (about 150 students per group). The tutorials were based on the peer instruction principle to encourage active learning, with senior post-graduate students trained to lead these sessions, and clickers used to record responses. Face-to-face tutorials have been part of the course design for a number of years and are considered essential for student success. During the tutorial classes, student had the opportunity to work out problems, similar to those found in the summative assessments. Senior post graduate students were present during these sessions to provide one-on-one assistance to students. In addition to the one-on-one support, the tutorial classes also included a section where concept quizzes in the form multiple choice questions were posed to the students. The students answered the questions, using clickers and the senior students would explain the concepts if misconceptions were detected. Marks for the tutorials consisted of a combination of participation and formative assessment. Participation in the first part of the class, the peer-led practice session, contributed 50% of the total mark. Students completed an assessment exercise after the peer-led session, also using clickers, which contributed the other 50% of the mark. Thus, students that attended the session and participated already scored 50% even if they had none of the answers correct. Tutorial marks were loaded onto the LMS on a weekly basis.

The textbook used in this course contains an online resource that provides lecturers with tests and other forms of assessments. Students were required to complete formative, open-book online assessments, called *Connect* quizzes, at the end of each study unit. Multiple attempts were allowed and only the highest mark was captured for each quiz.

Voluntary activities

Two types of voluntary activities were part of the blend, namely pre-reading for lectures and virtual classrooms as a revision exercise before the mid-term tests, called semester tests. Reading of relevant texts is an important aspect of any undergraduate course. Specifically, pre-reading in first-year biology has been correlated with improved exam performance (Freeman et al., 2014; Lieu, Wong, Asefirad, & Shaffer, 2017). However, Lieu, Wong, Asefirad and Shaffer (2017) showed that students are unlikely to read their textbooks unless an incentive is provided. Learnsmart, another feature of the online textbook, was therefore implemented to encourage students to read prescribed texts before face-to-face class sessions. Learnsmart is an online quiz system that is designed to guide students to understand concepts in different topics. Students have to answer specific questions based on the work and if they get the answer incorrect, an electronic version of the textbook will automatically open to the relevant section and prompt them to read the appropriate part. Students can work through the topics selected by the lecturer and will only be able to complete the Learnsmart exercise if a specified number of questions were answered correctly. Academically prepared students will be able to complete the Learnsmart assignments in a short period of time, while struggling students will take longer as the system will prompt them to read and revise topics until they can answer questions on a topic correctly. If a student completed the Learnsmart activities, a mark of 100% was allocated, regardless of the number of questions that were answered incorrectly. If students did not complete the Learnsmart or did only part of it, their marks were proportionally adjusted.

Virtual classrooms were conducted outside of class time using the Blackboard Collaborate system as a synchronous online activity. These tutorial classes were run by the same senior, post-graduate students who presented face-to-face tutorial classes. Students could submit questions before the time, they could also ask questions during the session or just log in and listen to the discussion. If students logged into a virtual classrooms, a participation mark of one was added to the LMS grading system, so that the total mark for the activity reflected the number of sessions attended.

The MLB 111 course is presented over 14 weeks, followed by a final examination. Entrance to the final examination is based on a progress mark (semester mark) and satisfactory participation in compulsory activities. The scores for all compulsory activities were combined and weighted to count towards the semester mark as follows: Semester test 1 (35%), Semester test 2 (35%), Formative assessment (30%). The formative assessment mark was a combination of face-to-face tutorial class tests (20%), class participation measured using clickers (5%) and Connect quizzes taken online (5%).

Even though participation in three types of activities was compulsory, students could achieve higher marks for each of them through diligence and effort. By comparison, scores obtained for voluntary activities provide a more direct reflection of engagement and commitment. These activity scores could vary over time, thereby representing patterns of engagement within and between groups. The distribution of learning activities throughout the course is presented in Figure 1. The placement of the two mid-term summative assessments, semester tests 1 and 2, divided the 14 weeks into distinct periods. We termed the period before semester test one *period 1,* and the period between semester test one and two, we called *period 2* (Figure 1). We used these two time periods to investigate any shifts in engagement patterns throughout the course of the semester.

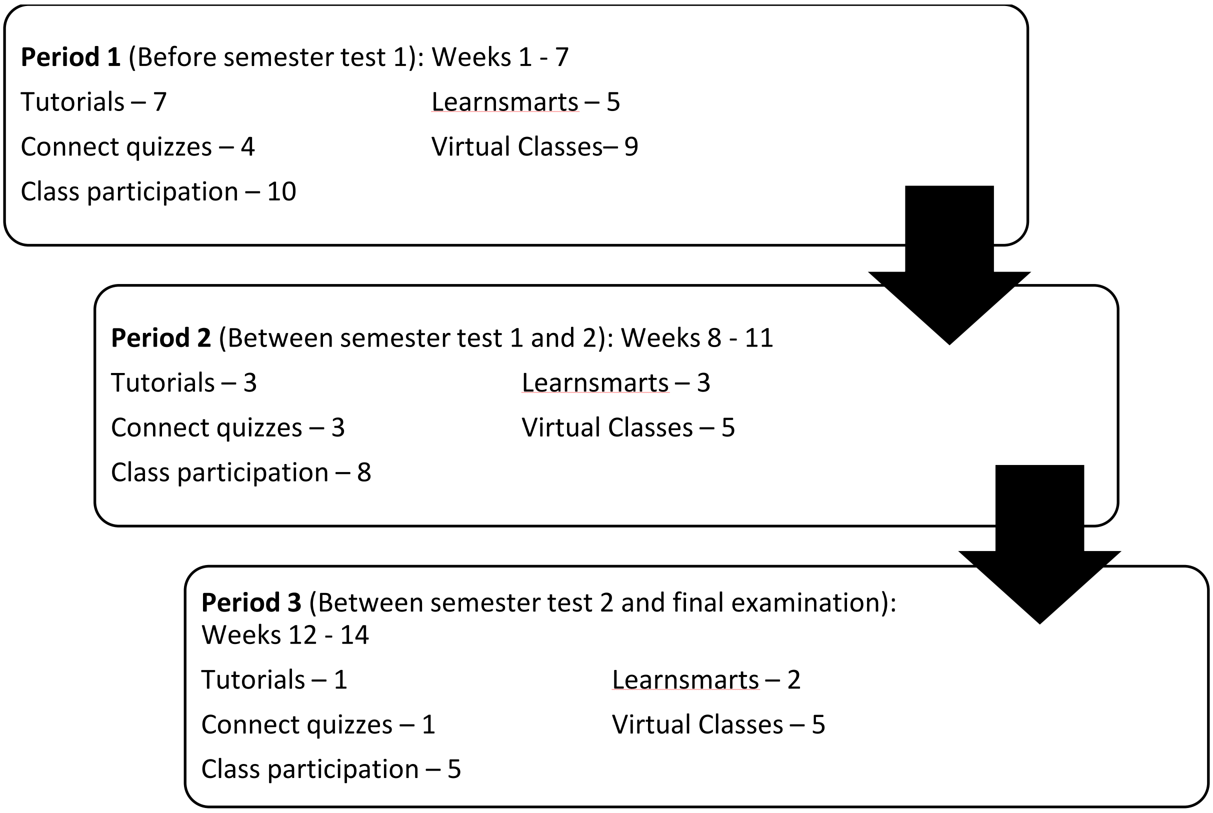

Figure 1: Distribution of activities across three time periods during the semester.

METHODS AND DATA ANALYSIS

In order to analyze the effectiveness and efficiency of the course we need to explore student engagement with learning activities and determine which of the activities in the course design contribute most to the success of these students. In this study we chose to use the concept of the MM to gain a more nuanced picture of student engagement. We have demonstrated in an earlier study (Kritzinger, Lemmens, & Potgieter, 2018) that students in first-year biology can be categorized in the three subgroups, at-risk, MM and likely-to-pass, based on their performance in the Grade 12 final examination for the subject Physical Sciences, which consists of equal parts of chemistry and physics. This categorization was validated over a two-year period to show that the short and medium term outcomes of these three groups are significantly different. The same categorization was used in this study to analyze student engagement with learning activities and their contribution to student performance.

