Contributions to mathematical ranking models in learning analytics

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Preface

This thesis is submitted in an article format, in accordance with the General Academic Rules (A.5.1.1.2) of the North-West University. Seven articles are included in this thesis.

- Van der Merwe, A., J. V. du Toit, and H. A. Kruger. 2016. "Student ranking by means of non-linear mathematical optimization of participation marks". *Lecture Notes in Management Science 8*: 113-119.
- Van der Merwe, A., H. A. Kruger, and J. V. du Toit. 2016. "A mathematical ranking model in learning analytics". *Proceedings of the 16th International Conference on Computational and Mathematical Methods in Science and Engineering.* Rota (Spain): 1525-1535.
- Van der Merwe, A., H. A. Kruger, and J. V. du Toit. 2017. "An early alert feedback system in learning". *International Conference ICT, Society, and Human Beings 2017.* Lisbon (Portugal): 187-191.
- Van der Merwe, A., H. A. Kruger, and J. V. du Toit. 2018. "Mathematical modelling for academic performance status reports in learning analytics". *ORiON 34*(1): 31-64.
- Van der Merwe, A.; J. V. du Toit, and H. A. Kruger. 2018. "Architecture for personalized academic feedback." *2018 WEI International Academic Conference Proceedings*. Vienna (Austria): 94-111.
- Van der Merwe, A., J. V. du Toit, and H. A. Kruger. 2018. "A prescriptive specialized learning management system for academic feedback towards improved learning". *Journal of Computer Science 14*(10): 1329-1340.
- Van der Merwe, A.; J. V. du Toit, and H. A. Kruger. 2018. "An academic progress feedback framework to improve learning at tertiary level". *Africa Education Review* (under review).

The co-authors of the articles in this thesis, Prof H. A. Kruger (Promotor) and Prof J. V. du Toit (Co-promoter), hereby give permission to the candidate, Mrs A. van der Merwe, to include the articles as part of a Ph.D. thesis. The contribution (advisory and supportive) of these co-authors was kept within reasonable limits, thereby enabling the candidate to submit this thesis for examination purposes. This thesis therefore serves as fulfilment of the requirements for the Ph.D. degree in Computer Science within the School of Computer Science and Information Systems in the Faculty of Natural and Agricultural Sciences at the North-West University.

A list of additional conference presentations arising from this study, is available in Appendix A.

Abstract

The emergence and rapid growth of the digital age has had an impact on nearly every aspect of our modern lives. Regarding tertiary education, teaching methods are changing, learning approaches are evolving and programs are becoming more accessible through the development of online learning. Although the obviously expected consequence should be an increased number of graduates and a more highly qualified generation of professionals, the student attrition rate at tertiary institutions has not improved. One of the reasons identified for this phenomenon is the observed academic complacency of enrolled students. Furthermore, many environmental, cultural, personal and psychological factors contribute to poor participation in academic activities. Studies confirm that inefficient feedback on their academic performance leaves students to belatedly realise that they will not be admitted to the final examinations. Learning at tertiary level needs to be improved by acknowledging its mutating character and implementing non-intrusive technology that embraces rather than rejects the unavoidable changes of the digital age.

In this study, an academic performance feedback framework that utilises mathematical modelling techniques to facilitate an enhanced feedback approach for improved learning is proposed and evaluated. Comprehensive feedback contains information that reports on current academic performance (feed backwards) and is prescriptive in that it generates individualised improvement goals (feed upwards) and interim targets for reaching the ultimate improvement goals (feed forwards). It furthermore adheres to specific criteria to affect positive change.

The literature study provides background on the current state of feedback in the educational environment, the definition and usefulness of learning analytics, mathematical modelling and how it can be applied to supplement learning analytics techniques, and frameworks. The attributes of feedback to be effective towards improved learning, were identified for incorporation into the framework. Learning analytics furthermore, presents valuable tools for managing and monitoring student participation in academic activities. However, it lacks some functionality in terms of calculating the academic performance of large groups of students and creating comprehensive feedback.

Several different mathematical ranking modelling approaches were employed to first emulate, and then improve on existing academic performance calculation techniques. These approaches included various non-linear programming models, a data envelopment analysis model, the analytic hierarchy process, linear programming models and a decision tree approach. In order to generate comprehensive academic performance status reports that conform to the criteria for effective feedback, algorithms that implement a linear programming model, a non-linear programming model and a decision tree approach, were developed.

A computerised demonstrator that incorporated the developed algorithms was created so as to establish the architecture required for use. The program was ultimately implemented and deployed in a specialised learning management system (SLMS), supplementing existing academic performance feedback. The SLMS implemented the improved mathematical models to dynamically create student academic performance feedback and was deployed parallel to an existing feedback approach, in a tertiary education environment. Evaluation of the SLMS was performed in a field test that provided some valuable insights to be considered for development of an academic performance feedback framework in tertiary education.

Accordingly, a model-based framework was developed for academic performance feedback. The framework consisted of concepts and models, with a decision support system included as a learning analytics supplemental tool. The framework was employed and evaluated and yielded a very high degree of student satisfaction, improved program management by lecturers and institutions, accurate decision support in learning analytics and enhanced communication between institutions and students. Mass deployment of the framework will contribute to tertiary education by facilitating improved techniques to create effective and comprehensive academic performance feedback. Students will consequently be better equipped to make informed decisions regarding their conduct towards academic progress.

Keywords

Academic performance feedback; feedback framework; improved learning; learning analytics; mathematical modelling; prescriptive analytics; specialised learning management system; student retention; tertiary education.

Declaration

This is to declare that I, Elma van Wyk, *translator, language editor and interpreter*, member no. 1002646 of the **South African Translators' Institute** have language edited the abstract, as well as Chapters 1, 2 and 9 drawn from *seven articles* of research entitled

CONTRIBUTIONS TO MATHEMATICAL RANKING MODELS IN LEARNING ANALYTICS

in the Thesis submitted in fulfilment of the requirements for the degree *Doctor of Philosophy in Computer Science* at the North-West University.

Signed: Date: 3 November 2018

Elma van Wyk (ms)
SATI member no. 1002646

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List of acronyms

AHP	Analytic Hierarchy Process
APA	American Psychological Association
BFU	Backwards, Forwards and Upwards
CMMSE	Conference on Mathematical Methods in Science and Engineering
CS	Computer Science
DD	Domain Design
DE	Decision Evaluation
DEA	Data Envelopment Analysis
DMIF	Distributed Model Integration Framework
DMU	Decision Making Unit
DSS	Decision Support System
E2Coach	Expert Electronic Coach
EL	Extraneous cognitive Load
EOU	Ease of Use
ER	Efficiency of Ranking
GPS	Grade Performance System
IFIP	Information Curriculum Framework of the International Federation for Information Processing
IL	Intrinsic cognitive Load
ILP-GP	Integral Linear Programming with Grey Possibility
IoE	Internet of Everything
IPA	Interpret, Process and Act
IQ	Information Quality
IR	Information Relevance
LA	Learning Analytics
LAS	Learning Analytics System
LMS	Learning Management System
MC	Mechanical Computations
MVP	Motivation, Volition and Performance
NB	Net Benefit
NGSS	Next Generation Science Standards
NLP	Non-Linear Program
NRF	National Research Foundation
ORSSA	Operations Research Society of South Africa
p-mark	Participation mark
PACE	Progress And Course Engagement
PSR	Performance Status Report

PU	Perceived Usefulness
SaaS	Software-as-a-Service
SARA	Student Advice Recommender Agent
SQ	System Quality
SCL	Student-Centred Learning
SLMS	Specialised Learning Management System
SP	Student Privacy
TC	Timely and Consistently
UA	User Advice
US	User Satisfaction

Chapter 1

Problem statement and research design

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1.1. Introduction

Chapter 1 purposes to introduce the problem statement by contextualising the research and explaining its design and the methodology utilised, to guide the reader through this study. Towards this goal, the following sections will follow:

- Research environment;
- Problem statement and primary research question;
- Secondary research questions;
- Research aim and objectives;
- Research paradigm, design and methodology;
- Thesis layout; and
- Contributions of this study.

The thesis is submitted in article format with one or more articles forming part of subsequent chapters. Therefore, all chapters contain their own reference sections.

1.2. Research environment

Although technological advances and the resulting employment of novel software applications in education have caused an increase in the number of student enrolments (Zielezinski, 2017), the dropout rates remain high (Karabo & Natal, 2013). Several researchers have studied this phenomena in the effort to determine the reasons for student attrition (Aljohani, 2016; Deen & Leonard, 2015; Dewberry & Jackson, 2018; Hurford, Ivy, Winters, & Eckstein, 2017). Furthermore, Aljohani (2016) argued that such studies seem limited in terms of generalisability in that they were performed within specific institutions and cultures. These factors themselves

can contribute to student dropouts (Karabo & Natal, 2013). There are several options on how to approach this problem. For example, institutions can research and better understand a specific problem or they can implement intervention measures applicable in any tertiary educational environment. One such measure is providing students with consistent and complete feedback on their academic progress at regular intervals, throughout the course of a module. For feedback to be effective, it must provide comprehensive information on how a student is currently performing, which goal(s) can be pursued to improve on current performance and specific actions that will lead towards reaching the goal(s) (Hattie & Timperley, 2007). These requirements are referred to as feeding backwards, upwards and forwards. Generally, existing academic performance feedback methods applied in tertiary education lack the latter two of these requirements (Thomas & Oliver, 2017). Comprehensive feedback will keep students informed on their performance from an early stage in a program, improving motivation and eliciting them to make changes towards improvement if required.

With the emergence of computing technology and its subsequent rapid and dynamic evolution, the teaching-learning environment has started to evolve (Newman & Scurry, 2015). Sophisticated software applications are progressively being used as teaching aids, changing the conventional classroom scene. Consequently, novel trends are transpiring in pedagogy and being implemented in traditional education, as well as in online learning. The introduction of new educational trends not only leads to substantially increased numbers of enrolled students, but also triggers the development of innovative methods to collect, analyse and report the data subsequently generated. Such development has seen traditional learning models in instruction gradually being replaced with modern trends like blended- and online learning (Reyes, 2015), flipped classroom (Yelamarthi, Drake, & Prewett, 2016) and problem-based methods (Martins, Sampaio, Cordeiro, & Viana, 2018). These trends necessitate the use of learning management systems, sites on social media networks and the incorporation of learning analytics. Learning analytics is defined as the real-time collection of data which are so large that conventional collection- and processing methods have proved inadequate (Sin & Muthu, 2015). It also encompasses the use of analyses on data to make multi-criteria decisions, to report, and to inform in the educational system (Fiaidhi, 2014). While blended learning methods in education are gaining popularity and being implemented more frequently, the process of accurately measuring and informing on student progress is proving to be somewhat of a challenge (Ai, 2017; Koban, Schneider, Ashar, Andrews-Hanna, & Landy, 2017).

Lecturers have to engage in general teaching activities and have the responsibility to keep students informed of their academic performance. Furthermore, a higher level of student engagement in learning, can lead to greater academic achievement (Finn & Zimmer, 2012). Studies also show that the implementation of self-monitoring initiatives in mainstream classrooms results in increased student motivation and improved academic achievement (Rock, 2005; Wells, Sheehey, & Sheehey, 2017). Students with academic motivation exhibit a sense of self-management and achieve greater academic success (Di Domenico & Fournier, 2015).

According to Fırat, Kılınç and Yüzer (2017), "*…motivation that initiates and sustains behaviour is one of the most significant components of learning in any environment"* (p. 63). Academic motivation is an enactment of a person's will to attend classes, partake in discussions and endeavour to learn and achieve in their studies (Beck, 2004). Therefore, apart from trying to affect some sort of long-term expectation (future time perspective) within a student, a lecturer can positively influence these factors by establishing an extrinsic motivational initiative in the classroom. An approach proven to contribute to student motivation, is through the use of a student hierarchy or ranking which can *"help students to understand success factors in the major."* (Barker & Garvin-Doxas, 2004, p. 134)

Students are graded on different forms of assessments during the course of a semester and lecturers use those grades to calculate a level of participation for each student in the form of a participation mark. Each lecturer uses a predetermined formula or system during the calculation process, relevant to the mode of delivery for that particular module. Participation marks are used to grant students admission to final examinations. However, time constraints are one of the main causes for lecturers to releasing such marks only at the end of a semester. Students often realise, too late, that they will not be allowed to complete a module. An academic ranking and progress system will enable lecturers to give regular feedback by presenting students with their growing participation marks. Such a ranking system should ideally assist in the timeous and accurate management of student marks (Liu & Cheng, 2005). Systems providing ranking feedback have also been utilised with success in many other fields (Ishizue, Sakamoto, Washizaki, & Fukazawa, 2018; Milošević, Nešić, Poledica, Radojević, & Petrović, 2017). A study by Du Toit (2015) involved the implementation of a computer program used to empirically calculate and regularly inform students of their academic progress during the course of a semester. The overwhelmingly positive feedback of the students revealed that the system did indeed act as an extrinsic motivational initiative. The students preferred being able to compare themselves with the rest of the class and they could see the effect(s) of missing out on certain class activities. One of the major challenges in implementing such systems on a large and growing scale, is the amounts of data that have to be processed manually.

By drawing on research in the field of Operations Research, mathematical programming techniques will be applied in the pursuit of a solution to this problem. Such models are widely used for the purpose of optimising complex and timely calculation processes (Taylor, 2013). Existing systems and models used by lecturers to determine and report on student progress, will be investigated. Mathematical programming models will then be formulated to improve on these existing approaches. The models will be evaluated so as to establish the requirements for an early-alert academic feedback framework. Implementation and subsequent use of such a framework will keep students informed on their academic performance and ranking relative to their peers, assisting them in self-monitoring their progress. It will also allow lecturers to either calculate marks in the conventional way, or present them with pre-calculated statistics on different possible models that can be used for this purpose.

1.3. Problem statement and primary research question

The problem investigated in this study is grounded in literature and experience which revealed that although student enrolment numbers are generally increasing in the digital age, institutions need an advanced student feedback approach that will encourage self-monitoring and motivation towards improved learning. Such an advanced feedback approach should provide information that feeds backwards, forwards and upwards. The primary research question for this study therefore is: *Can a model-based conceptual framework be developed for comprehensive academic performance feedback towards improved learning?*

1.4. Secondary research questions

The primary research question provided in Section 1.3 is supported by five secondary research questions that were formulated to facilitate the activities that ultimately must lead to the achievement of the study's objectives. The secondary research questions are as follows:

- *What is the current state of academic performance feedback in education?*
  An academic feedback framework is needed to improve learning to such an extent that student retention rates at education institutions will increase. This question serves to identify the improvements required to existing feedback systems and describes the tools that can facilitate them.
- *Can mathematical modelling be utilised to facilitate an improved approach for creating comprehensive academic performance status reports?*
  Acceptable mathematical models are to be developed to find improved approaches in creating student performance profiles that provide comprehensive feedback on the academic performance statuses of students. Such models are formulated for calculating academic participation profiles, creating student rankings and developing comprehensive academic performance status reports. Correlation between the resulting model outputs and those obtained from existing performance profiles, constitutes model evaluation.
- *What are the components and composition required for successful implementation of the academic performance status reports generated by the mathematical models?*
  The components that are required for successful implementation of the mathematical models in a computer program are to be determined. Arrangement of the components into an electronic system, is also to be addressed.
- *How can the modelling approach for creating academic performance feedback be implemented to improve learning?*
  Implementation of the established architecture for the academic performance feedback system on a practical platform, such as a specialised learning management system, is the focus of this question.
- *What are the concepts and models required for an effective academic performance feedback framework?*
  In light of the mathematical models, the components and the architecture arrangement required for implementation, the elements (concepts and models) necessary to

develop a framework for effective academic feedback towards improved learning need to be characterised and discussed. In addition, this question extends towards evaluating the developed framework and communicating the results.

1.5. Research aim and objectives

The primary aim of this study is to *propose* an academic performance feedback framework that utilises mathematical modelling techniques to facilitate an enhanced feedback approach for improved learning. To reach this aim, the secondary research questions listed in the previous section, are translated into the following objectives:

- To *conduct* a thorough literature survey of recent research on
  - Academic performance feedback;
  - Learning analytics;
  - Mathematical modelling; and
  - Framework development.
- To *formulate* mathematical programming models for improved approaches towards
  - Calculation of enhanced academic participation profiles of students;
  - Student academic ranking; and
  - Creating comprehensive academic performance status reports.
- To *establish* the architecture required for an electronic demonstrator of the mathematical modelling approach, in the form of a computerised early-alert feedback system.
- To *implement* and *evaluate* the academic performance feedback system as part of a specialised learning management system.
- To *validate* the concepts and models for the improved framework of academic performance feedback, in accordance with the requirements established through achieving the preceding objectives.

1.6. Research paradigm, design and methodology

A research philosophy relates to the source, character and development of knowledge in a project. It describes belief about the manner in which data about a phenomenon is collected, analysed and used (Bajpai, 2011). This study was conducted with pragmatic philosophical foundations with the ontological belief that "*reality is constantly renegotiated, debated, interpreted and therefore the best method to use is the one that solves the problem*" (Patel, 2015, p. 1). Within the context of this study (tertiary education and the digital age), reality is constantly changing. Pragmatism emphasises the link between philosophical matters regarding the nature of knowledge, and the technical matters (elements from the positivistic paradigm) relating to the methods used to generate it. Furthermore, it is a practical and applied research philosophy that enables a researcher to combine qualitative and quantitative techniques in the pursuit of a solution.

1.6.1. Research design

The nature of exploratory research is to explore certain aspects in a research area, while conclusive research is applied to generate solutions that are useful in decision-making and provides a way to verify the findings of exploratory studies (Dudovskiy, 2011). The research design for this study is a combination of exploratory and conclusive research due to the dual purpose of generating and verifying insights, and providing decision support.

An inductive research approach was followed to generate implications from data sets so that a theory can be developed from the patterns and relationships identified. It is based on learning (theory) from experience (premises) and also building upon existing theories. An action design research methodology was followed which is the union of action research and design science research. The purpose of action research is to "*develop scientific knowledge while simultaneously acting to solve real problems*" (Collato, Dresch, Lacerda, & Bentz, 2018, p. 239) and is implemented within an organisation, where the relationships exist between the researcher and study participants. Design science research on the other hand, "*address problem-solving oriented researches, converging in this aspect with the objectives of action research*" (Collato, *et al.*, 2018, p. 239) and may demand collaboration to effect change. Action design research is a convergence of the two methods and aims to solve problems that require actions (or interventions) through the design and development of an artefact that implements them. The goal, therefore, is problem-solving and improving knowledge by performing activities to design the artefact, and intervening in the organisation so that the artefact can be evaluated at the same time (Sein, Henfridsson, Purao, Rossi, & Lindgren, 2011). The research methodology involved the following stages: problem formulation; building, intervention and evaluation; reflection and learning; and formalisation of learning (Wing, Andrew, & Petkov, 2017). This approach is a cyclic process as indicated in Figure 1.1.

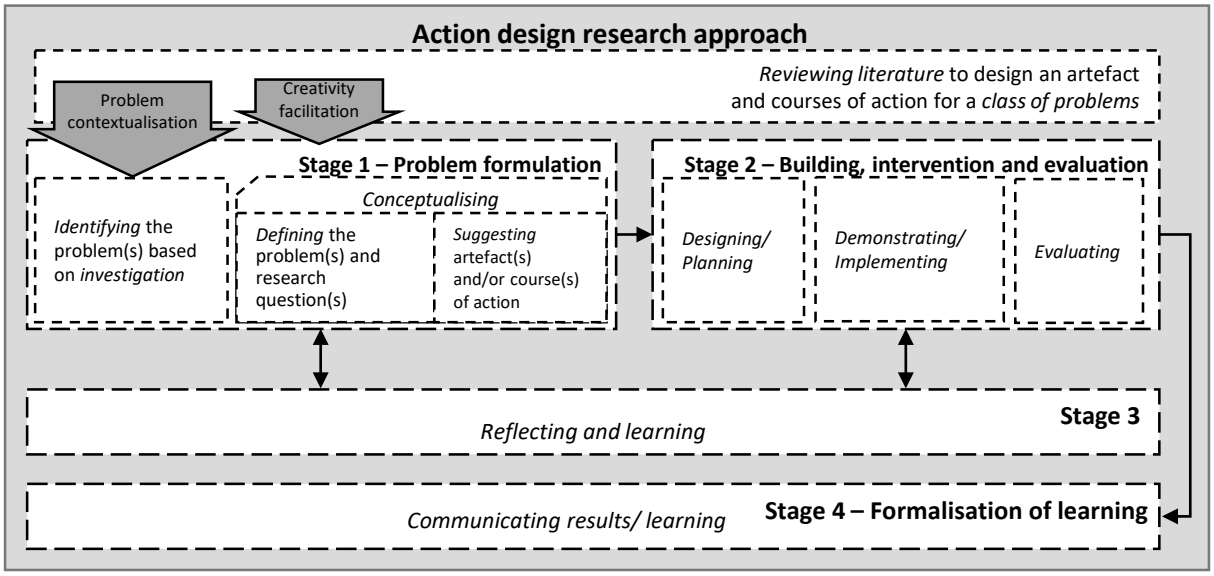

Figure 1.1: The action design research approach adapted from De Vries and Berger (2017)

In this study, *problem formulation* was performed through observations and experience gained from a pilot study, combined with a comprehensive literature study on recent and relevant topics. This involved the contextualisation and conceptualisation of the problem upon careful

evaluation of the literature on the current state of academic performance feedback in education. The perception that academic performance feedback can be significantly improved upon through the utilisation of mathematical programming models, was formed.

Accordingly, in the *building, intervention and evaluation* stage, the mathematical models were planned and formulated, the architecture for implementation of the models was established and they were deployed by means of a specialised learning management system (SLMS). This stage is iterative and follows these self-reflective cycles adopted from action research: designing or planning; demonstrating or implementing and evaluating (De Vries & Berger, 2017).

Reflection and learning were accomplished through the implementation, verification and validation of the developed system in the form of an SLMS. Development and evaluation of the academic performance feedback framework concludes the *formalisation* stage in this research design.

1.6.2. Study participants

A convenience sampling procedure was employed and the study participants consisted of students enrolled in various courses at a university in South Africa. The participants included five different groups from an undergraduate BSc in Information Technology. The curriculum is based on the Informatics Curriculum Framework of the International Federation for Information Processing (IFIP) (Liebenberg, 2015).

1.6.3. Data collection and analysis

Mixed-methods were employed for data collection and analysis. Existing empirical feedback procedures used in the relevant courses were supplemented with solutions provided by the mathematical programming models. Correlation analyses were performed to determine the similarity between the results achieved by these models and those from existing empirical methods. Architecture implementation was performed by means of a case study, complemented by questionnaires and informal interviews. A modified grounded theory approach was followed for development of the academic performance feedback framework, so as to incorporate concepts as well as models.

1.6.4. Ethical considerations

This research topic, methodology and design were subjected to evaluation for ethical concerns by the scientific committee of the School of Computer Science and Information Systems at the North-West University. The committee found no specific ethical concerns relating to the research. Participation in the study was optional and completely voluntary. Responses were analysed anonymously. Adherence to the following ethical considerations was ensured:

- Assurance of the privacy and anonymity of all individuals, entities and reputations involved in the research;
- Assurance of the accuracy of all primary data to the highest level of reasonable surety;

- The affording of appropriate and proper recognition to the original author or owner of all contributions;
- Proper evaluation and resolution of any unanticipated ethical considerations outside the above list.

1.7. Thesis layout

An illustration of the layout of this thesis is provided in Figure 1.2. The chapter contents are as follows:

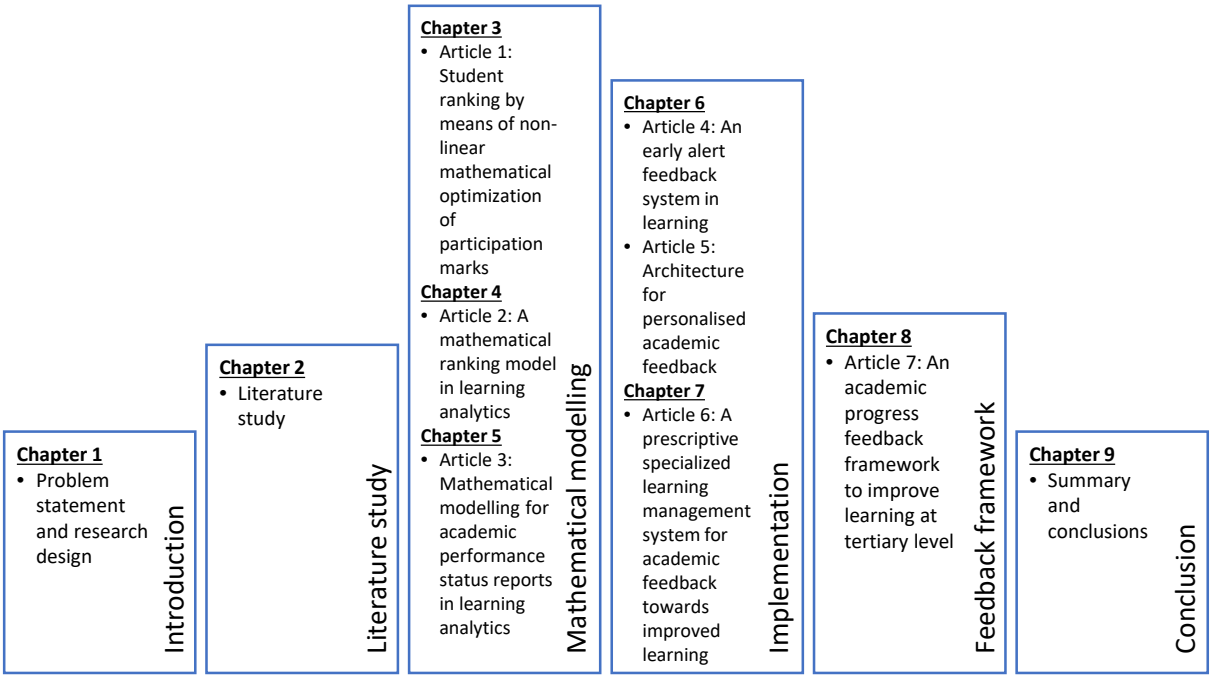

Figure 1.2: Thesis layout

Chapter 1: Research context and design

This chapter serves as introduction to the study by providing some background on the research environment, a problem statement and research objectives, and will outline the methodology to be followed.

Chapter 2: Literature study

The literature study provides an in-depth discussion on previous research and solutions relating to academic performance feedback, learning analytics, mathematical modelling in education, frameworks and framework development.

Chapter 3: Article 1 - *Student ranking by means of non-linear mathematical optimization of participation marks*

The article presented as Chapter 3, describes the development of a non-linear mathematical optimisation model implemented to improve the process of dynamically ranking students according to their academic performance. The model presented in this article yielded some disadvantages which are addressed in the article presented in Chapter 5.

Chapter 4: Article 2 - *A mathematical ranking model in learning analytics*

The concept of learning analytics is briefly outlined in this article followed by a discussion on the implementation of a multi-stage mathematical class ranking model as a method in learning analytics. Learning analytics is a relatively young subject field and is broadly used to describe the collection and analyses of data to make multi-criteria decisions, to report, and to inform in the educational system. The model uses the concept of Pareto optimality and an outputs-only data envelopment analysis model to rank students according to academic dominance. This model is also used to calculate output targets which can assist in academic improvement. The resulting method is time and resource consuming. An improved approach is presented in Chapter 5.

Chapter 5: Article 3 – *Mathematical modelling for academic performance status reports in learning analytics*

Chapter 5 consists of an article that contains an in-depth account of the mathematical models employed to create academic performance status reports that conform to the requirements for effective feedback. Towards this purpose, the article opens with an evaluation of existing feedback methods in tertiary education and the requirements for feedback to be effective. Application of non-linear programming, a data envelopment analysis model and the analytic hierarchy process are demonstrated as data analysis techniques. The following modified mathematical models are presented to address the challenges identified in these methods: a linear programming model that optimises the calculation of academic activity participation of students; a linear programming model implemented in a decision tree algorithm for improvement plans; and a non-linear programming model that can assist a lecturer in managing the average class participation levels in a module. Correlation analyses are done to determine acceptability of the solutions provided by the new models.

Chapter 6: Article 4 – *An early alert feedback system in learning*

The first article presented in this chapter serves as a brief introduction to the electronic implementation of the mathematical models discussed in Chapters 3 and 4. The software application was employed in a pilot study and evaluated against the attributes of effective feedback.

Article 5 – *Architecture for personalised academic feedback*

The second article included in Chapter 6 extends to establish the architecture required for successful deployment of the improved mathematical models discussed in Chapter 5. A representation of the essential elements and their interactions, is provided. Examples of the user interface are shown as part of its implementation in a pilot study. The article concludes with some user satisfaction statistics.

Chapter 7: Article 6 – *A prescriptive specialized learning management system for academic feedback towards improved learning*

Some specific requirements for deployment of the developed academic performance feedback system were identified in the pilot studies. Chapter 7 contains an article that describes the development of a specialised learning management system that addresses these specific requirements. The system was implemented and evaluated in a case study at a tertiary education institution.

Chapter 8: Article 7 – *An academic progress feedback framework to improve learning at tertiary level*

This chapter provides an article that represents the culmination of this research in the form of an academic performance feedback framework for improved learning. A complete feedback scenario in the tertiary environment is provided, followed by a discussion on the requirements for the framework that was developed. The concepts and models required for the framework are then identified and discussed. A graphical illustration of the feedback framework is given, followed by a discussion on the verification and validation process.

Chapter 9: Summary and conclusions

Chapter 9 will conclude on the success of the study in terms of how the aim and objectives were achieved, and discuss recommendations for implementation and provide directions for future research.

1.8. Contributions of the study

This study offers a unique contribution in the form of an academic performance feedback framework in tertiary education that conforms to the requirements established in literature, as well as those determined by actively interacting with the study participants and faculty, at a tertiary institution. To accomplish this, the following additional contributions are offered:

- Performing an in-depth literature study on recent research on the relevant topics so as to categorise and compile it in such a manner that it serves not only as a basis for this study, but also as a useful reference framework resource for other researchers working in this field.
- Successful formulation and evaluation of mathematical models to optimise the process of participation profile calculations. Demonstration of how faculty members can improve their feedback generation efficiency.
- The inclusion of academic ranking in the participation profiles of students presents a novel approach to stimulating self-motivation and self-monitoring postures among students, without compromising their academic privacy.
- Composition of the architecture required for application of the mathematical models in an academic performance feedback system and its implementation in an SLMS, verifies its sustainability in the tertiary educational environment.

- Implementation of the academic performance feedback framework and its utilisation by students will improve the retention rate by providing them with the following: timely and up-to-date reports on their current academic performance (feeding backward); individualised improvement targets which will ensure overall improvement (feeding upward); and distinct actions to perform that will assist them in reaching those goals (feeding forward).

1.9. Conclusion

Chapter 1 started with an introduction to the environment of the research study. This was followed by a contextualisation of the problem into a problem statement, aim and objectives. The research paradigm for this study was introduced and the research methods were listed accordingly. The thesis layout was presented graphically and explained in chapter intervals. The chapter concluded with an explanation of the contributions of the study.

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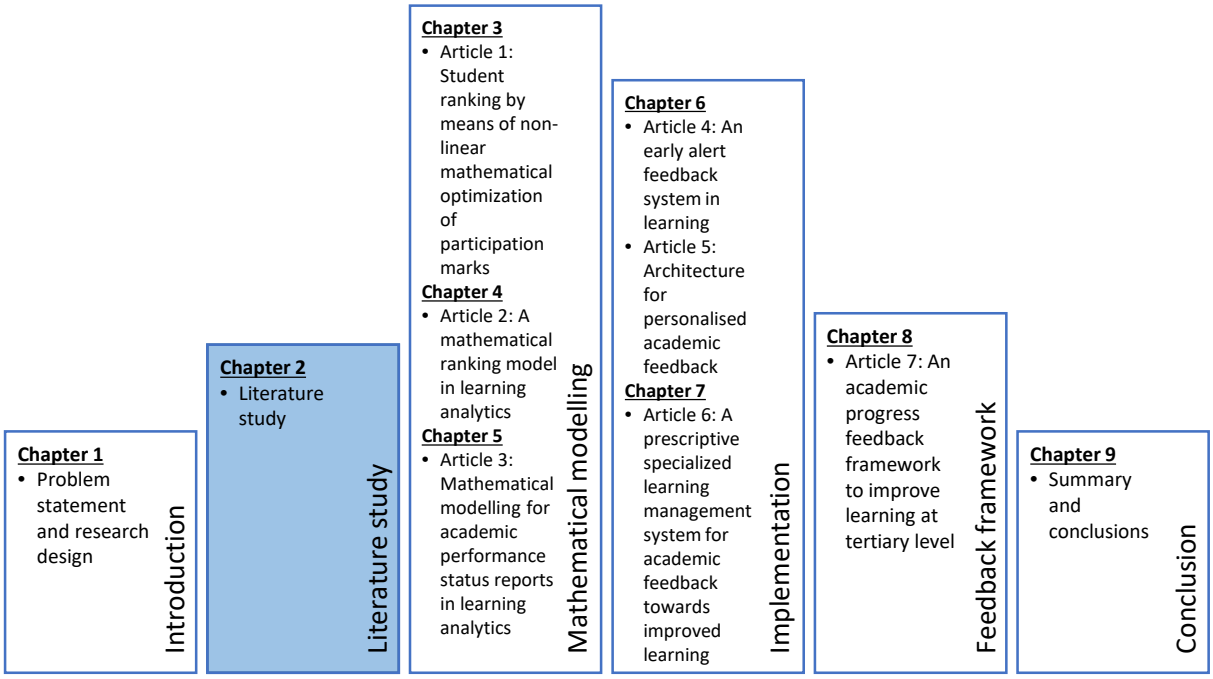
Chapter 2

Literature study



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2.1. Introduction

The elements that contribute to effective learning on tertiary level include but are not limited to, the relevant institution, faculty, students and numerous cultural, environmental and location factors related to each of them (Karabo & Natal, 2013). In an effort to facilitate improved learning, lecturers are constantly evolving their teaching regimes (Porter, Lee, Simon, & Guzdial, 2017; Zielezinski, 2017) and incorporating the latest technological developments for education (De Souza, Pereira, & Machado, 2018; Hamilton, 2016; Neetu, Kritesh, & Vibhor, 2018; Piper, Oyanga, Mejia, & Pouezevara, 2017). Apart from employing novel techniques like blended learning (Geçer, 2013) or roundtable and clustering (Sinaga, 2017), a lecturer must nurture an environment in which students feel motivated to improve their learning (Fırat,

Kılınç, & Yüzer, 2017). It has been found that students tend to compare themselves with their peers to determine the acceptability of their academic performance (Du Toit, 2015). Research has shown that due to the competitive nature of many students, a hierarchical structure such as an academic ranking can significantly enhance students' motivation to self-regulate their learning progress (Barker & Garvin-Doxas, 2004; Macfarlane, 2016; Parker, Perry, Hamm, Chipperfield, & Hladkyj, 2016).

Learning at tertiary level needs to be improved by acknowledging its mutating character and implementing non-intrusive technology that embraces rather than rejects the unavoidable changes of the digital age. In the aim to fulfil this need, the focus of this study is to create new academic performance feedback technology by utilising mathematical programming techniques and learning analytics, and to develop and implement an early-alert academic performance feedback framework. Realisation of the objectives of this study was published in articles and follow in the succeeding chapters. Each of these articles contains its own literature sections on the specific area covered in that paper. Chapter 2, therefore, supplements the research by creating a comprehensive understanding of recent work relevant to the actions performed in reaching the research goals. A brief overview of the process used to perform this literature study is provided in Section 2.2, followed by a review of the literature on the relevant research fields in Section 2.3. Section 2.4 contains a summary of the content analysis of the discussed literature and the chapter concludes in Section 2.5 with the chapter references provided thereafter.

2.2. Methodology

The literature review involves the collection and contextualisation of research published in academic journals, conference proceedings, periodicals, subject specific professional websites and additional sources with relevant scope. Materials investigated are included in the literature review based on relevance to the subject areas encompassed in this study, peer review, contemporaneity, study design, and geography. The information included in this review was obtained legally by means of institutional resources and all authors are credited in the References section at the end of this chapter.

2.3. An overview of the literature relevant to this study

The research fields relevant to this study include academic performance feedback, learning analytics, mathematical modelling and framework development. The origin, as well as some recent research in these fields, is discussed in this section.

2.3.1. Academic performance feedback

The importance of feedback has long since been identified in fields like employment (Herold & Greller, 1977), economic policy (Kendrick, 1988), sales (Kohil & Jaworski, 1994), psychology (Sully De Luque & Sommer, 2000), learning (Rosenholtz & Rosenholtz, 1981) and teaching (Brinko, 1993) among others. The effectiveness of feedback in its different forms has also been studied extensively in many different research areas. Examples include that of law

(Hess, 2015), business (Harms & Roebuck, 2010), accounting (Loftus & Tanlu, 2018), language (Lee, 2018), psychotherapy (Burlingame, et al., 2018), health (Boyoon, Kyehoon, Kwansu, & Shezeen, 2018), education (Cooper, Whitney, & Lingo, 2018; Rasi & Vuojärvi, 2018; Dose, 2018) and many more.

Providing feedback in the classroom is believed to be one of the most important factors contributing to cultivating an inherent impetus among students towards academic improvement (Harks, Rakoczy, Hattie, Besser, & Klieme, 2014; Shute, 2008). It is therefore important to correctly define the term *feedback* and to explain the meaning of academic performance feedback in the context of this study.

Although the term '*feedback*' is generally used in electronics to refer to the process of returning some of the output in a system as input (English Oxford Living Dictionaries, n.d.), Hattie and Timperley (2007) defined feedback as *"information provided by an agent (e.g., teacher, peer, book, parent, self, experience) regarding aspects of one's performance or understanding"* (p. 81). They further argued that feedback must address three key issues in working towards a goal. These include information on what the goal is exactly, what the current progress is and how to proceed further in working towards the goal. Depending on the area of study, researchers devise various definitions for the diverse forms of feedback. *Formative feedback* is regarded as information communicated to students or learners with the intention of modifying their attitudes in order to improve their learning (Shute, 2008). *Assessment feedback* is described as *"all feedback exchanges generated within assessment design, occurring within and beyond the immediate learning context, being overt or covert (actively and/or passively sought and/or received), and importantly, drawing from a range of sources"*, (Evans, 2013, p. 71). *Audio feedback* involves the use of audio devices to communicate performance information to students or learners (Cann, 2014). In a study to determine the possibility of predicting the cumulative exam scores of students, Kim and Shakory (2017) defined *evaluative feedback*, as the communication of assessment percentage scores. Evaluative feedback was also referred to as *performance* (Peters, Van der Meulen, Zanolie, & Crone, 2017) or *grade-oriented feedback* (Harks, Rakoczy, Hattie, Besser, & Klieme, 2014). Harks, *et al.* (2014) further defined *process-oriented feedback* as a compilation of specific tasks indicating a measure of personal effort in the case of failure. Process-oriented feedback provides detailed information on individual strengths, weaknesses and strategies on how to reach the learning goal. In the context of this study, the phrase '*academic performance feedback'* is used to describe specific feedback in the tertiary education environment. Academic performance feedback is defined as information provided by a lecturer or institution to students or learners that consists of a detailed layout of the goal in a specific scenario, the current academic performance and targets to work towards reaching the goal (Hattie & Timperley, 2007).