The first objective of this study was to analyze the different patterns of engagement amongst the groups over time. As the three groups have different outcomes, patterns of engagement could possibly be linked to the outcomes. MANOVA and ANOVA analysis with a Bonferroni adjustment for multiple comparisons and *post hoc* tests were performed to compare engagement patterns between the different groups in Period 1 and 2 respectively. The results indicated that the assumption of the homogeneity of variance (Levene's Tests) was not met and a Welch and Brown-Forsythe correction test was used to confirm the significant differences obtained by the ANOVA. For both tests, the results were highly significant, which indicates a significant difference amongst the three groups. Furthermore, the group sizes were roughly equal (at-risk=423, MM=315, LTP=343), indicating that an ANOVA would be robust against violations of homogeneity. *Post hoc* tests, namely Tukey HSD and Games & Howell were used to evaluate the differences between groups. The results from both post hoc test were almost similar and in this report only the results of the Tukey's test will be presented.

The second research question aims to evaluate the different learning opportunities and their contributions to success for the MM subgroup of students. The Chi-square Automatic Interaction Detector (CHAID) analysis was chosen as the method of choice for this analysis. CHAID analysis is a non-parametric test. Non-parametric decision tree algorithms, such as a CHAID decision tree model, have been used to predict customer attrition in the commercial sector, and have been shown to outperform parametric predictive models (Au et al., 2003; Seidel & Kutieleh, 2017). Au et al., (2003) state that in addition to precision and accuracy, the benefits of a decision tree method include model parsimony, robustness, handling of missing data and enabling the inclusion of entries with missing data. CHAID models are relatively simple to interpret, validate and implement and are thus suitable as a tool to use to study student related data. To facilitate the analysis of the MM group and to gain a clearer picture of engagement of the MM, an ANOVA was performed to determine if the subgroups within the MM engaged with the activities in the course differently.

The first step in the evaluation of the course design is a CHAID analysis of the complete data set for the whole sample to identify the strongest overall predictor variables. The analysis must then be repeated for each subgroup to check that the predictor variables that are the strongest indicators for specific groups within the sample have not been masked. However, due to the nature of the data and the fact that the at-risk and LTP groups are groups at the extremes of the scale, a CHAID analysis of the at-risk and LTP groups would not provide as much detail or prediction capacity as the analyses of the MM. The MM had a relatively even distribution of students who passed or failed the exam (MM-fail = 156 and MM-pass = 147). The MM-fail subgroup was therefore taken as a proxy for the at-risk group. This stepwise analysis is presented in Figure 2; firstly, for the entire group, to get an inclusive picture of the course design, and secondly for the MM group specifically.

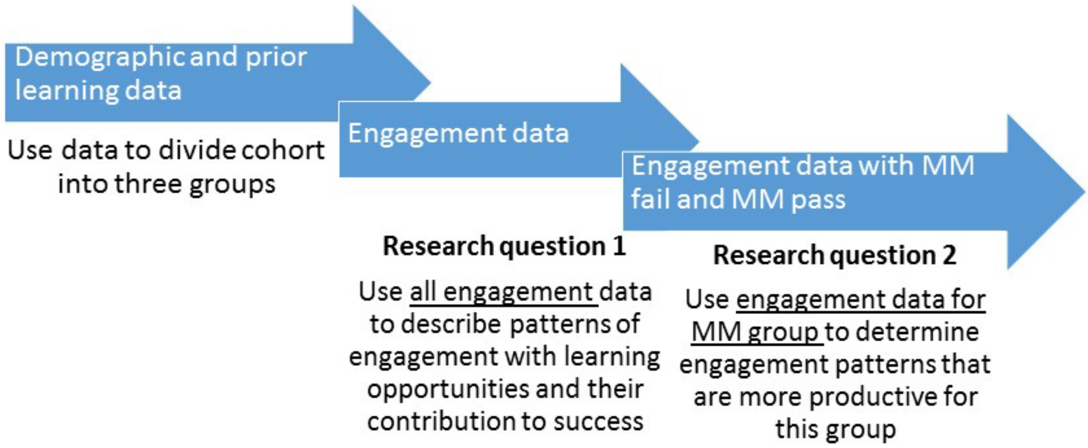

Figure 2: Steps in data analysis.

RESULTS

Analyzing the data generated a rich description of differences in engagement patterns amongst the three sub-groups as well as the blend of activities that had the biggest impact on academic performance. The MANOVA indicated a significant difference in the overall results (Pillai's Trace: $p < 0.001$) during both periods. Given that the model is significant overall, the ANOVA results with subsequent post hoc tests will be presented below.

Table 1 presents the mean scores for the three compulsory and two voluntary activities with a statistical analysis of these scores for the three subgroups during periods one and two, respectively. The mean scores for each of the activities were ranked consistently, with the lowest score for the at-risk group and the highest for the LTP. The only exception was virtual classroom participation, where the MM had the highest mean score in both periods. The ANOVA results for period 1 indicate that Connect quizzes and tutorial participation are the most important learning opportunities with the largest effect sizes with η^2 = 0.087 and η^2 = 0.072 respectively indicating a medium effect (Durlak, 2009; Richardson, 2011). In pairwise comparisons all the groups showed a significant difference at the five percent level except for class participation between the MM and LTP students ($p_{(2,3)}$=0.072), performance in Learnsmart between the MM and LTP ($p_{(2,3)}$=0.277) and the uptake of Virtual classrooms between the at-risk and MM ($p_{(1,2)}$=0.068) and at-risk and LTP ($p_{(1,3)}$=0.933). In period 2 the ANOVA results showed that Connect quizzes had the largest effect size (η^2 = 0.086) followed by the tutorial classes (η^2 = 0.040). The pairwise comparisons showed that at the 5% level most activities were significantly different amongst the groups except for the performance in tutorial classes between the at-risk and MM ($p_{(1,2)}$=0.120), Learnsmart performance between the MM and LTP ($p_{(2,3)}$=0.974) and the uptake of Virtual classrooms for all the groups.

The level of engagement with compulsory activities was high in period 1, but it declined for all three groups in period 2. Interestingly, the difference between subgroup participation in class changed. In period 1 there was no significant difference in class participation between the MM and LTP ($p_{(2,3)}$=0.277) but in period 2 the MM shift toward the at-risk students ($p_{(2,3)}$=0.002). The same worrying trend was seen in the performance in the tutorial classes where the MM and at-risk groups showed no significant difference in performance in period two ($p_{(1,2)}$=0.120) in contrast to period 1 ($p_{(1,2)}$<0.001). The scores for Connect quizzes were significantly different before the first summative assessment for all three groups ($p<0.001$), although it was still the case in period 2, the significance was lower between the MM and at-risk group ($p_{(1,2)}=0.015$). These shifts in levels of engagement are a worrying trend because the MM lost some of their advantage in terms of performance in period 2. While there may be a number of reasons for these shifts, from a course design perspective, the possibility of overload must be critically evaluated.

Table 1. Activity means and ANOVA results for periods one and two

		Activities before semester test 1 (period 1)					Activities between semester test 1 and 2 (period 2)				
		At-risk Group 1	MM Group 2	LTP Group 3	Between group significance	Eta squared	At-risk Group 1	MM Group 2	LTP Group 3	Between group significance	Eta squared
Compulsory activities	**Peer-led tutorial classes Average %**	77% (SD= 19%)	81% (SD= 15%)	88% (SD= 11%)	$p_{(1/2)}<0.001$ $p_{(1/3)}<0.001$ $p_{(2/3)}<0.001$	0.072	71% (SD= 21%)	74% (SD= 18%)	80% (SD= 12%)	**$p_{(1/2)}=0.120$** $p_{(1/3)}<0.001$ $p_{(2/3)}<0.001$	0.040
	Connect Online quiz Average %	62% (SD= 30%)	72% (SD= 26%)	82% (SD= 20%)	$p_{(1/2)}<0.001$ $p_{(1/3)}<0.001$ $p_{(2/3)}<0.001$	0.087	60% (SD= 29%)	66% (SD= 27%)	79% (SD= 20%)	$p_{(1/2)}=0.015$ $p_{(1/3)}<0.001$ $p_{(2/3)}<0.001$	0.086
	Participation in class total count	8.2/10 (SD= 2.5)	8.7/10 (SD= 2.0)	9.1/10 (SD= 1.7)	$p_{(1/2)}=0.007$ $p_{(1/3)}<0.001$ **$p_{(2/3)}=0.072$**	0.028	6.3/8 (SD= 2.1)	6.6/8 (SD= 1.9)	7.1/8 (SD= 1.3)	$p_{(1/2)}=0.037$ $p_{(1/3)}<0.001$ **$p_{(2/3)}<0.002$**	0.035
Voluntary activities	**Learnsmart Average %**	17% (SD= 28%)	26% (SD= 34%)	30% (SD= 36%)	$p_{(1/2)}<0.001$ $p_{(1/3)}<0.001$ $p_{(2/3)}=0.277$	0.031	8% (SD= 20%)	13% (SD= 26%)	13% (SD= 26%)	$p_{(1/2)}=0.012$ $p_{(1/3)}=0.005$ $p_{(2/3)}=0.974$	0.012
	Virtual classrooms total count	2.0/9 (SD= 1.5)	2.6/9 (SD= 2.0)	1.9/9 (SD= 1.4)	$p_{(1/2)}=0.068$ $p_{(1/3)}=0.933$ $p_{(2/3)}=0.019$	0.007	0.2/14 (SD= 0.7)	0.3/14 (SD= 0.8)	0.27/14 (SD= 0.7)	$p_{(1/2)}=0.401$ $p_{(1/3)}=0.576$ $p_{(2/3)}=0.952$	0.002
		Semester test 1					Semester test 2				
		38.2 (SD=14.7)	46.5 (SD=17.4)	62.0 (SD=16.8)	$p_{(1/2)}<0.001$ $p_{(1/3)}<0.001$ $p_{(2/3)}<0.001$	0.378	50.9 (SD=18.1)	57.8 (SD=17.4)	70.1 (SD=14.3)	$p_{(1/2)}<0.001$ $p_{(1/3)}<0.001$ $p_{(2/3)}<0.001$	0.230

The second research question aimed to analyze the activities that had the largest influence on the academic performance for the MM. However, as mentioned previously, an exploratory analysis for the whole group was also performed. Firstly, a CHAID analysis was performed with the exam as an outcome variable, coded as either a pass or a fail for the exam (Figure 3). The sample size for the entire group was large enough to keep the default setting for the CHAID analysis as set in SPSS namely, split group validation, parent nodes 100 and child nodes 50. The CHAID analysis software generates a "decision tree" that depicts mutually exclusive groups based on the best predictor variable. The sample was split with regard to the predictors by a step-wise regression analysis that identified the most powerful predictor on a specific level. The alpha level for this study was $p \leq 0.05$. The prediction capacity of the CHAID was high, with an overall prediction accuracy of 76% and the ability to predict which students might fail with a 76% accuracy. The tree diagram in Figure 3 shows that the most important contribution to success for all students was participation and performance in tutorials (TutorialAve ALL), followed by performance on the Connect online quizzes (ConnectAveAll). Four distinct groups can be distinguished; students that scored more than 91% for the tutorials had a chance of 97% of passing the exam. Students that scored between 86% and 91% had on average a 76% chance of passing the exam. These students increased their chances of passing the final exam to 92% by participation in the Connect online quizzes and achieving a mark of 87% or higher for them. However, for this same group the likelihood of passing the exam dropped to 66% if they scored below 87% for the Connect quizzes. Students that obtained between 82% and 86% for the tutorials had a likelihood of 49% to pass the exam. However, these students increased their likelihood of passing the exam to 65% if they scored above 81% for the Connect quizzes; and decreased their likelihood to 33% if they did not achieve 81% for the Connect quizzes. The likelihood of students passing the exam if they had below 82% for their tutorials was 23%. Their likelihood of passing increased to 37% if they also participated in the Connect quizzes and scored more than 81%, but dropped to 17% if they achieved less than 81% for the Connect quizzes. Thus, the two compulsory activities of overall tutorial participation and completing online Connect quizzes, contributed most to success of the students in the final exam of MLB 111.

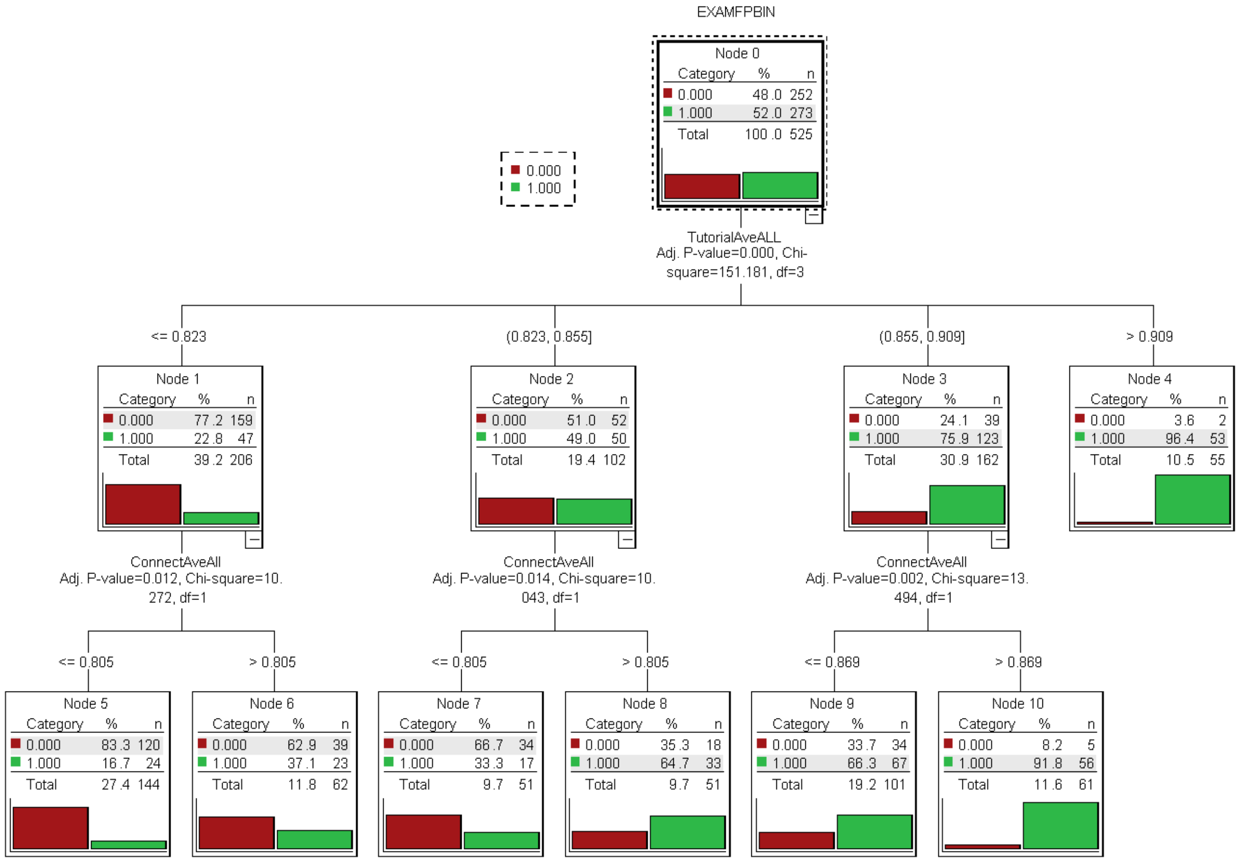

Figure 3: CHAID tree diagram for all students.

The analysis of the MM subset yielded valuable information regarding the learning opportunities that contributed to their success throughout the semester. As the MM group was a subset of only 315 students the parameters for the CHAID had to be adjusted namely, parent nodes 50 and child nodes 35. In period one, the first semester test was used as outcome variable. The CHAID showed that tutorial participation was the strongest predictor of success for this group (Figure 4). Students who scored 89% or above for their tutorials had a 70% chance of passing the test. Students with a score below 88% had only a 42% chance of passing the test while students who had less than 83% for their tutorials had a 23% chance of passing the test. This CHAID had a satisfactory overall prediction of 69% and could predict the students that would pass with 85% accuracy. The prediction capacity for period 2 with the second semester test as outcome variable was too low to be useful (43%).