Apart from forming contextually suitable definitions for feedback, researchers have also postulated on the attributes required for feedback to be effective. Wiggins (2012) argues that feedback needs to be goal-referenced, tangible and transparent, actionable, user-friendly, timely, ongoing and consistent. Thurlings, Vermeulen, Bastiaens and Stijnen (2013) confirm

that effective feedback is goal or task-directed, explicit, and unbiased. Studies show that when feedback does not conform to these requirements, its value towards improved learning diminishes (Cann, 2014). Since the importance of academic performance feedback and its consequences is topical on all levels of education, some examples will follow.

Koenig, Eckert and Hier (2016) studied the effect of performance feedback by itself as well as performance feedback combined with goal-setting on the writing fluency of elementary school children in the United States. Their research proved that both these interventions improved the writing fluency of the study participants. Furthermore, it was found that when the children were not provided with explanations on why certain goals needed to be met, they had lower goal commitment. The performance feedback was also more effective when provided to the children timeously. The participants ultimately recognised that their own performance history became the standard by which they could determine whether improvement had taken place or not. The study stressed the importance of consistency and timeliness as required attributes for feedback to be effective.

Harks, *et al.* (2014) investigated the differences between the effect of process-oriented and grade-oriented written feedback of a group of ninth grade children in their mathematics achievement, interest and their ability to perform self-evaluation. In their study, they describe process-oriented feedback as "*feedback that uses an individual and criterion reference standard, refers to specific tasks and processes, supports internal unstable attributions in the case of failure and provides elaborated feedback information on individual strengths*" (p. 272) whereas grade-oriented feedback refers to the traditional manner in which the children are provided with their assignment grades. The study participants were assigned to receive either process-oriented or grade-oriented feedback on their mathematics tests. Using a survey, it was found that process-oriented feedback was perceived to be more useful than grade-oriented feedback. This was confirmed by evaluating the participants' improvement in their mathematics achievement. The researchers reported no significant effects on the participants' self-evalutation capabilities and attributed this to the fact that feedback was provided to the particpiants only once. Process-oriented feedback needs to be given to students regularly to affect change in this regard (Labuhn, Zimmerman, & Hasselhorn, 2010). Also, in conclusion it was noted that students are more familiar with grade-oriented feedback and that the perceived usefulness in terms of student self-evaluation needs to be studied over an extended period of time (Harks, *et al.*, 2014).

Grawemeyer, Mavrikis, Holmes, Gutiérres-Santos, Wiedmann and Rummel (2017) evaluated a learner model called *iTalk2Learn* which is an intelligent learning platform for children between the ages of eight and twelve. The purpose of their research was to evaluate the influence of feedback based on the emotions of students as they were completing tasks (affect-aware feedback), in contrast with feedback based only on student performance. The platform is meant to detect, analyse and respond in real-time to the participants' speech and provide activities to help develop conceptual knowledge in a mathematical environment. To determine the sequence of the practice activities, a student needs analysis which is performed where the student's level of interaction with the feedback provided, is considered a key factor.

Grawemeyer *et al.* (2017) found that affect-aware feedback contributed to reducing boredom and disengagement from learning activities and may have an effect on the learning process.

Many more examples of research in pre-tertiary educational feedback can be found in literature. Table 2.1 summarises some of the more recent studies. This thesis provides a report on a study performed in the tertiary education environment. It is, therefore, important to appreciate the extent of contemporary work done in this setting. Some examples are summarised next.

Author(s)	Title	Research theme
Cutumisu and Schwartz (2018)	The impact of critical feedback choice on students' revision, performance, learning, and memory	The impact of critical feedback, revision choices and performance of 8th grade school children on their memory for feedback
Faber, Luyten and Visscher (2017)	The effects of a digital formative assessment tool on mathematics achievement and student motivation: results of a randomized experiment	Examining the effects of a digital feedback tool on the mathematics achievement of 3rd grade learners
Martin-Chang (2017)	Learning to read with and without feedback, in and out of context	Phonology within self-teaching
Fyfe (2016)	Providing feedback on computer-based algebra homework in middle-school classrooms	The effects of various types of feedback on computer-based algebra homework
Hattie, Fisher and Frey (2016)	Do they hear you?	Strategies towards students' acceptance and use of feedback
Sung, Liao, Chang, Chen and Chang (2016)	The effect of online summary assessment and feedback system on the summary writing on 6th graders: The LSA-based technique	The effect of concept and semantic feedback on the writing of summaries by students in the sixth grade
Timmers, Walvaren and Veldkamp (2015)	The effect of regulation feedback in a computer-based formative assessment on information problem solving	The effect of automated regulation feedback in an electronic formative assessment on 13-year-old students
Gielen, Peeters, Dochy, Onghena and Struyven (2010)	Improving the effectiveness of peer feedback for learning	Effectiveness of peer feedback and instructional intervention to support its use

Table 2.1: Recent studies in pre-tertiary education feedback

Torrance (2007) investigated the effect of various modes and methods of assessment on achievement and progress in tertiary education and training. He argues that the "*clearer the task of how to achieve a grade or award becomes, and the more detailed the assistance given by tutors, supervisors and assessors, the more likely candidates are to succeed*" (Torrance, 2007, p. 282). The research included a literature study in which the author noted that investigations into the use of explicit learning objectives were scarce, followed by parallel case studies across multiple learning and skill sector settings. To compare and contrast assessment experiences of students in these various settings, the study was conducted through distribution of questionnaires to students and conducting interviews with assessors or lecturers. Where achievement can be defined as generation of the necessary grades to accomplish a certain goal, competence-based assessment extends to reference success criteria in work-based learning environments. Such assessment ensures comprehension and accomplishment of learning outcomes rather than conveying studied material. Torrance (2007) noted an increase in the student retention rate and stated that an assessment and feedback reform is required to stimulate capacity building.

An important issue that needs to be considered in feedback in tertiary education is the way it makes students feel. If feedback evokes negative emotions, students are less likely to try improving their academic performance. Ryan and Henderson (2017) report a lack in research on the variables that determine which students are likely to perceive feedback as negative. They concluded that assessment feedback needs to be transformed so as to positively influence self-efficacy of students, among other traits. According to research, establishing goals and providing progress-to-goal information, demonstrate high success in encouraging active learning (Forsythe & Johnson, 2017). Students who exhibit a motivation to learn, believe that their basic abilities can be improved through application and experience. In order to suppress defensive behaviour which results in less effective feedback intake, students can therefore be steered towards improving their self-efficacy through guidance and consistent feedback. Furthermore, the following factors have been identified to improve feedback acceptance: face validity (the extent to which an assessment procedure reflects a student's performance or knowledge), source credibility (trust in the feedback source), message valence (positivity of feedback) and challenge interventions (constructive feedback that will result in improvement) (Boudrias, Bernaud, & Plunier, 2014). The utility of feedback is unmistakable as regression analysis techniques have also been used on early feedback to predict the final semester scores of students (Kim & Shakory, 2017). The expectations of students can be influenced by receiving regular feedback which in turn will assist in their motivation towards improvement (Ruthig, Jones, Vanderzanden, Gamblin, & Kehn, 2017).

Studies have been conducted for many years and remain topical regarding the contributing factors that improve learning and achievement from a student's perspective (Brookhart & Moss, 2015; Evans, 2013; Frey, Fisher, & Hattie, 2018; Hattie, 2009; Hattie & Timperley, 2007; Olwagen & Swart, 2018). Though the usefulness of feedback is evident in literature (Figure 2.1), it needs to conform to certain requirements to be effective in a specific environment.

Irrespective of the context (e-learning or on-campus), academic performance feedback in the educational environment needs to exhibit specific attributes. Wiggins (2012) stated that effective feedback must be goal-referenced, clear and concrete, actionable, user-friendly, opportune, continuing and consistent. Thomas and Oliver (2017) argued that feedback effectiveness is determined by its type, frequency and specificity. Olwagen and Swart (2018) asserted that effective academic performance feedback must address cognitive as well as motivational factors by being timely, focused, constructive, and goal-referenced. This will allow students to compare the actual outcome of their efforts with the desired outcome. Brookhart and Moss (2015) confirmed that lecturers must set learning targets that provide milestones in the pursuit of an ultimate goal which have smaller scope, can be achieved in a reasonable time and deliver focused, descriptive and actionable feedback.

Hattie and Timperley (2007) created a model for feedback which has been extensively cited in many research studies. The purpose of the model is to reduce the discrepancy between an existing understanding of performance and a goal by effectively addressing three major questions: *"Where am I going ... How am I going? … and Where to next?"* (Hattie & Timperley, 2007, p. 86).

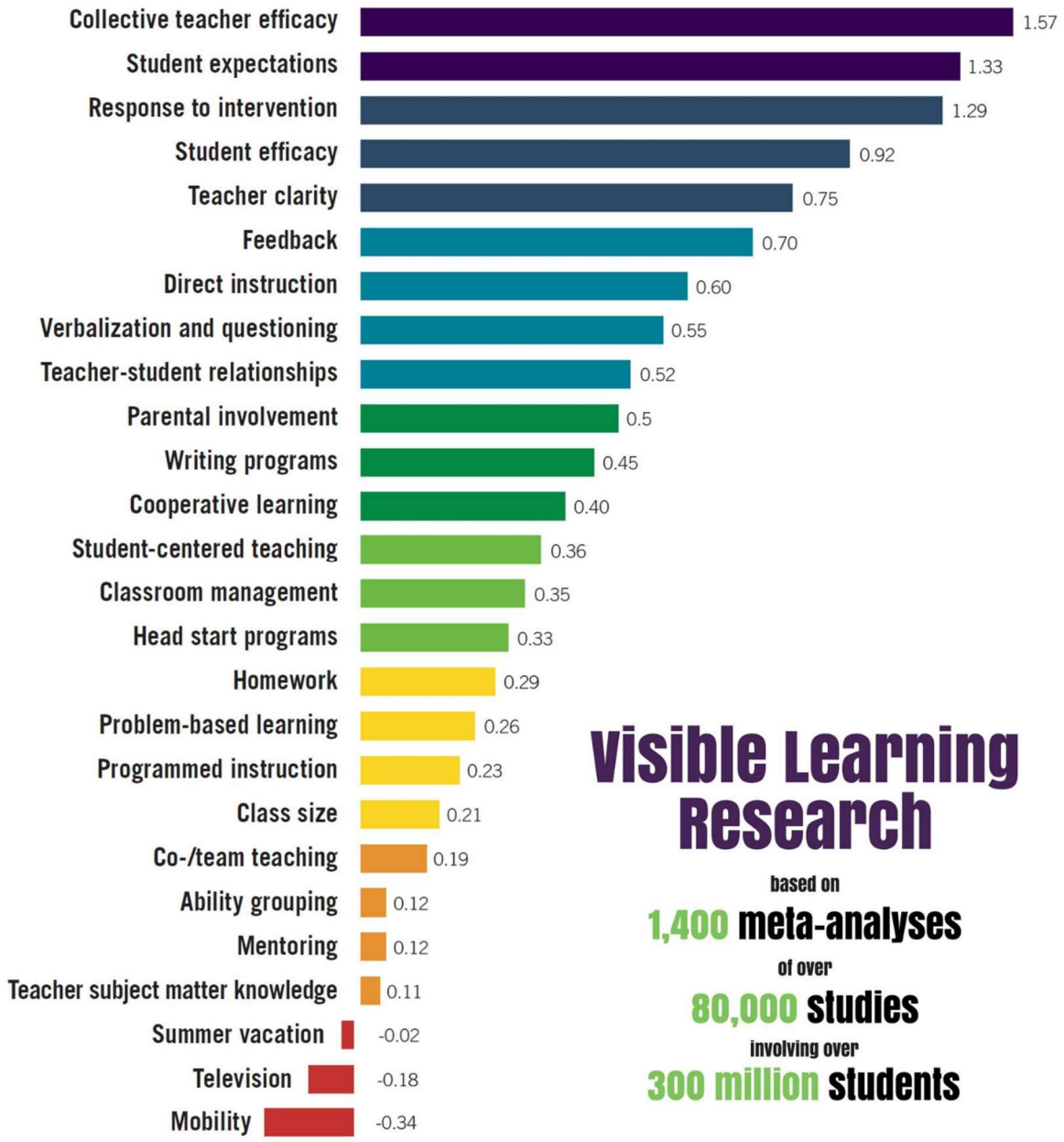

Figure 2.1: The factors that contribute to effective learning (Hattie, 2009)

The answers to these questions translate into feedback that reports upwards (setting an ultimate goal), backwards (providing information on a student's current performance), and forwards (providing short-term actions that will lead to reaching the ultimate goal). Ideally, feedback provided to students should cultivate a student-centred learning environment which is characterised by individualised focus, an environment that encourages growth in learning and promotion of student motivation to self-learning (Andrade, Huff, & Brooke, 2012). Although the properties of effective feedback and the issues that need to be addressed are known, supplying it is not a simple process without difficulties. Feedback can result in emotional distress depending on the students' dispositions and could even result in self-defensive behaviours (Forsythe & Johnson, 2017). Yuan and Kim (2015) reported that the mere physical separation between students and a lecturer in many settings can turn the process of supplying

feedback into a challenge. They proposed the use of media sharing, collaborative tools and screen casting technologies as possible solutions to bridge this gap. Also, members of faculty sometimes suffer from a reluctance to provide academic performance feedback for fear of the responses it may elicit from students (Rubin, 2006). The increase in student numbers and the lack of time lecturers have to provide sufficient insight into student progress, are two of the most common problems in terms of providing effective academic performance feedback to students (Hattie & Timperley, 2007; Rubin, 2006). Table 2.2 lists some additional studies that have been performed on aspects of feedback in the tertiary education environment, highlighting the need for improvement.

Author(s)	Title	Research theme
Lei, Cui and Zhou (2018)	Relationships between student engagement and academic achievement: a meta-analysis	Examining whether student engagement accurately predicts academic achievement
Ruthig, Jones, Vanderzanden, Gamblin and Kehn (2017)	Learning from one's mistakes: understanding changes in performance estimates as a function of experience, evaluative feedback, and post-feedback emotions	The emotional impact of feedback on subsequent student performance
Belcadhi (2016)	Personalized feedback for self assessment in lifelong learning environments based on semantic web	The introduction of a Semantic Web based intelligent personalised feedback framework which provides personalised feedback to enable self-assessment
Webb and Moallem (2016)	Feedback and feed-forward for promoting problem-based learning in online learning environments	Constructing, developing and evaluating conceptual models for improved problem/project-based learning environments with effective feedback
Sternad (2015)	A challenge-feedback learning approach to teaching International Business	Introduction of four phases: challenge, act, feedback and reflect in a challenge-feedback learning approach

Table 2.2: Recent studies in tertiary education feedback

The use of learning analytics towards improving student retention presents a solution to the problem of effective academic performance feedback, among other advantages (West, Heath, & Huijser, 2016). Tertiary institutions are progressively utilising learning management systems (LMSs) to communicate relevant matters to students and also to employ learning analytics to gather, process and report statistics on student usage of resources and more (Tempelaar, Rienties, & Giesbers, 2015). The subject field of learning analytics is defined and described in the next section, followed by examples of some recent research works.

2.3.2. Learning analytics

Siemens (2013) concluded that learning analytics "*has sufficiently developed, through conferences, journals, summer institutes, and research labs, to be considered an emerging research field*" (p. 1380). Learning analytics is defined as the collection and analysis of learning data which can be derived from a variety of sources (Fiaidhi, 2014). More specifically, *"Learning analytics is the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs"* (Gašević, Dawson, Rogers, & Gasevic, 2016). The learning data can consist of student navigation information, records of students signing into and out of

LMSs, information about student clickstreams, timestamps of access to resources and participation in forums within information systems (Rubel & Jones, 2016). Many students do not realise the utility presented by the use of LMSs and the added benefit of learning analytics.

Depending on its implementation, the purpose of learning analytics can vary but some examples are to

- Enhance the learning process through systematic measures of data related to learning in order to provide feedback to learners as well as lecturers (Tempelaar, Rienties, & Giesbers, 2015);
- Discover which students are at-risk of falling behind or failing a course, to predict the performance of these students and to determine if help from an external source is required (Fiaidhi, 2014);
- Translate feedback acquired through learning analytics into actionable learning interventions (Tempelaar, Rienties, Mittelmeier, & Nguyen, 2018); and
- Enhance learning by providing feedback on resource use and analysing personal data of students to stimulate a self-evaluation atmosphere (Bhattacharya & Coombs, 2017).

This study relates to the use of learning analytics in terms of how it can assist in improving the academic achievement of students. Therefore, a review on recent studies in learning analytics that aim to improve learning, is provided.

Learning analytics was used in conjunction with an evaluative mentoring approach in a computer related module at the University of Almería (Ruiz-Ferrández, Ortega, & Roca-Piera, 2018). It was indicated that, although large numbers of students enrol in the course titled *Computer Structure and Technology*, most of them fail to gain competency in the subject matter and discontinue the program. The purpose of the research was to improve the level of content understanding amongst the students by implementing some novel resources in the existing LMS used by the university, namely *Blackboard*. The added resources could be completed individually (contextual cards, summaries, self-evaluation tests and evaluative tests) and in groups (exercises, practices and mentoring). The learning analytics tools available through the use of an LMS were used in conjunction with evaluative mentoring sessions, to facilitate a deeper level of subject understanding. The mentoring sessions involved scheduled appointments with groups of students during which an academic mentor would discuss and evaluate the approaches followed to complete specific assignments. It was found that combining learning analytics with an evaluative mentoring approach facilitated improved subject matter understanding among students.

Koç (2016) used learning analytics tools to develop a theoretical model which explains the underlying relationship between the student participation in academic activities and their resulting achievement. The model was created for a web-based distance education course in Turkey. Learning analytical techniques were used on data pertaining to discussion forums and attendance of online lectures and student achievement was measured in terms of their performance in assignments and examinations. It was found that participation in discussion forums correlated with attendance and that both directly influenced the grades that students

achieved for their project assignments. The research provided an example of how learning analytics can be combined with other approaches towards improving student achievement in online courses.

Towards assisting lecturers as well as students with visualisation of the learning process, Villamañe, Alvarez and Larrañaga (2018) presented the Competence-Based Learning Environment. It is a visualisation platform that implements learning analytics methods to improve engineering education where students are expected to build not only theoretical knowledge but also competence in specific engineering practices. Visualisation is an important tool to assist students with self-reflection on their learning and can result in inspiring them to implement remediation methods with the view to improve. A learner model was presented that used learning analytics to provide information on completed work sessions (historical data), on the knowledge levels of students (knowledge model) and on the level of mastery in the desired exercises (competence model). The implemented system provided both lecturers and students with valuable information regarding the development of the skills of the engineering students.

An Internet of Everything (IoE) based educational model combined with a Learning Analytics System (LAS) model was presented by Ahad, Tripathi and Agarwal (2018). These models utilised deep learning theory to measure the level of student learning, retention and achievement. The added benefit of prescribing measures towards improving and correcting learning approaches through these models, was also argued. In the study, the entities and stakeholders involved were equipped with microchip based wireless sensors, fitted in wearable devices. These sensors gathered information about the entity and its environment. The accumulated information was encrypted and processed to be used in conjunction with the data analytics unit, to analyse system (*i.e.* network related) requests. An intricate LAS algorithm was used to create the relevant learning analytics model reported on. The resulting model presented advantages like content analytics that do the following: restructure the contents of modules dynamically in order to address the needs of students; customise a lecture plan for specific groups of students; and implement deep learning algorithms in order to train the system to suggest customisations to the teaching-learning strategies employed for specific groups of students. Although the approach presented many advantages, the challenges included the high cost of IoE, large volumes of varied data formats, high data generation rates, lack of timely availability of feedback and some security and privacy issues, among others. Therefore, these issues need to be attended to in research conducted regarding learning analytics in education.

Van der Stappen (2018) argued that while the main focus of learning analytics in higher education is on classroom-based learning, its implementation in the workplace presents further advantages to students, workers and trainers. A customisable learning dashboard was consequently developed for the workplace which enabled program managers in higher engineering education to evaluate *workplace learning* of their students. The dashboard was developed with specific mention of respect for the privacy of the personal data of students. A unique trait of the developed dashboard was its customisability in terms of the feedback

required. Program managers were interested in the activities that students participated in most, which they found most difficult and whether the perceived task difficulty had changed with time. It was found that the managers would use the dashboard as an exploratory instrument rather than to monitor the students. The research proved that a feedback dashboard can provide new and more timely feedback on the learning process of engineering students and ultimately affect evidence-based curriculum improvements.

Another example of research proving the successful implementation of learning analytics is a mobile application called MyLA (Kuhnel, Seiler, Honal, & Ifenthaler, 2017). The application collected data on learning behaviour and personality traits of students, at universities that focused on supporting personalised and self-regulated learning. The MyLA application presented a messaging platform for communication between students and lecturer. Such messages could be used by lecturers to adapt their teaching materials and students could better monitor their learning progress. The application consisted of three main units: a profile unit (containing profile data and a section where students were rewarded for using the application); a learning unit (with a messaging functionality and survey centre); and a progress unit (which consisted of personal motivational data entered by students and statistical charts that visualised personal data). A survey was used to test the usability of the application, whereas eye tracking technology was utilised to determine fixation points, first-look points and non-looking points. The participating students found that the application was intuitive and easy to use and provided informative feedback for improvements on the application design.

The literature on learning analytics shows that it is generally used to improve some aspect in the learning process and it is a field which is being widely researched and developed. Table 2.3 provides some information on additional research studies related to learning analytics in the educational environment.

Author(s)	Title	Research theme
Al-Rahmi, Alias, Othman, Marin and Tur (2018)	A model of factors affecting learning performance through the use of social media in Malaysian higher education	The use of social media for active collaborative learning and engagement
Sedrakyan, Malmberg, Verbert, Järvelä and Kirschner (in press)	Linking learning behavior analytics and learning science concepts: Designing a learning analytics dashboard for feedback to support learning regulation	An artefact illustrating the relationship between dashboard design and learning science for feedback to support learning
Viberg, Hatakka, Bälter and Mavroudi (2018)	The current landscape of learning analytics in higher education	An analysis of 252 papers on learning analytics in higher education to determine the approaches, methods and its effects
Banumathi and Aloysius (2017)	Predictive analytics concepts in big data – a survey	A literature study on various predictive analytics approaches in higher education
Leitner, Khalil and Ebner (2017)	Learning analytics in higher education—a Literature Review	A mixed-method analysis on the state of the art of learning analytics in higher education
Lonn, McKay and Teasley (2017)	Cultivating institutional capacities for learning analytics	Development and implementation of an institutional capacity for learning analytics

Table 2.3: Additional research studies on learning analytics in education

Author(s)	Title	Research theme
Casquero, Ovelar, Romo, Benito and Alberdi (2016)	Students' personal networks in virtual and personal learning environments: a case study in higher education using learning analytics approach	The effect of a virtual learning environment as opposed to a personal learning environment in higher education
De Laat and Prinsen (2014)	Social learning analytics: Navigating the changing settings of higher education	Introduction of Social Learning Analytics for encouraging active learning in open, social learning environments

Table 2.3: Additional research studies on learning analytics in education (continued)

Although learning analytics provides valuable information on different aspects in the educational environment, the type of feedback provided depends mainly on the demands of its users. In certain cases, the information required is more comprehensive than resource usage or monitoring statistics, as was the case in this study. In this context, the methods for processing and analysing student performance data to provide academic performance feedback needed to be performed by mathematical modelling approaches. The reasons for this include the large volumes of data and the aim to process and report its analyses in a timely manner. For this purpose, some works relating to mathematical modelling in education are discussed in the next section.

2.3.3. Mathematical modelling

In an educational institution, a great amount of time and human resources are spent trying to find an optimal solution to some objective function within a specified domain. Some problems involve a variety of different types of objective functions and different types of domains. The challenges faced in such cases usually include the large amounts of data that need to be considered and the fact that there is nearly always a deadline. These issues are relevant to this study because the student numbers are increasing as education is becoming more accessible (Karabo & Natal, 2013) and providing academic performance feedback to students needs to be done as soon as possible after completion of each assessment. Therefore the use of one or more mathematical model(s) to facilitate a learning analytics tool in analysing large amounts of student data, is justified.

A mathematical model can be described as an abstraction of a phenomenon or reality, expressed in terms of one or more sets of mathematical equations, consisting of mathematical symbols (Encyclopaedia Britannica, n.d.). Problem solving techniques like optimisation, control theory, information theory, dimensional analysis and computer simulation, among others, are often employed to model specific processes in science and engineering. Depending on the problem for which a solution is sought, an optimization model can be linear or non-linear, have one or more objective(s), and be constrained by one or more set(s) of equations. In this study, mathematical models are utilised for various purposes in an effort to efficiently analyse and process the data of groups of students, in a relatively short time. More specifically, linear and non-linear programming models were utilised to maximise and also minimise the possible average participation mark that a student can achieve in a specific scenario. Example implementations of such models in education, or how mathematical models would have been more appropriate, is briefly given here.

Mohamed (2016) stated that academic advising plays an important role in the success students achieve and in the retention rate at higher education institutions. An optimisation algorithm was used to perform an analysis of the relevant impacting factors. The approach scheduled the courses (all compulsory and a subset of the elective courses) required for a specific qualification without violation of any of the constraints. These included the required credit hours per semester, the total credit hours for elective courses, the number of courses per semester, the grade point average per semester and the budget per semester. The model furthermore needed to consider precedence, succession of courses and course priority. The objective was to maximise student satisfaction while helping them to achieve a high grade point average at the conclusion of their studies. A study plan was consequently suggested that satisfied the student preferences as well as the lecturer recommendations, as closely as possible. Students and lecturers were then given the opportunity to modify the study plan provided, according to their unique experiences from the past. The modifications were applied to the model and the method was repeated until both parties felt satisfied. The approach followed an iterative pattern in order to refine the input variables required for the best solution and was incapable of detecting conflicting constraints. It was also stated that the method lacked an explanation facility to explain study plan changes to students. These issues can be addressed by utilisation of a mathematical model that finds the “best” solution while adhering to all of the constraints. Such a model will also indicate where conflicting constraints exist.

A decision support system was developed by Chiu and Huang (2016) to combine Chinese rhetoric lessons with an outdoor learning activity in mobile learning. The fuzzy analytic hierarchy process (AHP) was used to analyse college students, system developers and instructors to verify the feasibility of the developed system. The AHP is a modelling tool which can assist a decision-maker in a complex situation by setting priorities when making the best decision (Emrouznejad & Ho, 2018). It uses preferential ratings for attributes of a specific element to provide an efficiency score in terms of inputs (attributes) and outputs (rated according to priority by the modeller). The AHP is simple to implement, relatively easy to use and provides flexibility for many applications where multiple criteria decision-making is required. It has been adopted in many fields like education, engineering, management, sports, and many more. However, in some applications imprecision may arise due to unquantifiable, incomplete or unobtainable information and partial ignorance. In such cases, fuzzy AHP is used to manage uncertain data and the vagueness encountered in determining the importance of attributes relative to one another.

In an effort to examine the possibility of measuring efficiency in the context of higher education, a data envelopment analysis (DEA) was performed by Johnes (2006). A DEA model is generally used to compare operating units of the same type (called decision making units or DMUs) according to their efficiency scores. An efficiency score is calculated as a relationship between the resources (called inputs) and the outputs of the DMUs. The result provides an indication of which unit(s) are more efficient than others. Although DEA can manage multiple inputs and outputs, there were significant problems in defining and measuring them, and the inputs and outputs had differing levels of importance. Also, some of the inputs could be

controlled by institutions while others could not. Generally these issues are managed by simply including all of the inputs in the model, whether they can be controlled or not. Johnes (2006), however, adopted a two-stage method in which the efficiency scores were calculated for a set of institutions by means of DEA, along with a subset of controllable inputs. These efficiencies are then analysed in a second stage in relation to the non-controllable inputs by means of a statistical technique. This approach assumed that the second stage input factors have an effect on the efficiency of the production units as opposed to the traditional DEA, in which all of the factors are assumed to affect the efficiency. The research presented an interesting implementation of a combination of methods to suit a specific problem.

Cheng and Esangbedo (2018) developed an Integral Linear Programming with Grey Possibility (ILP-GP) model for evaluating universities and compared it with results from a hierarchical model. The ILP-GP method is an optimisation method for solving multi-criteria decision-making problems. The study assessed the performance of universities based on differing measurement criteria, which means that uncertainties exist. These uncertainties were attended to by representing them as grey numbers according to the Grey System Theory. A grey system is one where parts of information are known while others are unknown. A system with no information has no solution whereas one with perfect information has a unique solution. A grey system will have a variety of available solutions for which some techniques can be implemented to find an appropriate one for a specific case. The evaluation criteria considered, included social contribution, environments, leadership, funding, research and development, and student guidance. Although the method facilitated a fair comparison of all the alternatives, the fact that the grey numbers were constructed on account of a survey completed by students, could lead to bias. The work provided a valuable contribution to the field of university rankings, in the form of an alternative evaluation method which can also be implemented in other fields like business, finance and more.

A mixed-integer linear programming model was developed by Qu, Yi, Wang, Wang, Xiao and Liu (2017) to assist in the allocation of teaching assistants to the available tutorial sessions in a department. Assistants had different capabilities and a maximum number of hours that they might be utilised. The objective of the study was to maximise the number of tutorials that could be taught whilst adhering to the model constraints. Extensions that were incorporated into the model, addressed time conflicts that could arise between tutorials, repeats of tutorials, managing the number of assistants assigned to one course or lecturer, and managing the number of days an assistant could work. Extensive numerical experiments were carried out to prove the computational efficiency of the model and its extensions.

A motivation, volition and performance (MVP) mathematical model was developed and evaluated statistically by Novak, Daday and McDaniel (2018). The MVP theory is an established integrative theory on motivation, volition and learning as introduced by Keller (2008) and was expanded through the incorporation of intentions, action control and information processing within the specific framework. It showed how environmental effects on behaviour combined with internal psychological constructs and processes, influenced learning. The MVP mathematical model was applied to evaluate the learning and attitudes of

students while using e-texts. Students were asked to complete a Likert scale questionnaire to determine the intrinsic cognitive load (IL) of the learning task, which is influenced by prior knowledge and complexity, and extraneous cognitive load (EL) involving processes that do not add to knowledge creation. The resulting model was a weighted sum of the positive (attention, relevance, confidence, IL and EL) and negative (academic background and prior knowledge) contributors to student satisfaction. It was found that the model could confidently be used to diagnose and remedy the learning experiences of students, and to analyse learning materials and environments.

Hoffait and Schyns (2017) applied data mining methods to identify students likely to struggle in completing their first year of tertiary study. Their method included the use of a random forest, logistic regression and artificial neural networks. Random forests consist of a collection of learning methods for classification and regression, among others. They function by creating multiple decision trees on training, resulting in a class representing the mode (classification) or mean prediction (regression) of the individual trees. In statistical modelling, logistic regression estimates the binomial parameters of a logistic function that models a binary dependent variable. Artificial neural networks are connectionist systems which *learn* to perform tasks without programming, by systematically studying examples. The study showed that these methods could successfully be utilised to predict students likely to struggle academically in order to facilitate intervention.

This section contains examples of how mathematical modelling approaches like an optimisation algorithm, AHP, DEA, linear programming with grey probability, mixed-integer programming, MVP modelling and data mining were used in education to solve some identified problem. These methods are relevant to this study as variations of them have been implemented to perform learning analytics functions in academic performance feedback. Table 2.4 lists some additional research studies in which mathematical models were used for solving some specific problems in education.

Author(s)	Title	Research theme
Chao and Junzheng (2018)	Cloud-service decision tree classification for education platform	Optimising the ideological education model of university students and introducing the cloud-service decision tree classification algorithm
Nannyonga, Ssebuliba, Nakakawa, Nabiyonga and Mugisha (2018)	To apprehend or not to apprehend: a mathematical model for ending student strikes at a university	A dynamic model for strike propagation at a university
Seman, Hausmann and Bezerra (2018)	Agent-based simulation of learning dissemination in a project-based learning context considering the human aspects	A PBL-classroom model for evaluating different scenarios of project-based learning applications by considering soft-skills and methodological perception
Liu and Zeng (2017)	A new mathematical model of a college-enterprise cooperation system	Introduction of an action-reaction based dynamic model of college-enterprise cooperation
Ali, Pant and Rana (2017)	Relative performance assessment of academic departments of higher educational institute using DEA with sensitivity analysis	Implementing DEA to evaluate the performance of different academic departments at a college in India

Table 2.4: Further research studies on mathematical modelling in education

Author(s)	Title	Research theme
Nieto-Chaupis, Matta-Sólis, Campomanes-Bravo, Perez-Siguas and Cumpen-Viduarre (2017)	Mathematical methodologies for the measurement of the quality of education in engineering programs in Peru	Application of a mathematical model based on individual student scores and project timing to measure the quality of education
Parkavi, Lakshmi and Srinivasa (2017)	Predicting effective course conduction strategy using datamining techniques	Development of a mathematical model to determine effective course conduction strategy
Ribic, Turcinhodzic and Tumbul (2017)	Modelling double-shift school timetables	Formulation of school shifts using the XHSST format and an integer linear program towards working in several shifts
Vasiliev and Mardashov (2017)	Methods and tools for education and research in the information society	Use of mathematical simulation models to construct an education system model for the information society
Fernandes, Pereira and Barbosa (2016)	A decision support approach to automatic timetabling in higher institutions	Mathematical modelling towards an automatic timetabling solution
Tambunan (2016)	Mathematical model for mapping students' cognitive capability	Creating a mathematical model to map the mathematics potential of students

Table 2.4: Further research studies on mathematical modelling in education (continued)

In the aim to develop a feedback framework that utilises mathematical models for some of the learning analytics functions, it was considered relevant to review literature on frameworks and framework development. This follows in Section 2.3.4.

2.3.4. Framework development

A framework is an abstract structure providing a hypothetical portrayal of a complex process, like academic performance feedback (Interglot translation dictionary, n.d.). Although feedback in the academic environment is not entirely a new concept, existing approaches are not necessarily conducive to improved learning. A study of the literature on academic performance feedback, learning analytics and mathematical modelling has highlighted the lack of effective feedback approaches. There is a need for an academic performance feedback framework that satisfactorily addresses the requirements for effective feedback (Olwagen & Swart, 2018). The aim of this study is to develop an academic performance feedback framework for improved learning in the tertiary environment. In order to create such a framework, it is necessary to establish a definition within the context of this study and investigate various developmental approaches that were followed in framework development for some specific goal.

Jabareen (2009) proposed a qualitative approach to build a conceptual framework for trends associated with multi-disciplinary bodies of knowledge. For this purpose a *conceptual framework* was defined as a network of interlinked concepts and *conceptual framework analysis* as a theorisation approach for building conceptual frameworks. Effective creation of a conceptual framework could be done according to the grounded theory methodology, which describes the process of induction, derivation of concepts and deduction to hypothesise the relationships between concepts. Conceptual framework analysis was described as an iterative approach with a continuous interplay between the collection of data and analysis. The steps for creating a conceptual framework are: mapping of the data; reviewing and classification of the data; identifying the concepts; deconstruction and classification of the identified concepts; integration of the concepts; synthesising and resynthesizing the concepts; conceptual

framework validation; and rethinking of the framework. Researchers sometimes perform variations of this process in the development of conceptual frameworks.

A Distributed Model Integration Framework (DMIF) was developed by Belete, Voinov and Morales (2017) that aims to link multi-disciplinary models that have been deployed on different hardware and software units. It was stipulated that the design of the framework should adhere to the user requirements and must also be verifiable. The framework consisted of the following three connected layers: the user interface; the integration layer (consisting of a technical integration module, semantic mediation module and dataset mediation module); and the resources layer. The research provided some important guidelines as to the development of a framework that spans different conceptual platforms, as is also applicable in this study.

Lee and Hannafin (2016) indicated that while student-centred learning (SCL) is increasingly more being implemented in high schools and tertiary institutions, a topical and comprehensive framework for designing, developing and implementing SCL was absent. SCL is an approach where students are identified as the owners of their own learning. The intersections of constructivist, constructionist and self-determination theories, in which SCL is rooted, were studied to identify its key constructs: autonomy, scaffolding and audience. Consequently, a design framework was introduced that incorporates the motivational, cognitive, social and affective features of learning. For each of the theories stated above, design assumptions were termed *own it, learn it* and *share it*. Design guidelines were developed accordingly.

It is a challenge for lecturers to provide formative feedback on student responses to open-ended problems because of the different formats they can take. Feedback needs to provide students with some sort of information or potential on how to improve. Diefes-Dux, Zawojewski, Hjalmarson and Cardella (2012) developed a framework for analysing instructor feedback on group responses to open-ended mathematical modelling problems and its impact. In developing the framework, formative feedback from graduate teaching assistants in a specific activity, were studied and analysed. It was discovered that feedback had form and substance. The forms of feedback that were identified included comments, questions, open recommendations and direct recommendations. The substance in this case was connected to the dimensions of the particular activity used for data collection. The framework was coded in segments and evaluated. It was found that the framework was generalizable to specific settings. Regarding feedback patterns of lecturers, the form and intent of feedback were dependant on the rubric criteria and the quality of the work submitted by students. Further studies on student interpretation to various feedback forms were planned.

Yelamarthi, Drake and Prewett (2016) proposed an instructional design framework that uses low cost technological aids and proven pedagogical methods to improve student learning, by improving traditional flipped classroom methodologies. An instructional design framework integrating situational learning aspects was combined with other frameworks that provide connections between learning outcomes, program configuration, student activities and roles, lecturer roles, available tools and assessment strategies. A strong relationship between student performance and interaction with lecturers was identified. Further findings proved that

students learned better when they participated in active learning activities. The applied flipped classroom methodology incorporated these findings with the additional approach of providing effective feedback. The developed framework therefore involved examination of the situational factors, incorporation of course learning objectives and ensuring alignment of the objectives with instructional design elements. The framework was implemented and evaluated in a first-year engineering program in which students are expected to view a pre-recorded lecture and attend discussions in class. This resulted in the development of a low-cost modified flipped model which improved student awareness in specific engineering applications and reinforced the critical thinking and problem-solving abilities of students.

Rubin (2006) recognised that many lecturers are hesitant to use peer feedback in their classrooms for fear of the responses and feedback capabilities of students, unfamiliarity with feedback and time constraints. A feedback framework in the form of an adaptation to the academic journal review process, was proposed. The purposes of the framework were to offer groups of students a way to give enhancing feedback on a project and to develop the abilities of students to give and receive feedback. In the process, the lecturer played the role of *editor* who received the submissions and selected the reviewers. Project groups were required to submit a preliminary report without any author identifying information. The editor then randomly appointed independent reviews from four class reviewers for each report. Each group was allowed two weeks to revise their projects, after which the final reports were submitted to the lecturer. The framework was created after careful consideration of the literature which yielded the following requirements for effective feedback: it should be specific and descriptive, it should be provided in a neutral, non-threatening way, it should include improvement information and it should bear the promise of a reward. After implementation of the described process, it was found that the quality of the group project reports had improved and students in general displayed improved abilities in accepting and providing feedback.

Two coding frameworks, one for lecturer feedback and another for student feedback, were developed by Adie, Van der Kleij and Cumming (2018) towards creating an understanding of feedback as a dialogic process. The elements that were deemed important in feedback dialogue include the differences between current performance and assessment goals, interaction between lecturer and student and the needs of students. The purpose of the coding frameworks was to enable analysis of teacher and student dialogues in feedback. Implementation of the frameworks illustrated the character of the different feedback contributions (non-dialogic to dialogic) to conversations. Transcripts of feedback conversations were studied by independent researchers in order to identify the following elements essential to the dialogic feedback process: specifying attainment and improvement; and constructing achievement and future goals. The work successfully linked engagement in dialogic feedback with the development of the self-regulatory skills of students. By questioning the students, lecturers encouraged students to justify and evaluate their learning by engaging in self-analysis. This also provided lecturers with useful information on the most effective teaching strategies. The frameworks "*contributed to the conceptual understanding of the nature of dialogic feedback and the empirical illustration of what this looks like in practice as*

contributing to the development of student self-regulatory skills, and learning for both teacher and student" (Adie, *et al.*, 2018, p. 721).

After development of a framework for K-12 science education, a group of specialists compiled and published a report with the required standards (Holthuis, Deutscher, Schultz, & Jamshidi, 2018). The essential elements identified and incorporated into a sixth-grade science curriculum, were project-based learning, assessments that were performance-based and structured group work. The framework was evaluated over the course of a three-year period and improved student engagement and participation were observed. Anecdotal evidence was also found on student motivation and interaction. A set of criteria for evaluating the success of other Next Generation Science Standards (NGSS)-aligned programs were developed and involved the following factors: performance expectation alignment; relevant scientific phenomena; learning tasks related to the phenomena; feedback and revision opportunities; and formative (evaluating theoretical knowledge) and performance (evaluating application abilities) assessments. The framework, therefore, provided a model for developing and evaluating new curricula that are aligned with the NGSS standards.

Framework development also extends to the learning analytics field as illustrated by West, Heath and Huijser (2016). A mixed-method approach was employed to develop a framework for dialogue on the implementation of learning analytics to improve student retention at higher education institutions. The approach involved surveys at institutional and teaching staff level, interviews with academics and discussions with colleagues at a national forum. The research aims were to identify the relevant factors for implementation of learning analytics towards student retention and their impacts. It was discovered that there were seven domains for discussion: the institutional context; transitional institutional elements; learning analytics infrastructure; transitional retention elements; learning analytics for retention; intervention; and reflection. It was concluded that although learning analytics is widely researched, implementations seem to be limited to specific institutions. Learning analytics should ideally concentrate on linking a student's academic journey to the operational plans of an institution.

In an effort to assess programs based on student reflections, a framework for dynamic program assessment for learning communities was developed by Kahn, Calienes and Thompson (2016). Students participated in the study by supplying their experiences on socio-cultural assumptions underlying a dynamic learning program. It was observed that students tend to talk about what collaboration meant to them and about the act of collaboration. The study challenged "*the mainstream view of academic assessment as a static and discrete practice that focuses on examining lag measures – … such as students' grades, retention and graduation rates, and progress through curricular sequences*" (Kahn, *et al.*, 2016, p. 20). After evaluating the framework, they concluded that dynamic programs should preferably be assessed dynamically, assessment practices should contribute to improving existing assessments and the assessment of learning community programs should be participated in broadly.

Jacobson, Kapur and Reiman (2016) proposed a conceptual framework to contribute to learning in complex physical and social systems which provide information on educational research. The opinion was that the elements required for the framework were distributed over neuronal, cognitive, intrapersonal, interpersonal and cultural levels. The research resulted in an outline of the focus areas, conceptual perspectives and some examples of complex systems. The addressed phenomenon, therefore, is the debate of learning and educational research, with the aim to provide "*concepts for describing what form theories of learning should take, specifying conceptual requirements of what they should describe, and identifying gaps in conceptual areas of theoretical import*" (Jacobson, *et al.*, 2016, p. 213).

As technology and resource use in education changes, assessment and feedback design remains a topical research field. Rather than focusing on institutions, Bearman, Dawson, Boud, Bennett, Hall and Molloy (2016) developed a practical framework aiming to inspire innovative thinking when educators design or modify assessments. This resulted in development of the Assessment Design Decisions Framework which classified assessment considerations into six categories: assessment purpose; assessment context; learning outcomes; activities; feedback procedures; and feedback interactions. The advantage presented by the framework was that it would assist educators in identifying the nuances of personal, departmental, disciplinary and institutional environments when they design or modify assessments. Such distinctions will provide valuable insight in this study, towards creating and evaluating an academic performance feedback framework.

The literature review in this section purposed to define a framework and to illustrate approaches followed in diverse perspectives towards describing some phenomena within the educational context. Additional sources on framework and framework development, are shown in Table 2.5.

Author(s)	Title	Research theme
Adachi, Tai and Dawson (2018)	A framework for designing, implementing, communicating and researching peer assessment	A peer assessment framework by considering faculty accounts of their practices
Chukwuere (2018)	The application of a culture-oriented e-learning system framework for developers: an approach for developing countries	Development of an effective framework that can assist developers in delivering learner culture-oriented e-learning systems
Machika and Dolley (2018)	Framework for a learning management system at a university of technology with a weak information technology maturity system	A discussion of a framework for development of a learning management system within a university of technology
Fourie and De Klerk (2017)	Facilitating the continuing education needs of professional cataloguers in South Africa: a framework for self-directed learning	A self-directed learning framework based on models on professional practice, self-directed learning theory, and the personality trait of self-directedness
Correira, Dos Santos and Passmore (2016)	Understanding the coach-coachee-client relationship: a conceptual framework for executive coaching	A framework to describe how coaching processes operate psychologically
Lidsay (2016)	More than 'continuing professional development': a proposed new learning framework for professional accountants	A framework for professional learning in accounting incorporating professional competence and career adaptibility

Table 2.5: Supplementary sources on framework and framework development

Author(s)	Title	Research theme
Ferreira and Otley (2009)	The design and use of performance management systems: an extended framework for analysis	Performance management systems framework to describe the structure and function of performance management systems

Table 2.5: Supplementary sources on framework and framework development (continued)

The ultimate goal of this study is to develop a framework that describes academic performance feedback in a changing tertiary education environment. To this end, an overview of some recent literature relevant to frameworks, and framework development in education, was provided.

2.4. Content analysis

The concepts relevant to this study were discussed in Section 2.3. The scope and novelty of research in academic performance feedback, prove that this research field remains topical. Requirements for the feedback process and attributes for it to be conducive to improve learning, were also highlighted. Learning analytics is a relatively new research area and the number of studies is steadily increasing. The review on learning analytics proved that such tools are essential for implementation in the scope of this study. The need for using mathematical models as part of learning analytics was explained, followed by some examples of how such models are already being used for specialised purposes in education. As the development of a framework for academic performance feedback using mathematical models for learning analytics is the main goal of this study, a review on the literature of frameworks followed. Irrespective of the purpose of the framework, development starts with studying the relevant literature followed by identification of the elements essential to the specific field of application. Step-by-step procedures are commonly provided to guide potential users in implementation of the frameworks, in various settings.

2.5. Conclusion

In this chapter, an overview of recent literature on academic performance feedback, learning analytics, mathematical modelling and framework development was provided. This included discussions of some examples in each of these subcategories, which were further supplemented by tables listing additional literature examples in each field.

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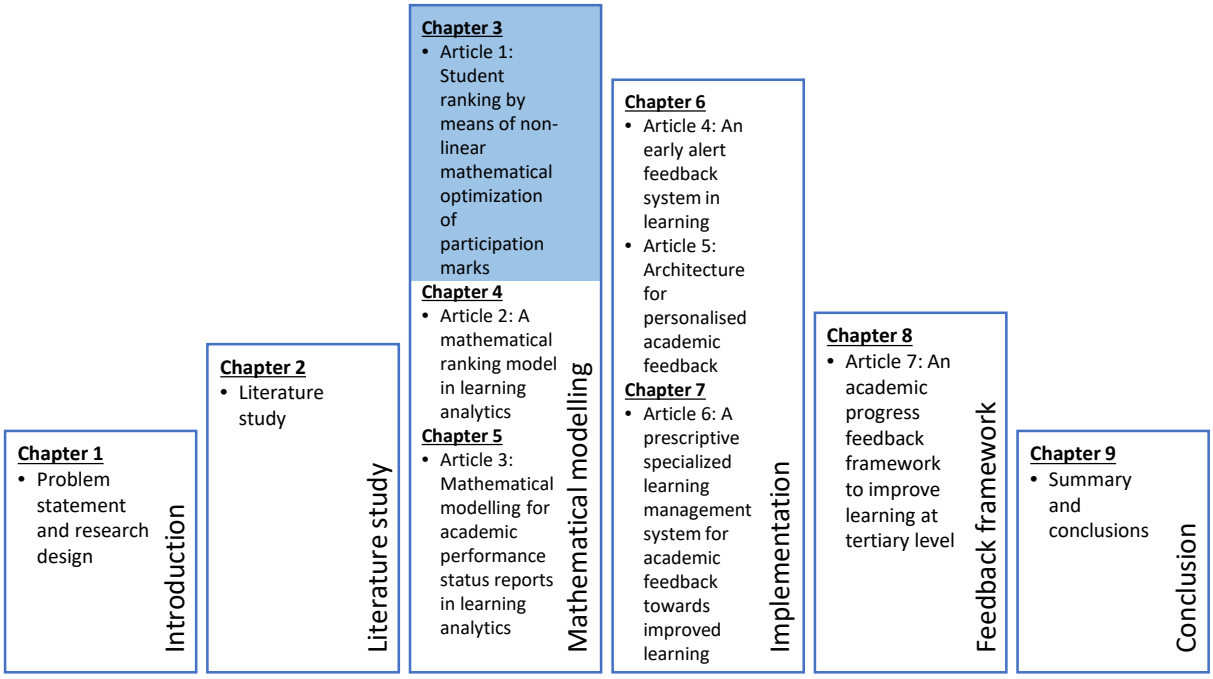
Chapter 3

Article 1: Student ranking by means of non-linear mathematical optimization of participation marks



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3.1. Preamble to Article 1

The title of the article presented in this chapter is *Student ranking by means of non-linear mathematical optimization of participation marks*. The paper was presented at the *8th International Conference on Applied Operational Research* held in Rotterdam, The Netherlands from 28-30 June 2016. This was a peer reviewed conference and the article was published in Volume 8 of its proceedings, titled *Lecture Notes on Management Science*, in June 2016.

Article 1 is the first of three papers in the section on mathematical modelling. It describes the development of a non-linear mathematical programming model implemented to improve the process of dynamically ranking students according to their academic performance. The paper starts by describing some issues that contribute to the decreasing student numbers observed

at tertiary institutions. It further describes the feedback scenario in this setting and elaborates on advantages and disadvantages of an existing feedback method. A participation mark for a student is calculated as the weighted sum of a set of grades accumulated over the course of a semester. Towards finding an improved approach to calculate the average participation marks of students, a non-linear programming model was formulated and solved and successfully eliminated the need for time-intensive empirical calculations. The students were ranked according to the calculated marks and the resulting student ranking correlated favourably with that obtained in the existing method. Although the non-linear model optimised participation mark calculation and ranking, the method did not provide students with targets towards improving their academic performance. This issue is addressed in the next article chapter.

The referencing style required by the journal was that of the American Psychological Association (sixth edition)[1]. More information on submission, the peer review process, and author guidelines of the journal can be found in Appendix B.

[1] The article is presented in its final published form. Consequently, the page numbers of the article, as it appears in the proceedings, are displayed along with the principal thesis information.

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Student ranking by means of non-linear mathematical optimization of participation marks

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Abstract

Ranking students according to their growing participation marks could encourage them to develop self-motivational attitudes toward their academic progress. This paper describes the ranking of students by means of a non-linear mathematical optimization model. The model uses optimization techniques to find the best weights for calculating students' participation marks, effectively eliminating manual evaluation of all possible equations. The optimal weights are used to calculate the average participation marks and the students are ranked accordingly.

Introduction

In recent years, an attitude of indifference among students relating to their academic performance has been noted in Computer Science (CS) education (Du Toit, 2015). Although the common perception among students is that their main responsibility is partaking in lectures, they feel that lecturers have to provide guidance and motivation for them to achieve (Geçer, 2013). The role of the lecturer has changed from just teaching and controlling the learning process to following and facilitating it. A successful lecturer creates an environment in which students harbor a responsibility towards a positive class atmosphere (Ozel, 2015). However, a great obstacle in these classes which inhibits a lecturer's ability to inspire students is the large student numbers which have to be dealt with (Hattie, 2005).

Studies show that the implementation of self-monitoring initiatives in mainstream classes, result in increases in students' participation and subsequent academic achievement (Rock, 2005). Students that self-motivate exhibit a sense of self-management and achieve greater academic success (Di Domenico & Fournier, 2015). Finn and Zimmer (2012) found that a higher level of student engagement in learning, leads to greater academic achievement. Students who try to self-regulate their studies display a sense of responsibility in terms of controlling and performing actions relating to their studies (Garcia, 1996). Barker and Garvin-Doxas (2004) argue that using a hierarchy structure in a class can assist students in understanding improvable factors which determine their academic success and will also enable a lecturer to identify students that are underperforming.

Numerous different methods have been developed in the ranking of individuals. Gao *et al* (2015) followed a fuzzy hierarchical approach to evaluate college sport coaches by using an analytic hierarchy process to determine the appropriate weight levels for each influential factor. After that they employed a fuzzy comprehensive evaluation, derived from the fuzzy set theory (Gottwald, 2010), to calculate a grade or ranking for each coach. Another example is the ranking of the top 150 National Basketball Association players by Mertz (2015). He used linear regression techniques in a statistical model to determine the factors which will have the greatest impact on a player's ranking.

A study by Du Toit (2015) involved the implementation of a computerized mathematical program used to inform students on their academic progress during the course of a semester. The program empirically calculated sets of participation marks for each student, using different combinations of a general mathematical equation and ranked the students according to the average of each set. The students were presented with their class ranking at regular intervals.

Lecturers usually predetermine a mathematical equation to be used for calculation of the participation marks of students. These marks also present some indication of the level at which students participate in their subjects and are eventually used to determine whether a student will be allowed to write exam or not. The purpose of the system developed by Du Toit (2015) was to facilitate the ranking of students by considering all the different options available for the calculation of participation marks. To pass a CS module, a student needs to achieve certain module outcomes in the specific subject. However, because of the nature of CS education, student performance and progress are determined not only through theoretical assessments but also practical assignments, class tests, exams and participation in class activities. Lecturers

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therefore require a high level of student participation during the majority of the classes to be able to sufficiently prepare them for summative assessments, but struggle to motivate students effectively.

The aim of this research was to develop and solve a mathematical model that:

- Uses non-linear programming techniques to find the best weight distribution, for varying numbers of factors, in calculating participation marks in undergraduate CS modules;
- Calculates the average participation marks of students using the optimized weights; and
- Ranks the students according to their average marks.

The ranking program implemented by Du Toit (2015) is briefly outlined in the next section. This is followed by a discussion on the development and solution of the non-linear mathematical ranking model. The paper ends with a section describing future developments and the incorporation of data envelopment analysis (DEA) in the ranking process, as well as some concluding remarks.

Development of the non-linear mathematical ranking model

The content in CS modules has the feature that new concepts are taught based on the preconception of existing knowledge among the students. So if students neglect to attend class, certain basic concepts are not mastered. Lecturers usually have insufficient insight into student participation from the very start of a new semester. This means that a lecturer cannot always identify students who fall behind early on. More insight into the predicted average- and minimum participation marks of each student can help the lecturer to timeously recognize individuals who are at risk of falling behind in such a way that they will not be able to complete the module successfully. A system that provides such insights to lecturers can also be used to inform the students on their progress from the very start of the semester and present an incentive to perform better.

In general, lecturers require the following insights into student progress, at regular intervals:

- The minimum possible participation mark for each student;
- How each student performs relative to the rest of the class based on student ranking;
- What the expected average participation mark for the entire class is; and
- What the expected throughput of the class is in terms of exam admission.

Students are granted admission to exams if they have a participation mark of forty percent or more (Du Toit, 2015). Factors, that are considered in the calculation of participation marks can include, among others, average scores per student for class attendance, practical assignments, informal tutorial tests, and formal semester tests. Formative tutorial tests, during which students are also encouraged to discuss basic concepts with their peers, are often given in class to assess basic theoretical knowledge needed to complete practical assignments. Summative semester tests are used to determine the level of proficiency with which individual students have mastered theoretical and practical subject content. The impact that each of these factors need to have on the participation mark sometimes vary according to the preference of the specific lecturer, because of different teaching and learning methods employed. Lecturers adhere to certain weight guidelines when calculating the participation marks in CS and would typically inform students how the participation mark for a module is to be calculated. Du Toit's (2015) model can be formulated as follows:

$$P = s_1x_1 + s_2x_2 + \cdots + s_nx_n \tag{1}$$

$$\text{Subject to} \quad \sum_{i=1}^{n} x_i = 1 \tag{2}$$

$$x_i \bmod k = 0 \tag{3}$$

$$l \leq x_i \leq u \tag{4}$$

$$0 \leq s_i \leq 1 \tag{5}$$

$$x_i \geq 0 \tag{6}$$

$$l, u \geq 0 \tag{7}$$

where P is the participation mark, s_i is the average score for factor i, x_i is the weight assigned to factor i, (3) ensures that x_i is a multiple of k, l is the lower limit for all the weights, u is the upper limit for all the weights, n is the number of factors used, and $i = 1, \ldots, n$.

In undergraduate modules, it is generally accepted that no one single factor should carry a weight of more than forty percent of the resulting participation mark (Du Toit, 2015). Also, weights assigned manually to the factors are generally in multiples of five. In the described scenario, the following values will therefore apply: $k = 0.05, l = 0.05,$ and $u = 0.4$.

The ever-changing nature of CS regularly triggers lecturers to implement new types of assessments in their classes (Landau *et al*, 2014). This means that during the course of a semester, a lecturer can decide to add a new type of assessment and want to let it count as another factor in calculating the participation mark. Although the inclusion of such new innovations can benefit the students, the lecturer is then bound by the disclosure made at the beginning of the semester regarding the calculation of the final participation marks. So stipulating a general equation to be used for the participation marks would allow the lecturer to determine the specific factors during the course of the semester and also enable the students to control the weights by improving in the areas still available to them.

Du Toit's (2015) ranking program uses the model in (1)-(7) to calculate a participation mark for every combination of different weight levels that are allowed by the constraints. This means that for each factor used in a calculation, there are 8 $(= \frac{0.4}{0.05})$ or less weight levels that may apply and the sum of all the weights must add up to 1 (100%). So, for each factor a lecturer decides to include in the calculation of the participation marks, the number of equations available due to adding and redistributing weights, increase exponentially. The total number of possible equations available for the number of factors from 3-12 was determined empirically and is shown in Table 1.

Note that because the use of one or two factors in the calculation of participation marks would violate constraint (2), these scenarios are not considered. Apart from the fact that calculating 315 different sets of marks per student for only four factors manually is impractical, the scenarios available in these equations do not consider that some factors could be more important than others. For instance, generally a semester test average must bear more weight than the class test average, and the class test average is more important than attendance.

The following additional constraint is therefore added to the model:

$$x_i \geq x_{i+1}, \quad i < n \tag{8}$$

The addition of the constraint in (8) saw the number of possible equations for participation mark calculation decrease considerably (see Table 2). For three factors, and with the inclusion of constraints (2)-(8), Du Toit's program (2015) would typically calculate a total of four participation marks per student, using the equations given in Table 3.

The program would then determine the minimum-, maximum-, and average participation marks, and rank the students according to the average marks. An example set of calculated marks for six students, is displayed in Table 4.

Table 1. Number of available equations for participation marks calculation

Factors (n)	*Number of equations*
3	15
4	315
5	2 226
6	8 856
7	23 898
8	47 748
9	74 097
10	91 828
11	92 257
12	75 570
Total	416 810

Table 2. Number of available equations for participation marks calculation with the additional constraint

Factors (n)	*Number of equations*
3	4
4	23
5	46
6	61
7	63
8	58
9	47
10	38
11	28
12	21
Total	389

Table 3. Available participation mark equations for $n = 3$ factors

Equation 1	$0.4s_1 + 0.3s_2 + 0.3s_3$
Equation 2	$0.35s_1 + 0.35s_2 + 0.3s_3$
Equation 3	$0.4s_1 + 0.35s_2 + 0.25s_3$
Equation 4	$0.4s_1 + 0.4s_2 + 0.2s_3$

Table 4: Participation marks per student using all available equations

	Equation 1	*Equation 2*	*Equation 3*	*Equation 4*	*Minimum*	*Average*	*Ranking*
Student A	60%	59%	61%	63%	59%	60.84%	4
Student B	91%	92%	91%	91%	91%	91.40%	1
Student C	81%	80%	81%	81%	80%	80.89%	2
Student D	53%	54%	54%	55%	53%	53.99%	6
Student E	64%	65%	65%	66%	64%	65.05%	3
Student F	58%	59%	58%	57%	57%	58.31%	5

Additional statistics provided by the program include the throughput figures and average class participation mark for each available equation. These numbers assisted the lecturer in deciding what the best weight distribution for the factors would be and in providing minimum participation marks and rankings to students. Students had insight into their progress in the module but were also able to systematically increase the average participation mark *en masse* by working harder in those factors on which they could still have an impact.

The program also presented the lecturer with additional class statistics, as shown in Table 5.

Table 5: Class statistics for the four different equations

Equation	*Number of students with no exam admission*	*Average class participation mark*
1	12	54.08%
2	12	55.54%
3	13	54.82%
4	17	52.62%

In this example, the statistics enabled the lecturer to see the effect of using the various equations on the resulting number of students without exam admission, and on the average participation mark. Feedback received from the students in the class was overwhelmingly positive. Most of them felt that knowing their exact rank in relation to the rest of the class, motivated them to work harder in the areas which they knew could still cause their positions to improve. Although successful, the system effectively searched for the best weights to use by empirically calculating all of the possibilities and manually selecting one option. The purpose of the proposed model was to find the optimal weights and calculate the participation mark only once. To develop a model that optimizes the calculation process, certain system requirements needed to be considered. These requirements include to:

- Determine the minimum- and maximum participation mark for each student;
- Determine the average weight for each factor and use them to calculate the average participation marks;
- Rank the students based on their average participation marks; and
- Determine the resulting throughput.

The mathematical model implemented to optimize this problem can therefore be written as follows:

$$\textit{Maximize/minimize} \quad P = \sum_{i=1}^{n} s_i x_i \tag{9}$$
$$\textit{Subject to} \quad \sum_{i=1}^{n} x_i = 1 \tag{10}$$
$$x_i \bmod k = 0 \tag{11}$$
$$l \leq x_i \leq u \tag{12}$$
$$x_i \geq x_{i+1}, \qquad i < n \tag{13}$$
$$0 \leq s_i \leq 1 \tag{14}$$
$$x_i \geq 0 \tag{15}$$
$$l, u \geq 0 \tag{16}$$

where P is the participation mark, s_i is the average score for factor i, x_i is the weight assigned to factor i, (11) ensures that x_i is a multiple of k, l is the lower limit for all the weights, u is the upper limit for all the weights, n is the number of factors used, and $i = 1, \dots, n$.

Implementation of the mathematical ranking model

The model was implemented in an Excel spreadsheet and, due to the non-linearity caused by constraint (11), was solved utilizing the Evolutionary Solver (Baker, 2011). This procedure generally finds heuristic solutions when optimal answers are not guaranteed. The score data set implemented in Du Toit's (2015) program (Table 6), was used to obtain the maximum-, minimum- and average participation marks per student. The data set contained the average scores of three factors, for six students. The factors represented a semester test (s_1), class test average (s_2), and average score for practical assignments (s_3). For each of the students in Table 6, the participation mark was maximized and minimized using Evolutionary Solver. These results are shown in Table 7.

Table 6. Mark set used in the non-linear optimization program

	s_1	s_2	s_3
Student A	66%	73%	37%
Student B	97%	84%	93%
Student C	78%	87%	77%
Student D	70%	49%	37%
Student E	71%	66%	55%
Student F	64%	47%	65%

Table 7. Results achieved by non-linear optimization program

Student	*Max. participation (%)*	*Min. participation (%)*
A	63.0000	59.4000
B	91.9000	91.2500
C	81.4000	80.4000
D	55.0000	52.7500
E	65.8000	64.4500
F	59.2000	57.4000

The results obtained yielded the same maximum- and minimum participation marks when compared to Du Toit (2015) in all instances but one, where the difference was negligible. The model provided the average weights (x_i) for each of the factors (s_i), which were used to calculate the average participation mark per student and to determine the student ranking. The resulting ranking was the same as those achieved by Du Toit (2015).

Future developments and conclusions

Optimizing the system further by implementing DEA principles is currently being investigated. DEA is a method used to measure the efficiency of decision making units (DMUs) with multiple inputs and –outputs, relative to one another (Seiford & Zhu, 2003). It is commonly implemented in cases where different operating units need to be compared with one another and can be solved as sets of linear programs (one for each DMU), also described in Adler *et al* (2002). Determining fair and effective inputs where students are concerned can be very difficult. A method will be investigated, similar to the one used by Kao and Lin (2008) who used DEA without inputs to allocate universities to classes of differing levels. All universities in the same class are considered equally efficient and better than those in lower classes. Their method determined the Pareto optimal universities by implementing the following model:

$$Maximize \quad E_k = \sum_{j=1}^{m} Y_{kj} w_j \tag{17}$$

$$Subject\ to \quad \sum_{j=1}^{m} Y_{ij} w_j \leq 1 \qquad i = 1, \dots, n \tag{18}$$

$$w_j \geq \varepsilon > 0, \qquad j = 1, \dots, m \tag{19}$$

where E_k is the composite index, Y_{ij} is the measure of unit i in criterion j, w_j is the weight for criterion j, n is the number of units to be evaluated, m is the number of criteria, and ε is a small positive number.

This model provides only the ultimate goal, so a DMU is ranked high if it performs very high in one criterion. When the DMUs are students, the nature of ranking and the relationship between the criteria, prompts the use of the dual formulation of this model, given in (20)-(22), which will present each student with intermediate targets to reach for improving his/her position in the ranking.

$$Maximize \quad E_k = \sum_{i=1}^{n} \lambda_i - \varepsilon \sum_{j=1}^{m} s_j \tag{20}$$

$$Subject\ to \quad \sum_{i=1}^{n} Y_{ij}\lambda_i - s_j = Y_{kj} \qquad j = 1, \dots, m \tag{21}$$

$$\lambda_{ji}, s_j \geq 0, \qquad i = 1, \dots, n;\ j = 1, \dots, m \tag{22}$$

where E_k is the composite index, Y_{ij} is the measure of unit i in criterion j, w_j is the weight for criterion j, n is the number of units to be evaluated, m is the number of criteria, ε is a small positive number, $\theta = \sum_{i=1}^{n} \lambda_i$, $(Y_{kj} + s_j)/\theta$ is the target, and $j = 1, \dots, m$.

In conclusion, this paper discussed the development of a non-linear mathematical model which was successfully solved to determine the best weight distribution for existing score data sets. The model was implemented in CS modules, enabling the lecturer to provide the students with regular performance updates by informing them on their progress and ranking in relation to their peers. The reaction of the students was very positive. It gave them a sense of control over their own progress and compelled them to improve their positions, creating a self-motivational class setting.

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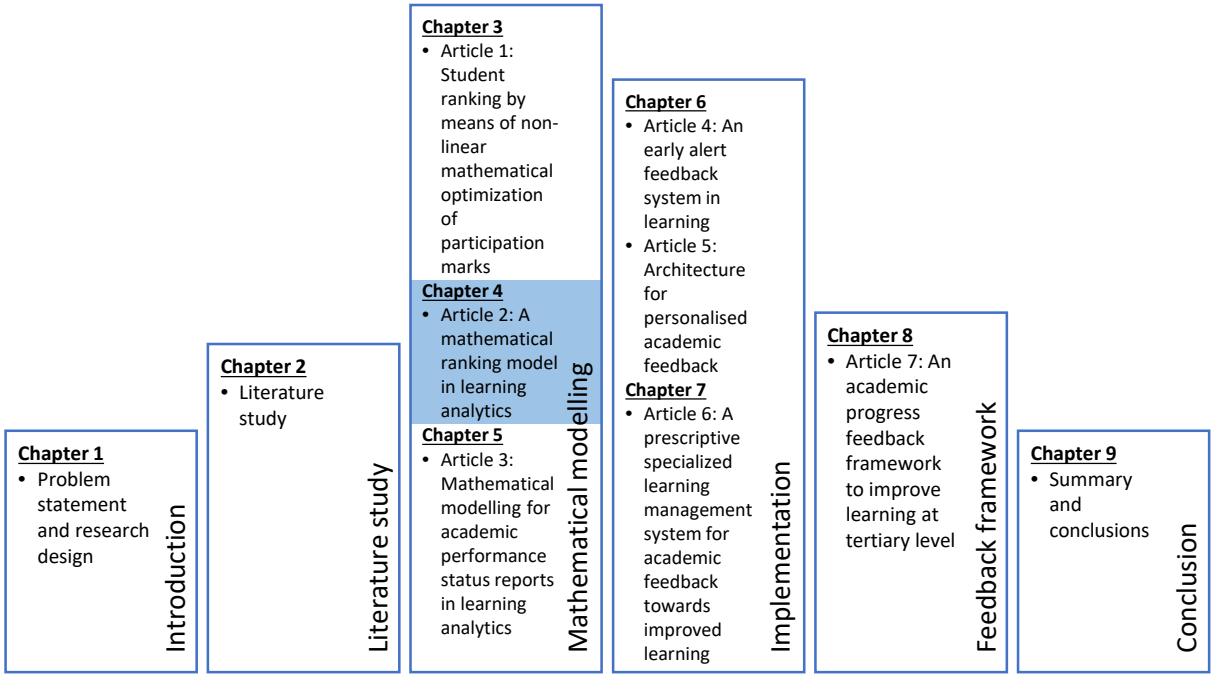
Chapter 4

Article 2: A mathematical ranking model in learning analytics



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Article 2:

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4.1. Preamble to Article 2

The article presented in Chapter 4 is titled *A mathematical ranking model in learning analytics*. This article was presented at the peer refereed *16th International Conference on Computational and Mathematical Methods in Science and Engineering (CMMSE)*, which was held in Costa Ballena (Rota), Cádiz, Spain from 4-8 July 2016.

The manuscript presented here is the second paper in the section on mathematical modelling. Acting as a continuation of the article presented in Chapter 3, this paper presents a multi-stage mathematical class ranking model, which applies the principle of Pareto optimality to determine an academic performance efficiency score for the students in a class and sort them into classes of similar efficiency, according to dominance. An outputs-only based data envelopment analysis model is utilised to calculate targets for students to advance to a higher class of academic efficiency. The model provides improvements in learning analytics through

the creation of a student output efficiency class-ranking as well as calculating individualised improvement targets for each student. The advantages presented by this model are discussed, followed by some disadvantages which will be addressed in the article presented in Chapter 5.

The referencing style required by the journal in which it was published, was the IEEE reference order style[1]. More information on submission, the peer review process, and author guidelines of the journal can be found in Appendix C.

[1] The article is presented in its final published form. Consequently, the page numbers of the article, as it appears in the proceedings, are displayed along with the principal thesis information.

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A mathematical ranking model in learning analytics

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Abstract

The introduction of new educational trends triggers the development of innovative methods to collect, analyse and report the data subsequently generated. This paper discusses the implementation of a multi-stage mathematical class ranking model as a method in learning analytics, applied to a Computer Science module. The model applies the principle of Pareto optimality in an outputs-only data envelopment model to categorise students into classes of similar efficiency which are ranked according to dominance. The model is then adapted to calculate improvement targets for each student.

Key words: class ranking, data envelopment analysis, learning analytics, Pareto optimality, student ranking.

1. Introduction

Development in educational technology has seen traditional learning models in instruction gradually being replaced with modern trends like blended- and online learning [1]. These trends include the use of learning management systems, sites on social media networks and the incorporation of learning analytics (LA). LA includes the real-time collection of data, or "big data", which are so large that conventional collection methods have proved inadequate [2]. It also encompasses the use of analyses on big data to make multi-criteria decisions, report and inform in the educational system [3]. While blended learning methods in education are gaining

popularity and being implemented more frequently, the process of accurately measuring student progress is proving to be somewhat of a challenge.

LA presents an important instructional application in the form of monitoring individual student performance [4]. The timely collection of data also enables lecturers to measure the progress of students at any stage of instruction. It has been found that regularly informing students on their academic progress and ranking in relation to their peers, stimulates a competitive attitude which effectively motivates them to try and outperform their class mates [5]. LA also enables lecturers to use predictive modelling techniques which can:

- Provide students with early academic outcome alerts [4]; and
- Help identify and provide interventions for academically at-risk students at an early stage [3].

In this paper, a multi-stage class ranking model will be implemented as a LA method to rank students and provide improvement intervention targets. The model uses a data envelopment analysis (DEA) approach which is a special linear programming application in which the performance efficiency of a specified number of operating units with the same objectives is measured relative to one another [6].

In the next section, the concept of Pareto optimality and how it relates to this work is discussed and the mathematical model used for DEA is formulated and explained. This is followed by an outline of the dual-formulation used to determine intermediate improvement targets for students. Section 3 describes the application of the multi-stage mathematical model on a data set of a Computer Science module, followed by a discussion of the results and some concluding remarks.

2. Pareto optimality and DEA

DEA is commonly implemented in cases where different operating units, or decision making units (DMUs), need to be compared with one another. Typical examples include banks, hospitals, fast-food outlets within a certain chain, or in this case, students according to academic performance.

DEA compares a certain number of DMUs based on their inputs or resources and their outputs [7], by calculating an efficiency score that represents the relationship between its inputs and outputs. The result gives an indication of whether a particular unit is less efficient than the others. It is however very difficult to determine fair, comparable inputs

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where students are concerned. Consider for instance the accuracy of data relating to the number of hours study time per student, or lifestyle factors.

A similar problem was addressed by Kao and Lin [8] who implemented a DEA model without inputs to categorise Management Colleges into classes of differing levels. All colleges in the same class were considered equally efficient based on their outputs, and could not be compared to one another. This class ranking model will be applied to arrange students into different classes of efficiency, where all students in the same class are considered equally efficient. As far as can be ascertained, the DEA outputs-only class ranking has not previously been used on students in such an application.

One of the advantages of this model is that the principle of Pareto optimality applies, meaning that Pareto-efficient students are categorised into one class, and they dominate those in lower classes. In a traditional DEA output-oriented method, a DMU, or in this case a student, is considered Pareto-efficient if none of the output scores can increase without decreasing another one of the output scores or without increasing at least one of the input scores [9]. In mathematical terms, student k_0 is Pareto-efficient if no other feasible student $k \neq k_0$ exists so that $y_{kj'} > y_{k_0 j'}$ for some output criteria j' and $y_{kj} > y_{k_0 j}$ where $j \neq j'$ and $x_{kr} \leq x_{k_0 r}$ for all input criteria r, where y_{kj} are the output levels for student k, with $j = 1, \dots, s$, x_{kr} are the input levels for student k, and $r = 1, \dots, m$.

For this application, it means that all students considered to be Pareto optimal should be categorised as equally efficient and receive the same ranking, while those they dominate must be ranked lower. Consider for example, a data set of five students, denoted by A to E. These students must be evaluated on two outputs, which are scores for class attendance and class assignments, shown in Table 1.

Table 1: Example data set

	Output1 (Attendance)	Output2 (Assignments)	Total
Student A	20	70	90
Student B	80	70	150
Student C	65	60	125
Student D	50	90	140
Student E	50	50	100

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If the two criteria are considered equally important, it would mean that student B is the most efficient, followed by students D, C, E, and A respectively. However, student performance is rarely measured with criteria that are considered equally important. Attendance cannot be compared to assignments, so it will be more rational to search for those students who dominate others. This is done by calculating an efficiency score for each student. The dominance relationship of the students represented by the data set, are shown in Figure 1.

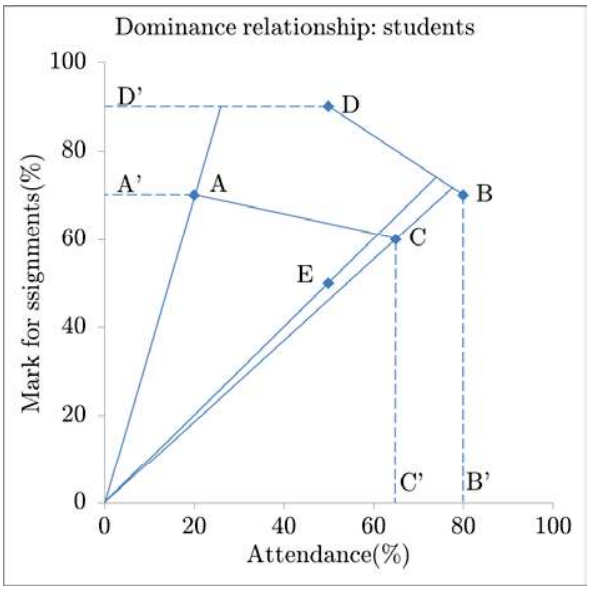

Figure 1: Dominance relationship of the example data set

Students D and B lie on the Pareto optimal frontier, denoted by line segments D'DBB', and are called Pareto optimal because they dominate students A, C, and E. The dominant students are categorised into the highest class and have the highest ranking. Students A and C are dominated because they lie inside the frontier and are categorised into a lower class. Likewise, student E is dominated by students A and C and is in the lowest class. This means that students D and B who are members of the dominant set will have the highest class ranking, followed by students A and C, and student E will have the lowest class ranking. Although student E had a higher total score than student A, he/she was categorised into a lower class. This happens when a student performs predominantly well in all the criteria then the equal weights method results in a higher ranking, whereas the dominance method favours a student who performs exceptionally well in a specific criterion.