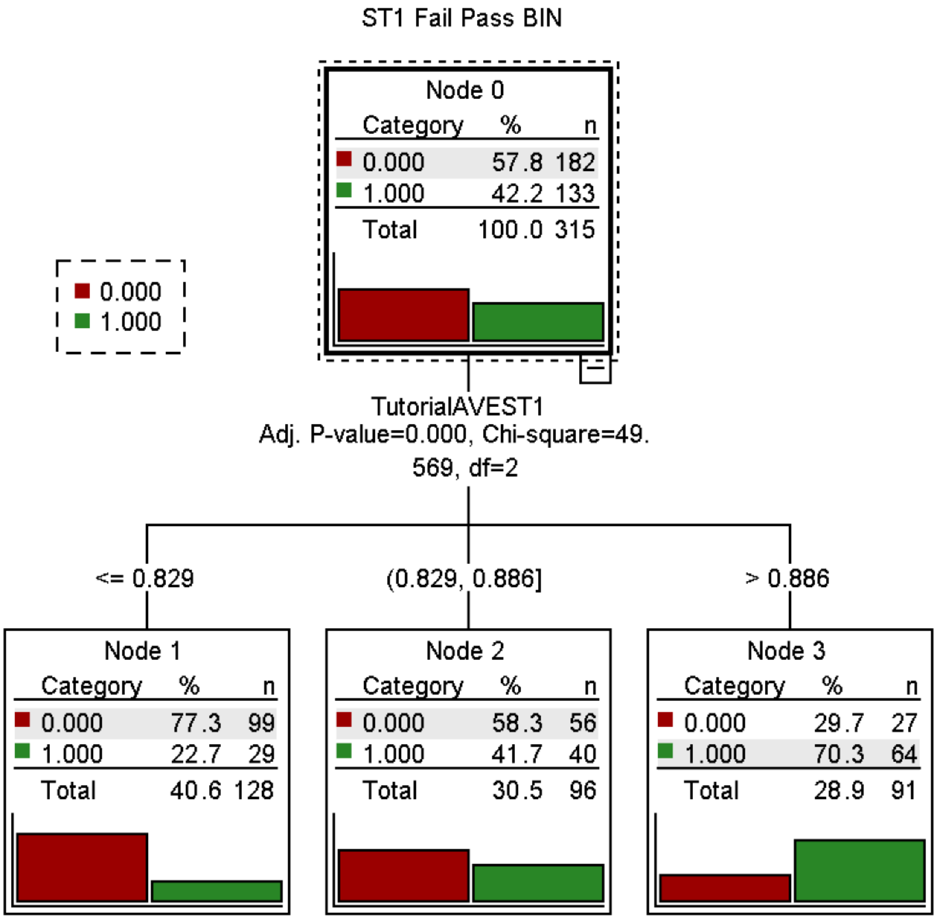

Figure 4: Analysis of the MM students with the first summative assessment as outcome variable.

The final analysis for the MM included the averages for all activities completed throughout the semester as predictor variables with the exam as outcome variable (Figure 5). Tutorial performance was once again the best predictor of success. Students with a tutorial mark of 88% or above had an 81% chance of passing the exam while students who achieved between 85% and 87% had a 60% chance of passing the exam. Students with a score of 81% to 85% had a 46% chance of passing the exam. The last group of students, who scored below 81% for their tutorials had a 27% chance of passing the exam. This CHAID had an overall prediction capacity of 69% and had the ability to predict students that failed with 88% accuracy. This picture corresponds to what was obtained for the whole sample (Figure 3), except that, due to sample size, the diagram does not reflect the influence of a secondary predictor variable.

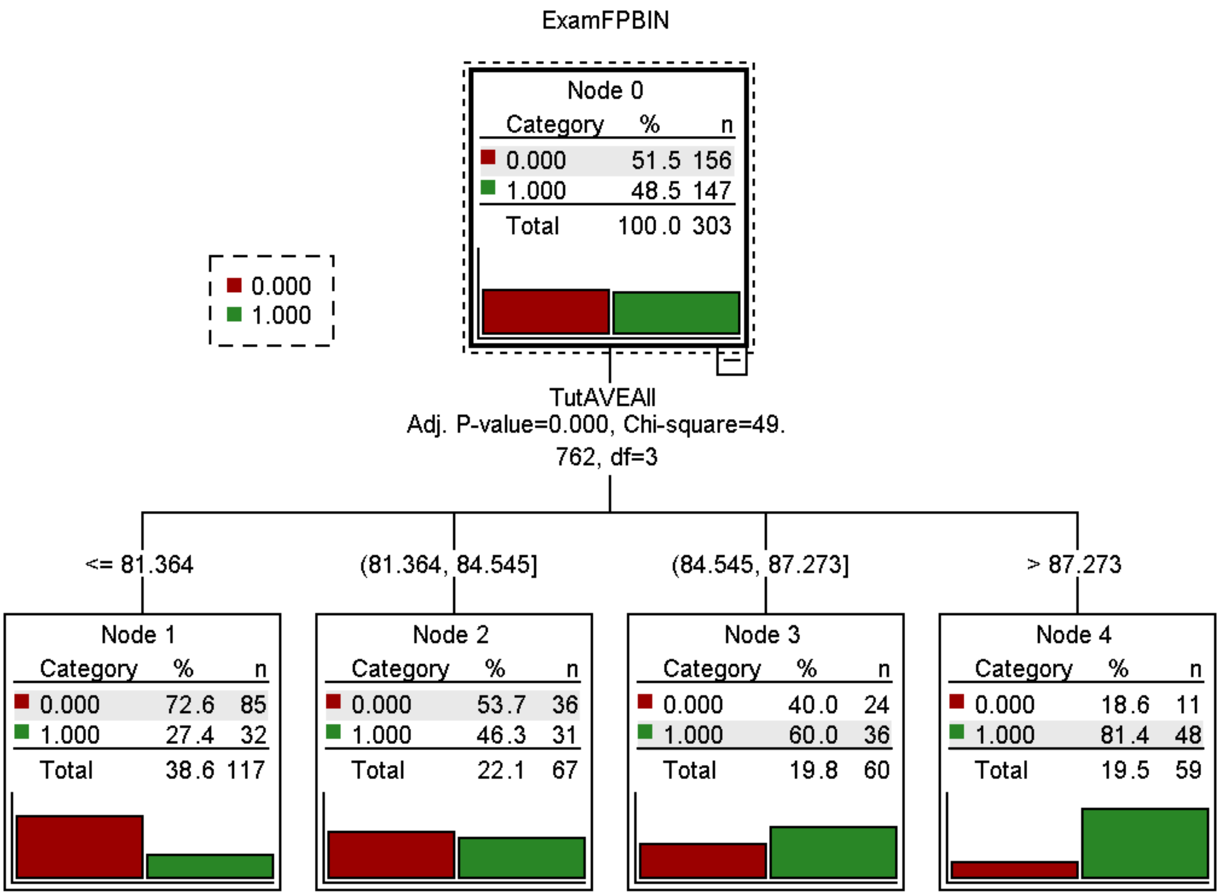

Figure 5: MM analysis with the exam as outcome variable.

The CHAID analysis of the MM group prompted further investigation into the engagement patterns within the group itself. The MM group was divided into students that passed and students that failed the exam; and an ANOVA analysis was done to investigate differences between these two groups, similar to the analysis for the first research question. The ANOVA was performed using the average scores per group (MM-F or MM-P) for each learning opportunity for period one and two (Figure 1). Table 2 lists the three compulsory and two voluntary activities with a statistical analysis of the scores for these activities by the two groups within the MM subgroup for periods one and two.

Table 2: Engagement with learning opportunities between groups within the MM

		Activities before semester test 1 (period 1)				Activities between semester test 1 and 2 (period 2)			
		MM fail exam (MM-F)	MM pass exam (MM-P)	Between group significance	Eta squared	MM fail exam (MM-F)	MM pass exam (MM-P)	Between group significance	Eta squared
Compulsory activities	Peer-led tutorial classes (Average %)	80% (SD=9%)	87% (SD=5%)	0.001	0.145	75% (SD=12%)	77% (SD=12%)	0.144	0.007
	Connect Online quiz (Average %)	67% (SD=26%)	79% (SD=18%)	0.001	0.058	62% (SD=25%)	73% SD=22%)	0.001	0.043
	Participation in class (total count)	8.7 (SD=1.5)	9.2 (SD=1.2)	0.001	0.024	6.7 (SD=1.5)	7.1 (SD=1.4)	0.10	0.022
Voluntary activities	Learnsmart (Average %)	19% (SD=30%)	35% (SD=36%)	0.007	0.056	9% (SD=22%)	17% SD=30%)	0.004	0.027
	Virtual classroom (total count)	3.0 (SD=2.3)	2.5 (SD=1.9)	0.340	0.016	0.26 (SD=0.86)	0.33 (SD=0.84)	0.431	0.002
		Semester test 1				Semester test 2			
	Summative assessment marks	29.7% (SD=8.6%)	43.0% (SD=10.4%)	0.001	0.329	36.6% (SD=7.7%)	47.8% (SD=7.7%)	0.001	0.344