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Finding the dominant sets for calculating the efficiency score, or composite index E_k, is done by implementing a basic DEA model without inputs. Pareto optimal students are therefore determined using the following simple DEA output-only model [8]:

$$\text{Maximise} \quad E_k = \sum_{j=1}^{m} y_{kj} w_j \tag{1}$$

$$\text{subject to} \quad \sum_{j=1}^{m} y_{ij} w_j \leq 1, \qquad i = 1, \dots, n \tag{2}$$

$$w_j \geq \varepsilon > 0, \qquad j = 1, \dots, m \tag{3}$$

where E_k is the composite index for every student k, y_{ij} is the output measure of student i in criterion j, w_j is the weight for criterion j, n is the number of students to be evaluated, m is the number of criteria, and ε is a small positive number.

The purpose of constraint (3) is to ensure that all outputs are considered when calculating student efficiency, which means that no weights are allowed to be zero. For each student, the optimal weights are selected for calculating the composite index E_k. If $E_k = 1$, student k is considered Pareto optimal, categorised as a member of the current dominating set and excluded from further calculations. If $E_k < 1$, then student k is Pareto non-optimal and remains in the list of students still to be categorised. This process is repeated k times, once for each of the students. Table 2 compares the rankings of the equal weights method to the classes in the dominance method.

Table 2: Equal weight rankings vs. dominance class rankings

Equal weight method		Dominance method	
Ranking	Student	Class	Student
1	B	1	B
2	D	1	D
3	C	2	A
4	E	2	C
5	A	3	E

Here the difference in ranking is evident in the case of student A, who performed poorly in output 1 and good in output 2. The equal weights method ranked student A 5th, whereas the dominance method ranked this student into class 2.

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The algorithm for determining Pareto optimal students and the subsequent class ranking [10], according to model (1)-(3) follows.

Algorithm 1: Class ranking multiple DMUs

Input: Let $N = \{DMU_1, \dots, DMU_n\}$ be the set of n DMUs, and $\alpha \in \mathbb{Z}^+$.

Output: A number of sets, $C_1, \dots, C_f$, where all units in C_i have the same ranking, and are ranked higher than those in C_j for $i, j \in \{1, \dots, f\}$ and $i < j$.

```
f ← 1;
while N ≠ ∅ do
    Initialise C_f
    α ← 1;
    while α ≤ n do
        k ← DMU_α;
        Apply model (1)-(3) and calculate E_k
        if E_k = 1 then
            Add unit k to C_f
            Delete unit k from N
        end
        α ← α + 1;
    end
    f ← f + 1;
end
```

Algorithm 1 will repeat until all the students have been categorised into classes. Although this stage determines the classes and resulting class rankings, students can only improve their positions if they knew which criteria need to be improved and by how much. To provide them with such intervention actions, intermediate targets must be set for each student. This is done using the dual formulation of model (1)-(3) [8]:

$$\text{Minimise} \quad E_k = \sum_{i=1}^{n} \lambda_i - \varepsilon \sum_{j=1}^{m} s_j \tag{4}$$

$$\text{subject to} \quad \sum_{i=1}^{n} y_{ij}\lambda_i - s_j = y_{kj}, \qquad j = 1, \dots, m \tag{5}$$

$$\lambda_{ji}, s_j \geq 0, \qquad i = 1, \dots, n; \; j = 1, \dots, m \tag{6}$$

where E_k is the composite index, y_{ij} is the output measure of student i in criterion j, n is the number of students to be evaluated, m is the number

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of criteria, and ε is a small positive number. Denote $\theta = \sum_{i=1}^{n} \lambda_i$, then $(y_{kj} + s_j)/\theta$ is the target, and $j = 1, \dots, m$.

Although the calculated efficiency E_k is the same as in model (1)-(3), model (4)-(6) presents student k with targets to make an improvement, providing that the student is not a member of the highest class already. If a student belongs to the fth class with $f \neq 1$, this model calculates $f - 1$ targets to show how much the student must improve in each criterion to be categorised in the next higher class.

The multi-stage model is therefore implemented in two phases: calculating the Pareto optimal students and categorising them into classes using model (1)-(3), and determining intermediate targets for all dominated students to improve their class rankings using model (4)-(6). The implementation of this multi-stage model on a data set of marks for students in a Computer Science module follows.

3. Implementation of the multi-stage mathematical model

The multi-stage model was implemented to obtain the class ranking of students according to their academic progress in a Computer Science module. The data set contains four criteria for 26 students enrolled in the module. The criteria are average scores for assignments, attendance, formative assessments, and summative assessments. Table 3 presents the four initial output criteria for each student, the total of the four criteria, and the class ranking resulting from Algorithm 1.

Table 3: Average output scores (rounded), total of output scores, and resulting class ranking of the students

Student	Output1 Assignments	Output2 Attendance	Output3 Formative assessments	Output4 Summative assessments	Total	Class
2	98	100	100	95	393	1
3	75	100	97	83	355	2
9	88	100	93	92	373	2
10	74	100	93	68	335	3
13	66	89	77	87	319	3
23	62	100	85	72	319	3
24	77	100	90	65	332	3
1	14	63	73	65	215	4
6	58	89	75	63	285	4
11	65	100	88	53	306	4

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12	64	100	73	57	294	4
17	68	78	90	58	294	4
19	41	100	73	63	277	4
8	54	88	58	44	244	5
15	24	89	83	57	253	5
18	43	100	63	58	264	5
20	52	89	60	55	256	5
21	36	75	85	59	255	5
25	26	67	83	60	236	5
26	25	100	65	55	245	5
5	41	78	62	57	238	6
7	35	100	58	22	215	6
14	53	78	10	44	185	6
22	43	89	40	54	226	6
16	26	78	52	46	202	7
4	21	78	35	35	169	8

The students are categorised into 8 classes, which are ranked in order of dominance. The number of students in each class is shown in Figure 2.

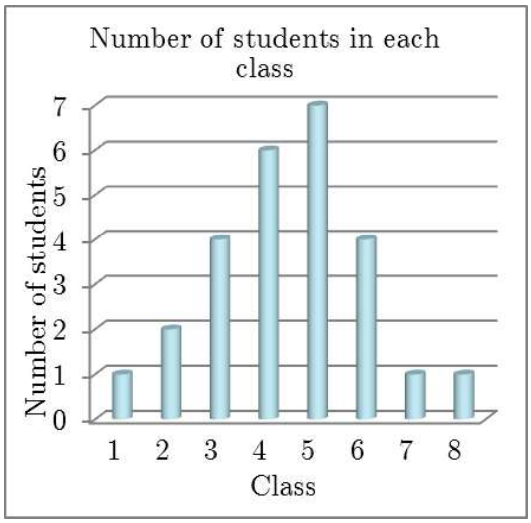

Figure 2: Number of students categorised into each class

From Table 3 it follows that student 2 is categorised into class 1 and therefore ranked higher than all the others. Students 3 and 9 are members of class 2, which means they are dominated by student 2, and themselves dominate the rest of the students. The students in classes 1 to 3 performed

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well in all the criteria but especially so in output 2, attendance. The class ranking of these groups will therefore not differ very much from an equal-weighted ranking. However, a student with a higher total score can be dominated by one with a lower total score. Consider for example the data of students 1 and 5 which are repeated in Table 4.

Table 4: Comparison between students 1 and 5

Student	Output1 Assignments	Output2 Attendance	Output3 Formative assessment	Output4 Summative assessment	Total	Class
1	14	63	73	65	215	4
5	41	78	62	57	238	6

Student 5 is a member of class 6 and has a total score of 238, which is much higher than that of student 1 who is a member of class 4 and has a total score of 215. The dominance method here favours student 1 who has performed well in outputs 3 and 4, and poorly in output 1, as opposed to student 5 who had rather average scores for all those outputs.

The second stage of the model provided each student with intermediate targets which, if reached should categorise the student into a higher class. The targets are in the form of scores for each of the criteria. Suppose for example, that student 5 who is a member of class 6 wants to improve his/her class level, then targets are calculated by solving model (4)-(6). These targets for student 5 are shown in Table 5.

Table 5: Intermediate targets for class level improvement for student 5

Class level	Output1 Assignments	Output2 Attendance	Output3 Formative assessment	Output4 Summative assessment
6 (current)	41	78	62	57
5	42	96	66	58
4	45	87	74	63
3	62	100	85	73
2	57	100	79	73
1	67	100	79	73

The current class of student 5, with output scores of 41, 78, 62, and 57 respectively, is level 6. If the student wants to advance to level 5, output 1

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needs to improve from 41 to 42, output 2 needs to improve from 78 to 96, and so forth.

This LA technique presented students with early academic outcome alerts, helped to identify academically at-risk students and also provided real-time intervention targets which students could use for improvement.

4. Conclusions

The increased use of blended- and online learning techniques in education, leads to learning management systems and LA progressively being implemented to manage and supervise data resulting from such modules. One of the requirements of LA is that lecturers must provide students with real-time feedback on their progress in their studies. This led to the search for novel and improved methods for measuring student progress and performance while also calculating reachable targets for student improvement.

This paper discussed the successful implementation of a multi-stage mathematical ranking model in a Computer Science module. The first stage of the model used the principle of Pareto optimality implemented in an output-only DEA model to categorise the students into classes of similar efficiency which were then ranked according to dominance. The second stage implemented the dual-formulation of the DEA model which provided each student with an intermediate target per relevant criterion, for class level improvement.

The mathematical ranking model implemented in this study enabled the comparison of students in terms of incomparable criteria. Students who had the same totals were for instance not necessarily categorised into the same class and students in the same class could not be compared. Although they could see which criteria they needed to improve for increased efficiency, not all of the targets could in reality be reached. Consider for example a formative assessment which generally constitutes a semester test. Depending on the lecturer, the mark cannot change after the test has been taken.

The addition of features which would allow students within the same class to be compared, as well as determining intermediate targets for only some of the criteria while others remain fixed, are currently being investigated.

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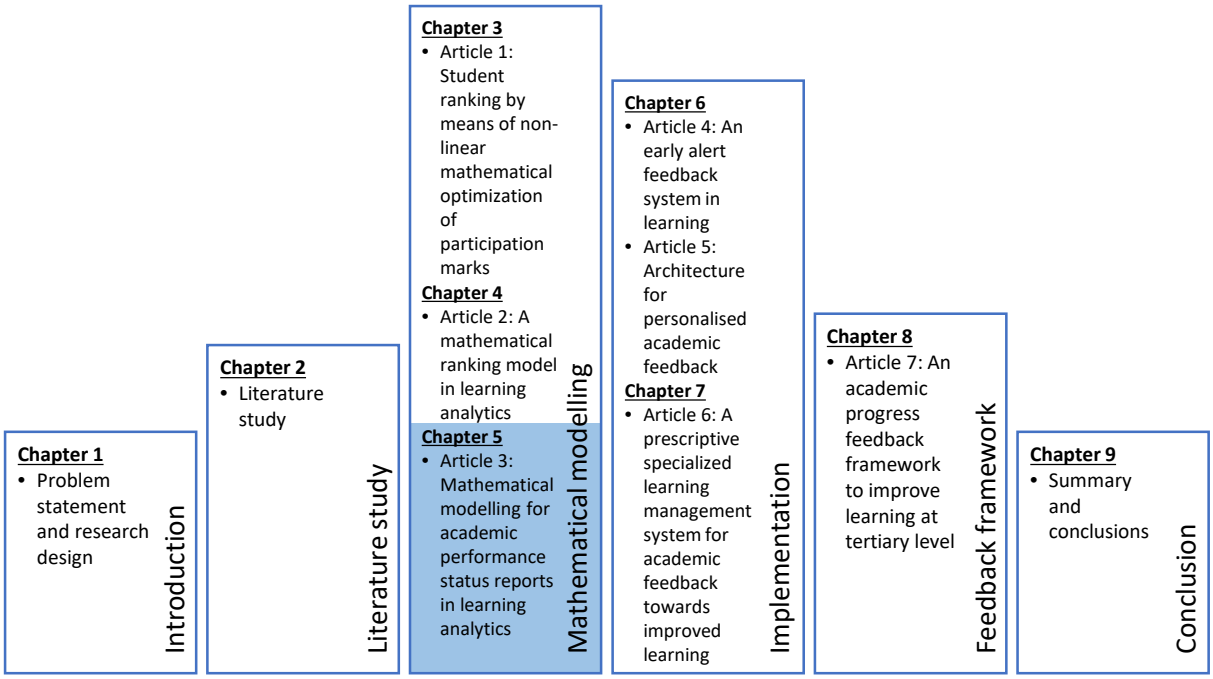
Chapter 5

Article 3: Mathematical modelling for academic performance status reports in learning analytics



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5.1. Preamble to Article 3

Chapter 5 presents an article published in the biannual journal, *ORiON*, which is the official journal of the *Operations Research Society of South Africa (ORSSA)*. The title of the paper is *Mathematical modelling for academic performance status reports in learning analytics* and was submitted for double-blind peer review in December 2017. It was consequently accepted for publication in March 2018 and published online in July 2018.

The article presented in this chapter serves as the concluding work in formulating mathematical ranking models to facilitate an improved approach towards the calculation of participation profiles for academic performance feedback. An existing empirical method, *benchMark*, as well as the methods described in Chapters 3 and 4 are briefly reviewed. This is followed by discussions on a linear programming model for improved efficiency in calculation of participation profiles, a decision tree algorithm for improvement plans and targets and a non-linear programming model that can guide a lecturer towards a target participation mark class average and to identify subject material with which students are struggling. Correlation analyses were performed between the academic rankings obtained from the existing approach and from applying the mathematical models. The research discussed in this chapter contributes to the field of academic performance feedback by addressing the feed backwards, forward and upwards requirements.

The referencing style applied in this article[1] was the Vancouver (numerical) standard, as stipulated by the journal. More information on submission, the peer review process, and author guidelines of the journal can be found in Appendix D.

[1] The article is presented in its final published form. Consequently, the page numbers of the article, as it appears in the proceedings, are displayed along with the principal thesis information.

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Mathematical modelling for academic performance status reports in learning analytics

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Abstract

The fast changing nature of the educational environment and the subsequent increase in the volumes of generated learner data, have found existing data analysis techniques lacking in certain fields. These techniques form part of the analysis and reporting phases of learning analytics and need to adapt to accommodate the changing face of education. In this paper, a set of interrelated algorithmic solutions that utilise mathematical programming models to generate and provide learning feedback in the form of academic performance status reports, is presented. Three existing mathematical models, more specifically the *benchMark* program, an outputs–only data envelopment analysis and a traditional analytic hierarchy process were evaluated for providing the information required to assist students in improving their academic achievement. The requirements include providing students with their current academic performance status, setting interim improvement goals and calculating improvement targets towards reaching those goals. The evaluated models did not address the requirements satisfactorily. The solution proposed in this paper consists of an algorithm that implements a linear programming model to generate performance status reports based on the current assessment scores of a group of students in a module. The output is used in a second algorithm that utilises the remaining improvement opportunities available to generate a participation future time perspective. The resulting schedule together with each individual student's current assessment scores, is used to calculate discrete improvement goals for each student as well as targets towards reaching those goals. A third algorithm provides a lecturer with some insight into the mastering of module content.

Key words: Analytic hierarchy process, data envelopment analysis, educational feedback, learning analytics, linear programming, non–linear programming.

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1 Introduction

The pace at which technology is advancing necessitates role players in education to adapt their teaching and assessment techniques [24]. Most of the activities relevant to education can now be performed by means of a computer. This makes online learning, where students do not need to be at a campus to interact with a lecturer, possible. The subsequent increase in student numbers results in an increase in the learner data being generated which includes the use of resources, academic performance, and even effectiveness of teaching tools. Analytical methods used to process student data consequently need to adapt as well. Many tools implemented as educational aids already perform some analytical functions on institutional, regional, national, and international level [39].

Predictive analytics incorporates statistics, machine learning and data mining to discover meaningful patterns in data [25]. The focus of learning analytics is, however, on the learning process rather than on an institutional level [39]. It presents the potential to predict and improve student success and resulting retention by incorporating the measurement, collection, analysis and reporting of learner data [8]. Although many methods exist with which these actions can be performed, measurement and collection of learner data are mostly context dependent. Various methods for analysing and reporting such data are commonly implemented in academic environments by means of *learning management systems* (LMSs), which consider learning activities, course administration, and tracking [40]. Examples like PACE (Progress and Course Engagement), GPS (Grade Performance System) [31], and E2Coach (Expert Electronic Coach) [27] are only some LMSs that determine and provide alerts regarding academic issues. Other systems that can furthermore present interventions include the Student Advice Recommender Agent (SARA) [17] and the MiGen teacher assistance tool, which is a system that was developed with some visualization and notification capabilities [26]. However, Stantchev *et al.* [40] argue that LMSs are not yet optimally contributing towards the improvement of learning because they mostly address institutional needs rather than those of the students. Students need specific information relating to their progress in a course to enable change [13].

Learning analytics can change the value of higher education by assisting in the identification of students who are at risk of failing and to provide them with interactive solutions on how to improve during the semester (term). Barker and Garvin–Doxas [4] proposed the use of a hierarchical structure for the purpose of progress feedback to create a communicative environment between a lecturer and the students. Studies show that ranking is an important determinant of student behaviour [14, 42]. Therefore, a solution in the form of a student ranking incorporated into the analysis and reporting phases of learning analytics, is proposed.

Ranking models have been applied in the ranking of NBA basketball players [28], college sport coaches [19], alternatives in sports tournaments, products, political candidates [6], and others such as the PageRank algorithm introduced by Google [21]. The main aim of this study is to evaluate existing ranking models that may be used for student feedback and to develop an improved ranking feedback model by implementing mathematical programming techniques in three interrelated algorithms. Three models were chosen for evaluation in this specific research project. They include *benchMark* [11], an outputs–only based *data envelopment analysis* (DEA) model [22], and the traditional *analytic hierarchy*

process (AHP) [2]. The *benchMark* program was selected because it is an empirical student ranking model that ranks students according to their academic progress in a module. It was successfully implemented in a software application and was evaluated in an academic environment with positive results. Furthermore, the *benchMark* program is directly related to this study. The outputs–only based DEA was chosen because in general, no measurable inputs (*e.g.* numbers of hours studied) are available on students. It allows the calculation of outcome improvement targets and it is an established ranking method. The AHP is another technique that ranks items influenced by several factors, or in this study, to rank students according to their formative assessment outcomes like class test scores, practical assignments, *etc.* Appropriate adjustments and pairwise comparisons were made in this study to eliminate traditional inconsistency– and normalisation problems. This process also allows for the allocation of weights (as predetermined by a lecturer) to the factors. The AHP was applied in this context to operate as an additional means of appraising the rankings obtained in other methods.

The motivation for the study is founded in the repeated observation that student attendance in some courses at tertiary institutions, seems to wane after the initial contact session. Students think that because the semester had just started their absence cannot yet affect their academic progress and when they do return to class, they do not know what to do to improve their performance [11]. There is a demand for an academic performance feedback system that will continuously provide students with information on their current academic status in a module as well as how to improve from an early stage in the semester [18].

The remainder of this paper is organised as follows: Section 2 provides some background on a typical teaching–learning environment and a short discussion on the requirements for effective feedback. Subsequently, the three chosen ranking models are discussed in Section 3. Finally, an improved mathematical ranking model that provides effective feedback to students is proposed in Section 4. This is followed by a discussion in Section 5 and conclusions in Section 6.

2 The teaching–learning environment

In a typical classroom environment, the role of a lecturer ranges from teaching and facilitation to assessment and grading. Students are expected to prepare for and attend contact sessions where lecturers will discuss previously completed work, explain how it relates to new concepts, and introduce and discuss new material. Often during contact sessions students are expected to complete class assignments and may also be given homework related to topics discussed during class. Regular formative assessments in the form of class tests, practical assignments or informal tuition tests among others, can be taken without prior notice. This form of assessment provides lecturers with valuable information on the success of the teaching techniques employed when introducing new material to students.

Lecturers grade formative assessments and use them to compile an overall semester mark for each student. This mark, called a participation mark (p–mark), is the measurement by which students are granted admission to the final examination. Some lecturers also reward students for class attendance by letting it contribute a small quantity towards the

p–mark. In the calculation of the p–mark a lecturer has the responsibility to decide which factors he/she wants to consider, and how the averages in each of these factors are to be calculated. The p–marks can then be calculated as the weighted sum of the average marks obtained for each factor according to

$$p = y_1 w_1 + y_2 w_2 + \cdots + y_n w_n, \tag{1}$$

where p is the participation mark, $y_1, \cdots, y_n$ are the respective average marks calculated, $w_1, \cdots, w_n$ are the respective weights, and n is the number of factors. A lecturer normally decides on applicable weights for each of the respective factors. In some environments, if the p–mark is larger than a certain minimum threshold the student is allowed to write the final examination. The final module mark is then calculated as the average of the p–mark and the examination mark. This means that students have the opportunity to start building half of their module mark from as early as the first scheduled contact session. Students are, however, not always aware of how they are progressing towards their p–marks. Regular and interactive feedback is needed to keep students informed on how their p–marks are growing.

Ranking is considered a feedback format that will effectively inform students on their positions in a hierarchy based on their outputs. The proposed solution will provide feedback in the form of *performance status reports* (PSRs) throughout the semester. For a PSR to be effective it must address three key issues [18]. Firstly, students must know what the goal is that they are working towards. This requirement is referred to as *feed–up*. At the start of a semester in an academic environment such a goal can be to pass a module or get a distinction. However, as the semester advances and students start to progress or regress, interim goals based on their performance can help them reach their ultimate goals. Secondly, they must know what progress they are making towards reaching the goals, or *feed–back*. Lastly, students must be informed as to which activities they have to perform in order to enhance their progress, or *feed–forward*. Furthermore, Wiggins [45] provided some attributes to which the information in a PSR must conform to. Apart from having to provide feed–back, feed–forward and feed–up, the reports generated by the solution in this paper will also be evaluated for referring to a goal, being actionable, user–friendly, timely, ongoing and for being provided consistently. In the next section, different methods for presenting student progress in the form of academic rankings, are evaluated.

3 Ranking as feedback in learning

Ranking as a hierarchical structure is used in the academic environment for many purposes, among others for evaluating quality in higher education [9, 16], for determining the success of different departments within a university [5], for student selection [15] and for ranking specific student attributes to determine the probability of success [35, 37]. In this section, the three selected models will be discussed and applied to the same data set. This set contains marks for 26 students in four factors that were achieved in a fourth–year module presented at a tertiary institution. The factors (denoted F_1 to F_4 respectively) are a semester test, class tests, theoretical assignments and attendance. The data set is provided in Appendix A.

3.1 The *benchMark* model

A software application called *benchMark* was developed by Du Toit [11] for the purpose of timeously calculating p–marks and rankings for a group of students. The program creates a participation profile for each student which is continuously provided to them as PSRs throughout the semester.

The model utilised in this program is a standardised form of equation (1). After completion of each assessment the new set of marks is used to calculate a new average for each factor. Each student's current factor averages are then used to create a p–mark according to

$$p_\alpha = \sum_{j=1}^{n} y_{\alpha j} w_j, \tag{2}$$

where w_j is the weight assigned to factor j, $y_{\alpha j}$ is the calculated average for factor j of student α, and n is the number of factors. A unique attribute of *benchMark* is that instead of requiring a specific known weight for each factor beforehand, it empirically calculates a set of possible p–marks for each student using a range of permissible weights per factor. Permissible weights have minimum and maximum values, with their sum constrained to be 1. A drawback to this approach is the exponential increase in the number of possible p–marks that need to be calculated as the number of factors increase. Initially it was found that the calculation of all possible combinations of weights would result in an intractable problem [11]. To cater for this, a priority sequence constraint was implemented on the weights and they were constrained to be in multiples of a predetermined number k. The priority sequence constraint requires the lecturer to predetermine the order of importance for each of the factors. It was empirically determined that by enforcing these constraints the search space was reduced considerably, resulting in a tractable problem.

The program also calculates the average of all the possible p–marks for every student, including the minimum and maximum. After each execution of the program the maximum, minimum and average p–mark, and a student ranking according to the average p–marks, are available. Statistics relating to the current pass/fail rate, the number of distinctions and the number of students without admission to the examination, are also available. During the semester students are frequently given feedback on their latest factor averages, their minimum p–marks, and ranking. Instead of informing the students what the respective weights for the factors are going to be at the start of a semester, the option exists to provide them with the order of the priority of the factors. This affords some freedom in selecting a specific factor weight distribution closer to the examination and students have a discrete measuring tool with which they can gauge their progress and/or improvement in the module. The program therefore guarantees that the final weight distribution selected at the close of a semester, will not cause any student's final p–mark to drop lower than the minimum mark provided to them after having processed all relevant assessments.

The model was implemented and tested with $k = 0.05$. The priority sequence applied in the evaluations was $w_1 \geq w_2 \geq w_3 \geq w_4$ with the weights applying to F_1 to F_4 respectively. Based on these constraints the program calculated a set of 23 possible p–marks for each student from which each respective student's average p–mark was calculated. For illustration purposes the participation profiles of the top seven students are presented in Table 1 (the profiles of all the participants are provided in Table 9 in Appendix B).

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Student	F_1	F_2	F_3	F_4	Max	Min	Avg	Rank
2	100.00	95.24	97.92	100.00	98.29	97.58	97.85	1
9	93.33	91.51	87.75	100.00	93.15	91.35	92.33	2
3	96.67	82.62	75.05	100.00	89.22	85.43	87.44	3
13	76.67	87.13	65.83	89.00	83.35	78.25	81.05	4
10	93.33	68.15	74.07	100.00	84.89	78.78	81.04	5
24	90.00	64.76	76.67	100.00	82.86	77.07	79.37	6
23	85.00	72.14	61.85	100.00	79.75	74.31	77.35	7

Table 1: Participation profiles created by *benchMark* for the top seven students. $F_1 - F_4$ are the factor averages arranged according to weight priority. The columns Max, Min and Avg, are the maximum, the minimum and the average participation marks, respectively. The column Rank is the student ranking according to average participation marks. All marks are indicated in percentages.

Apart from providing student p–marks and ranking status, other advantages of the *benchMark* program include the following:

- Performance status can be provided to students as frequently as assessments are graded; and
- Additional throughput– and performance information is available to the lecturer.

Although *benchMark* has been successfully implemented, it uses all weight combinations allowed within the model constraints to empirically calculate the p–marks and ranking.

The disadvantages that were identified are listed below.

- Although some students (especially those at the top of the ranking) prefer to know their ranking, others exhibit a rather indifferent attitude towards their progress and feel that they need discrete information on how to improve to higher ranking positions. The *benchMark* program does not provide improvement targets that will assist in improving students' ranking.
- The program uses empirical calculations in a sequential algorithm to create a set of p–marks for each student and to set up statistical information. It was found that for less than 80 students the execution time is reasonable and the program can be executed a few minutes prior to a contact session [11]. However, for large student numbers program execution time does not scale linearly and it may be more practical to perform the calculations only once a week.
- The *benchMark* program initially has a steep learning curve, both for students and lecturers.
- Execution of the *benchMark* program needs continuous human involvement making importing of marks and calculating new p–marks rather labour intensive.
- Without the priority sequence– and the multiples–of–k constraint sets the search space is so large that the problem is intractable.

To address some of the disadvantages identified in evaluating *benchMark* (the human factor, the iterative and sequential nature of the program, and its intractability), the model was formalised in the non–linear mathematical model [43] that follows.

$$\text{Maximise/minimise } p_\alpha = \sum_{j=1}^{n} y_{\alpha j} w_j, \tag{3}$$

subject to the constraints

$$\begin{aligned}
\sum_{j=1}^{n} w_j &= 1, & & (4)\\
w_j \ mod \ k &= 0, & j = 1, \ldots, n, & (5)\\
l \leq w_j &\leq u, & j = 1, \ldots, n, & (6)\\
w_j &\geq w_{j-1}, & j = 1, \ldots, n, & (7)\\
w_j &\geq \epsilon, & j = 1, \ldots, n, & (8)
\end{aligned}$$

with $k \in \mathbb{R}^+$, $l \in \mathbb{R}^+$, $u \in \mathbb{R}^+$ and ϵ a small positive number.

The objective function is similar to the formulation in (2). The constraint set in (5) ensures that each w_j is a multiple of k while (7) represents the sequence ordering requirement of *benchMark*. Weights are constrained to be between an upper and lower limit in (6).

The model is non–linear (due to constraint set (5)) and may be solved using any non–linear mathematical programming software. For the purpose of this study it was decided to obtain a heuristic solution using the Evolutionary Solver in Excel. Evolutionary solvers are designed to mimic the process of biological evolution in certain ways. A full discussion of heuristic solutions and the optimisation of non–smooth models is beyond the scope of this paper and detailed explanations can be found in Baker [3]. The choice of a solver was based on the fact that the solution generated in this manner does not rely on the mathematical structure of the model but rather on solutions generated by combining previous solutions along with some randomness [33]. It should be noted that there is no guarantee of a global optimum and human judgement is required when solving a model using an evolutionary approach. The implementation of a heuristic solution using an evolutionary solver is simple and allows for easy use of mathematical functions such as the modulus function in constraint set (5).

The same data set used to illustrate *benchMark*, was used to evaluate the non–linear model in (3)–(8). The model was solved again with $k = 0.05$, and the same priority sequence applied to the factors as in *benchMark*. The maximum and minimum p–marks were calculated accordingly, and the average p–mark was determined from these two values only. The students were again ranked according to the average p–marks as produced by the model in (3)–(8).

Table 2 shows the calculated p–marks, the top seven of the subsequent rankings, and the associated weights generated by this heuristic solution.

The ranking for all 26 students (all student rankings can be found in Appendix B, Table 10) differs marginally from that produced by *benchMark*. Student 10, for example, is ranked 4 th whereas this student was ranked 5 th by *benchMark*. The reason for this difference is the fact that *benchMark* calculated the average p–mark for each respective student from all 23

	p–marks (%)				Weights for minimum p–mark				Weights for maximum p–mark			
Student	Max	Min	Average	Rank	w_1	w_2	w_3	w_4	w_1	w_2	w_3	w_4
2	98.63	97.78	98.21	1	0.40	0.40	0.15	0.05	0.40	0.20	0.20	0.20
9	93.15	91.44	92.30	2	0.35	0.30	0.30	0.05	0.25	0.25	0.25	0.25
3	90.20	86.13	88.17	3	0.35	0.30	0.30	0.05	0.40	0.20	0.20	0.20
10	84.52	80.04	82.28	4	0.35	0.35	0.25	0.05	0.35	0.25	0.20	0.20
24	84.27	78.33	81.31	5	0.35	0.35	0.25	0.05	0.40	0.20	0.20	0.20
13	80.54	77.17	78.29	6	0.35	0.30	0.30	0.05	0.35	0.35	0.15	0.15
23	80.80	74.95	76.90	7	0.35	0.30	0.30	0.05	0.40	0.20	0.20	0.20

Table 2: Results of the top seven students, obtained by the non–linear model.

of the empirically calculated possible p–marks as opposed to the non–linear model which used only the calculated maximum and minimum values. To produce a more structured comparison between the two rankings, a Spearman's rank correlation coefficient [7] was calculated. Spearman's rank correlation coefficient (ρ) is a nonparametric assessment of the statistical relationship between two different rankings which expresses the relationship between them in terms of a monotonic function. It is expressed as

$$\rho = 1 - \frac{6\sum_{i=1}^{m} d_i^2}{m^3 - m}, \quad 0 \leq \rho \leq 1, \tag{9}$$

where d_i is the difference between the two ranks at the ith position, and m is the number of ranking positions. The rank correlation coefficient between the two rankings was calculated as 0.99, proving a very strong positive association between them. This is to be expected considering the similar constraints applied in both methods.

Formalisation of the *benchMark* model in a non–linear mathematical model yielded improvements on some of the disadvantages identified earlier:

- The need for continuous human intervention is reduced as the model parameters are specified at the onset of execution and the calculations are repeated for each student by means of an algorithm.
- The evolutionary solver is easy to implement and converges to acceptable solutions for the entire data set, faster than *benchMark* did. This model can therefore be used more frequently and for large student numbers.
- Although a heuristic solution does not always guarantee to be optimal, the model does find acceptable solutions. This was proven by the high Spearman's rank correlation coefficient calculated for the respective rankings resulting from the *benchMark* program and the non–linear mathematical model.

The *multiples–of–k* constraint set (5) was enforced in the non–linear model so that the resulting ranking could be compared with that obtained in *benchMark*. However, this constraint creates a non–linear relationship between the decision variables and some predetermined constant.

Enforcing this constraint set was justified in *benchMark*, but its exclusion will result in a linear mathematical model which, under certain conditions, can be solved in polynomial

time [30]. The model was therefore modified and solved as a linear model, which is discussed in more detail in Section 4.1.

Another drawback to the *benchMark* and non–linear modelling approaches is that no discrete improvement targets are calculated with which students can attempt to improve their rankings. This means that although these methods address the feed–back requirement for effective PSRs, no feed–forward or feed–up is provided. In a pilot study done by Du Toit [11] it was noted that although students at the top of the ranking felt motivated to improve, those in the middle and lower parts of the ranking indicated that they wanted more information on exactly how to improve. One of the attributes PSRs must have, is that they must be actionable. In other words, students have to be provided with some form of incentive or target that shows them what they can do to improve their rankings or more specifically, feed–forward. This problem was partly addressed by implementing an outputs–only based data envelopment analysis (DEA) on the student mark data set [44], and is discussed next.

3.2 Class–ranking by means of an outputs–only based DEA

DEA is a mathematical programming method commonly employed to compare service units called *decision making units* (DMUs) in a specified environment, based on a calculated ratio between their inputs and outputs [29]. However, student input data such as study environment, hours of study or lifestyle aspects are considered either unavailable or unreliable. Therefore, a model that utilises inputs was not included in this study. Outputs–only based DEA effectively categorises DMUs considered equally efficient into groups or classes. Examples of such analyses include the class–ranking of management colleges [22], and of secondary schools [23]. To be able to compare the student rankings, an outputs–only DEA was performed on the marks (factor averages) obtained in certain outputs (factors) [44]. The students were treated as DMUs and the factor averages were considered the outputs. This method effectively searches for the most favourable weights and calculates an efficiency score for each student [22] by solving the model in (10)–(12).

$$\text{Minimise } E_\alpha = \sum_{j=1}^{n} y_{\alpha j} w_j, \tag{10}$$

subject to the constraints

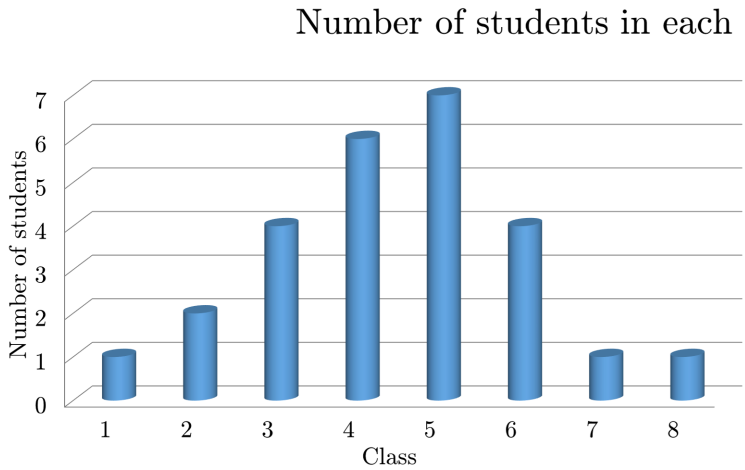
$$\sum_{j=1}^{n} y_{ij} w_j \leq 1, \qquad i = 1, \ldots, m, \tag{11}$$

$$w_j \geq \epsilon > 0, \qquad j = 1, \ldots, n, \tag{12}$$

where E_α is the composite index for student α, y_{ij} is the output measure of student i in factor j, w_j is the weight for factor j, n is the number of factors, m is the number of students to be evaluated, and ϵ is a small positive number ensuring all factors are considered.

This model was used to create a class–ranking that effectively sorted the students into groups of similar efficiency. The principle of Pareto optimality applies wherein the efficiency score (E_α) represents the ratio of the current student's performance to that of all the other students in that specific factor. If $E_\alpha = 1$, then student α is considered Pareto optimal which means that no output can increase without decreasing another [41]. Such a student would then be categorised into the highest available class, lie on the Pareto frontier, and is said to dominate those in lower classes. If $E_\alpha < 1$, then student α is Pareto non–optimal and is said to be dominated by those in higher classes. Detailed discussions of Pareto optimality and the dominance principle can be found in Kao and Lin [22], and Seiford and Zhu [38].

The outputs–only DEA was also performed on the same data set containing marks for 26 students, in which the four factors as described in the previous sections, are considered as outputs. This resulted in a class–ranking that categorised the students in the data set into 8 different classes of efficiency (Figure 1).



Student	Class	⋮	⋮
2	1	8	5
3	2	15	5
9	2	18	5
10	3	20	5
13	3	21	5
23	3	25	5
24	3	26	5
1	4	5	6
6	4	7	6
11	4	14	6
12	4	22	6
17	4	16	7
19	4	4	8

Figure 1: Class–ranking of the 26 students.

Figure 1 shows the class–ranking: one student was classified into class 1, followed by two students in class 2 and so forth. The student class–ranking cannot directly be compared to the rankings obtained in Section 3.1, for a few reasons. The outputs–only based DEA method calculates the efficiency scores by determining the weights that will benefit each student most, with no predetermined factor priority sequence included. Also, the basis for calculating E_α is determined by the outputs of the students on the Pareto frontier and is therefore not necessarily the same for each dominated student [16]. Although the class–ranking produced by this model cannot be compared to the rankings resulting from the methods in Section 3.1, the students classified into the first three classes, correspond with the top seven from Section 3.1.

One of the disadvantages identified in Section 3.1, was that neither the *benchMark* program nor the non–linear model offered students any actionable targets with which they could attempt to improve their rankings. A major advantage presented by the outputs–only DEA model formulated in (10)–(12), is that by implementing its dual formulation, discrete

improvement targets per student per factor could be calculated. The dual formulation [22] is expressed in (13)–(15).

$$\text{Minimise } E_\alpha = \sum_{i=1}^{m} \lambda_i - \epsilon \sum_{j=1}^{n} s_j, \tag{13}$$

subject to the constraints

$$\sum_{i=1}^{m} y_{ij}\lambda_i - s_j = y_{\alpha j}, \quad j = 1, \ldots, n, \tag{14}$$

$$\lambda_i, s_j \geq 0, \quad i = 1, \ldots, m; \; j = 1, \ldots, n. \tag{15}$$

The variable definitions are the same as for the model in (10)–(12). Furthermore, let $\theta = \sum_{i=0}^{m} \lambda_i$, then the target for factor j can be calculated as $(y_{\alpha j} + s_j)/\theta$ and $j = 1, \ldots, n$. For each student not in class 1 ($c \neq 1$), this model would calculate $n(c-1)$ improvement targets, one per factor for every class higher than the current. Consider, for instance, Table 3 that shows Student 1 who was categorised into class 4.