In period one, the scores for tutorials, Connect quizzes, participation in class and Learnsmart were significantly different between the MM group that failed the exam (MM-F) and the MM group that passed the exam (MM-P). The effect sizes for Connect quizzes and Learnsmart were $\eta^2 = 0.058$ and $\eta^2 = 0.056$ respectively, indicating a medium effect. Tutorial classes had a large effect size $\eta^2=0.145$ and class participation had a small effect size $\eta^2=0.024$. In period two, class participation and tutorial participation were not significantly different at the $p=0.05$ level. The effect size for tutorial classes decreased to η^2=0.007. There was a significant difference in performance in Learnsmart (p=0.004) with a medium effect size of η^2=0.027. The whole of the MM group shifted towards the at-risk as shown in Table 1 and this shift can also be seen in Table 2. The CHAID analysis for the MM with semester test 1 as outcome variable (Figure 4) showed that performance in tutorials is the most important predictor of success for the MM students. We note two results for the MM group. Firstly, the effect size of the Learnsmart assignments were larger in the MM analysis (η^2=0.056 and η^2=0.027) than for the analysis of the whole group, indicating that Learnsmart might have a positive impact on the MM if implemented differently. This is a significant finding that confirms the value of using a stratified sample because the contribution of Learnsmart to differentiate between students that passed and students that failed would have been obscured otherwise. Secondly, in time period 2 we see that the difference in engagement in peer-led tutorial classes and participation in the theory classes between the MM-F and MM-P were not significant at the 5% level anymore. During period 2, students are challenged by the workload. Lecturers could counteract the potential overload by a strategic choice of the learning opportunities to avoid overload.

DISCUSSION

In this section, the results will be presented and discussed in relation to findings reported elsewhere in the literature. The results of the analysis revealed that on average, the at-risk students attended and participated in tutorial classes less than the MM and LTP students, this was also true for the theoretical classes. The results of a meta-analysis by Credé, Roch, and Kieszczynka (2010) show that class attendance correlates with performance within individual courses and overall GPA and that this association is even stronger in science than in non-science classes. The results of the CHAID analysis agree with the findings of the meta-analysis and the CHAID shows that tutorials, specifically, are the activity that contribute the most to academic performance in the course (tutorials are also face-to-face classes). The results of Kooker (1976) have indicated that class attendance, in this case compulsory tutorial attendance, might be disproportionately beneficial to lower performing students, which supports the decision to make tutorial attendance compulsory for this first-year course. In addition, the tutorial and theory classes serve multiple purposes in facilitating the seven principles of good undergraduate education (Chickering & Gamson, 1999), such as promoting reciprocity and promoting cooperation among students by incorporating peer learning (Lasry et al., 2008). The use of clickers in the class also facilitates prompt feedback and contact between lecturers and students. The tutorial classes were also used to explicitly communicate the expectations of the course and to promote time on task. Tutorial classes are human resource and cost intensive practices but, as shown in these results, an essential component of the blended learning course. Careful consideration should be given as to the necessity for making the tutorial classes compulsory for the likely-to-pass students. It might be possible to waive this requirement for these students after the first summative assessment on condition of good performance. This could potentially alleviate some of the human resources requirements of the tutorial classes and provide tutors and lecturers with more capacity for at-risk students.

Knowing what you do not know focuses your learning (Chickering & Ehrmann, 1996) and online testing such as the Connect quizzes and the Learnsmart assignments provided students with prompt feedback on a regular basis. Gikandi et al., (2011) showed in a review article that effective online formative assessment offers learners opportunities for interactivity and formative feedback that engages them with valuable learning experiences. Their findings, however, did not show correlation with improvement in marks, although the results of Petrović, Tralić, and Predrag, (2015) showed that online self-assessment (online quizzes) are beneficial for learning outcomes. In the CHAID analysis, Connect assignments were shown to be predictors of success in the exam and first summative assessment (Figure 3) for the entire group. Pre-class reading and completion of Learnsmart assignments were not indicated as an important predictor of success in the CHAID analysis, but it should be noted that there was still a significant difference in performance in this activity between the at-risk and LTP group (Table 1) and between the two groups in the MM analysis (Table 2). The effect size for the significant difference for Learnsmart was also medium in period one, indicating that although performance in this online activity was low it may contribute significantly to the success of the MM students. Both Gross et al., (2015) and Lieu et al., (2017) showed that pre-class preparation can increase student performance, which was the intention with the Learnsmart assignments. Based on the potential benefit that pre-reading and assessment exercises such as Learnsmart may have for all students, especially the MM, we conclude that the course design could be modified to implement it in a more constructive manner. A flipped classroom approach with Learnsmart as a compulsory pre-reading activity may be especially valuable for the MM. However, course overload should be avoided and perhaps, reducing face-to-face classes could be implemented to provide time for the pre-reading activity.

The benefits and uses of virtual classrooms have been described for distance and fully-online education where it is mostly used as formal spaces where students and lecturers can "meet" in order to provide a platform for discussion. It is not usually used as a formal lecture system in blended learning (Hofmann, 2017) but is rather worked into the blend when some students are unable to attend at physical class locations. No recent studies on the effectiveness of this teaching modality could be found to relate to our results.

The research indicates that students do not engage with voluntary activities, possibly due to overload. When adopting blended learning, lecturers run the risk of simply adding online components to the courses without consideration of the additional time that these activities add to the workload of the students. It is thus important to evaluate the course in terms of notional hours and adjust the activities within the blended learning design accordingly.

The findings of this study validated blended course design by showing that the two most important predictors of student performance were complementary to each other in terms of modality and purpose: class tutorials cater strongly for concept development through social learning, whereas Connect quizzes enable individual students to commit concepts to long-term memory through drill and practice.

CONCLUSIONS AND IMPLICATIONS FOR COURSE DESIGN

The overall aim of this paper was to interrogate the learning design of the blended learning environment of a first-year biology course. In particular, we wanted to determine which activities contribute most to the success of the MM students (RQ2). As expected, small-groups of face-to-face tutorials were the learning opportunity that contributed most to the success the students for *all three groups* and specifically for the MM. In addition, Connect quizzes also contributed to the success of the students, especially those in the lower performing groups. Engagement with voluntary activities was low overall. However, performance on the Learnsmart assignments for the two subgroups of the MM group were significantly different in both periods with small to medium effect size, indicating that Learnsmart might have a positive impact on the MM if implemented differently. Even within the MM subgroup, students that failed engaged with the resources less than MM students that passed. In addition, the engagement of all students with learning opportunities decreased in period 2 as compared to period 1. We conclude that lecturers have to be mindful of overload, especially for the MM and at risk-students. Given the potential benefit of Learnsmart we propose that it be used as a compulsory pre-reading exercise and that face-to-face class time be reduced to provide time for this activity.

Based on the findings, we make the following recommendations for the design of a blended learning course for first-year biology that is both effective and efficient.

- Ensure that online activities complement face-to-face activities where each make a unique contribution to learning.
- The format of large, face-to-face classes (theory classes) could be adjusted to resemble the smaller face-to-face tutorials classes.
- Contact time for large, face-to-face classes could be reduced to provide students with more time for other activities such as pre-reading.

- Tutorial classes should be made compulsory for lower performing students while this obligation could be waived for well performing students after the first summative assessment.
- Regular, online formative assessment, with timely feedback, should form an integral part of the blended learning course.
- Pre-reading assignments before theory classes, could be considered as a compulsory activity.
- The course design should be carefully considered to avoid potential work overload so as to ensure the persistent engagement of all groups.
- Enrichment opportunities in the form of virtual classrooms could be provided for LTP.

In conclusion, many studies have attempted to interrogate the implications of introducing blended learning strategies, usually as a response to course redesign. This study contributes to that body of knowledge in three ways; firstly, this study interrogated the contribution of all learning opportunities to student success using CHAID analysis. This is a relatively easy method of investigating course design, which enables informed decision-making about optimal combinations of learning opportunities. Secondly, the holistic evaluation of the course validated the blended course design by demonstrating the essential and complementary contributions of face-to-face and virtual learning opportunities to student performance. Lastly, the study demonstrated the value of studying student engagement in a course by stratifying the data into three distinct performance groups, making it possible to design a course that will benefit the largest group of students.