	Factor(%)				
c	F_1	F_2	F_3	F_4	
4	45.00	55.00	50.00	75.00	(current)
Targets for improvement (%)					
3	49.00	58.00	53.00	80.00	
2	64.00	71.00	77.00	98.00	
1	65.00	94.00	84.00	100.00	

Table 3: Improvement targets for Student 1.

If Student 1 wanted to progress to class 3, the semester test (F_1) must improve from 45% to 49%, class tests (F_2) from 55% to 58% and so forth. Likewise, for each student not categorised into the highest class, targets were calculated in each factor for improvement into the next higher class. Unfortunately the model does not cater for factors that have been completed. A semester test for example, is written once in the middle of the term and the mark cannot change after that. Also, any changes in student marks will have a ripple effect on the entire class–ranking as follows:

- the model would need to be solved again and new optimal weight sets will be determined for each student;
- new weights per student could mean that the Pareto frontier for each class could change; and
- the outputs of all students are used in calculating the improvement targets. This means that even if a student reaches a target, the class–ranking might not change if other students improved in the same factor.

Another drawback to the outputs–only based DEA is that because the output of a student is compared to that of every other student, the size of the problem increases considerably when performing this analysis for modules with large student numbers. A solution to this problem is proposed through the construction of an algorithmic approach which is discussed in detail in Section 4.2.

The outputs–only DEA model can be used to calculate individual improvement targets for each student, but it has certain disadvantages. Another student ranking was generated in this context by means of the AHP for comparative purposes, and is discussed in the next section.

3.3 An AHP model for ranking students

The *analytic hierarchy process* (AHP) is a mathematical method used to make decisions when multiple objectives or criteria need to be considered [34]. The method is used to find the best contender among a certain number of alternatives (students), based on a number of criteria (factors).

Each one of the students is compared to the others in terms of each of the factors. This is followed by a comparison of the importance of the factors resulting in an average rating for every student.

Typically, the following steps are performed [29]:

1. Develop a ranking for each student for each factor:
   - develop a pairwise comparison matrix for the students in each factor;
   - normalise the resulting matrices;
   - find the normalised principal eigenvector, or priority vector; and
   - check the consistency of the pairwise comparisons.
2. Develop the weights for the factors:
   - develop a pairwise comparison matrix for the factors;
   - normalise the resulting matrix;
   - find the priority vector; and
   - check the consistency of the pairwise comparisons.
3. Calculate the weighted average rating for each student. Rank them according to their average ratings.

Pairwise comparisons are based on a preference scale which usually ranges from 1 to 9 [1]. The ratings show how much one alternative is preferred above another, and vice versa. In this application pairwise comparisons were made with student factor averages and the rating scale was modified as follows: At tertiary level an *admission point score* (APS) is used to determine whether a learner who completed the South African National Senior Certificate, may study at a South African university [12]. An adaptation of the APS system was therefore used for generating the pairwise comparison ratings of student averages where the difference between the mark for factor j of student α and student β is calculated as

$$y_{\alpha j} - y_{\beta j}, \quad \alpha, \beta \in \{1, \ldots, m\} \ \textit{and} \ \alpha \neq \beta, \tag{16}$$

with m representing the number of students. These calculations are then associated with the normal AHP preference scale of 1–9. Table 4 shows this association for $y_{\alpha j} \geq y_{\beta j}$. For cases where $y_{\alpha j} < y_{\beta j}$, the inverse of the rating is used. If for example $y_{\alpha j} < y_{\beta j}$ for the interval 20%–29% then the corresponding rating would be 1/4.

if $y_{\alpha j} \geq y_{\beta j}$	Rating
0%	1
1-9%	2
10-19%	3
20-29%	4
30-39%	5
40-49%	6
50-59%	7
60-79%	8
$\geq$ 80%	9

Table 4: Preference rating for pairwise comparison of academic marks.

The non–linear model discussed in Section 3.1 yielded a set of weights used for calculating the minimum and maximum p–marks of each student (Table 2). To enable comparison between the AHP ranking and those obtained in previous sections, the weights were pre–set to averages calculated as

$$\bar{w}_j = (\bar{w}_{j(max)} + \bar{w}_{j(min)})/2, \tag{17}$$

where $\bar{w}_j$ is the average weight for factor j, $\bar{w}_{j(max)}$ is the average of all the weights calculated for factor j for the maximum p–marks and $\bar{w}_{j(min)}$ is the average of all the weights calculated for factor j for the minimum p–marks. The weights used in the AHP are 0.35, 0.30, 0.20 and 0.15 for $\bar{w}_1$ to $\bar{w}_4$, respectively. The weights can be varied at the lecturer's discretion but lecturers do not always know what the expected class throughput resulting from specific weight combinations might be. This problem was addressed by formulation of a non–linear weight selection model and is discussed in more detail in Section 4.3.

Consistency checks on pairwise comparisons are usually required because with a large number of decision alternatives inconsistent comparisons occur frequently. A consistency ratio is calculated [10] using the formula

$$CR = CI/RI, \tag{18}$$

where

$$CI = (\lambda_{max} - m)/(m - 1) \tag{19}$$

is the consistency index with λ_{max} the principal eigenvalue, m the number of students, and RI is a random consistency index [36]. Generally, the degree of consistency is acceptable if $CR < 0.10$. The scale used for pairwise comparison of student marks in this study is considered consistent because it compares each pair of marks by means of a mathematical equation (Table 4). Therefore, it was not necessary to perform consistency checks for these pairwise comparison matrices.

The number of comparisons (s_m) to be made for m students and n factors, is expressed as

$$s_m = mn(\frac{m-1}{2}). \tag{20}$$

Accordingly for the mark set of 26 students and four factors, a total of 1300 pairwise comparisons were made.

The process was implemented on the same mark set used previously. The marks of the students were rated according to Table 4 by calculating the difference between each pair of marks and setting up the pairwise comparison matrix based on the given preference scale. The matrix was completed and normalised for all of the 26 students in the set after which the averages were calculated to determine each factor priority vector. This step was performed for all four of the factors. Using the preference weights as discussed previously, a composite rating $r_{\alpha j}$, was calculated for each student by finding

$$r_\alpha = \sum_{j=1}^{n} \gamma_{\alpha j} w_j, \qquad \alpha = 1, \ldots, m, \tag{21}$$

for student α, with $\gamma_{\alpha j}$ the average priority rating of student α in factor j, w_j the pre–set weight for factor j, m the number of students, and n the number of factors.

The students were then ranked according to the calculated composite ratings. Table 5 shows the top seven rankings determined by the AHP (the complete set is available in Table 11, Appendix B).

	Priority Vector				Composite Rating	Pairwise Ranking
Student	F_1	F_2	F_3	F_4	$r_{\alpha j}$	
2	0.1019027	0.1226755	0.145867	0.0612267	11.0826	1
9	0.0793605	0.1101616	0.1166742	0.0612267	9.334351	2
3	0.0872195	0.0810881	0.0704773	0.0612267	7.813273	3
10	0.0793605	0.0506373	0.0643211	0.0612267	6.501559	4
24	0.0614319	0.0370232	0.0824396	0.0612267	5.828006	5
23	0.0491764	0.0670063	0.0387908	0.0612267	5.425578	6
13	0.0326883	0.0977652	0.0460599	0.0283514	5.423514	7

Table 5: Top seven of the student ranking resulting from the AHP.

The use of the AHP on student marks in different factors, is an unconventional approach to student ranking. It creates a ranking without the calculation of p–marks and can be used to provide an alternative form of feedback. The Spearman's rank correlation coefficient, ρ (Section 3.1) was calculated to compare the AHP ranking to those obtained previously. The AHP ranking correlated with the *benchMark* ranking by $\rho = 0.97$, and with that of the non–linear model, by $\rho = 0.98$.

One of the problems with using the AHP is that although the resulting ranking highly correlated with those from other methods, a different normalisation order can lead to different rankings [32]. Another disadvantage is that the AHP is difficult to use with large

volumes of data because the number of pairwise comparisons that need to be made is directly related to the number of alternatives to consider [20]. This method also did not address the feed–up or feed–forward requirements. Despite these difficulties, the results showed the AHP to be another technique which can be used for ranking students. For this study, the AHP also acted as an efficient control measure, by which the rankings obtained in the other methods could be evaluated according to the Spearman's rank correlation coefficient.

The existing mathematical models discussed in Section 3 were implemented on the same data set to generate different student rankings. The rankings were evaluated according to specific criteria essential to a PSR, as identified in literature and practice. Although some of the criteria were addressed, other issues remain unattended. To this end, a solution consisting of three different but related algorithms, is proposed and is discussed in Section 4.

4 Proposed mathematical model for effective PSRs

The requirements for effective PSRs in an academic environment were identified in Section 2 and used as evaluation guidelines for the three methods evaluated in Section 3. An effective PSR needs to address these important aspects: it must feed–up or provide a goal to work towards, feed–back or present current performance, and feed–forward or offer actions to perform towards reaching the goal. The evaluated methods were implemented as mathematical models which were chosen for specific reasons and applied on the same data set for comparative purposes. Although each one of those methods offered a ranking solution and addressed some of the requirements, none of them satisfied all of the criteria for PSRs. The *benchMark* program, non–linear model and the AHP model provided feed–back but neither feed–forward nor feed–up. The outputs–only based DEA model addressed the feed–forward criteria by providing factor improvement targets and partially addressed the feed–back criteria in the form of a class–ranking. However, numerous disadvantages were identified that makes this method unsuitable for the use in PSRs. Evaluation of these methods is illustrated in Figure 2.

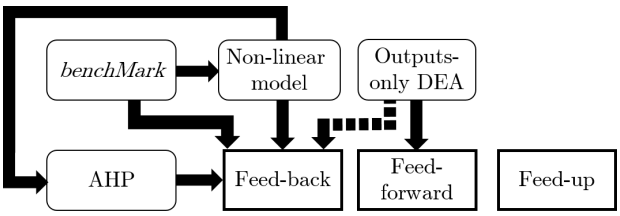


Figure 2: Evaluation of selected methods for PSRs.

As Figure 2 illustrates, none of the methods comprehensively addressed the feed–up requirement which demands that students be continuously presented with new goals aimed at progression. The requirements for an effective PSR has therefore not been addressed completely. Evaluation of the methods in Section 3 presented some valuable insights that led to the proposal and development of an algorithmic solution that is illustrated in Figure 3 and discussed in subsequent sections.

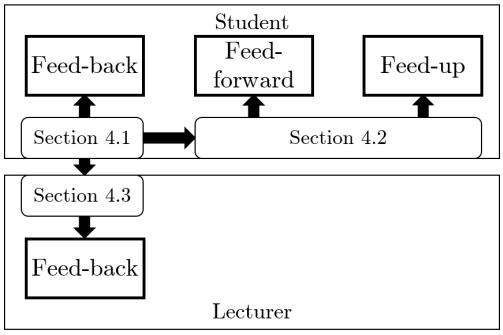


Figure 3: Proposed solution to address PSR criteria.

An important issue to consider when generating the information required for PSRs, is the fact that as time passes by, so does a student's opportunity for improvement. At the start of a semester when only a few assessments have been completed, the factor averages are calculated from the only scores available. Each assessment therefore has a greater influence on the calculated p–mark at an early stage. As a semester elapses and the number of assessments remaining in each factor decreases, the contribution of each individual assessment towards the p–mark diminishes and the opportunities to improve decreases. Figure 3 illustrates how the requirements for PSRs relate to one another in the proposed solution. A linear model for p–mark calculation and its associated algorithm are discussed in Section 4.1. This is followed by the algorithmic approach to calculate improvement scenarios in Section 4.2. The algorithms in Sections 4.1 and 4.2 provide the information required for a student PSR. Section 4 will conclude with a weight selection model that provides feed–back to a lecturer, which is discussed in Section 4.3.

4.1 Linear model for p–mark calculation

To address the feed–back requirement, p–mark calculation is performed by means of a linear model according to the framework proposed in Figure 3. The linear model is based directly on the non–linear model (3)–(8) discussed in Section 3.1. It was converted to a linear model by omitting constraint set (5) which stipulated that the weights be in multiples of a number k. This constraint set can be excluded because no empirical calculations are required to find a solution. The model was implemented by means of Algorithm 1.

The linear model was solved for the data set in Appendix A. For the purpose of validating the model the p–marks were used for compiling a student ranking. This ranking correlated favourably with that of the *benchMark* program ($\rho = 0.96$) as well as with that of the non–linear model ($\rho = 0.97$). It may therefore be accepted that the proposed linear model produces acceptable results and may be used in the proposed framework of Figure 3 to address the feed–back requirement. The results of this model are attached in Appendix C and are used as input to the algorithm implemented to address the feed–forward and feed–up requirements, which is discussed in the next section.

4.2 Improvement target calculation and potential participation plan

At the start of a semester a lecturer typically plans a certain number of assessments to be taken by the students in each of the factors. As the semester progresses and assessments

Algorithm 1: Linear modelling of p–mark calculation

Input : $Y = \{\bar{y}_1, \ldots, \bar{y}_m\}$ is an array representing the current factor averages for a group of m students in n factors.

Output: A set of arrays $P = \{\bar{p}_1, \ldots, \bar{p}_m\}$ with the minimum and maximum p–marks, their associated weights, and the average p–marks for m students.

```
1 for i = 1 to m do
2     read ȳ_i from Y;
3     calculate minimum p–mark and associated weights for student i;
4     calculate maximum p–mark and associated weights for student i;
5     calculate average p–mark for student i;
6     populate p̄_i with the values calculated in lines 3–5;
7 end
8 output P;
```

are given by the lecturer, the remaining assessments in each of the factors decrease. Feed–forward is therefore dependent on the point in time at which it is generated and must consider completed as well as remaining assessments in each factor. This time dependency means that different scenarios exist according to which students can complete a semester but with limited combinations of assessments available in each factor. An algorithmic approach was followed to determine the available scenarios at any specific point in time. The purpose of the algorithm is to provide a student with a future time perspective based on assessments planned for the remainder of the semester, the student's current factor averages and minimum p–mark. This perspective will provide students with insight into the effect that their continued participation or lack thereof, can have on their minimum p–marks.

The approach takes as input the current factor averages for a student at a specific time during the semester, the number and layout of the assessments remaining in each one of the appropriate factors and the required percentage improvement (δ). A table, based on truth table layout principles, is developed containing all the possible participation scenarios for the remainder of the semester. If there are assessment opportunities remaining, there would be a total of 2^s possible participation scenarios. The assessment plan is then used to eliminate participation scenarios that are impossible within the time constraints stipulated. This approach effectively caters for students engaging in, or missing out on any number of the remaining assessments. The algorithm provides output in the form of a set of participation scenarios based on the remaining possibilities and shows corresponding scores that a student must achieve in each scenario to affect the desired improvement in each factor. The projected change in the minimum p–mark is also shown for each scenario. The algorithmic approach is based on mathematical modelling principles and is shown below.

The algorithm starts by developing the participation scenarios in lines 1–4 and continues to calculate the scores required in upcoming assessments to produce the desired improvement

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Algorithm 2: Potential participation plan for a student

Input : $\bar{y} = \{\bar{y}_1, \ldots, \bar{y}_n\}$ is an array representing the current factor averages for a student in n factors, $A = \{\bar{a}_1, \ldots, \bar{a}_s\}$ and array denoting the s remaining assessment sessions and δ the required percentage factor improvement.

Output: An array $\bar{x}_r$, with r possible improvement scenarios.

1 declare $q(2^s, n)$; `// to store all scenarios for` s `sessions`
2 **for** $c = 1$ *to* 2^s **do**
3 | populate q with participation scenario c;
4 **end**
5 remove duplicate rows in q;
6 $r \leftarrow number_of_rows(q)$;
7 declare $marks(r, n)$; `// scores required for a required improvement of` δ
8 declare $min_f_assessments(n)$; `// minimum assessments per factor to cause a required improvement of` δ
9 **for** $j = 1$ *to* n **do**
10 | determine e_j from $\bar{a}_j$; `// remaining number of assessments in factor` j
11 | determine t_j from $\bar{a}_j$; `// 'total number of assessments in factor` j
12 | **for** $u = 1$ *to* e_j **do**
13 | | read y_u from $\bar{y}$;
14 | | calculate $newValue$ according to equation (22) with y_u, δ, and $\eta_u = u$;
15 | | **if** $q(j, u)$ *is possible* **then**
16 | | | $marks(j, u) = newValue$;
17 | | | set $min_f_assessments(j)$;
18 | | **else**
19 | | | $marks(j, u) =$ "*not possible*";
20 | | **end**
21 | **end**
22 **end**
23 declare $x(r, n+1)$; `// for` r `scenarios,` x `has a required score per factor and minimum change in` p`--mark`
24 $row \leftarrow 1$;
25 **while** $row \leq r$ **do**
26 | **for** $element = 1$ *to* n **do**
27 | | **if** $q(row, element) \leq min_f_assessments(element)$ **then**
28 | | | populate $x(row, element)$ using $marks(row, element)$;
29 | | **end**
30 | **end**
31 | $row \leftarrow$ row + 1;
32 **end**
33 ouput $\bar{x}_r$;

in line 14 according to

$$marks_j = \frac{\delta t_j + e_j y_{\alpha j}}{\eta_j} \tag{22}$$

where $marks_j$ is the score the student must achieve in the next η_j assessments of factor j, t_j is the total number of assessments in the semester for factor j, e_j is the remaining number of assessments for factor j and $y_{\alpha j}$ is the current factor average in factor j for student α. In lines 15–22, these scores are used to determine the minimum number of assessments to be completed to achieve an improvement of δ in the factors for which it will be possible. In lines 23–32 the possible scenarios are reduced further by comparing the number of assessments in the remaining scenarios to the minimum required in each factor.

For a number of s remaining assessment sessions, this approach can be illustrated according to Figure 4.

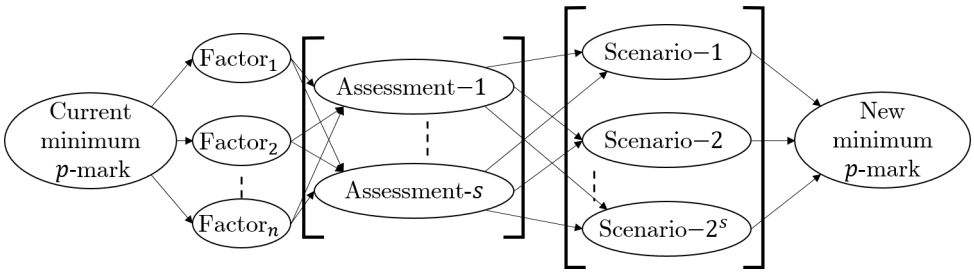

Figure 4: Expansion diagram for potential participation.

As an illustrative example, consider the student data set in Appendix A with four factors and 26 students and an example set of five remaining assessment sessions as shown in Table 6.

Assessment session				
1	2	3	4	5
Attendance (F_4)	Attendance (F_4) Theoretical assignment (F_3)	Class test (F_2)	Attendance (F_4)	Attendance (F_4) Theoretical assignment (F_3)

Table 6: Example of a future assessment plan for the remainder of a semester.

In session 1, a student can participate in one attendance (F_4). In session 2, a student can participate in one attendance (F_4) and one theoretical assignment (F_3), and so forth. In this example, assessments can be taken in more than one factor per session and it is assumed that if a student participates in one session, all assessments given during that session are completed. By attending class in the second session for example, a student can obtain a mark for attendance (F_4) as well as a theoretical assignment (F_3). Assume that each factor is represented by a number that increases when a student participates in an assessment. In the example, a set of four numbers will then represent assessment participation in $F_1, \ldots, F_4$ respectively. The possible participation options available for the assessment plan given in Table 6 were generated by means of a truth table in Algorithm 2 and is illustrated in Figure 5.

Each node represents a unique participation scenario for the semester, with self–loops indicating no further participation for the remaining assessment sessions. The set $\{0, 1, 0, 2\}$,

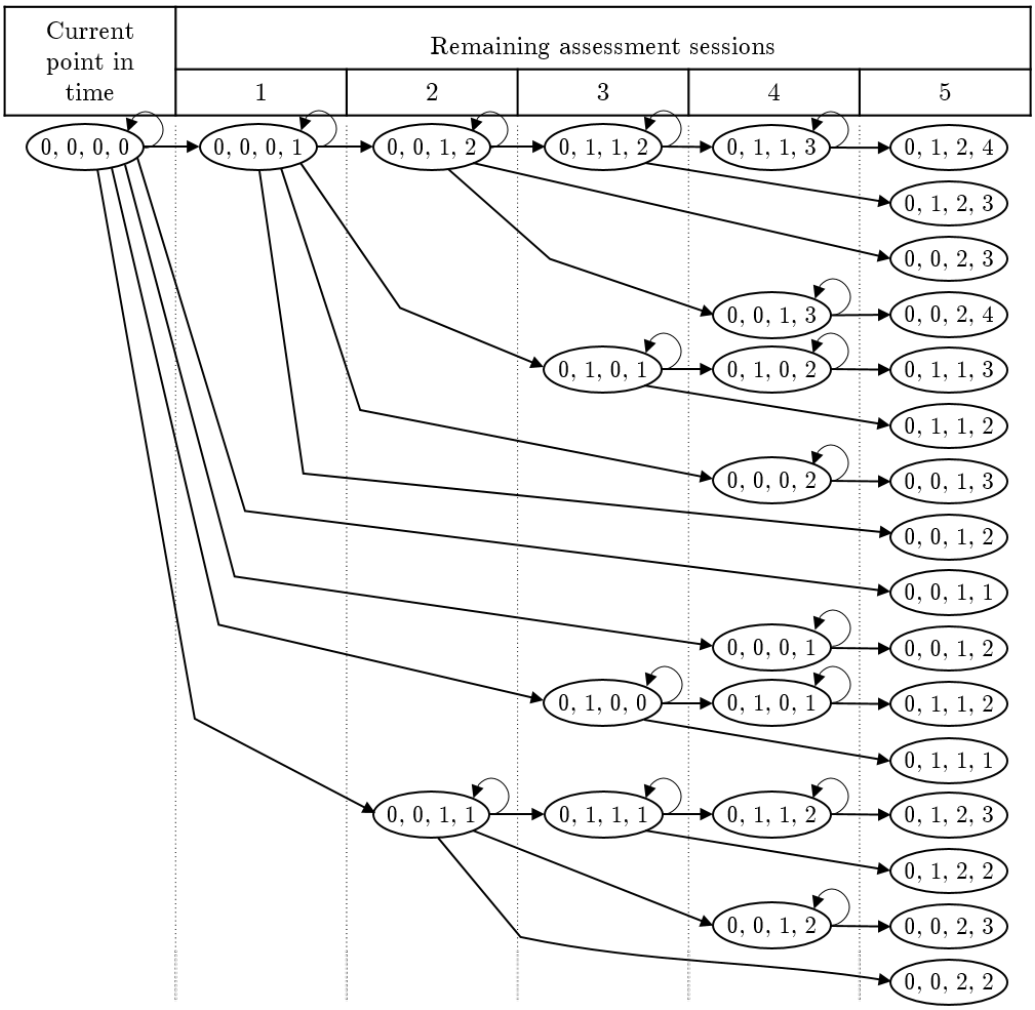

Figure 5: Possible participation scenarios for a student with the assessment plan as laid out in Table 6.

for example, represents a scenario in which the student will have completed only one assessment in F_2 and two assessments in F_4 at the close of the semester.

The total number of possible participation scenarios for this assessment plan is $2^5 = 32$. The algorithm was implemented for the assessment plan in Table 6, for Student 22. Table 7 shows a potential participation plan with an improvement target of $\delta = 5\%$.

The table shows the current factor averages and minimum p–mark for Student 22, followed by the scenarios possible for a 5% improvement in the relevant factors. Note that for attendance (F_4) a student can either get 100% for being in class or 0% for being absent. The scores for F_4 were, therefore, calculated as

$$marks_j = \frac{y_{\alpha j}(t_j - e_j) + 100\eta_j}{t_j}, \tag{23}$$

with similar variables as in (22). The layout of the assessments in Table 6 and their time

Improvement of a maximum of 5% on factor averages for Student 22					
Current performance status report:					
	F_1	F_2	F_3	F_4	Current minimum p–mark(%)
Factor averages(%):	40.00	54.07	42.67	88.89	45.48
Number of remaining assessments at current stage in the semester:	0	1	2	4	
Total number of assessments for the entire semester:	1	4	9	12	
Improvement plan:					
The scenarios for which improvement is possible in F_2, F_3 and F_4	Scores (%) required for a 5% improvement:				Increase in minimum p–mark(%)
	F_1	F_2	F_3	F_4	
$Scenario_1 = \{0, 1, 2, 2\}$	0.00	74.07	65.17	75.92	2.78
$Scenario_2 = \{0, 1, 2, 3\}$	0.00	74.07	65.17	84.26	2.86
$Scenario_3 = \{0, 1, 2, 4\}$	0.00	74.07	65.17	92.59	2.96

Table 7: Improvement plan for Student 22 with an improvement of $\delta = 5\%$ on the current factor averages.

dependency were used to establish which scenarios can lead to an improvement of 5%. As the assessment plan included no more available assessments in F_1, the improvement plan shows all the possible scenarios to produce an improvement of 5% on F_2 and F_3.

Consider $Scenario_3$ in Table 7: to increase the current factor averages of F_2 and F_3 by 5%, the student will need to complete at least one assessment in F_2 with a score of 74.07% and at least two assessments in F_3 with an average score of 65.17%. The average for F_4 will increase to 92.59% if the student participates in all four assessments available. If all of these conditions are met, the increase in minimum participation mark will be 2.96%. Although this increase in minimum p–mark seems small, it is important to note that it is dependent on the required improvement and the point in time at which these scenarios are calculated. Early in the semester, the number of remaining assessments per factor will have a greater influence on the extent to which the minimum p–mark can change than at a later stage. Furthermore, due to the small value of δ the resulting change in minimum p–mark is also small. The algorithm was also implemented for the same student with $\delta = 10\%$, and resulted in the same three scenarios shown in Table 7. The maximum possible increase in minimum p–mark for $Scenario_3$ in this instance was 5.9%. Should a higher improvement percentage be required, it may be possible that the targets cannot be reached because the remaining number of assessments is not enough. In the example a required improvement of 15% under the same conditions, will be impossible.

An advantage of using this algorithm is that by setting $\delta = 0\%$ and consequently excluding

any improvement, it can be used to generate a projected report for a student who does not plan to participate in any number of further assessments. Students can build their factor averages up to a certain stage and then fail to participate in any further assessments for numerous reasons, for example illness. Providing them with a projected status record that shows how much their minimum p–marks can decrease, can provide the motivation for their continued participation. $Scenario_0 = \{0, 0, 0, 0\}$ was generated for the current factor averages of Student 22 and the assessment plan in Table 6 and showed that the student's minimum p–mark can decrease by 7% if there is no further participation in any further assessments. This scenario will have more serious consequences earlier in the semester when there are many assessments to be completed for each factor.

Algorithm 2 effectively addresses the feed–forward as well as feed–up requirements. Feed–up is provided in the form of the predicted increase or decrease in minimum p–mark. Feed–forward is presented in the form of target scores that a student must obtain to reach said change in the minimum p–mark.

Although the combination of Algorithms 1 and 2 effectively and efficiently addresses all three requirements for student PSRs, lecturers sometimes require additional information before deciding on the weights to use for final p–mark calculation. To assist a lecturer in deciding which weight combination to select for calculation of the final p–marks, a non–linear model was formulated and implemented in an iterative algorithm. This algorithm was developed to provide feed–back solely to the lecturer and is discussed next.

4.3 Non–linear programming model in a weight selection algorithm

The linear model in Section 4.1 produced not only the p–marks and subsequent student ranking, but also the weights used to calculate the maximum and minimum p–marks per student. A lecturer decides only at the close of a semester which factor weights to use for the calculation of the final p–marks. Generally, lecturers have certain guideline throughput objectives (*e.g.* a 70% pass rate or p–mark class average) according to which they can measure the success of a group of students. It will, however, be useful to know throughout the course of a module whether a certain objective is reachable with the marks available at a certain point in time. To this end, a non–linear model was formulated to determine the required weights that will produce a p–mark class average as close as possible to some predetermined target. The model is expressed in (24).

$$\text{Minimise } z = |p_t - p_a|, \tag{24}$$

subject to constraints (4) and (6)–(8) in Section 3.1. In this model, p_t represents the target p–mark class average, p_a is the current p–mark class average calculated with fixed weights as

$$p_a = \frac{1}{m}[w_1 y_{11} + \cdots + w_m y_{m1} + \cdots + w_1 y_{1n} + \cdots + w_m y_{mn}], \tag{25}$$

with m the number of students and n the number of factors. Due to the non–linearity of the model, it can be solved using a heuristic approach. As with the non–linear model in Section 3.1, the Evolutionary Solver in Excel was used. The approach for determining the weights by means of the model in (24) was implemented according to Algorithm 3.

Algorithm 3: Non–linear modelling of weight selection

Input : $Y = \{\bar{y}_1, \ldots, \bar{y}_m\}$ is an array representing the current factor averages for m students in n factors, p_a the actual p–mark class average and p_t the target p–mark class average.

Output: $\bar{w} = \{w_1, \ldots, w_n\}$ is an array with the weights required to reach p_t.

```
find w̄ by solving model (24) using Y and p_a;
if (p_t was not reached with w̄) then
    if (upper limits on w̄ is mandatory) then
        solve model (24) until no further improvement;
    else
        relax upper limits on weights;
        find w̄ by solving model (24) using Y and p_a;
    end
end
output w̄;
```

To evaluate the model, it was implemented on the data set in Appendix A with a target p–mark class average of 70%. Initially the resulting set of weights that was produced by the algorithm was such that a p–mark class average of 70% could not be reached due to the upper limits imposed on the weights by constraint set (6) in Section 3.1. When the upper limit constraints on the weights are relaxed, the target p–mark class average of 70% can be obtained using the resulting weight set. In the example, the weights required to reach a p–mark class average of 70% were 0.66, 0.12, 0.11 and 0.11 for w_1 to w_4 respectively.

The model produces insight which a lecturer can use to determine how close to a specific target the entire class is. Although useful results can be obtained, they must be approached and interpreted with caution. Issues that need to be considered include:

- The model is solved heuristically which means that optimal solutions cannot be guaranteed. Although minor deviations may appear, empirical experiments have shown that the results were consistently acceptable.
- When constraints like upper limits are enforced on the weights, the target p–mark class average may not necessarily be reachable. In such an instance the model can be solved iteratively so that a solution as close as possible to the target p–mark class average can be reached.
- The weights resulting from an iterative approach may not conform to assurances made to students at the onset of the semester. A lecturer can for example, indicate at the start of a semester that no factor weight will exceed 0.4 but the algorithm may show that to reach a target p–mark class average of 70%, w_1 must be 0.66. In such a case the lecturer will either need to discuss the possibility of allowing the weight ranges to change with the students, or be content with a p–mark class average that is lower than the target.

Implementation of Algorithms 1 and 2 saw the feed–back, feed–up and feed–forward requirements for efficient PSRs being met. The model in Section 4.3 used the resulting

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p–marks obtained in Section 4.1 as input to determine an estimate of the weights required to reach a class average as close as possible to a specific target.

5 Discussion

None of the existing models evaluated in Section 3 fully addressed all of the requirements for effective PSRs. In Section 4, three algorithms were discussed that not only address the requirements but also provide additional feed–back to a lecturer. The three algorithms are closely related because the feed–back is used to generate the feed–forward and feed–up which are included in a PSR. This is illustrated in Figure 6.

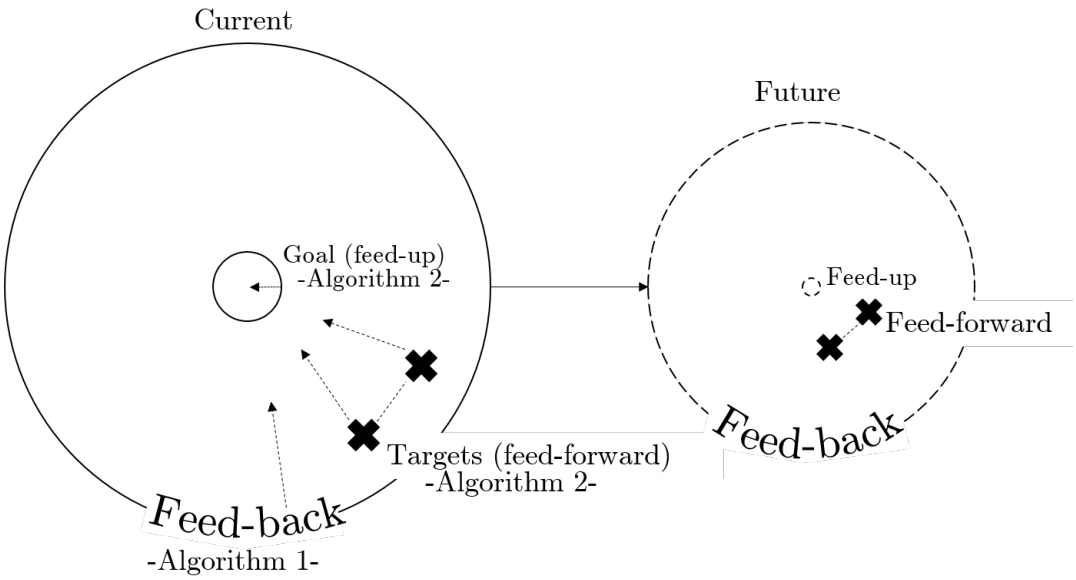

Figure 6: Algorithmic solution to effective PSRs.

In Figure 6, the arrows represent the passing of time and show how feed–back is required to set interim goals, or feed–up, as well as to calculate improvement targets as feed–forward. As time passes, the number of completed assessments grows and the number of remaining assessments decreases. Feed–back therefore progressively gets more accurate and closer to the final marks that will be used for examination admission. The decreasing size of the feed–back circle is therefore an indication of the decreasing number of remaining assessments. The interim goal(s) as well as the related improvement targets, are calculated based on completed and remaining assessments and therefore get stricter as time passes and the remaining assessments decrease. This means that closer to the end of a semester, certain improvements may not be possible to achieve within the remaining available assessments. The algorithmic solutions offer specific as well as general contributions towards PSRs in the academic environment. These are discussed below.

5.1 Specific remarks

The ranking produced by Algorithm 1 proves to be acceptable because of the high Spearman's ranking correlation between it and those obtained from *benchMark* and the non–linear model discussed in Section 3.1. The algorithm eliminates the need for iterative empirical calculations. Furthermore, the weights calculated by Algorithm 1 are considered more accurate than those obtained by *benchMark* because they are not restricted to be integer or in multiples of a predetermined number.

Algorithm 2 uses the minimum p–mark and its associated weights to develop a future time participation perspective for a student. The scenarios according to which the required improvement can be reached are determined and provided. The algorithm can be used to generate a participation plan at any point in time during the semester.

Algorithm 3 provides additional progress information to a lecturer which can be used to determine the weights required to reach a target p–mark class average. The calculated weights may also provide a lecturer with some insight into how successful students were in each factor. A specific factor weight which is much higher than all the others would for example indicate that the students overall performed much better in that factor than in all the others.

Although the proposed algorithmic solutions provide the information essential to PSRs, some disadvantages were identified and are listed accordingly. Algorithm 2 was developed to generate participation scenarios for an individual student. The algorithm can be used iteratively to generate improvement plans for an entire class. However, depending on the marks, the same improvement percentage will not be possible for all students. Therefore every time the lecturer generates an improvement plan for a student, an improvement percentage related to the student's current performance is required. This makes execution of the algorithm for an entire class rather labour intensive.

If the upper limit weight constraints in Algorithm 3 need to be relaxed because a target p–mark class average cannot be reached, the resulting weights may not conform to the guidelines set by the lecturer at the start of the semester.

5.2 General remarks

The purpose of the proposed algorithmic solutions was to address the demand for a system that will continuously provide students with academic performance status reports in a module, at any point in time during a semester. The discussed algorithmic solutions address the feed–back, feed–forward and feed–up requirements and furthermore exhibit the attributes necessary for it to be constructive and to motivate students to improve.

The proposed framework provides ongoing feed–back that is timely because it can be used as frequently as required. The results are readily available and can be made available to students instantly. The approach is user–friendly and consistently uses an updated set of the students' current marks to obtain the information needed for feed–back. Furthermore, the suggested approach provides a student with personalised and goal–referenced feed–up which is based on the student's current performance. The feed–forward improvement targets are presented in the form of actionable scores that a student needs to acquire in a

specified number of upcoming assessments, in each factor.

The collective algorithmic approach sufficiently generates feed–back, feed–up and feed–forward for academic PSRs based on a set of students' current performance. Implementation of the framework could also be useful in environments where PSRs are required for motivation to participate in specific learning opportunities or assessments or also, for example, in sports activities or tournaments.

6 Conclusions

The purpose of this study was to evaluate existing mathematical models against the requirements for effective PSRs and develop an improved algorithmic approach for that purpose. An example data set containing the marks for 26 students in four factors (Appendix A) was used throughout the study to evaluate the methods and solutions.

Three existing models were evaluated. The *benchMark* program was assessed and formalised in a non–linear mathematical model. Although these options did address feed–back in PSRs, other disadvantages made them impractical to use regularly and under certain conditions. An outputs–only DEA was performed to group students into classes of similar efficiency. Improvement targets (feed–forward) were then calculated to help students advance to one class higher. The interim goal (feed–up) for each student was not clear because it was not linked to the p–mark. The method was independent of weight constraints and impractical to use for classes with many students. The analytic hierarchy process provided a means to rank students without calculating their p–marks but did not address the feed–up or feed–forward requirements.

To address the deficiencies, a set of related algorithmic approaches in which alternative mathematical models are implemented, was developed. The reports generated were consequently assessed in terms of the required attributes for effective PSRs. Three algorithms were developed to attend to the requirements for PSRs. Firstly, a linear programming model was implemented in an algorithm to address the requirements of feed–back in the form of a student ranking. The next algorithm generated a future participation and improvement plan for each student and addressed the feed–up and feed–forward requirements for PSRs. A non–linear model was implemented in a third algorithm to provide additional feed–back to a lecturer during the course of a semester.

Some aspects that are currently receiving attention to improve the proposed algorithmic approach include the calculation of the maximum possible improvement per individual student in a class and automatic generation of the future perspective plans; and development of an interactive user–friendly graphical interface that combines the different algorithmic activities.

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Appendices

A. Data set used in the mathematical models

Table 8 presents the data set containing the factor averages of 26 students in four factors, where the factors (denoted F_1 to F_4 respectively) are a semester test, class tests, theoretical 14 assignments and attendance. This set was used in the paper to evaluate the relevant ranking methods.