CHAPTER 4: CONCLUSION, RECOMMENDATIONS AND FUTURE WORK

INTRODUCTION

The aim of this study was to investigate, in a holistic manner, a large first-year blended learning course to generate useful information about successful learning strategies and the effectiveness of the different activities in the blend to inform course design and student advising. The study also sought to explore the use of the concept of the MM to optimize the blend and to improve academic advising for the largest group of students. Holistic investigations of blended learning courses have not been abundant and the concept of the MM has not been applied in the context of a single course. Firstly, this study aimed to identify the MM using data readily available at the start of the academic year. Subsequently, an investigation was conducted to identify the learning strategies associated with success to inform possible interventions aimed at the MM and at-risk students. The effectiveness of the blended learning course, with an emphasis on the MM, was investigated. The broad aims were served by posing the following research questions:

In chapter 2 the following research questions were addressed:

> RQ1. Which pre-entry characteristics differentiate effectively between students who are likely-to-pass (LTP), borderline students and students at-risk of failing?
>
> RQ2. Which learning strategies in first-year biology are associated with good academic performance?

The overall aim of this study was to evaluate the effectiveness of the blended learning environment. In chapter 3, this was achieved by dealing with the following research questions:

RQ 1. What are the differences between the likely-to-pass, borderline and at-risk groups of students in their engagement with learning opportunities?

RQ 2. Which of the activities in the blended learning environment are associated most strongly with success for the borderline students?

This chapter provides an overview of the main theories that formed the foundation of the study followed by a synthesis of the results with respect to the individual research questions. The chapter also discusses the implications of these results and identifies recommendations that emanate from this study. Figure 1 provides an overview of the flow of data-analysis leading to a point where data-driven decision making about course design and student advising can take place. This chapter also gives an overview of the limitations of this study and discusses the contribution of the study to the field of research.

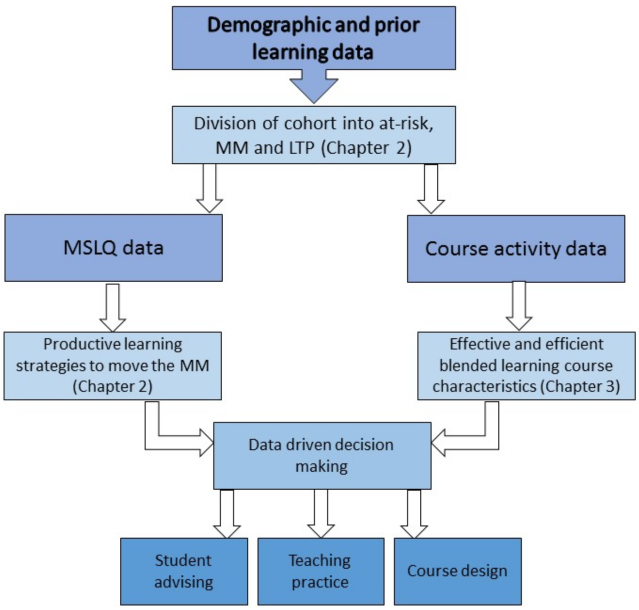

Figure 1: Flow of data-analysis and main outcomes of the study.

The theoretical frameworks for this study provided the conceptual basis for the interpretation of the data to address issues of student success, especially those of the MM. Self-regulated learning is a theory that describes effective strategies that learners apply during learning. From the literature we know that most successful leaners are skilful self-regulators. SRL as operationalized in the MSLQ and the College readiness theory (Conley, 2007a) provided the conceptual framework to pinpoint student behaviours associated with success in MLB 111. In addition to the strategies described for successful students (Chapter 2) a profile can be developed for the MM students. The findings reveal that they display behaviours similar to the at-risk students which should ideally be avoided. There are also instances where the MM report the same learning strategies as the LTP students and these strategies should be encouraged. The MM seemed to have some of the cognitive and metacognitive skills required for success in place. For example, the MM students performed better on the items related to rehearsal and reported that they memorise key words and repeatedly studied class notes. They also scored significantly higher than the at-risk students in two of the items in the metacognitive self-regulation subscale and seemed to be able to set goals and sort out confusion in a timely manner. However, identification of core learning material seems to be a problem for the MM students. The MM students seem to lack elaboration skills such as relating ideas to other courses or to other course activities. The resource management strategies (Pintrich et al, 1991) and academic behaviours as described by Conley (2007) are closely related and refer to amongst others, study skills and the successful utilization of the resources available. In this subscale of the MSLQ the MM and LTP responded differently to quite a few items. MM should be encouraged to persist when they lose interest in the content or when they find the work difficult. The MM should also be encouraged to work with other students to complete course assignments.

Self-regulated learning and academic behaviours are student centred theories that describe the skills students must possess to be successful, however not all responsibility for successful learning rests with the students. Institutions, more specifically in this study, the lecturers must take responsibility to create enabling environments for students to encourage productive student behaviours while discouraging unsuccessful learning strategies. The theory of effective pedagogical practices (Chickering and Gamson, 1987; Chickering and Ehrmann, 1996) formed the foundation for analyzing the course structure in terms of effectiveness and efficiency. The theory served this study well to validate the blended course design. Aside from the seven principles as set out in the theory, lecturers must also aim to instil critical SRL skills and academic behaviours linked to success. For instance, the demonstration of elaboration techniques to encourage deep learning or the structuring of courses to include peer learning could be beneficial to the students. If lecturers know which skills to purposefully include in the teaching and course design, many students especially the MM will benefit. Stressing the importance of time management to allow time for rehearsal or intentionally including motivational components into face-to-face lectures could positively influence students. In addition, the intentional teaching of learning strategies, integrated into an effective and efficient course structure should provide students with an enabling environment to foster successful learning. The results and recommendations that emanated from this study can inform course design and student advising to create an environment where students could be successful.

SYNTHESIS OF THE RESULTS

Conclusions from previous chapters

The results that emanated from this research are discussed and summarized in specific chapters as follows: chapter 2: 'Learning strategies for first-year biology: Towards moving the "murky middle"' and chapter 3: 'Investigating the effectiveness of a blended first-year biology course'. This section synthesizes the results to meet the overall research aim of the study as stated in chapter 1. The study had the overall aim of generating actionable information on productive learning strategies and academic provisioning (course design). The information generated in the research could be used to inform academic advising, course design and teaching practice. In short, the main findings and implications related to the research questions are as follows:

RQ1. Which pre-entry characteristics differentiate effectively between students that are likely-to-pass (LTP), the murky middle and students at-risk of failing? (chapter 2)

> **Results:** It was shown that Grade 12 Physical Sciences marks are the most powerful predictor that differentiates effectively between the three groups of students and that the MM students are those within the performance band of 72% to 81% for Physical Sciences in grade 12. The prediction of success for the subgroups of students after categorization holds true in the medium term (two years). The MM students are likely to fail at least one subject per year and the at-risk students are likely to fail two courses per year.
>
> **Implication:** Identification of the MM students early in their academic careers, in conjunction with well-designed interventions may help the MM to increase their chances of success. Interventions could take the form of student advising or training in learning strategies. University admissions committees should reconsider the admission of students with a Physical Sciences mark below 70% to mainstream programmes. They should preferably be admitted to academic development programs where extensive academic and psychosocial support is provided.

RQ2. Which learning strategies in first-year biology are associated more strongly with good performance than with marginal or poor performance? (chapter 2)

> **Results:** A list of seven learning strategies associated with success was generated that could be incorporated into student advising as part of soft skills training. Metacognitive self-regulation, rehearsal, and effort regulation were the subscales that differentiated most convincingly between the groups. In addition, the ability to relate course material to other courses (elaboration) and the ability to manage the resources well were linked to good performance. One scale in which the MM clearly tended more toward the at-risk group was effort regulation; this was the learning strategy for which intervention could make a meaningful contribution toward the prospect of success for the MM.

Implications: Lecturers could adjust their teaching practice to incorporate and demonstrate SRL skills during lectures. Professional development courses for lecturing staff to teach them how to demonstrate and promote productive learning strategies and student behavior, such as rehearsal, organization, peer learning and metacognitive self-regulation could be developed. In conjunction with the professional development of lecturers, the training of faculty student advisors to teach learning strategies may be beneficial to students. These include learning strategies, such as time management, metacognitive self-regulation and elaboration. In addition, the tutors that facilitate the peer-led tutorials could be trained to reinforce the skills taught by lecturers and student advisors.

RQ 1. What are the differences in the engagement with learning opportunities by the likely-to-pass, murky middle and at-risk groups of students? (Chapter 3)

Results: An association was found between engagement and performance in compulsory activities. The LTP students participated more and performed better than the MM, who in turn participated in more activities than the at-risk students. The participation of at-risk and MM students in compulsory learning opportunities declined during the semester. The engagement in optional activities was low overall.