Student	$F_1(\%)$	$F_2(\%)$	$F_3(\%)$	$F_4(\%)$
1	73.33	64.74	13.92	62.50
2	100.00	95.24	97.92	100.00
3	96.67	82.62	75.05	100.00
4	35.00	35.27	21.01	77.78
5	61.67	56.90	40.59	77.78
6	75.00	63.10	57.59	88.89
7	58.33	22.39	34.68	100.00
8	58.33	43.76	53.53	87.50
9	93.33	91.51	87.75	100.00
10	93.33	68.15	74.07	100.00
11	88.33	53.38	64.91	100.00
12	73.33	57.01	63.71	100.00
13	76.67	87.13	65.83	88.89
14	10.00	44.40	52.97	77.78
15	83.33	57.27	23.65	88.89
16	51.67	46.19	26.36	77.78
17	90.00	58.15	68.42	77.78
18	63.33	58.30	42.67	100.00
19	73.33	63.38	41.01	100.00
20	60.00	55.24	51.58	88.89
21	85.00	59.46	35.90	75.00
22	40.00	54.07	42.67	88.89
23	85.00	72.14	61.85	100.00
24	90.00	64.76	76.67	100.00
25	83.33	60.46	26.07	66.67
26	65.00	55.48	24.53	100.00

Table 8: Data set utilised in the mathematical models in this study.

B. Participation profiles of the 26 participants as calculated by *benchMark*

Participation profiles of the 26 participants as calculated by *benchMark*.

Student	F_1	F_2	F_3	F_4	Max	Min	Avg	Rank
2	100.00	95.24	97.92	100.00	98.29	97.58	97.85	1
9	93.33	91.51	87.75	100.00	93.15	91.35	92.33	2
3	96.67	82.62	75.05	100.00	89.22	85.43	87.44	3
13	76.67	87.13	65.83	89.00	83.35	78.25	81.05	4
10	93.33	68.15	74.07	100.00	84.89	78.78	81.04	5
24	90.00	64.76	76.67	100.00	82.86	77.07	79.37	6
23	85.00	72.14	61.85	100.00	79.75	74.31	77.35	7
17	90.00	58.15	68.42	77.78	76.02	71.62	73.66	8
11	88.33	53.38	64.91	100.00	76.66	69.08	72.28	9
12	73.33	57.01	63.71	100.00	73.51	65.73	68.79	10
6	75.00	63.10	57.59	88.89	70.80	66.24	68.60	11
19	73.33	63.38	41.01	100.00	69.43	61.49	66.24	12
21	85.00	59.46	35.90	75.00	68.52	60.65	63.67	13
25	83.33	60.46	26.07	66.67	67.63	57.73	61.88	14
15	83.33	57.27	23.65	88.89	67.36	56.52	61.80	15
18	63.33	58.30	42.67	100.00	66.08	57.21	61.75	16
20	60.00	55.24	51.58	88.89	63.58	57.18	59.97	17
5	61.67	56.90	40.59	77.78	61.67	54.97	58.73	18
26	65.00	55.48	24.53	100.00	61.25	51.28	57.37	19
1	73.33	64.74	13.92	62.50	63.76	52.40	57.35	20
8	58.33	43.76	53.53	87.50	60.33	52.67	55.53	21
22	40.00	54.07	42.67	88.89	56.06	47.97	51.61	22
16	51.67	46.19	26.36	77.78	49.81	43.33	47.25	23
7	58.33	22.39	34.68	100.00	47.60	38.88	42.50	24
14	10.00	44.40	52.97	77.78	45.59	33.46	39.69	25
4	35.00	35.27	21.01	77.78	41.57	32.90	37.16	26

Table 9: Participation profiles created by *benchMark* in Section 3.1, for the 26 students. $F_1 - F_4$ are the factor averages arranged according to weight priority. The columns Max, Min and Avg, are the maximum, the minimum and the average participation marks, respectively. The column Rank is the student ranking according to average participation marks. All marks are indicated in percentages.

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The maximum, minimum and average p–marks, student ranking, and corresponding weights for calculating the minimum and maximum p–marks for 26 students using the non-linear model in Section 3.1.

	p–marks (%)				Weights for minimum p–mark				Weights for maximum p–mark			
Student	Max	Min	Average	Rank	w_1	w_2	w_3	w_4	w_1	w_2	w_3	w_4
2	98.63	97.78	98.21	1	0.40	0.40	0.15	0.05	0.40	0.20	0.20	0.20
9	93.15	91.44	92.30	2	0.35	0.30	0.30	0.05	0.25	0.25	0.25	0.25
3	90.20	86.13	88.17	3	0.35	0.30	0.30	0.05	0.40	0.20	0.20	0.20
10	84.52	80.04	82.28	4	0.35	0.35	0.25	0.05	0.35	0.25	0.20	0.20
24	84.27	78.33	81.31	5	0.35	0.35	0.25	0.05	0.40	0.20	0.20	0.20
13	80.54	77.17	78.29	6	0.35	0.30	0.30	0.05	0.35	0.35	0.15	0.15
23	80.80	74.95	76.90	7	0.35	0.30	0.30	0.05	0.40	0.20	0.20	0.20
11	78.99	70.83	73.55	8	0.35	0.35	0.25	0.05	0.40	0.20	0.20	0.20
17	76.87	72.75	74.12	9	0.30	0.30	0.30	0.10	0.40	0.20	0.20	0.20
12	73.51	66.55	68.87	10	0.35	0.35	0.25	0.05	0.25	0.25	0.25	0.25
6	71.92	66.90	68.57	11	0.35	0.30	0.30	0.05	0.40	0.20	0.20	0.20
19	70.21	61.98	64.73	12	0.35	0.30	0.30	0.05	0.40	0.20	0.20	0.20
21	68.47	61.61	63.90	13	0.30	0.30	0.30	0.10	0.40	0.30	0.15	0.15
15	67.40	59.07	61.85	14	0.35	0.30	0.30	0.05	0.40	0.30	0.15	0.15
18	66.08	57.46	60.33	15	0.35	0.30	0.30	0.05	0.25	0.25	0.25	0.25
25	63.97	59.13	60.75	16	0.30	0.30	0.30	0.10	0.40	0.30	0.15	0.15
20	63.93	57.49	59.64	17	0.35	0.30	0.30	0.05	0.25	0.25	0.25	0.25
1	62.87	51.85	55.52	18	0.30	0.30	0.30	0.10	0.40	0.35	0.15	0.10
5	59.72	54.72	56.39	19	0.35	0.30	0.30	0.05	0.40	0.20	0.20	0.20
8	60.78	53.24	55.75	20	0.35	0.35	0.25	0.05	0.25	0.25	0.25	0.25
26	62.00	51.75	55.17	21	0.35	0.30	0.35	0.05	0.4	0.20	0.20	0.20
22	56.41	47.33	50.36	22	0.40	0.30	0.25	0.05	0.25	0.25	0.25	0.25
7	54.75	41.93	46.20	23	0.35	0.35	0.25	0.05	0.25	0.25	0.25	0.25
16	50.73	43.74	46.07	24	0.35	0.30	0.30	0.05	0.40	0.2	0.20	0.20
14	46.29	33.60	37.83	25	0.40	0.35	0.20	0.05	0.25	0.25	0.25	0.25
4	42.26	33.02	36.10	26	0.40	0.30	0.25	0.05	0.25	0.25	0.25	0.25

Table 10: Resulting maximum, minimum, and average p–marks, ranking and weights calculated by means of the non–linear model in Section 3.1.

The student ranking of the 26 students, as determined by the AHP discussed in Section 3.3.

Student	Priority Vector F_1	F_2	F_3	F_4	Composite Rating $r_{\alpha j}$	Pairwise Ranking
2	0.1019027	0.1226755	0.1458670	0.0612267	11.082600	1
9	0.0793605	0.1101616	0.1166742	0.0612267	9.334351	2
3	0.0872195	0.0810881	0.0704773	0.0612267	7.813273	3
10	0.0793605	0.0506373	0.0643211	0.0612267	6.501559	4
24	0.0614319	0.0370232	0.0824396	0.0612267	5.828006	5
23	0.0491764	0.0670063	0.0387908	0.0612267	5.425578	6
13	0.0326883	0.0977652	0.0460599	0.0283514	5.423514	7
17	0.0614319	0.0280258	0.0869943	0.0148856	4.954059	8
11	0.0541918	0.0172421	0.0495889	0.0612267	4.324156	9
15	0.0568494	0.0347459	0.0065793	0.0283514	3.588964	10
12	0.0260657	0.0276756	0.0418947	0.0612267	3.498863	11
6	0.0306510	0.0374787	0.0359753	0.0283514	3.341923	12
19	0.0260657	0.0368469	0.0181735	0.0612267	3.299577	13
25	0.0568494	0.0312238	0.0097345	0.0093700	3.261681	14
21	0.0491764	0.0297609	0.0133239	0.0127000	3.070979	15
18	0.0171022	0.0287135	0.0199034	0.0612267	2.776450	16
1	0.0260657	0.0377650	0.0051790	0.0087337	2.279836	17
26	0.0190688	0.0175284	0.0075953	0.0612267	2.263566	18
20	0.0147006	0.0158600	0.0259862	0.0283514	1.935315	19
5	0.0162776	0.0262947	0.0150281	0.0148856	1.882403	20
7	0.0128273	0.0058818	0.0127885	0.0612267	1.799583	21
8	0.0128273	0.0103791	0.0252893	0.0182904	1.540473	22
22	0.0074831	0.0158520	0.0177094	0.0283514	1.516930	23
14	0.0043365	0.0113759	0.0277737	0.0148856	1.271811	24
16	0.0104266	0.0141118	0.0089887	0.0148856	1.191343	25
4	0.0064634	0.0068808	0.0068640	0.0148856	0.793206	26

Table 11: Ranking of the 26 students produced by the AHP in Section 3.3.

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C. Results of the linear model in Section 4.1

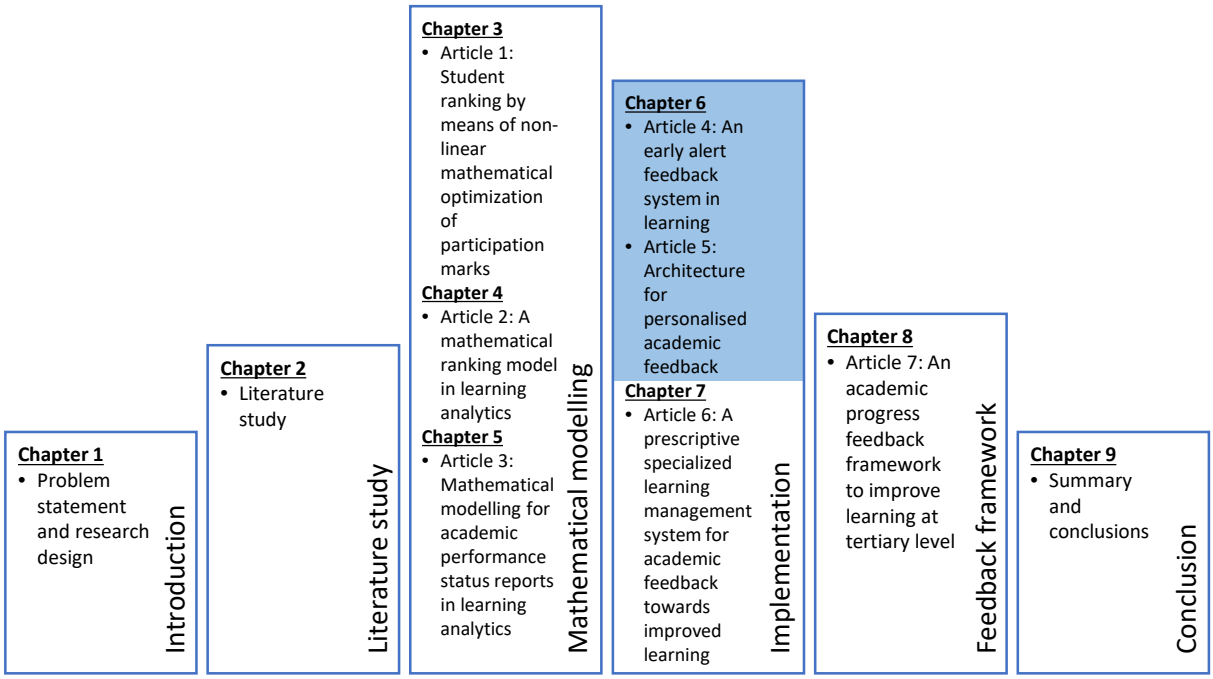
The maximum, minimum and average p–marks, student ranking, and corresponding weights for calculating the minimum and maximum p–marks for the 26 students using the linear model in Section 4.1.

	p–marks (%)				Weights for minimum p–mark				Weights for maximum p–mark			
Student	Max	Min	Average	Rank	w_1	w_2	w_3	w_4	w_1	w_2	w_3	w_4
2	98.63	97.70	98.17	1	0.40	0.40	0.19	0.01	0.40	0.20	0.20	0.20
9	93.19	90.96	92.07	2	0.33	0.33	0.33	0.01	0.40	0.20	0.20	0.20
3	90.20	84.93	87.57	3	0.33	0.33	0.33	0.01	0.40	0.20	0.20	0.20
10	85.78	78.73	82.26	4	0.33	0.33	0.33	0.01	0.40	0.20	0.20	0.20
24	84.29	77.37	80.83	5	0.33	0.33	0.33	0.01	0.40	0.20	0.20	0.20
13	80.99	76.67	78.83	6	0.33	0.33	0.33	0.01	0.40	0.40	0.10	0.10
23	80.80	73.27	77.03	7	0.33	0.33	0.33	0.01	0.40	0.20	0.20	0.20
17	76.87	72.25	74.56	8	0.33	0.33	0.33	0.01	0.40	0.20	0.20	0.20
11	78.99	69.19	74.09	9	0.33	0.33	0.33	0.01	0.40	0.20	0.20	0.20
12	73.51	65.04	69.28	10	0.33	0.33	0.33	0.01	0.25	0.25	0.25	0.25
6	71.92	65.47	68.69	11	0.33	0.33	0.33	0.01	0.40	0.20	0.20	0.20
19	70.21	59.65	64.93	12	0.33	0.33	0.33	0.01	0.40	0.20	0.20	0.20
21	68.88	60.27	64.57	13	0.33	0.33	0.33	0.01	0.40	0.40	0.10	0.10
25	66.79	56.72	61.76	14	0.33	0.33	0.33	0.01	0.40	0.40	0.10	0.10
15	67.50	55.09	61.29	15	0.33	0.33	0.33	0.01	0.40	0.40	0.10	0.10
18	66.08	55.22	60.65	16	0.33	0.33	0.33	0.01	0.25	0.25	0.25	0.25
1	66.36	54.15	60.26	17	0.33	0.33	0.33	0.01	0.40	0.40	0.10	0.10
20	63.93	55.94	59.93	18	0.33	0.33	0.33	0.01	0.25	0.25	0.25	0.25
5	59.72	53.30	56.51	19	0.33	0.33	0.33	0.01	0.40	0.20	0.20	0.20
8	60.78	51.88	56.33	20	0.40	0.40	0.19	0.01	0.25	0.25	0.25	0.25
26	62.00	48.85	55.43	21	0.33	0.33	0.33	0.01	0.40	0.20	0.20	0.20
22	56.41	45.48	50.95	22	0.40	0.30	0.29	0.01	0.25	0.25	0.25	0.25
7	54.75	39.09	46.92	23	0.33	0.33	0.33	0.01	0.40	0.20	0.20	0.20
16	50.73	41.77	46.25	24	0.33	0.33	0.33	0.01	0.40	0.20	0.20	0.20
14	46.29	32.60	39.45	25	0.40	0.40	0.19	0.01	0.25	0.25	0.25	0.25
4	42.26	30.90	36.58	26	0.33	0.33	0.33	0.01	0.25	0.25	0.25	0.25

Table 12: Resulting maximum, minimum, and average p–marks, ranking and weights calculated by means of the linear model in Section 4.1.

Chapter 6

Models implementation: Articles 4 and 5



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6.1. Introduction

Chapter 6 serves to introduce two short papers presented during the development of software applications that implement the models described in Chapters 3 to 5. This was the first phase in establishing the architecture required for an electronic demonstrator of the mathematical modelling approach.

6.2. Preamble: Article 4 - An early alert feedback system in learning

The title of Article 4 is *An early alert feedback system in learning* and it was presented as a peer reviewed short paper in the *ICT, Society and Human Beings* track of the *Multi Conference on Computer Science and Information Systems* held in Lisbon, Portugal on 20-23 July 2017.

After formulating and solving the non-linear programming model to emulate the participation mark calculation process of the empirical program, *benchMark*, a software application of the model was created. Article 4 reveals how this system was implemented in a pilot study and evaluated for compliance to the requirements for effective feedback. It shows that although the process of calculation of the participation profiles can be improved by means of a non-linear programming model, the information supplied was not comprehensive to the point of feeding backwards, forward and upwards. This resulted in the introduction of the outputs-only data envelopment analysis model discussed in Chapter 4 and improved upon by means of the decision tree algorithm in Chapter 5.

Article 4[1] was composed according to the sixth edition of the American Psychological Association (APA) standard. More information on submission, the peer review process, and author guidelines can be found in Appendix E.

[1] The article is presented in its final published form. Consequently, the page numbers of the article, as it appears in the proceedings, are displayed along with the principal thesis information.

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AN EARLY ALERT FEEDBACK SYSTEM IN LEARNING

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ABSTRACT

The fields of teaching and learning are evolving as a result of new techniques like blended-, online-, and exploratory learning being implemented. Lecturers need to ensure successful teaching and also create an environment in which students can learn effectively. Two important factors that a lecturer can control to enhance learning are instruction and feedback. A learning analytics system was developed for the latter, utilizing mathematical programming models, which enables a lecturer to provide real-time progress feedback to students at regular intervals during the course of a program. This paper highlights flaws identified in some existing feedback scenarios, discusses the development of an electronic feedback system, and explains how its implementation can keep students informed on their progress from an early stage of instruction and present them with actionable targets for reaching their ultimate goal.

KEYWORDS

Data envelopment analysis; early alert feedback system; mathematical modelling; student ranking

1. INTRODUCTION

The parties involved in a teaching and learning environment are the lecturers, who must establish an optimal learning setting, and the students who must participate and learn. Although the common perception among students is that their main responsibility is partaking in lectures, they still feel that lecturers have to provide guidance and motivation for them to achieve success (Geçer, 2013). In order to enhance learning, lecturers must adopt effective instruction- and subsequent feedback methods that jointly creates an ideal environment for learning. They supplement their teaching regimes with examples, topical case studies relating to new work, and in-depth class discussions. The pace at which technology is advancing enables lecturers to adapt their teaching and assessment techniques (Landau, et al., 2014) by augmenting them with the use of learning management systems (LMSs) (Sin & Muthu, 2015). Different forms of LMSs are used to aid the learning process and are readily accepted by students. Most LMSs have analytic capabilities which can provide useful feedback statistics regarding students' use of certain fields in the LMS (Siemens, 2011). Together with effective teaching, feedback plays an equally important role in enhancing the learning environment (Hattie, 2005).

With all the challenges lecturers face (Brühwiler, 2011), the role of the lecturer has indeed shifted from explicit teaching to facilitating and trying to create an environment in which students accept responsibility for their own learning progress (Ozel, 2015). Additionally, with the incorporation of novel teaching methods like blended learning and online facilitation, many new systems are being implemented to aid in the teaching and learning processes (Reyes, 2015) but methods in student feedback are still lacking. Feedback can be defined as information that is provided about a person's progress in his/her efforts towards reaching a specific goal (Wiggins, 2012). Analytical methods used to process student data need to adapt so as to ensure effective-, learning enhancing feedback. The use of a hierarchy structure to provide feedback can assist students in understanding improvable factors which determine their academic success (Barker & Garvin-Doxas, 2004). For feedback to be helpful to students, it needs to be target/goal-referenced, demonstrable and obvious, actionable, user-friendly or manageable, timely, dynamic, and consistent (Wiggins, 2012).

The changing face of education has highlighted flaws in existing teaching and learning environments relating to feedback, which can be addressed by the development and implementation of novel learning analytics systems. Section 2 will outline some of the shortcomings identified in previous research. In section

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3, the development of a learning analytics system in the form of an early alert feedback system as solution to the identified shortfalls, will be discussed. This is followed by section 4, which will evaluate the developed system according to the criteria for effective feedback. The paper will conclude with some closing statements and plans for future work.

2. LEARNING INHIBITING SHORTFALLS IDENTIFIED IN FEEDBACK

Studies by Bond, et al. (2000) have shown that while feedback is hard to record, feedback frequency is mostly low. Although lecturers realize the value that feedback provides, the associated administrative tasks can be so time consuming that even if they wanted to provide early or frequent feedback, it can be an almost impossible task. Hattie and Timperley (2007) found in their research, that there are three important issues that should be addressed by a feedback model. It must provide a student with information on completed tasks that helps him/her understand what the goal is, how to progress to that goal, and which activities to perform to reach the goal. Students need to understand how they are progressing toward their end-goal, and to get directions on how to attain that goal (Wiggins, 2012). Lecturers use different ways to provide students with information on their progress, many of them unofficial.

Du Toit (2015) developed a computer program, benchMark, which assisted lecturers in calculating the participation levels of students, taking into consideration the activities in which they were required to participate. The program calculates average marks for each class activity (class attendance, practical assignments, etc.) that a lecturer in a specific module expects the students to participate in. An overall participation mark is then calculated as the sum of these averages, each multiplied by a weight representing that activity's importance. If, for example, the averages of two activities were 35% and 45%, then the participation can be calculated as $50\% \times 35 + 50\% \times 45$, meaning they are equally important, or $40\% \times 35 + 60\% \times 45$, meaning the ratio of importance is 40:60 for activity_1:activity_2, with a total of 100%. To write the equation in a general form for an example of 4 activities, let w_1 denote the weight level of activity 1, likewise w_2, w_3, and w_4 the weights for activities 2, 3, and 4 respectively. Subsequently, let s_1 denote the average (of all marks achieved) for activity 1, and s_2, s_3, and s_4 the averages for activities 2, 3, and 4 respectively. The overall participation mark, p, is then calculated according to the following equation:

$$p = s_1 w_1 + s_2 w_2 + s_3 w_3 + s_4 w_4 \qquad (1)$$

The program orders the activities according to importance and constrains the weights to be in multiples of 5. It empirically calculates a set of participation marks for each student, using all of the different weight combinations allowed by the model. Feedback is provided in the form of spreadsheets wherein students are identified by means of their student numbers. It shows their activity averages, the minimum participation mark, and their ranking in relation to the rest of the class. The program has the unique capability of performing these calculations as frequently as required by the lecturer, who will have access to the maximum-, minimum-, and average participation marks as well as other useful statistical information. The benchMark system enables lecturers to present students with regular updates on their progress in the form of participation marks (Du Toit, 2015).

In a pilot study, it was found that the students were very satisfied with the feedback frequency and most of them wanted the system to be implemented in all of their programs. Table 1 presents a short summary on some statistical insights gained from this study.

Table 1. Summarizing statistics of student responses on the benchMark system

Question	% of 25 students agree
The frequency of feedback is acceptable.	96%
The marks system should be implemented in all of my modules.	88%

The benchMark system presented timely, goal-referenced, and dynamic feedback to students. Issues that were however identified included concerns regarding privacy (personalization), ease of use of the system (user-friendliness), and the lack of actionable goals that will help in creating a future perspective (demonstrable).

Section 2 summarized the operation of an existing feedback system that has been implemented in actual teaching/learning environments and identified areas in which improvement is required. Section 3 will discuss the development of the early alert feedback system which uses the optimizing attributes of mathematical models to perform its calculations.

3. DEVELOPMENT OF AN EARLY ALERT FEEDBACK SYSTEM

The positive response elicited by benchMark (Du Toit, 2015), justifies its use as a steady foundation for development of a two stage early alert feedback system. In the first stage, an NLP model was formulated and solved for each student in order to eliminate the repetitive nature of benchMark:

$$\begin{aligned} &maximize/minimize && p_\alpha = \sum_{j=1}^{n} s_{\alpha j} w_j && (2)\\ &subject\ to && \sum_{j=1}^{n} w_j = 1 && (3)\\ & && w_j \bmod k = 0 && (4)\\ & && l < w_j \le u && (5)\\ & && w_j \ge w_{j+1}, \quad j < n && (6)\\ & && 0 \le s_{\alpha j} \le 1 && (7)\\ & && l, u \ge 0 && (8) \end{aligned}$$

where p is the participation mark, s_i is the student average for activity i, w_i is the weight assigned to activity i, (4) ensures that w_i is a multiple of k, l is the lower limit for all the weights, u is the upper limit for all the weights, n is the number of activities used, and $i = 1, \dots, n$. Minimizing the model yields a minimum participation mark and its corresponding weights, and maximizing the model yields a maximum participation mark and its corresponding weights. An average participation mark is determined from the results, according to which a student ranking is created. The model is therefore solved twice per student before the average participation marks are calculated. Applying an existing student data set, the student ranking obtained by solving the NLP model was compared to that resulting from benchMark, by calculating the Spearman's rank order correlation coefficient (Puth, 2015). This coefficient was calculated for the two sets of rank values and resulted in a value of ρ=0.99, which shows that there is a very strong positive association between the rankings resulting from benchMark and the NLP. This model represents an adaptation of the benchMark program but is optimized in terms of the number of calculations, and follows a consistent process.

A feedback system should provide students with information on personalized (user-friendly) actions towards reaching a goal (actionable). In the second stage of the feedback system, the activity averages for each student are used to perform an output oriented data envelopment analysis (DEA) which determines an efficiency score for each student based on performance (Kao & Lin, 2008), and divides them into classes of equal efficiency:

$$\begin{aligned} E_k = \quad & Maximize \sum_{j=1}^{n} s_{kj} w_j && (9)\\ subject\ to \quad & \sum_{j=1}^{n} s_{ij} w_j \le 1, \ i = 1, \dots, m && (10)\\ & w_j \ge \varepsilon > 0, \qquad j = 1, \dots, n && (11) \end{aligned}$$

where E_k represents the efficiency score for student k, s_{ij} is the average of student i in activity j, w_j is the weight for activity j, n is the number of students to be considered, m is the number of activities, and ε is a small number. This class-ranking is used for solving the dual formulation of the outputs-only DEA (in (12) to (14)) to present each student with personalized targets to reach in each of the activities to improve his/her position on the class-ranking.

$$\begin{aligned} E_k = \quad & Minimize \sum_{i=1}^{m} \lambda_i - \varepsilon \sum_{j=1}^{n} q_j && (12)\\ subject\ to \quad & \sum_{i=1}^{m} s_{ij} \lambda_i - q_j = s_{kj}, \ j = 1, \dots, n && (13)\\ & \lambda_{ji}, q_j \ge 0, \qquad i = 1, \dots, m; \ j = 1, \dots, n && (14) \end{aligned}$$

where E_k represents the composite index for student k, s_{ij} is the average of student i in activity j, w_j is the weight for activity j, n is the number of students to be evaluated, m is the number of activities, ε is a small positive number, q_j is the change in activity j, let $\theta = \sum_{i=1}^{n} \lambda_i$, then $(s_{kj} + q_j)/\theta$ is the target for

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activity j, and $j = 1, \dots, m$. The model successfully calculates personalized improvement targets for each activity, indicating how much each student needs to improve in each activity, to progress to a level of higher efficiency.

The two-stage early alert feedback system successfully addresses most of the concerns lacking from existing feedback systems. It consistently incorporates an optimized method for calculating participation marks and provides personalized, actionable improvement targets that demonstrate to students how they can improve.

4. RESULTS

Wiggins (2012) presented seven criteria for effective feedback according to which the success of the developed system will be evaluated (Table 2).

Table 2. Criteria and evaluation of the developed system

Criteria	Evaluation
Target/goal-referenced	The system provides students with feedback directly related to activities needed to reach their goal.
Demonstrable, obvious	Students are presented with tangible results related to each sub goal (activity).
Actionable	The DEA model provides targets that show students how to improve in each activity.
User-friendly	A certain amount of explanation from the lecturer is needed for students to effectively understand the feedback.
Timely	The system can calculate feedback information as often as required by the lecturer.
Dynamic	Every time feedback is provided in real-time, all previous sets of marks are included. This means that students can see how they are progressing by comparing their latest results with all those previously calculated.
Consistent	The marks are consistently calculated by solving the same optimized models for all students.

One of the most important advantages the developed system presents to lecturers, is that the mathematical models are consistent. This means that whenever an activity has been completed, the marks can be imported into the database and a new set of feedback statistics can be calculated automatically.

5. CONCLUSIONS

This paper discussed the need and development of an early alert feedback system that regularly provides students with information on their ultimate goal, how the goal can be achieved, which activities to perform to reach that goal, and which is easy to use. A two-stage early alert feedback system was developed that implements an NLP to consistently calculate an average participation mark for each student and that uses a class-ranking method to calculate personalized improvement targets for each student in each activity. The system was evaluated according to the seven attributes of successful feedback presented by Wiggins (2012).

To efficiently address remaining concerns regarding student privacy as well as user-friendliness, the system is to be implemented in an electronic dashboard that will allow individual students private access to solely their own marks and statistics. Also, for very large student numbers, a specialized solver is required to implement the dual formulation of the outputs-only DEA because of an exponential increase in decision variables. Therefore an improved model for activity target calculation is currently being developed.

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6.3. Preamble: Article 5 - Architecture for personalised academic feedback

The manuscript presented here as Article 5 is titled *Architecture for personalised academic feedback*. This paper was presented as a short paper in the *Education & Humanities* track at *The WEI International Academic Conference*, held from 17-19 April 2018 in Vienna, Austria.

This second article in Chapter 6 identifies the three main elements, the student, lecturer and system, required for implementation of the linear programming model for participation profile calculation and the decision tree algorithm for improvement goals and targets, as described in Chapter 5. The architecture of the three components is shown graphically, followed by a preliminary evaluation of its composition into a usable software application. The system was evaluated as a stand-alone application with positive results.

The style guidelines proposed for composing the manuscript[2] was the American Psychological Association (APA) standard. Additional information regarding the submission process, the peer review process, and author guidelines can be found in Appendix E.

[2] The article was formatted for online publication and is presented in its final form. Consequently, the page numbers of the article, as it appears in the proceedings, are displayed along with the principal thesis information.

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ARCHITECTURE FOR PERSONALIZED ACADEMIC FEEDBACK

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ABSTRACT

The determinants for success in a module taken at a tertiary institution depends on different factors subject to the mode of delivery. The entities involved include the institution, faculty members and the learners. Achievement in on-campus teaching-learning is determined by the development of study material and assessments, instruction and facilitation by the lecturer, as well as student behaviour by attending contact sessions, studying and taking part in assessments. An increase in student enrolment numbers is being observed due to advances in e-learning, implementation of new teaching techniques, and financial assistance programs that are becoming more readily available to students. Nevertheless, universities struggle to increase their student retention rates. In an effort to prevent these rates from decreasing, this paper proposes an architecture aimed at providing students with information on their academic progress or lack thereof at regular intervals, and incentives towards improving their academic statuses. Existing studies on effective feedback are discussed briefly in order to establish the measurements by which the proposed architecture should be evaluated. The architecture is presented graphically and evaluated on the criteria established for improving the learning experience and preventing students from dropping-out. Results indicate that the architecture can be implemented in any module by incorporating it in a learning management system. It adheres to the requirements for effective feedback thereby promoting academic improvement, resulting in improved student retention.

Keywords: Academic feedback, feedback architecture, learning analytics, student retention

1. Introduction

In a traditional tertiary educational setting, lecturers present contact and facilitation sessions and use a combination of assessment techniques to calculate the grades that determine whether students pass or fail. Assessments can be formative (in the form of hand-written or electronic class assignments/tests, homework and practical assignments) and/or summative which usually happens at the conclusion of a semester/term in the form of an examination. Students are expected to actively participate in contact sessions, perform a certain degree of studying, and successfully partake in assessments for module completion. Among the actions that a lecturer is expected to perform, is the timely grading of assessments and corresponding feedback to students. This can be a very time-consuming activity that can unnecessarily compromise teaching quality, especially when student numbers are high.

In contrast, the future of tertiary education seems promising as an increase in student enrolment numbers is observed annually (Deen & Leonard, 2015). Several factors contribute to this, including an increase in programs being presented online (Naresh, et al., 2016), implementation of novel teaching techniques (Slechtova, et al., 2015; Sood, 2016) and financial aid schemes catering for specific student groups (Loyalka, et al., 2013; Vergolini & Zanini, 2015). However student drop-out rates have not decreased, in fact studies show that in South Africa 20% of students drop out in their second year and 25% in their third year of tertiary studies (Shay, 2017). Two of the reasons for this are that students do not appear to be properly prepared for the workload they encounter at tertiary level (Deen & Leonard, 2015) and the pace at which learning needs to take place is too steep (Du Toit, 2015). Although studies are being conducted on how to improve secondary education so that the level of preparedness for tertiary level improve (Deen & Leonard, 2015; Karabo & Natal, 2013; Shay, 2017), research into feedback methods that inform students how they are doing in their modules, also needs attention.

Feedback should ideally be given to students regularly and consistently in a semester so that they still have the opportunity to change and improve rather than dropping out later on. Another requirement is to provide students with more specific information or targets to reach towards improving their current academic standings (Van der Merwe, et al., 2017b). That means that with the increase in student enrolment numbers, lecturers still need to perform all of the tasks required from them and generate informative feedback frequently throughout the semester. Many studies have been done on assessment feedback which essentially provides a student with

real-time information during completion of an assessment (Evans, 2013; Stegmann & Malan, 2016; Wu, et al., 2016). This type of feedback is content specific and cannot be implemented generically in any random module. The issue of progress and improvement feedback therefore remains only partially solved.

The purpose of this study is to propose and develop an architecture for personalised academic feedback in an effort to assist with the problem universities are experiencing in terms of student retention. Existing methods of generating and providing feedback will be investigated in order to identify specific issues that need to be addressed. The architecture consists of models, algorithms and interfaces that can be implemented generically in any module.

The remainder of this paper is organised as follows. Section 2 contains a discussion on research related to progress feedback in an academic environment and issues that remain unsolved. This is followed by Section 3 wherein the criteria for evaluating the architecture proposed in this study, is discussed. Section 4 contains a description of the architecture design for personalised academic progress feedback. In Section 5, implementation of the architecture as part of a pilot study and evaluation according to the criteria established in Section 3, is discussed. The paper concludes in Section 6 with a summary and recount of the objectives reached in this study.

2. Related work

Due to the observed increase in student enrolment numbers in both online and on-campus settings, data processing and related progress feedback processes need to adapt so as to preserve the quality of teaching-learning. Implementation and evaluation of feedback in the educational environment is a widely researched topic (Martin-Chang, 2017; Nakata, 2015; Ryan & Henderson, 2017; Tempelaar, et al., 2015). Assessment feedback in particular is a popular subject especially in online learning environments (Evans, 2013; Webb & Moallem, 2016). Research on generic academic progress feedback methods that can be implemented in any required module however, is not readily available. Researchers agree that feedback in general needs to provide insight into how a student is doing, what the ultimate goal is, and steps to follow towards reaching the goal (Hattie & Timperley, 2007).

Towards finding techniques for student data processing into the required format for feedback, the feasibility of using mathematical modelling techniques as part of a learning analytics subsystem in a tertiary educational setting, was investigated (Van der Merwe, et al., 2017a). It was

found that the analytical processes required to generate feedback in the correct format can be performed by certain mathematical models. In terms of processing student progress feedback, a non-linear programming model was implemented to calculate what is referred to as a participation mark for each student. These marks represent the students' participation levels in the academic activities presented during a semester. Another method that was used to successfully perform academic peer ranking, was the dual formulation of a data envelopment analysis (DEA) model. This method allowed academic feedback to students in relation to their peers by using a class-ranking method (Kao & Lin, 2008), without the calculation of actual grades. The method also provided a means to calculate improvement targets for each individual student. The study addressed some needs relating to academic progress feedback but certain flaws were identified (Van der Merwe, et al., 2017a). Due to the non-linearity of the model utilised to generate the progress feedback, the solutions found were heuristic in nature and therefore did not guarantee optimality. Moreover, an exponential increase in the number of variables required for the dual formulation of the DEA was observed. Any change in student performance therefore meant a repeat of the solution process. The program selected to find solutions to mathematical models depended on the size of the problem. Large groups of students can therefore mean that a specialised software package is required to solve the model, which can have further financial implications. Another issue that was identified is the protection of student privacy which could not be guaranteed due to entire class lists being available to students.

The implementation of learning analytics principles in academic progress feedback presents the opportunity to address the problem relating to student privacy. According to Rubel and Jones (2016) the matters that need to be addressed to ensure that student privacy is properly protected include student access, data capturing, risk-benefit ratio of data processing and reporting, and student autonomy. Picciano (2014) asserts that precautions need to be taken when gathering, processing and reporting student data. To this end, student access to academic information needs to be regulated so that integrity is retained. Park and Jo (2015) found that students feel positively towards the use of dashboards which isolate their information. Such technology also encourages students to reflect on their own performance (Yousef, et al., 2015) which means that they are likely to respond to information such as improvement targets. Feedback presented in such a format can therefore have a positive influence on learning by encouraging students to modify their behaviour.

The problems that were identified in existing feedback systems include that they provide mostly content specific feedback during assessments, the processing methods are time-consuming and systems do not effectively protect students' privacy in terms of their grades. These issues were taken into consideration when developing the components of the architecture (Sections 3 and 4) and used as evaluation criteria to assess its success (Section 5).

3. Addressing the deficiencies in existing feedback methods

The criteria for successful feedback demand that the information be provided timely and consistently, be goal-specific, generically, personally and actionable (Hattie & Timperley, 2007). Existing feedback techniques partially cater for these measures but were found lacking in terms of time-optimised methods implemented to process student data and not providing sufficient information to enable improvement and protection of student privacy. These issues were set as the main requirements for the architecture developed in this study.

In general, the phases that need to take place in order for feedback to have a positive influence on an activity are data generation and capturing, data processing and formatting, feedback and behaviour modification (Wiggins, 2012). The entities required to perform these phases include the students who generate the data, receive feedback, and make changes to their behaviour; the lecturer who facilitate feedback and interventions; and a system to process and structure the data into the format required for feedback to be effective. Regarding the design of the system, a subcomponent implementing learning analytics techniques is utilised to combine the data processing and formatting actions required as part of the feedback architecture. There are three main areas of research in learning analytics namely instrumentation development, analytical methods and the effects of interventions (Roll & Winne, 2015). More specifically, learning analytics among other actions, include the analysis and interpretation of data related to student behaviour and contexts (Koç, 2016). With the incorporation of learning analytics tools however, more ethical issues regarding student privacy need to be addressed (Rubel & Jones, 2016). Special consideration needs to be given to who may be granted access to which student information and whether the collection and processing of the data lead to enhancement of the learning process.