Implications: The reason for the decline in engagement in compulsory activities is likely to be complex and varied, but there are two possible causes within the sphere of influence of lecturers and advisors that deserve attention, namely course design and student behavior. Careful consideration should be given to course design to avoid overload, making sure that every learning opportunity in the course design is essential in terms of the contribution that it makes to the principles of good undergraduate education.

In addition, the course design can be addressed by considering the credit load and creating a credit map for the course. In this way, lecturers can determine if the workload falls within the notional hours allocated to the course. As students do not seem to engage meaningfully in optional activities, careful consideration should be given to the purpose of these activities. The presentation of the optional activities may be adjusted if research shows that it could have a positive impact on student learning. Student behavior can be addressed by actively advocating the advantages of attending face-to-face classes or allocating credits for class attendance. Monitoring of class attendance by faculty student advisors and intervention when engagement is not satisfactory may also be of value, especially for the MM group.

RQ 2. Which of the activities in the blended learning environment are associated most strongly with success for the MM? (Chapter 3)

Results: Small face-to-face tutorial classes and online quizzes contributed the most to success by the MM. While participation in pre-reading exercises was low for the whole cohort, evidence was found that it had the potential to contribute to the successes achieved by the members of the MM subgroup who passed the course.

Implications: The research confirmed the value of the blended course design, as there was convincing evidence that both face-to-face classes and online quizzes contributed to student success. Advocating the value of face-to-face classes and online quizzes could motivate students, to engage and persist throughout the semester. Making students aware of the pitfalls of not engaging in course activities and providing incentives for participation have the potential of motivating them to attend face-to-face tutorials and complete online quizzes. As tutorials contribute to the success of the MM specifically, selection of high quality tutors and training of these tutors should be a priority. Faculty student advisors should emphasize the importance of participation in the activities that contribute to success. Providing incentives for pre-reading activities, such as Learnsmart may also contribute positively to the performance of students.

SUMMARY

The first part of the data analysis (Chapter 2) shows that it is possible to categorize the cohort in terms of their prospects for success based on prior learning data alone, and that the categorization holds true in the medium term. Subsequent to the categorization of students, learning strategies and blended course design were analyzed using the MM group as a lens to examine these two facets in detail. The analysis of learning strategies, using the MSLQ, shows that the MM lacked, among other strategies, grit and did not have the same metacognitive self-regulation skills as successful students. The lack of grit was confirmed in the analysis of engagement in learning opportunities (Chapter 3) in which the level of participation in, and performance of activities, such as online quizzes and tutorial classes, declined for the MM after the first summative assessment. The holistic analysis of the blended learning course (Chapter 3) also validated the blended learning design by showing that both the small face-to-face classes and online quizzes contributed to student success. When considering the seven principles of good undergraduate teaching, the practice of using face-to-face classes promotes contact between students and lecturers, encourages active learning and time-on-task opportunities. In addition, it also stimulates reciprocity between students, and enables the communication of high expectations. Online quizzes, on the other hand, promote time-on-task opportunities and allow for prompt feedback. In this way, the lecturers show that they respect diverse ways of learning. In combination, these two core components of the course design serve all the principles of effective instruction.

By combining the findings of chapter two and three, three main areas of interventions can be highlighted, namely teaching practice, course design and student advising. The professional development of lecturers and tutors should incorporate purposeful SRL learning strategies into teaching practice. This may have a positive influence on student learning. Course design plays an important role in student success. Designing a blended learning course to serve the principles of effective instruction may support student learning. When considering course design, lecturers should be aware of the contribution that different activities make toward student success while taking into account the dangers of overloading the courses. Student advising can complement course design and teaching practice by communicating the significance of participation in various activities, promoting the importance of perseverance and by training students in the learning strategies that have been shown to be effective.

LIMITATIONS OF THE STUDY

This research study was exploratory using powerful quantitative techniques to analyze the data. Typically, the drawbacks of a purely quantitative study would be the lack of depth (Gelo, Braakmann, & Benetka, 2008). However, the holistic approach taken in this study attempts to address this problem. The results of this study are not generalizable to all education settings. However, the methodology employed and the concepts generated can be applied in other settings. For example, the methodology used in this research can be transferred to most educational situations since participants were divided into different performance groups, The study showed that the concept of 'the 'murky middle' (MM), first described on a macro level from an analysis of a large dataset of 700 000 students over multiple institutions was also useful as a method of analysis in a single course. The specific factors shown to predict student success by means of the CHAID analysis in this study may not be transferable to other settings. However, using CHAID as a method for prediction and analysis of engagement in educational research shows great potential and could be explored further. The research was conducted on a dataset of one year only, but longitudinal tracking of students in subsequent years was performed to enhance the validity of the findings. Ideally, student success in the medium- to long- term should also be investigated to add to the validity of the inferences made in this study.

RECOMMENDATIONS FOR FURTHER RESEARCH

The subject literature abounds with reports on the factors determining the performance of at-risk students. However, the MM is a relatively unexplored group of students and many avenues for research emanate from this study. Little is known about the characteristics of the MM and the factors that influence their success in the long-term. This research explored the short- to medium- term chances of success for the MM students. However, long-term success prospects have yet to be investigated. Indicators that predict attrition later in the academic careers of the MM is an unexplored area and many avenues for research into the kinds of behavior and motivations that influence these students have been opened for further investigation. Exploration of the factors that affect the throughput rates for these students hold the promise of identifying interventions that may improve success. Studies of the design and impact of such interventions are expected to provide a fruitful opportunity for future research.

This study also explored the learning strategies of successful students within the biology class. It is not known whether the learning strategies that are deemed successful for biology will also be successful for other science-based subjects in subsequent years of study. More research on the successful learning strategies applied in other subjects and the transferability of these strategies is needed. This study did not attempt to address the motivational component of SRL. Research on the factors that affect motivation, especially those factors that affect the murky middle, as conceptualized in the MSLQ, is still needed to improve our understanding of student success in the case of borderline students.

Part of this research investigated the effectiveness of a blended learning course for biology, highlighting those course components which could contribute to success. Investigations into the effectiveness of course design for other science subjects would add valuable insights. To facilitate the redesign of blended courses, professional development courses for lecturers could be instrumental in the design and implementation process. Future research could also include the development of a “learning to learn” course for students to cultivate effective learning strategies and self-regulation skills.

CONTRIBUTIONS OF THE STUDY

The results of this study could contribute to the field in the following ways:

Firstly, unlike studies on student success that focus on at-risk students, this study elaborates on the concept of the MM and attempts to contribute to the research in the field of student success by showing that it is possible to identify the MM early in their academic careers based on prior learning data alone. The MM is a group of students who are not normally flagged as being at-risk early on in their academic careers but who are at-risk of failing later. These students fail on average one course per year. These failures accumulate over time and may result in the student dropping out of their courses for various reasons that have not been documented at this point but are likely to include financial constraints, a too heavy course load or a lack of perseverance. This study also shows that these students represent a group of undergraduates that is large enough to deserve attention since they are roughly equal in number to the at-risk students who may drop out in the first year.

Secondly, the study provides actionable information on the learning strategies of successful students. It categorizes the students into three distinct groups to determine learning strategies that improve chances of success for all students, in particular for the MM.

Thirdly, the study shows that in a blended course design, online quizzes and peer-led tutorial classes contribute the most to student success and specifically to the success of the MM students.

Lastly, CHAID as a method of analysis is not widely used in educational research although it is a robust method with high precision and accuracy. The presentation of the results in tree diagrams is also easy to interpret and implement. This study showed that CHAID could be used effectively for various analyses, such as the division of students into groups and determining the effectiveness of different learning activities.

In general, the results of this study can be used in numerous ways to improve student success, especially in the first year. The implementation of the recommendations may foster the kinds of behavior that could benefit the MM throughout their academic careers to prevent attrition after the first year. The results of the study may also inform changes to the admission criteria for the University of Pretoria, as the results show that students who achieved 72% or below for Physical Sciences in Grade 12 are not adequately prepared for the demands of mainstream programs. Potentially, these students could be channeled into an academic development program to increase their chances of success.

PRACTITIONER'S REFLECTION

I am a Natural Scientist by training, with an MSc degree in Botany. Starting a PhD in science education was a rewarding experience with valuable lessons to learn. As scientists we see teaching as a way to impart knowledge to students. This PhD, aside from the academic knowledge gained, helped me understand that teaching is so much more than knowledge transfer. The process of learning is as much a social activity as it is an individual activity and many role players are involved in the learning process to ultimately secure a successful outcome. During this study I learned that aside from the subject knowledge that we share with the students we also need to teach them other skills that will help them in their careers later on. This experience has made me a better, more reflective teacher.

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APPENDIX A

Modified wording of MSLQ to fit South African Context

Question number	Scale	Modified wording
32	Organization	When I study for this course I make an outline of the material to help me organise my thoughts.
33	Metacognitive self-regulation	During class time I miss important points because I'm thinking of other things. (reverse coded)
34	Peer learning	When studying for this course, I try to explain the material to a classmate or friend.
35	Time management	I study in a place where I can concentrate on my course work.
36	Metacognitive self-regulation	When studying for this course, I make up questions to help focus my reading.
37	Effort regulation	I feel so lazy or bored when I study for this course that I give up before I finish what I planned to do. (reverse coded)
38	Critical thinking	I find myself questioning things I hear or read in this course to decide if I find them convincing.
39	Rehearsal	When I study for this course, I practice saying the material to myself a number of times.
40	Help seeking	Even if I have trouble understanding the material in this course, I try to do the work on my own, without help from anyone. (reverse coded)
41	Metacognitive self-regulation	When I become confused about something I'm reading for this course, I go back and try to figure it out.
42	Organization	When I study for this course, I go through the content material and try to find the most important ideas.
43	Time management	I make good use of my study time for this course.

44	Metacognitive self-regulation	If course content is difficult to understand, I change the way I study the material.
45	Peer learning	I try to work with other students from this course to complete the course assignments.
46	Rehearsal	When studying for this course, I work through my class notes and the course materials a number of times.
47	Critical thinking	When a theory, interpretation, or conclusion is presented in course or in the course materials, I try to decide if there is good supporting evidence.
48	Effort regulation	I work hard to do well in this course even if I don't like what we are doing.
49	Organization	I make simple charts, diagrams, or tables to help me organise course material.
50	Peer learning	When studying for this course, I set aside time to discuss course material with other students from the class.
51	Critical thinking	I treat the course material as a starting point and try to develop my own ideas about it.
52	Time management	I find it hard to stick to a study schedule. (reverse coded)
53	Elaboration	When I study for this course, I make use of information from different sources, such as lectures, course material, and discussions.
54	Metacognitive self-regulation	Before I study new course material thoroughly, I page through it to see how it is organised.
55	Metacognitive self-regulation	I ask myself questions to make sure I understand the material I have been studying in this course.
56	Metacognitive self-regulation	I try to change the way I study in order to fit the course requirements.
57	Metacognitive self-regulation	I find that I study for this course but don't know what it is all about. (reverse coded)
58	Help seeking	I ask the lecturer and tutor to clarify concepts I don't understand well.

59	Rehearsal	I memorise key words to remind myself of important concepts in this course.
60	Effort regulation	When course work is difficult, I either give up or only study the easy parts. (reverse coded)
61	Metacognitive self-regulation	I determine what I am supposed to learn from the material before I start studying.
62	Elaboration	I try to relate ideas in this subject to those in other courses whenever possible.
63	Organization	When I study for this course, I go over my class notes and make an outline of important concepts.
64	Elaboration	When studying for this course, I try to relate the material to what I already know.
65	Time management	I have a regular place set aside for studying.
66	Critical thinking	I try to play around with ideas of my own related to what I am learning in this course.
67	Elaboration	When I study for this course, I write brief summaries of the main ideas from the textbook and my class notes.
68	Help seeking	When I can't understand the material in this course, I ask a tutor in this course for help.
69	Elaboration	I try to understand the material in this course by making connections between the course materials and the concepts from the lectures.
70	Time management	I make sure that I keep up with the assigned work for this course.
71	Critical thinking	Whenever I find a claim or conclusion in this course, I think about possible alternatives.
72	Rehearsal	I make lists of important items for this course and memorize the lists.
73	Time management	I attend all classes for this course.
74	Effort regulation	Even when course materials are boring and uninteresting, I manage to keep working until I finish.

75	Help seeking	I try to identify students in this course whom I can ask for help if necessary.
76	Metacognitive self-regulation	When studying for this course I try to determine which concepts I don't understand well.
77	Time management	I find that I don't spend much time on this course because of other activities.(reverse coded)
78	Metacognitive self-regulation	When I study for this course, I set goals for myself in order to direct my activities in each study session.
79	Metacognitive self-regulation	If I get confused taking notes in this course, I make sure I sort it out afterwards.
80	Time management	I rarely find time to review my notes or course material before a test. (reverse coded)
81	Elaboration	I try to apply ideas from course material in other course activities such as lectures and discussions.

APPENDIX B

Summary of subscale ANOVA analysis with mean and standard deviation.

Scale	Group	Mean	Standard Deviation	Significance of ANOVA	Tukey *post hoc* (Group 1 & 2)	Tukey *post hoc* (Group 2 & 3)
Rehearsal (4 items)	1	7.1	2.59	0.005	0.037	0.840
	2	7.8	2.38			
	3	7.9	2.39			
Organisation (4 items)	1	7.7	1.91	0.053	0.425	0.494
	2	7.9	1.93			
	3	8.2	1.87			
Metacognitive self-regulation (12 items)	1	24.9	4.22	0.002	0.165	0.216
	2	25.7	4.00			
	3	26.5	3.82			
Elaboration (6 items)	1	12.7	3.17	0.013	0.880	0.065
	2	12.9	3.19			
	3	13.7	2.98			
Critical thinking (5 items)	1	8.9	2.75	0.021	0.314	0.399
	2	9.3	2.78			
	3	9.7	2.70			
Time and study environment (8 items)	1	21.1	3.56	0.013	0.463	0.207
	2	21.6	3.77			
	3	22.3	3.33			
Effort regulation (4 items)	1	10.4	1.99	0.000	0.145	**0.010**
	2	10.8	2.20			
	3	11.5	1.89			
Peer learning (3 items)	1	6.3	1.85	0.015	0.311	0.350
	2	6.6	1.67			
	3	6.8	1.64			

APPENDIX C

Ethical clearance and consent form

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

Faculty of Natural and Agricultural Sciences
Ethics Committee

E-mail: ethics.nas@up.ac.za

Date: 02/07/2016

ETHICS SUBMISSION: LETTER OF APPROVAL

Prof M Potgieter
Faculty of Natural and Agricultural Sciences
University of Pretoria

Reference number: EC160510 028R
Project title: Self-regulated learning in first year Biology

Dear Prof Potgieter,

We are pleased to inform you that your submission conforms to the requirements of the Faculty of Natural and Agricultural Sciences Ethics committee on the condition that the only participation of the subjects is as described in the proposal narrative.

Please note that you are required to submit annual progress reports (no later than two months after the anniversary of this approval) until the project is completed. Completion will be when the data has been analysed and documented in a postgraduate student's thesis or dissertation, or in a paper or a report for publication. The progress report document is accessible of the NAS faculty's website: Research/Ethics Committee.

If you wish to submit an amendment to the application, you can also obtain the amendment form on the NAS faculty's website: Research/Ethics Committee.

The digital archiving of data is a requirement of the University of Pretoria. The data should be accessible in the event of an enquiry or further analysis of the data.

Yours sincerely,

Chairperson: NAS Ethics Committee

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

Dear Student

INFORMED CONSENT

Motivated Strategies for Learning Questionnaire (MSLQ)

The University of Pretoria strives to improve the teaching and learning for students by doing research projects on various aspects of student study skills and learning strategies.

As part of a pilot project the MLB 111 class will be required to do the MSLQ. This survey is designed to measure students' use of learning and study strategies and methods within a course. This is a self-scoring, self-interpreting inventory that a student can use to measure aspects of learning and improve on problem areas.

By participating in the MSLQ, you confirm that you are aware of the following information:

- There are no known risks in participating in this study.
- There will be no costs for participating.
- Participation will not affect your marks in any way.
- You may decline to answer any question and you have the right to withdraw from participation at any time. However, your participation will be greatly appreciated since the findings of this study are expected to benefit students who enrol in the programme in future.
- All information gathered will be handled with the strictest confidence and no personal information will be made public.
- Should the data be used for research and publication purposes you will remain anonymous at all times.

Should you have any queries regarding this process please do not hesitate to contact Mrs. A Kritzinger at Angelique.kritzinger@up.ac.za

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Appendix D

Published article