The actions that have to be performed by the system are a combination of specific interrelated methods. In previous research it was found that non-linear programming and data envelopment analysis techniques failed to provide precise answers within an acceptable amount of time (Van

der Merwe, et al., 2017a). The mathematical models were consequently reformulated and solved in a related study (Van der Merwe, et al., 2017b). A linear programming model was implemented to generate student progress feedback in the form of their latest assessment grades and an academic student ranking which students could use to compare their progress with their peers. The academic ranking is a list on which the students are ranked according to their overall academic standings. The use of this model decreased the data processing time considerably, making it feasible to implement for timely and consistent feedback. Furthermore, an algorithmic approach was developed for improvement target calculation, which takes as input the solution of the linear model as well as a semester plan provided by the lecturer. A semester plan is unique to a specific module and typically consists of a time-dependent layout of the planned contact sessions and assessments for the remainder of a semester. The program automatically created a dynamic decision tree structure according to which all the possible scenarios for student participation in the sessions available for the remainder of the semester, were calculated. A user (student/lecturer) could nominate to what extent grade improvement is required and the system would use the student's current calculated academic standing and the developed decision tree to provide a proposal as to which future assessment participation should take place. The algorithm therefore provided personalised improvement targets per student as well as specific grades that students must achieve to guarantee improvement.

The discussed approaches will provide the information necessary to be classified as feedback and can be implemented in the system. However, each student's individual progress information needs to be available to that student alone as opposed to the entire class, as well as to the lecturer. Learning management systems (LMSs) are progressively being used for the implementation of specific learning analytical operations and serve as communication medium between students and lecturers (Ülker & Yilmaz, 2016). Such systems typically allow the users (students and lecturers) access to module content only if they are registered participants of that specific course. Appropriate regulation of access to personalised student data processed by the system, can be achieved by combining a LMS with an additional user authentication process.

In summary, there are three main components that must play a dynamic role in an architecture for personalised academic progress feedback that can be implemented generically (i.e. in any module). They are the students who are enrolled in the specific module, the system and the lecturer. Furthermore, the system should conform to the following requirements:

The methods used to perform the data analysis and feedback formatting processes must be time-optimised regardless of the number of enrolled students, so that reporting of academic progress can take place consistently;

Feedback must provide academic progress, personalised improvement targets related to each individual student's current progress and specific information on how to reach said targets; and

Student privacy must be protected by allowing each student sole access to their own personalised progress and improvement profile.

The architecture development according to the requirements stipulated above, is discussed in the next section.

4. Personalised academic feedback architecture design

Personalised academic feedback can be successfully achieved through implementation of the architecture shown graphically in Figure 1. The picture shows the three main components (student, system and lecturer) and how they relate to one another in the academic environment.

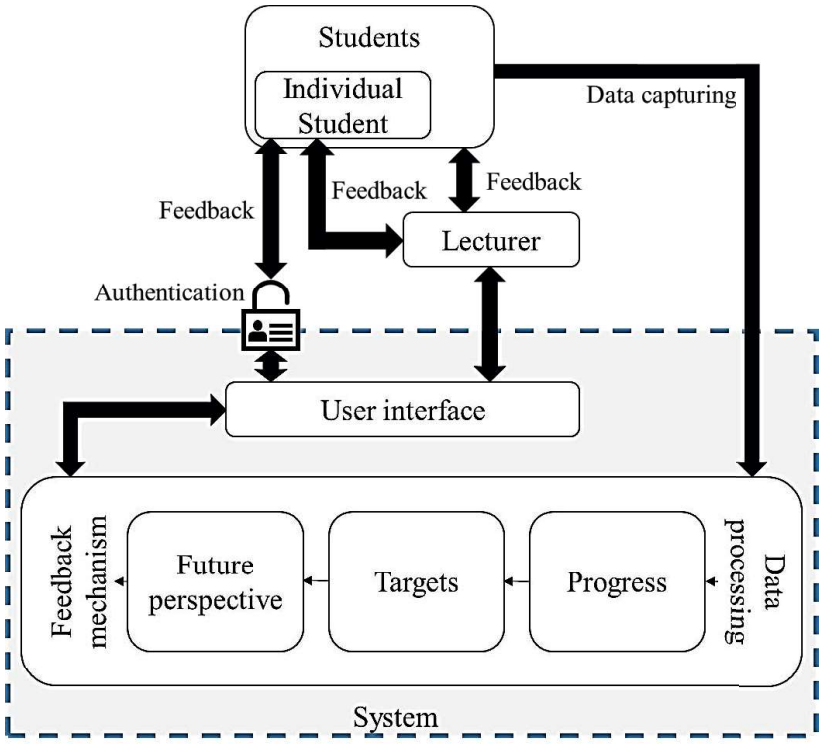

Figure 1: Architecture towards personalised academic feedback

The data generated by each student is captured in a traditional way through the completion of an assessment and the consequent grading. Student grades are imported into the system electronically and formatted using spreadsheet functions, into the correct format for processing. The methods discussed in the previous section are then implemented to process the raw data and prepare them for feedback. A user authentication system is incorporated into the system in the form of a graphical user interface, for use by individual students. This allows for each individual student to sign into the system and gain access to a personalised academic progress report and an academic ranking position without viewing or compromising the information of the rest of the class. The use of an authentication process effectively protects the privacy of each individual student. A lecturer is exempt from using the authentication process and have access to the progress profiles of the entire class. This enables a lecturer to determine which sections of the module content have not properly been mastered by reviewing the levels of student performance in specific topics.

The proposed architecture is independent of module content and can therefore be implemented generically to be used for any module in the academic environment. The

methods discussed in Section 3 are used by the system for processing and formatting into the correct feedback format. The techniques require no manual data processing and formatting to be performed by the lecturer, as this is done by means of a computerised system. Data processing and formatting is therefore optimised in terms of time. Feedback is formatted into the three required forms of information: it provides each student's current academic progress, it supplies interim targets to improve by a predetermined percentage, and it offers specific milestones to reach towards achieving those targets.

After a student logs into the system, the current academic progress is shown as in Figure 2.

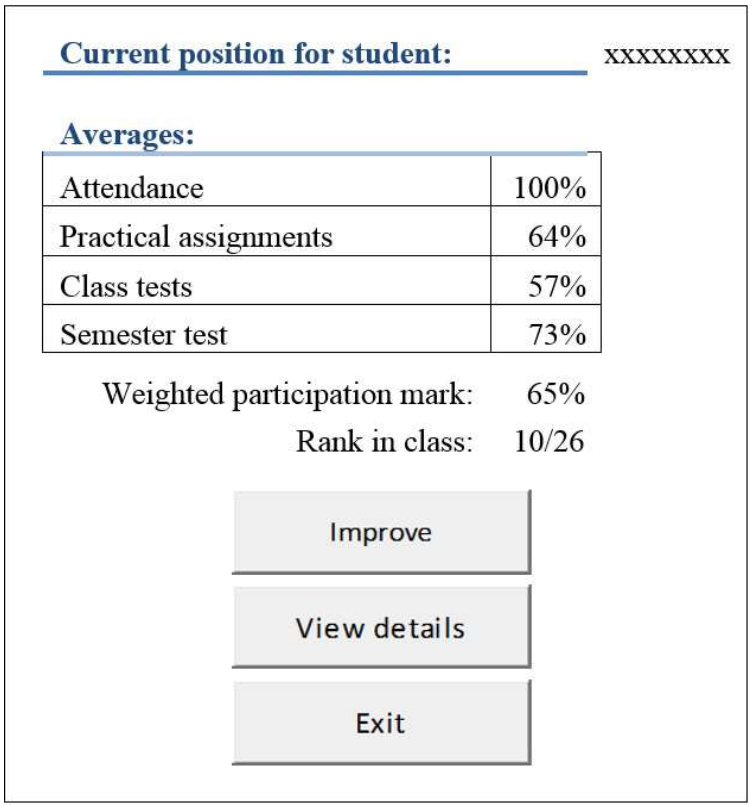

Figure 2: Academic progress page of a student

The current averages for each of the categories that the lecturer of the specific module grades (in this particular case attendance, practical assignments, class tests and a semester test), are shown. This is followed by the student's current overall average (participation)

mark of 65% and ranking position of 10 relative to the rest of the class. The average mark is calculated as the weighted sum of the average grades for the four named categories (1%, 33%, 33% and 33% respectively). The weights are selected by means of an algorithm that is discussed in detail in Van der Merwe et al. (2017b). The interface also provides the student with the option to view possible improvement targets and to view further details. By selecting the 'View details' option, the student will be provided with a more detailed layout of the grades of the individual assessments that have been completed towards obtaining the current progress profile (Figure 3).

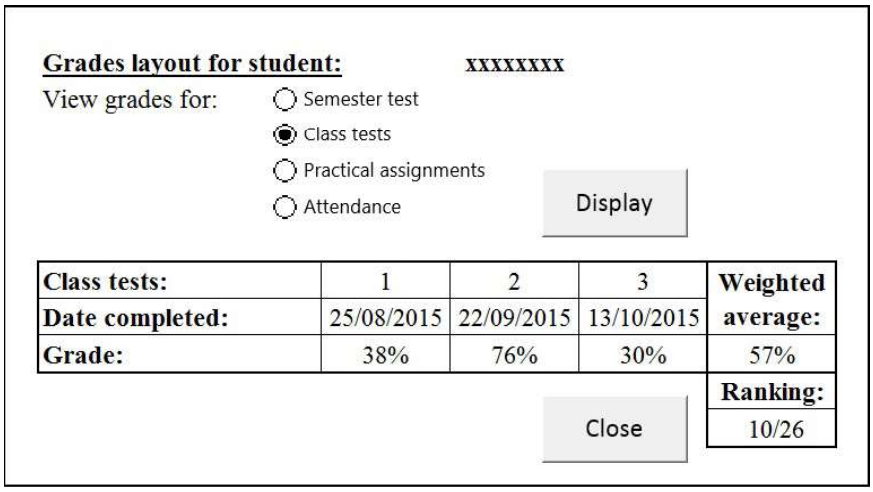

Figure 3: A typical detailed layout of the class test grades for a student

The information is provided per category, in spreadsheet format. If the student was to select the 'Improve' option (in Figure 2), the following plan will be displayed.

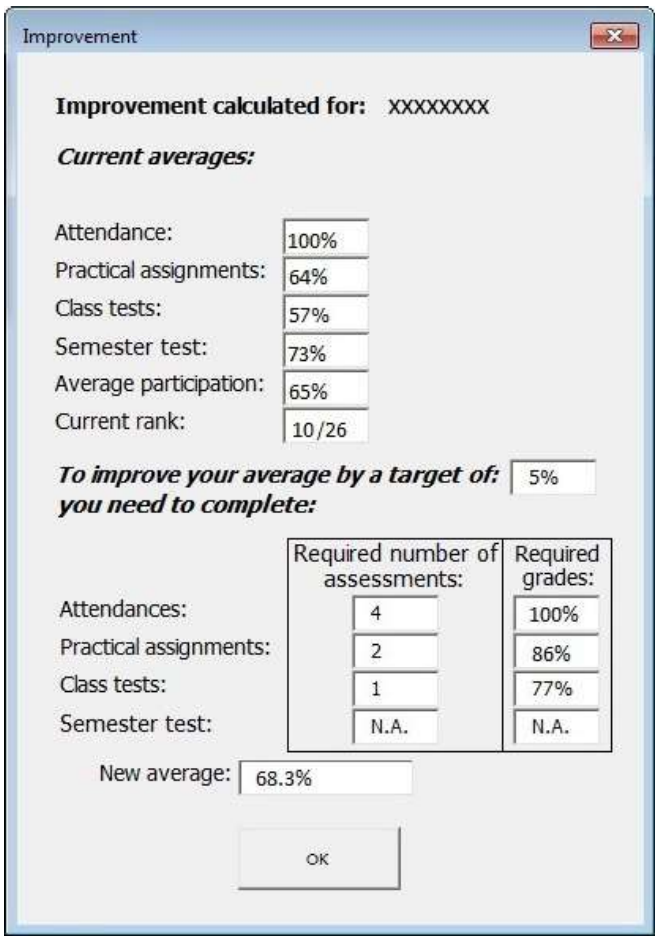

Figure 4: Improvement targets calculated for an individual student

The lecturer provided a semester plan at the onset of the semester which consisted of the planned number and types of assessments (attendance, practical assignments, class tests, and the semester test) for a specific module. The system used the semester plan to determine the remaining number of assessments in each category. Figure 4 shows a typical improvement plan for an individual student consisting of the current progress profile, followed by a targeted maximum improvement of 5% in the overall average, the number of assessments the student is required to complete in each of the relevant categories, the grades that the student is required to obtain in those assessments and the expected increase in the overall average as long as that all the named conditions were met. In this example, only one semester test was required for the module and at the time of producing the report, it has already been completed. The resulting improvement plan was therefore determined for the remaining three categories. Figure 4 shows that if the student completed four more

attendances with scores of 100% in each, two more practical assignments with an average score of 86% and one more class test with a score of 77%, then the new overall average will improve to 68.3% provided that the weights assigned to the categories remain unchanged (i.e. 1% for attendance, 33% for practical assignments, 33% for class tests and 33% for the semester test).

5. Evaluation of the architecture

The architecture presented in this paper was implemented in a pilot study, in three different modules at a tertiary institution. The system included a preliminary version of the user interface as shown in Figures 2 through 4. After assessment grading, the student scores were imported into the system and processed for feedback. The lecturers of the modules were given unrestricted access to the feedback which allowed them to act on information about at-risk students. The lecturers of the modules had access to the progress profiles of the entire group of enrolled students. They agreed that it provided valuable insight which aided them in early detection of students who were at-risk of dropping out. This enabled them to implement the measures considered necessary to assist such students. Additionally, they could also identify when specific module content has not been mastered satisfactorily.

The students actively used the feedback function of the architecture with 97% out of the 99 respondents indicating that they preferred to be informed of their progress at all times. A total of 90% of the students also indicated that they wanted the system to be implemented in all of their modules. Moreover, 85% of the students said that the feedback made them feel in control of their own progress (Figure 5).

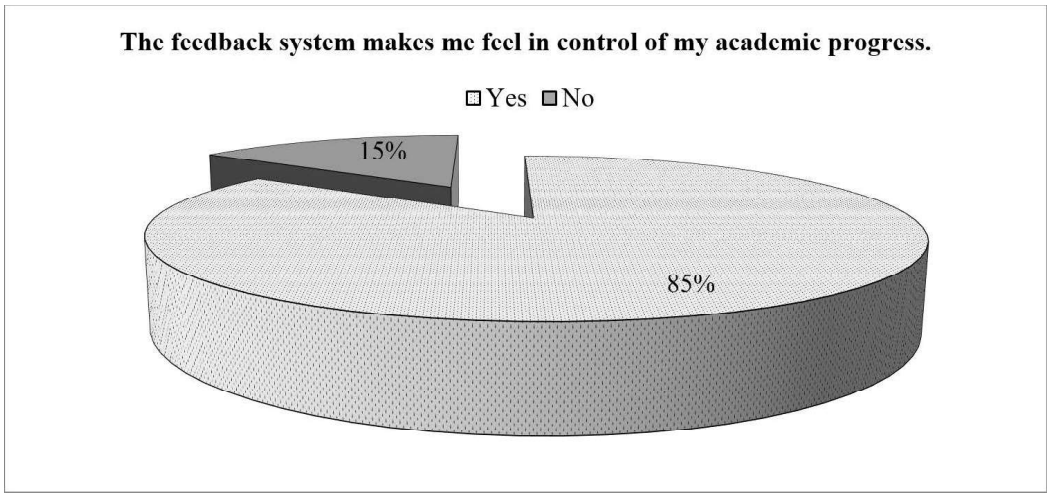

Figure 5: Student responses regarding control over their progress

Students furthermore showed a very positive attitude towards being able to monitor their progress (Figure 6). It is concluded that with the passing of time and the consequent decrease in the number of assessments remaining, some students believed that they had less control over what influence they could still have on their progress.

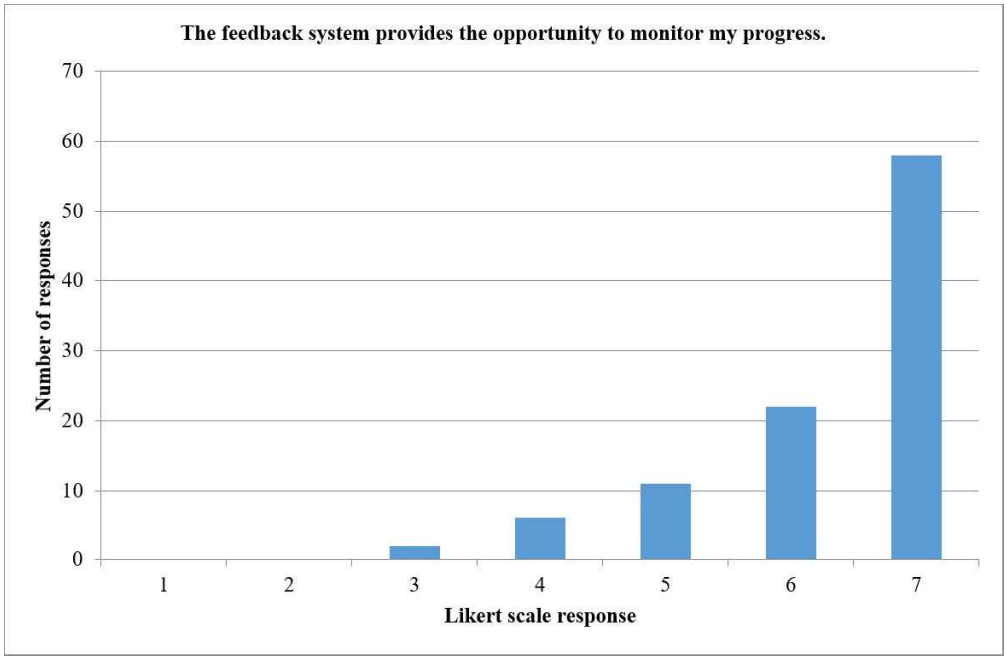

Figure 6: Student responses on monitoring their academic progress

Out of a total of 99 respondents, some 80 students regarded the feedback frequency (i.e. at every contact session) as acceptable and 85 indicated that they were satisfied overall with the system. Furthermore, only eight students thought that it was not important to know their academic progress throughout the semester.

The feedback provided to students adhered to the requirements for effective feedback as stipulated by Hattie and Timperley (2007) as outlined in Section 3. The additional criteria set in Section 4 were met as follows. The mathematical and algorithmic methods used for data processing and subsequent formatting into feedback are optimised in terms of time and feedback can therefore be provided consistently throughout a semester. The feedback given to students provide academic progress, personalised improvement targets related to each individual student's current progress and specific information of how to reach those calculated targets. Student privacy is protected through the use of the authentication system which provides each student with a personalised progress and improvement report.

6. Conclusions

The observed increase in student enrolment numbers in tertiary education environments due to various reasons has not resulted in increased student retention rates. Among several reasons for this phenomenon are that students do not seem to be prepared for the workload nor the pace at which learning needs to take place at tertiary level. Accordingly, lecturers are expected to continue performing the teaching tasks that are expected from them as well as additional administrative tasks towards enhancing learning. In this study, an architecture for personalised academic feedback was presented. The purpose of the architecture is to assist lecturers in the generation and provision of effective feedback that will inform students on their academic progress thereby affording better control over their studies.

A literature study was performed to establish the properties required for feedback to be effective. Requirements that needed to be addressed included incorporation of time-optimised methods that perform the data analysis and feedback formatting and that feedback must provide academic

progress, personalised improvement targets related to each individual student's current progress and specific information on how to reach said targets. Another issue that needed to be addressed and that was added as an evaluation criterion for the architecture proposed, includes the protection of student privacy. The proposed architecture supplied feedback that conforms to the requirements to be effective and the system successfully addresses the discussed evaluation criteria. The architecture was presented graphically, after which it was implemented in three modules presented at tertiary level. It successfully protected student privacy and provided feedback that was timely, consistent, goal-specific, generic, personal and actionable. The students' positive reaction suggests that the architecture promoted academic improvement, which may result in improved student retention.

Students generally use learning management systems to gain access to academic material and module specific information while lecturers obtain valuable information gained from utilising learning analytics. Further development of the system is planned regarding improved student access by incorporating the system into a learning management system and allowing students to view their academic progress and improvement plans online.

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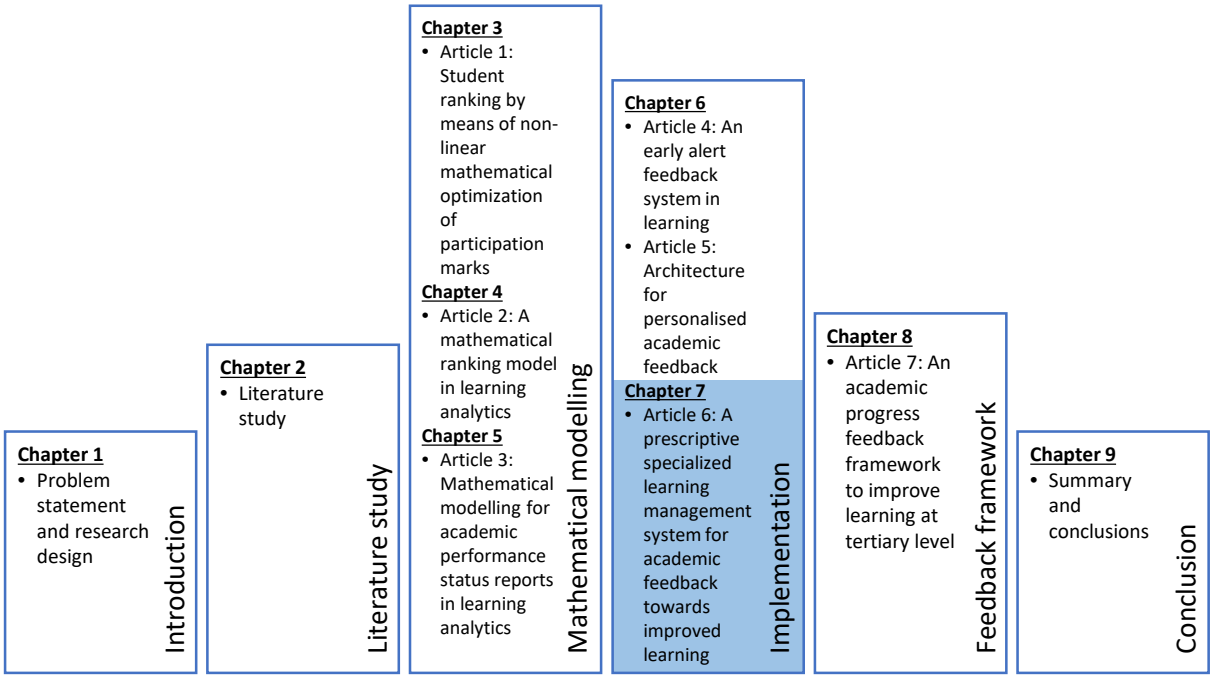
Chapter 7

Article 6: A prescriptive specialized learning management system for academic feedback towards improved learning



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Appendix B: Algorithm for determining improvement plan (Van der Merwe *et al.*, 2018b) 142

7.1. Preamble to Article 6

The paper comprising this chapter was published in the peer reviewed *Journal of Computer Science*. The title of the article is *A prescriptive specialized learning management system for academic feedback towards improved learning*. It was submitted in July 2018, accepted for publication in September 2018 after three review rounds and published in October 2018.

The implementation section of this thesis concludes in Chapter 7. In the preceding chapter, the three main elements required for effective implementation of the mathematical ranking models were identified and incorporated into a stand-alone program. The article presented in this chapter, describes how these elements (student, lecturer and system) are applied in a specialised learning management system (SLMS). Supplementary to the existing methods of providing academic feedback to students, the SLMS was used to deliver feed backwards, forward and upwards. The SLMS was evaluated for learning management system satisfaction and effectiveness as an action-support recommender system with very positive results.

The article presented in Chapter 7[1] was compiled according to the author/date system of references which was specified in the journal template. Supplementary information on the template, submission and review process are available in Appendix F.

[1] The article is presented in its final published form. Consequently, the page numbers of the article, as it appears in the proceedings, are displayed along with the principal thesis information.

Journal of Computer Science

Original Research Paper

A Prescriptive Specialized Learning Management System for Academic Feedback towards Improved Learning

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Abstract: The dynamic nature of technological advances is causing changes in many fields and especially in tertiary education. Student numbers are increasing annually and institutions need to maintain education quality whilst ensuring student retention. A specialized learning management system (SLMS) was developed in this study that provides students with comprehensive feedback which will enable them to better manage their academic performance. It will also assist institutions/lecturers in identifying at-risk students early in a semester to facilitate retention. The system uses a prescriptive analytics engine implemented by means of mathematical modelling techniques together with an algorithmic approach to process academic student data in real-time. Feedback is delivered timely and is comprehensive in the sense that it presents students with individualized instructions towards improvement in a module. The system was implemented in a field test and evaluated according to validation criteria established from a literature study on related research efforts. A survey was conducted to measure user response in terms of the identified factors. The results showed that the SLMS conforms to the attributes essential to an action-recommender system and was favorably accepted by the target users.

Keywords: Academic Feedback, Learning Analytics, Specialized Learning, Management System

Introduction

The success of education is determined by various factors with an institution, a faculty and students all playing contributing roles towards reaching this goal. The face of education is changing due to new teaching-learning techniques being implemented on a variety of different platforms. A troubling yet consistent pattern that has been observed in education, is the simultaneous decline of student motivation and engagement over the progression of a school year (Patall *et al.*, 2018). A similar pattern has been recognized in student participation in academic activities at tertiary institutions (Du Toit, 2015). An activity as simple as attending classes, for example, is a greater predictor of possible tertiary academic success than high school grades (Carroll and St. Peter, 2017). The benefits for students in attending classes are obvious but lecturers need to change the ways in which they teach and assess by incorporating new technological advances into their teaching methods so as to also motivate them to participate in academic activities (Massingham and Herrington, 2006). This plays an integral role in the employability development of students (Jepson and Ryan, 2018).

Academic motivation is an enactment of a person's will to attend classes, partake in discussions and endeavor to learn and achieve success in their studies (Beck, 2004). Studies show that the implementation of self-monitoring initiatives in mainstream classrooms result in increases in students' participation and subsequent academic achievement (Rock, 2005). Students who try to self-regulate their studies display responsibility in terms of controlling and performing actions relating to their studies (Garcia, 1996). Also, students that self-motivate exhibit a sense of self-management and achieve greater academic success (Di Domenico and Fournier, 2015).

Continuous new developments in computer technology has had an impact on education in the sense that activities are gradually becoming more dependent on the Internet (Fındık-Coşkunçay *et al.*, 2018). This has led to the emergence and growth of e-learning wherein course material and various other resources are made

Science Publications

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available to learners over the Internet. One of the most commonly used types is a Learning Management System (LMS) which is generally used to administer, document, track, report and deliver educational resources and assessment material. LMSs implement learning analytics tools that can be functional for creating student activity profiles from their digital footprints, thereby assisting lecturers and institutions with various administrative tasks. Many of these systems perform very specific tasks like talent management (Bersin, 2015) or Software-as-a-Service (SaaS) learning management (Lin, 2015). Such systems are referred to as specialized Learning Management Systems (SLMS) because they perform specific actions within an exact field and towards explicit goals. A LMS that simply provides statistics on student resource use, will not have such a motivating effect on students. An SLMS however, will not only inform students on their current academic performance but will also provide them with ways to improve towards the close of the semester (term). Such an SLMS will require specialized information like the number and formats of the assessments planned for a semester and utilize techniques, like mathematical modelling and learning analytics to continuously create improvement plans for individual students, based on their current performance. The resulting SLMS can be considered an action-support recommender system (Kaklauskas *et al.*, 2013) which will assist students in deciding what actions to take in order to improve their academic standings.

Learning analytics as a research field describes the measurement, collection, analysis and reporting of learner data and can be used to determine which students appear to be at risk of failing a course (Sclater *et al.*, 2016). Research of the incorporation of such analytical tools into an SLMS, the extent of usefulness towards the learning experience as well as the way in which the information is reported, remain a concern. There are specific issues that need to be addressed when academic feedback is presented to students and lecturers (Van der Merwe *et al.*, 2018a). Although feedback is essential to the improvement of learning, it needs to be provided in such a way that it is correctly interpreted by the users (Lee, 2018). This can be done effectively through development of an ideal SLMS interface to use for presentation of properly formatted feedback.

The main problem is that although technology advances have caused an increase in student enrolment numbers, the retention rates remain low. The research question of this study is therefore to determine if an SLMS that uses mathematical modelling and learning analytics techniques can improve learning and the subsequent student retention rates.

Research and development of a specialized product in education that has the purpose to improve learning, are typically done according to specific phases as described by Darmawan *et al.* (2018). The phases are discussed in concurrent sections in this study which commenced with problem identification in the introduction. This will be followed by a literature study on current work relating to the use of LMSs, learning analytics, feedback in the academic environment and software development in the next section. The development of the SLMS is discussed in the section titled "Method" in which evaluation criteria for system validation is also outlined. A field test in the form of a case study and deficiency corrections is then discussed in "Field testing". This is followed by a discussion on the research findings and the paper closes with concluding remarks.

Related Work

Due to the special nature of an SLMS, its evaluation criteria cannot be limited only to that of a LMS. Consideration needs to be given to the methods implemented to perform special functions as well as the output it provides. Therefore, the SLMS must be evaluated against the criteria for a LMS and specialized learning analytics that provide output towards action-support recommendations.

The frequency of use of a LMS by end-users gives an indication of how successful it has been implemented. To properly evaluate the user satisfaction level when using LMSs, Almarashdeh *et al.* (2018) investigated the factors that influence students' satisfaction with LMSs in tertiary education programs. These factors were taken into consideration in establishing evaluation measures for user satisfaction of the SLMS developed in this study. These measures are outlined in the next section.

Learning analytics is a concept that describes the collective processes applicable when working with large quantities of student data (Dietz-Uhler and Hurn, 2013). It is traditionally implemented as part of a LMS and used to provide information regarding individual students' use of specific resources supplied to them by a lecturer (Yulianto *et al.*, 2018). Researchers demonstrate differing perceptions on the use of learning analytics and its usefulness for improved learning (Ellis *et al.*, 2017). There is concern regarding the interpretability of learning analytics in terms of what it indicates about student activity as opposed to measuring the quality of learning that is actually taking place (Ellis *et al.*, 2017). Various investigations have been done to improve one or more of the phases (measuring, collecting, analyzing and reporting) of learning analytics for the purpose of improving the type of information available to both the lecturer and the student (Hernández-Lara *et al.*, 2018; Schumacher, 2017; Van der Merwe *et al.*, 2018b; Yulianto *et al.*, 2018). By combining learning analytics with data mining techniques, valuable information relating to students who appear at risk of failing the program, curriculum structures and prediction of

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academic performance, can be gained. Lecturers typically use learning analytics to identify students who do not actively access the resources given so that they can intervene at an early stage during the program and prevent students from falling behind. However, depending on the type of material shared on LMSs, such information does not necessarily present an accurate estimate of which students are at risk of failing.

Daniel (2015) argues that to effectively improve learning, specialized learning analytics in the form of prescriptive analytics is also required. This form of learning analytics enables a decision maker (the student) to gain perspective on specific actions that need to be performed in the near-future in order to improve learning. Data must be collected consistently throughout the learning process and implemented to create a structure which will enable a student to make informed choices on alternate actions of participating in academic events, based on valid predictions. Academic data can be analyzed in this way to create a personalized learning experience for each student (Daniel, 2015). Ellis *et al.* (2017) found that there were some concerns relating to data collection and interpretation as part of learning analytics and they worked to combine observational and self-report data towards finding a solution. Suthers and Vebert (2013) stated that learning analytics methods should be supplemented with techniques that provide more comprehensive information on the extent of student success.

Implementing learning analytics to keep students informed of their academic performance can improve student retention rates (De Freitas *et al.*, 2015). An academic status report can be compiled from the grades that a student achieved in all of the formative assessments completed, from the very start of a semester up to the present. Such assessments can include formal tests, informal tuition tests, practical assignments or even class attendance. For each of these groups, an average mark is typically calculated which contributes a certain percentage towards a participation mark. A participation mark represents a student's level of participation in academic activities throughout a semester and can be used to determine whether a student is allowed to take the final examination. Van der Merwe *et al.* (2018b) presented the use of mathematical modelling techniques to perform data analyses on student data in order to generate and produce academic status reports. A linear programming model was utilized to determine, for each individual student, the weight distribution for each of the assessment groups that would result in a minimum and maximum participation mark, provided that the weights remain within predetermined limits. For the formulation of the linear program, refer to Appendix A. An academic status report at a specific point in time during a semester typically consists of the group averages that a student has achieved up to that stage, the current minimum participation mark and ranking level that informs the student how he/she is progressing in relation to the rest of the class. Furthermore, an algorithm was developed to generate an individualized improvement plan for each student as well as targets towards the calculated improvement. The algorithm is available in Appendix B. The research embodies the combination of learning analytics with mathematical programming techniques as prescriptive analytics. The resulting academic performance profiles created for students, conformed to the three requirements for feedback to be effective which include feed-backwards (a current performance status report), feed-upwards (improvement goal) and feed-forward (activities to be performed towards reaching the improvement goal) as set by Hattie and Timperley (2007). Detailed discussions of the models can be found in Van der Merwe *et al.* (2018b). The feedback must be presented to either a student or lecturer user in such a way that the best choice of action(s) for improved learning can be made easily. Towards this end, Jameson *et al.* (2014) created a set of criteria for an action-support recommender system, which were considered to establish evaluation measures for the SLMS developed in this study.

The SLMS created in this study is a specialized LMS, uses learning analytics techniques and provides academic feedback in a user-friendly interface. This section presented a brief introduction on recent work in these research fields towards setting criteria for evaluating the SLMS. These criteria are stated in the next section, followed by a presentation of the developed system.

Method

This study was conducted according to the positivistic paradigm for Information Systems (Siponen and Tsohou, 2018). An action design research method was used to develop the SLMS which was implemented in a case study. Data was collected by means of a structured questionnaire in a convenience sampling procedure. Figure 1 presents the interconnection between the development and implementation elements.

The developed SLMS consists of components from varying research fields, requiring it to be evaluated in terms of a combination of criteria. In order to evaluate student satisfaction with the new SLMS, the following criteria were adopted form Almarashdeh *et al.* (2018):

- *Information Quality* (IQ) that refers to the output provided and can be measured in terms of accuracy and reliability

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- *System Quality* (SQ) can be measured in terms of availability and response time
- The *perceived Ease of Use* (EOU) refers to how user friendly the system is to the end-users
- *Perceived Usefulness* (PU) refers to the expectation of the users in terms of the effect it will have on their work performance
- The *User Satisfaction* (US) of the students can be measured according to their expectation of the system and the subsequent confirmation of the expectations
- The *Net Benefit* (NB) of a LMS is measured according to its efficiency and indicates the balance of the positive and negative effects on a user

During development of the SLMS, the following criteria needed to be considered in terms of an action-support recommender system (Jameson *et al.*, 2014):

- The information provided must be *relevant* (IR) to assist the user in making informed decisions
- The content must be displayed to the user so that it is effectively *interpreted*, *processed* and *acted* (IPA) upon
- Mechanical tasks like *computations* (MC) must be done by the system
- The system must correctly *advise* (UA) the user on the proper action(s) to take
- The *domain* must be *designed* (DD) in such a way that the user can make an informed decision
- The system must *evaluate* (DE) the different decisions that a user can make

The criteria were translated into a survey that users completed upon using the SLMS. The survey constructs and their relations to the criteria are shown in Table 1. Feedback was provided to students in spreadsheet format throughout the semester and the SLMS was only presented to students after finalization of the semester test. Therefore, system quality (SQ) in terms of availability and response time, was not evaluated by means of the survey.

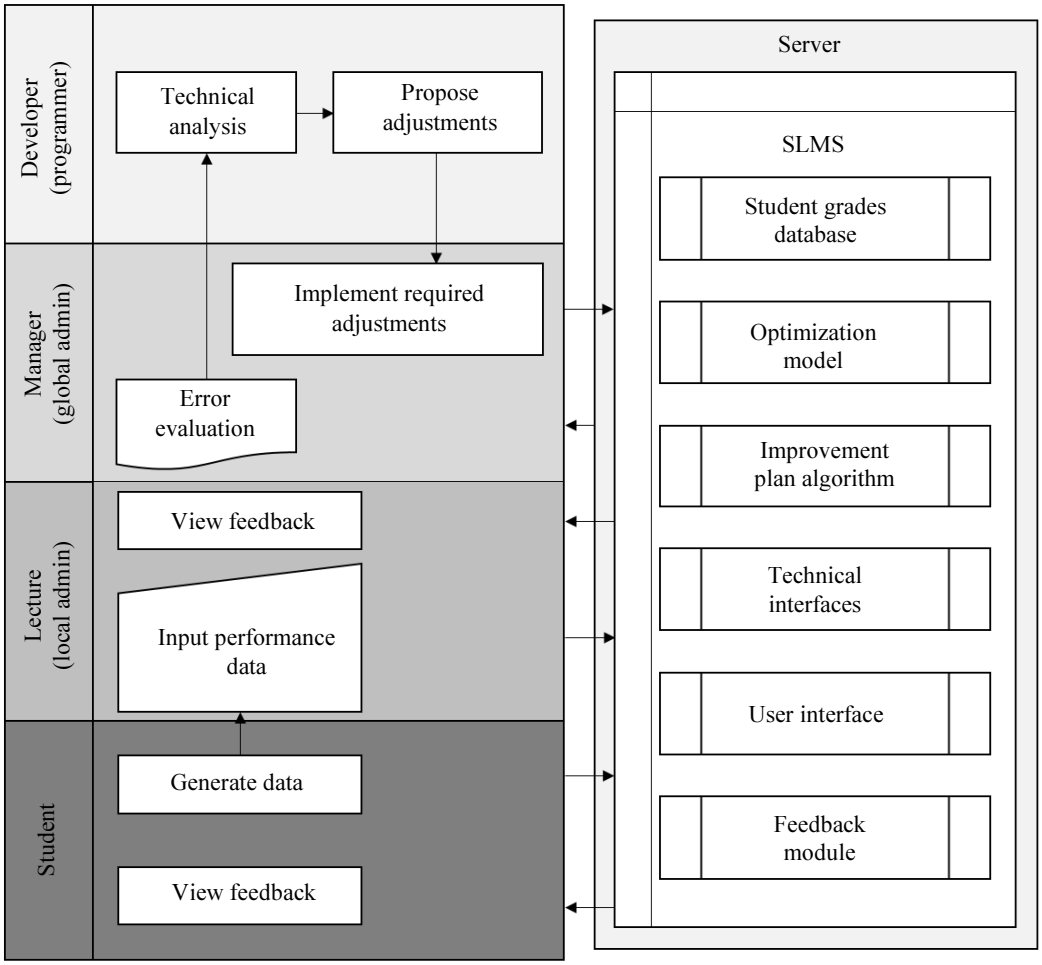

Fig. 1: Interaction between the relevant elements

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Table 1: User survey

Criteria	Constructs
NB, IQ	1. The feedback system keeps me informed on my current academic standing (current marks and level of participation) throughout the semester.
NB, UA	2. The feedback system provides me with effective improvement goals (how much I can still improve on my participation mark).
NB, UA, IQ	3. The feedback system effectively provides for specific targets (which assessments to complete and what marks to achieve in them) that will help me to make informed decisions on how and when to participate in academic activities throughout the semester.
PU, IR, US	4. The feedback system will help me to monitor my progress throughout the semester.
PU, IPA	5. The feedback system will motivate me to participate in upcoming academic activities.
PU, IPA, UA	6. The feedback system will provide me with essential tools to self-regulate my academic conduct participation in upcoming activities).
EOU, IPA	7. The feedback system is easy to use.
EOU, IPA	8. The feedback delivered is easy to understand and interpret.
IR, US	9. I will use the feedback system throughout a semester.
DD	10. I prefer to receive feedback in: a) Spreadsheet format as provided up to now; b) The new SLMS; or c) Both formats.

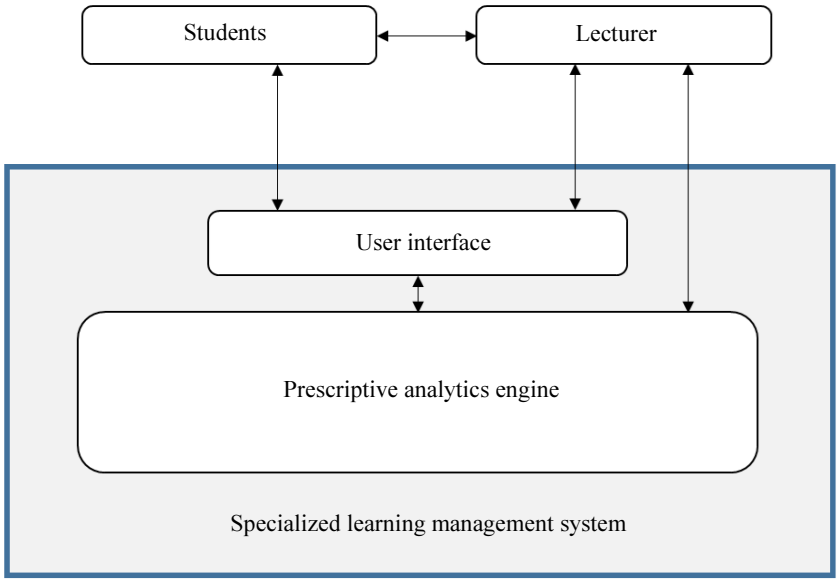

Fig. 2: Structure of the SLMS

The Mechanical tasks (MC) such as computations were done by implementing the prescriptive analytics engine as described by Van der Merwe *et al.* (2018b) and was subsequently not evaluated in the survey. Respondents were invited to indicate their level of agreement with statements 1-9 on a Likert scale ranging from one (totally disagree) to seven (totally agree). For evaluation of the Domain Design (DD), students were asked to select which feedback format between the normal spreadsheet format and the SLMS they preferred to use. Decision Evaluation (DE) is automatically performed when the SLMS is used because the minimum and maximum improvement options that can be implemented are both provided to a student so that an informed decision can be made.

As existing grading systems are commonly stored in spreadsheet format, the SLMS was developed with a user front-end application in MS-Excel. Figure 2 shows the main components of the SLMS and the interaction between them.

After processing the student data, the information that needs to be provided to the students as feedback has to be structured in such a manner that the students can understand its meaning and correctly interpret the actions that they are suggested to take. To this end, a graphical user interface was designed to import the processed data and provide it to the students in the correct format.

Normally, during the course of a semester, a lecturer requires the students to take different forms of assessments. The grades for these assessments are then used

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to create an academic performance profile for each student. It was found in a pilot-study that receiving feedback in spreadsheet format could easily result in misinterpretation of the information (Van der Merwe *et al.*, 2016). An example of such feedback, with additional explanations, is shown in Fig. 3.

The SLMS gives students access to their grades either in the typical spreadsheet format, or they can view an interpretation of their performance profiles as shown in Fig. 4.

To effectively advise a student on options towards academic improvement, the system uses an algorithmic approach discussed by Van der Merwe *et al.* (2018b) to determine viable possibilities. The algorithm considers a semester plan typically provided by a lecturer and creates a decision tree with all of the possible participation scenarios for a student. The decision tree and a student's existing performance status are then used to calculate the maximum and minimum possible improvement on an existing participation mark. Figure 5 shows an example of an improvement plan for a student in a module where there are: One class test, two practical assignments and four attendances remaining for a semester.

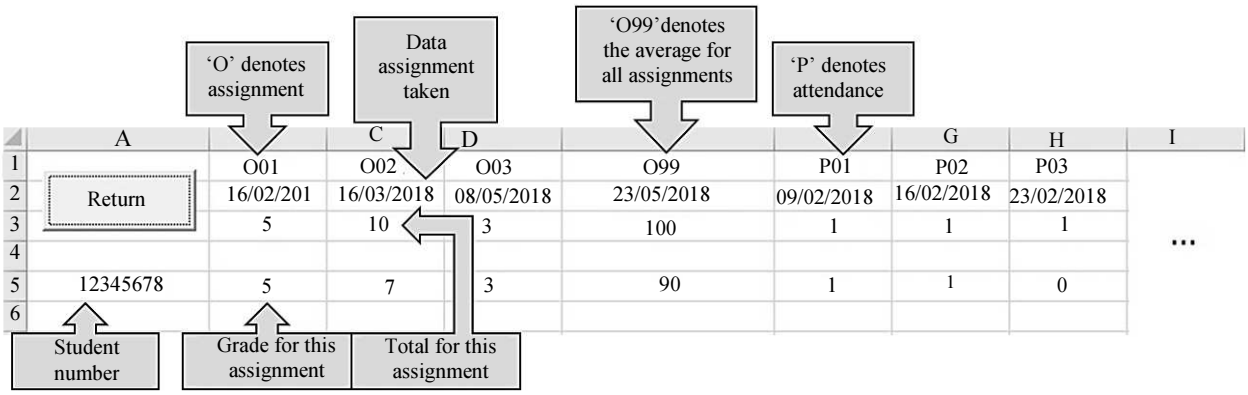

Fig. 3: Example of a student performance report in spreadsheet format

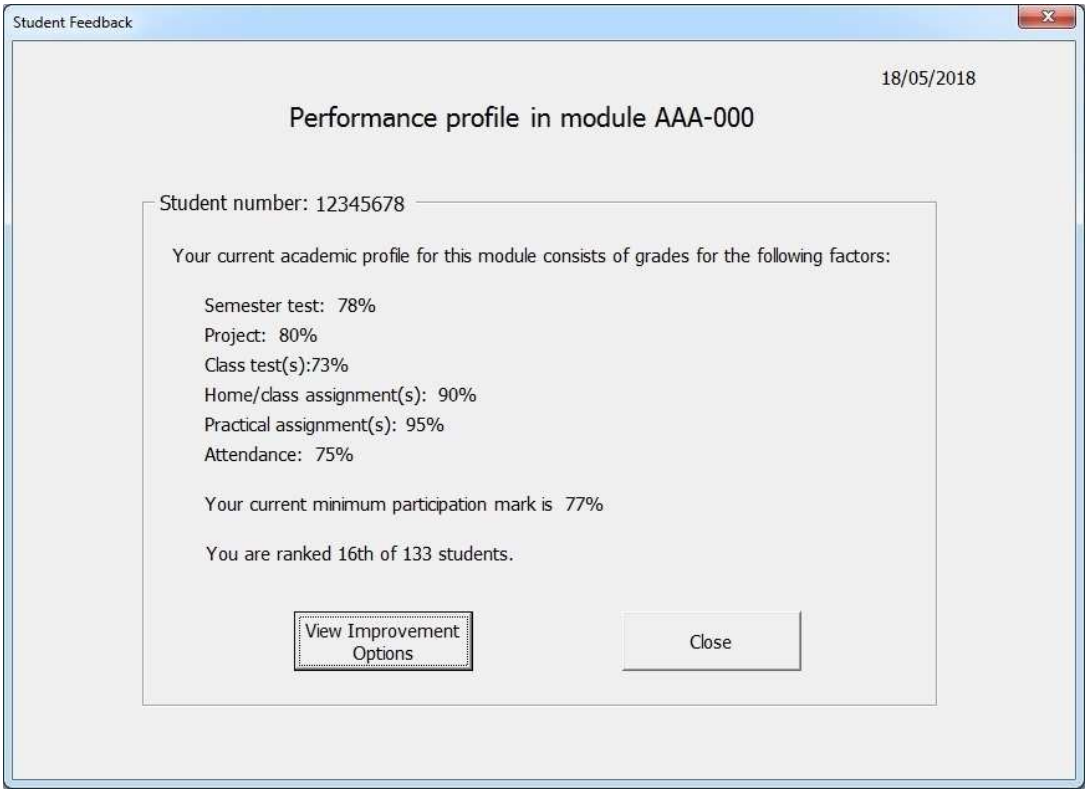

Fig. 4: Example academic performance profile

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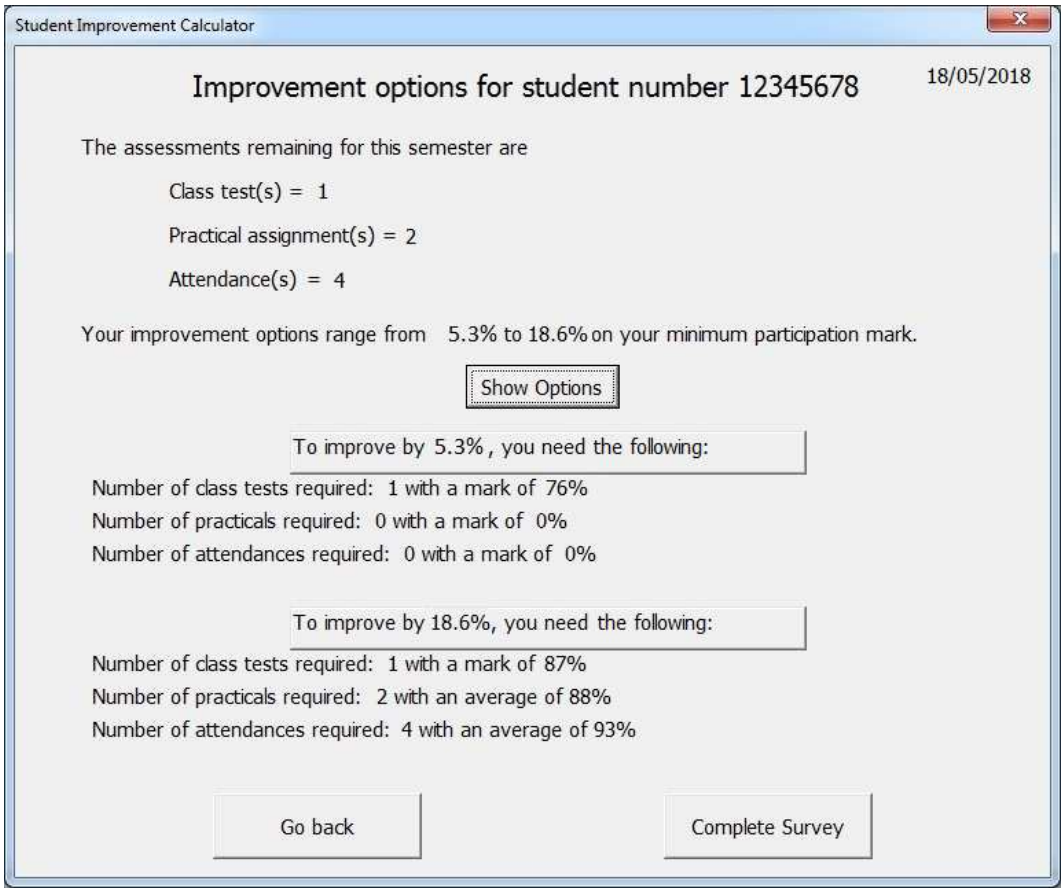

Fig. 5: Example improvement plan calculated in terms of assessments remaining for a semester

In the example scenario, the student's participation mark will improve only if the student achieves a grade of 76% in the next class test. The system shows the minimum and the maximum level of assessment participation and the required grade(s).

The student survey contains constructs created from literature and adapted for evaluation of an SLMS and was detailed in this section. The measurement instrument as well as the SLMS developed in this study was also presented. The field test environment and implementation along with the survey results are discussed in the next section.

Field Testing

The developed SLMS was presented to students enrolled in a third year module at an institution for tertiary education during a contact session and they were invited to partake in the field test by using the system and completing the created survey. They were provided with their grades and participation marks via spreadsheets throughout the semester and the SLMS was provided to them only after completion of the semester test. The semester test is a formative assessment typically taken in the middle of a semester and constitutes the largest sum towards the final participation mark. Students were asked to use the SLMS and compare it with the existing spreadsheet feedback process.

The students reacted favorably towards the SLMS, openly commenting that they found the system very helpful and informative as opposed to the normal spreadsheet feedback. There were 129 students enrolled in the module and a total of 97 (75%) survey responses were received upon completion of the field test.

The most promising result found after evaluating the responses was that 93% (students who responded with a six or seven on the Likert scale) indicated that they would use the SLMS throughout the semester if implemented early on. Figure 6 shows how satisfied students felt towards utilizing the SLMS across an entire semester. The results show that the students view the SLMS and its prescriptive capabilities to be useful. One of the students mentioned that having access to a layout of the remaining assessments for a semester as well as an individual improvement plan can assist students in balancing their academic workload better. A total of 86% of the students commented that the SLMS was easy to use with 82% indicating that it was easy to understand and interpret.

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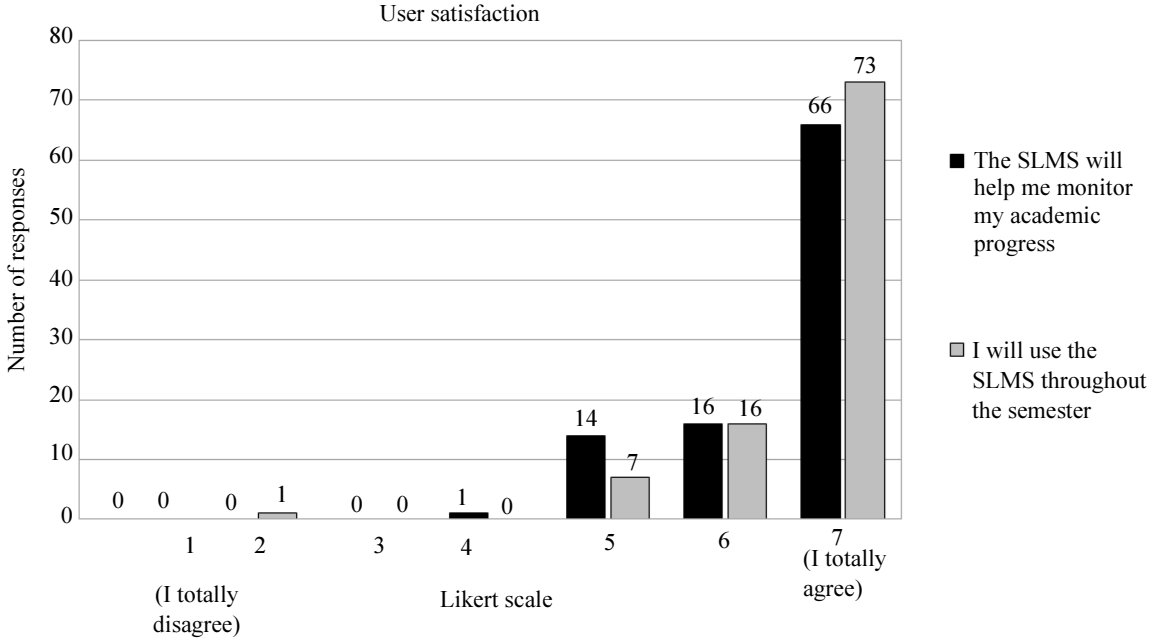

Fig. 6: User satisfaction with the SLMS

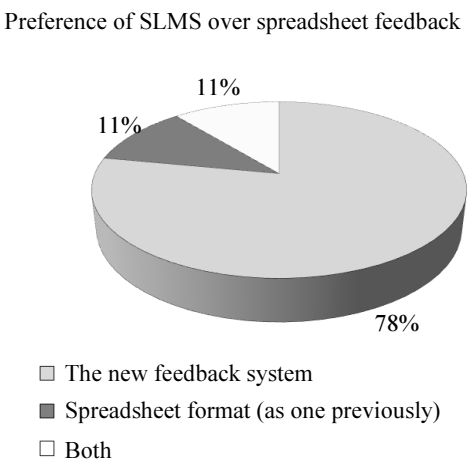

Fig. 7: Student preferences on feedback format

When the question was posed as to which feedback format the students preferred, 78% of the respondents indicated that they wanted to receive academic feedback by means of the SLMS. Moreover, 11% felt that they wanted to use the SLMS and still have access to the spreadsheet containing the complete set of grades and the remaining 11% preferred feedback in the normal spreadsheet format only. Dissemination of these results is illustrated in Fig. 7.

The response averages for the remaining factors are shown in Fig. 8. The figures show that the students consider the information provided to be relevant to the point that they will be effectively assisted to make informed decisions regarding their future participation in academic activities. It can also be deduced that they approve of the newly-developed user interface and feel that the feedback provided will be correctly interpreted.

Although obtaining high ratings in the survey, the Information Quality (IQ), Net Benefit (NB) and User Advisor (UA) factors scored slightly lower than the other factors. It is believed that this is due to the survey being conducted so close to the end of the semester which meant that students had little opportunity to implement the advice given to them by the system.

This section contained a discussion on the implementation of the developed SLMS in a tertiary education environment. This was followed by an outline of the results obtained in the accompanying user survey. The next section intends to discuss the research contributions that this study provides as well as special features unique to the SLMS.

Discussion

LMSs are widely used for, among others, administration, tracking and delivering educational resources, whereas SLMSs are created for very specific purposes presenting an ideal platform for supplying students with academic feedback. The following research contributions are presented by this study.

A unique feature that this study contributes towards is the time-dependent improvement plans provided to individual students.

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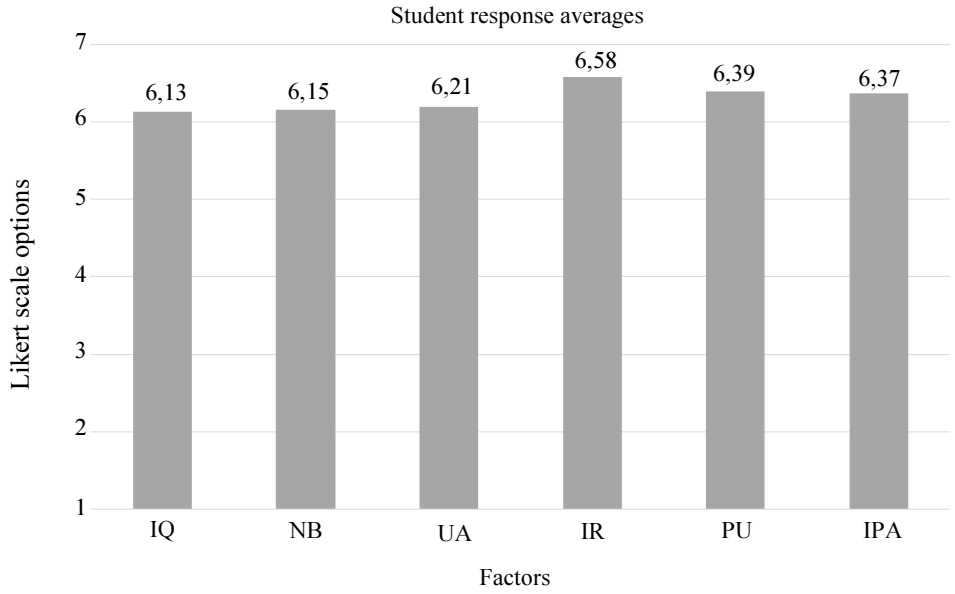

Fig. 8: Response averages for the remaining factors detailed in Table 1

During an investigation into existing academic feedback methods, little evidence was found of dynamic and individualized improvement plans being presented to students. The SLMS constructed in this study utilizes specialized analytical methods to address this problem. Furthermore, the system will improve student retention by assisting lecturers to identify at-risk students and address academic-related problems at an early stage in the semester.

The academic feedback provided is dynamic and presented in real-time. The prescriptive analytical engine incorporated in the SLMS implements a mathematical modelling technique and algorithm and can be used as frequently as needed to create updated academic performance profiles for each individual student. This also means that feedback is available to students at all times and they can access it as frequently as required.

The SLMS provides comprehensive academic feedback. Research has shown that students need additional information for them to cultivate a responsibility towards their academic conduct. This study addresses this issue by providing students with information related to their current academic performance level. The individualized improvement plans generated by the SLMS are unique in that they provide each student with an exclusive and time-dependent set of instructions on how to improve upon his/her current academic status by considering the remaining assessment opportunities for a specific module. The results have shown that students believe the developed SLMS will help them to better monitor their progress and regulate their studies.

The research further offers empirical confirmation that most students prefer to receive feedback via an SLMS that provides supplementary information on their academic performance than from normal spreadsheets. It further shows that most students readily accepted the structured manner in which the new system provided the feedback. The feedback gives students the opportunity to personally identify learning problems they may have which can help to build their self-confidence and improve their ability to regulate their own progress. The respondents further indicated that the SLMS was easy to use and that the resulting feedback was easily interpreted. This contrasts with the students' reactions towards the normal spreadsheet format in that they frequently returned to the lecturer with enquiries about result interpretations.

Providing an academic ranking can assist students in monitoring their performance in relation to their peers, without detailed knowledge of their grades. The student ranking can also assist a lecturer to identify which students need additional instruction and the individualized improvement plans will furthermore make it simple for a lecturer to guide a student towards learning success. A lecturer implementing an SLMS like the one developed in this study will further benefit from its use by having instant online access to the academic performance profiles of all the students enrolled in a particular course. The feedback can likewise be accessed by students online from any platform, providing potential for use in distance learning courses.

Although the SLMS was readily accepted by the responding students, some remaining challenges need to be further investigated:

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- The mathematical modelling techniques and algorithmic approach utilized to create the student performance profiles, were discussed in a related study (Van der Merwe *et al.*, 2018b) and are implemented here as black-box tools. This means that in general a lecturer has limited control over the implicit and explicit constructs inside the mathematical model and algorithm. Expanding the system to allow lecturers such access needs to be investigated
- Although the system is simple to use and to publish to students, combining these methods into a single system will facilitate central organization and processing of student data. Incorporation of the system into an existing LMS therefore remains a future challenge
- Although the number of students who prefer to receive feedback in the normal spreadsheet format was a minority, it means that some of the information they would like to see is not included in the new SLMS. As a detailed layout of their grades for individual assessments is available, it can only mean that they want to be able to compare grades obtained in individual assessments to those of their peers. This issue needs to be considered for possible future improvements on the SLMS

This section provided a brief discussion on research contributions made by the development and evaluation of the SLMS. It further stated some issues that can be addressed in future developments. The next section will close the paper by providing some concluding remarks.

Conclusion

It was stated earlier that combining different methodological approaches can increase the value of learning analytics towards the quality of learning. Academic feedback in a module presented at tertiary level is key to assisting students with regulating their studies, as well as lecturers with improving student retention rates. The main concern of this study was to develop, implement and evaluate a system that utilizes mathematical modelling and algorithmic techniques as prescriptive analytics to provide students with academic status reports, improvement plans and specific actions to take towards the recommended plans. The SLMS would provide not only timely academic performance feedback to students in a tertiary educational environment but also act as an action-recommender system by providing them with discrete advice as to which actions to take towards improved learning and performance.

This study was performed according to a research and development cycle published by Darmawan *et al.* (2018) and the developed SLMS was evaluated for user satisfaction and acceptance, as well as its effectiveness as an action-recommender system. The literature study investigated research, related to the use of an LMS and a recommender system and established criteria by which similar SLMSs could be evaluated. The SLMS was consequently implemented and evaluated for several criteria contributing to the level of LMS acceptance and action-recommender system effectiveness.

A field test was performed by implementing the SLMS in a tertiary module after which a survey was conducted to measure user response in terms of the identified factors. The results showed that the SLMS conforms to the attributes essential to an action-recommender system and was favorably accepted by the target users.

Although the developed SLMS currently acts as a stand-alone application for any tertiary module, it is being considered to incorporate the system into an existing LMS. Such a combined system will improve the general security of users, overall system integrity and enable access to the system on mobile devices. Future research and development on refining the system for mobile devices, is underway.

Author's Contributions

Annette van der Merwe: Design of the research plan, development of the SLMS, writing the manuscript.

Tiny du Toit: Supervisor of research, revising themanuscript.

Hennie Kruger: Supervisor of research, revising the manuscript.

Ethics

This article is original work and has not been submitted for publication elsewhere. Respondents participated voluntarily with the knowledge that they were contributing to a research paper. The study has been approved by the scientific committee at a tertiary education institution. The authors have read and approved the manuscript.

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Appendix A: Linear Programming Model (Van der Merwe *et al.*, 2018b)

The average participation mark for each student is calculated from the maximum and minimum determined by solving this linear programming model:

$$Maximise\ /\ minimise\ \ p_\alpha = \sum_{j=1}^{n} y_{\alpha j} w_j, \tag{1}$$

$$subject\ \ to\ \mid \sum_{j=1}^{n} w_j = 1, \tag{2}$$

$$l \le w_j \le u, \qquad j = 1,\ldots,n, \tag{3}$$

$$w_j \ge w_{j-1}, \qquad j = 2,\ldots,n, \tag{4}$$

$$l, u \ge 0, \tag{5}$$

$$w_j \ge \varepsilon, \qquad j = 1,\ldots,n, \tag{6}$$

where, w_j is the weight assigned to factor j, $y_{\alpha j}$ is the calculated average for factor j of student α and n is the number of factors.

Appendix B: Algorithm for Determining Improvement Plan (Van der Merwe *et al.*, 2018b)

The algorithm shown uses the current factor (different types of assessments) averages for a student at a specific time in the semester, a detailed layout of the remaining assessments and the percentage improvement δ required. Using truth table layout principles, a set of possible participation scenarios for the remainder of the semester is created. For s assessment opportunities, this will result in 2^s scenarios. The assessment plan is then used to eliminate participation scenarios that are impossible within the time constraints stipulated.

Input:	$\bar{y} = \{y_1, \ldots, y_n\}$ is an array representing the current factor averages for a student in n factors, $A = \{\bar{a}_1, \ldots, \bar{a}_s\}$ an array denoting the remaining s assessment sessions and δ the required percentage factor improvement.
Output:	An array $\bar{x}_r$ with r possible improvement scenarios.

```
1   declare q(2^s, n);                    'to store all scenarios for s sessions
2   for c = 1 to 2^s do
3       | populate q with participation scenario c;
4   end for
5   remove duplicate rows in q;
6   r ← number_of_rows(q);
7   declare marks(r, n);                  'scores required for a required improvement of δ
8   declare min_f_assessments(n);         'minimum assessments per factor to cause a required improvement of δ
9   for j = 1 to n do
10      determine e_j from ā_j;           'remaining number of assessments in factor j
11      determine t_j from ā_j ;          'total number of assessments in factor j
12      for u = 1 to e_j do
13          read y_u from ȳ;
14          calculate newValue according to equation (7) with y_u, δ and η_u = u;
15          if q(j, u) is possible then
16              | marks(j, u) = newValue;
17              | set min_f_assessments(j);
18          else
19              | marks(j, u) = "not possible";
20          end if
21      end for
22  end for
23  declare x(r, n + 1);                  'for r scenarios, x has a required score per factor and minimum change in p-mark
24  row ← 1;
25  while row ≤ r do
26      for element = 1 to n do
27          if q(row, element) ≤ min_f_assessments(element) then
28              | populate x(row, element) using marks(row, element);
            end if
29      end for
30      row ← row + 1;
31  end while
32  output x̄_r;
```

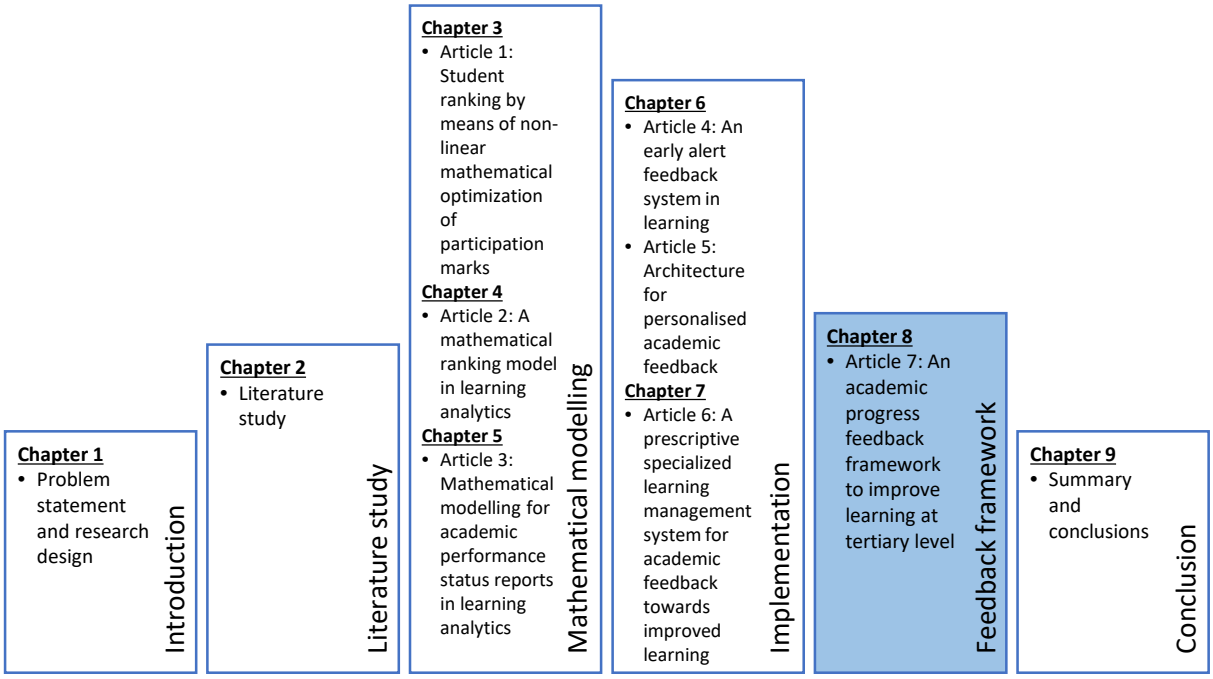
The scores required in upcoming assessments to produce the desired improvement in line 14 is calculated according to:

$$marks_j = \frac{\delta t_j + e_j y_{\alpha j}}{\eta_j}, \tag{7}$$

where, $marks_j$ represents the grade a student should achieve in the next η_j assessments of factor j, t_j is the total number of assessments in the term for factor j, e_j is the remaining number of assessments for factor j and $y_{\alpha j}$ is the current factor average in factor j for student α.

Chapter 8

Article 7: An academic progress feedback framework to improve learning at tertiary level



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Article 7:

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8.1. Preamble to Article 7

The article presented in Chapter 8 is titled *An academic progress feedback framework to improve learning at tertiary level*. This paper was submitted to the journal *Africa Education Review* in September 2018 and was still under review at the time of submission of this thesis. Consequently the article is presented here in the form of the submitted proof.

Article 7 is the sole paper presented in the feedback framework section of this thesis. This chapter serves as the culmination of this research in the form of an academic performance feedback framework for improved learning. An outline on the issues relating to student retention at South African universities, serves as the introduction to this article. In an effort to improve the quality of learning by instilling self-motivational and monitoring mind-sets among students, a model-based academic performance feedback framework was developed. The paper describes the typical feedback scenario in the tertiary education environment so as to identify the elements necessary for the framework. Through careful consideration of the requirements for effective feedback, the research performed in the preceding chapters and the identified elements, the models and concepts necessary for the framework were established. The framework was developed according to a combination of methods described in literature and implemented at a tertiary institution in South Africa. It was then evaluated for effectiveness of feedback and protection of student privacy. Insight into the evolving nature of academic performance feedback was also inferred and reported.

Article 7[1] was created according to the Chicago Manual (Author-Date) style, as stipulated by the journal. Further information on submission, the peer review process, and the author guidelines of the journal are provided in Appendix G.

[1] The article that follows is presented in its final submitted form.

Africa Education Review

An academic progress feedback framework to improve learning at tertiary level

Journal:	*Africa Education Review*
Manuscript ID	Draft
Manuscript Type:	Original Article
Keywords:	Academic progress, decision support system, feedback framework, learning analytics, tertiary education
Abstract:	The dawn of democracy in South Africa in 1994 has resulted in challenges in many fields, especially in education. University enrolment rates are high and the output quality of school learners in general is delicate which threatens the graduate quality of tertiary institutions. Contrary to rising student enrolments, the attrition rates have not improved. One contributing factor is the lack of comprehensive insight into students' academic performance throughout the course of a program. New systems are being developed and implemented in both online and on-campus programs and can be utilised to improve student performance feedback. In this study, academic feedback in tertiary education is studied and a model-based academic progress feedback framework is proposed to improve learning. The framework was implemented in a case study at a South African university and evaluated using a survey. The framework was readily accepted by the end-users and conformed to the features and requirements identified in literature.

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An academic progress feedback framework to improve learning at tertiary level

Abstract

The dawn of democracy in South Africa in 1994 has resulted in challenges in many fields, especially in education. University enrolment rates are high and the output quality of school learners in general is delicate which threatens the graduate quality of tertiary institutions. Contrary to rising student enrolments, the attrition rates have not improved. One contributing factor is the lack of comprehensive insight into students' academic performance throughout the course of a program. New systems are being developed and implemented in both online and on-campus programs and can be utilised to improve student performance feedback. In this study, academic feedback in tertiary education is studied and a model-based academic progress feedback framework is proposed to improve learning. The framework was implemented in a case study at a South African university and evaluated using a survey. The framework was readily accepted by the end-users and conformed to the features and requirements identified in literature.

Keywords

Academic progress; decision support system; feedback framework; learning analytics.

1. Introduction

Since the first democratic election in South Africa in 1994, changes have occurred in many research fields, especially in education (Suransky and Van der Merwe 2016). Research on education in South Africa remains topical and range from studies in ethnicity (Jawitz 2012), gender factors (White et al. 2011) and free education (Nordstrum 2012), among others. The increase in university enrolment rates as opposed to the generally weak output quality of Grade 12 learners, which in turn lowers the standard of graduates delivered by tertiary institutions, is and remains a challenge (Modisaotsile 2012; Shay 2017).

Successful learning depends on efficient teaching, technological advances, student participation, and other factors. The main role players in a tertiary teaching-learning environment are the lecturers and the students. The purpose of both is to accomplish successful learning and help improve student achievement. One of the most important factors to stimulate effective learning, is feedback (Hattie 2009).

Feedback in learning comprises information that a lecturer or teacher provides a learner with, relating to accomplishment or content understanding (Hattie and Timperley 2007). Although academic performance feedback and its effect on learning have been extensively researched in recent years (Belcadhi 2016; Semley et al. 2016; Stegemann and Malan 2016), students' learning methods have started to change. Related activities like learning analytics and performance feedback to adapt correspondingly.

Learning analytics entails collection and analysis of teaching and learning data, purposing to deliver positive and negative feedback to students and lecturers (Fiaidhi 2014). Decision support systems (DSSs) are commonly used to aid in decision-making, especially in rapidly changing environments and present the ideal tools with which some learning analytics functions can be implemented (Fadiya 2017).

The inspiration for this study was founded in the observation that the quality of student learning on tertiary level in South Africa is weakening, although the resulting enrolment numbers are escalating annually. The main aim of this study is to propose and implement a model-based academic progress feedback framework in an effort to improve learning on tertiary level.

A literature study on educational feedback, learning analytics and using a DSS for learning analytics functions, follows in Section 2. The research method is outlined briefly in Section 3. Section 4 contains a description of the feedback scenario and evaluation measures according to which the proposed framework will be assessed. The new feedback framework is presented in Section 5. Validation and formal evaluation of the proposed framework follows in Section 6, research contributions in Section 7 and concluding remarks in Section 8.

2. Literature review

Numerous research projects have been completed on what feedback entails and what issues it should address to be effective (Hattie and Timperley 2007; Wiggins 2012). The Oxford dictionary defines feedback as "information about reactions to a product, a person's performance of a task, etc. which is used as a basis for improvement" (English Oxford Living Dictionaries n.d.). Wiggins (2012, 11) defines feedback as "information about how we are doing in our efforts to reach a goal." The specific purpose of feedback is clearly stipulated as something to be used for improvement towards reaching some objective.

In the educational environment, assessment feedback is a widely researched field (Belcadhi 2016; Evans 2013; Krause et al. 2009; Miller 2009). The term broadly encompasses assessment design in a learning environment so that feedback relating to the posed questions is created at some stage during assessment (Evans 2013). Some believe that feedback is more valuable to

individuals than to groups (Krause et al. 2009). The effect of feedback is determined by its design and by the way in which it is received and acted upon. Miller (2009) introduced a formative computer-based assessment framework aimed at improving self-regulated learning and used feedback as an instrument to support student learning. Although the utilitarian value of assessment feedback was investigated, one of the findings was that the students thought feedback should occur soon after an activity rather than being delayed. The collation of feedback should therefore be done in as short a time as possible to benefit students.

Whatever the objectives are when studying feedback, researchers agree that it is an important factor in improving learning. Wiggins (2012) argues that endless feedback is more important to learners than endless teaching. Academic progress feedback is not necessarily subject related but rather provides information on how a student is performing or progressing in the aim to pass a module. The process of generating such feedback can be time consuming, especially with large student numbers (Krause et al. 2009). Modern analytics techniques offer attractive methods for processing and analysing large data volumes thereby converting them into insight (Daniel 2015). The demand for improved productivity and achievement is progressively being addressed through incorporation of different forms of analytics into educational systems. These include institutional, information technology, academic, and learning analytics, among others. Learning analytics is concerned with "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning" (Daniel 2015, 913). It can be implemented to generate feedback on learners' academic progress thereby promoting evidence-based decision-making. Higher education institutions are increasingly implementing big data analytics tools to assist them in decision-making (Rubel and Jones 2016). Ruipérez-Valiente et al. (2016) found that although learning management systems (LMSs) collect different forms of student data, not many provide appropriate visualisations about the learning process. The purpose of learning analytics systems can vary but to improve learning, it should assist in the decision-making process and also help with detecting problem-cases early on. It was found that using learning analytics should be extended to not only augment the teacher's information but also provide students with self-awareness tools (Ruipérez-Valiente et al. 2016).

The value of effective feedback depends on numerous variables but in particular on the timely availability of data as well as the uniqueness of the information that can be provided (Tempelaar et al. 2015). Model-driven DSSs use optimisation, algebraic, financial, analytic, or simulation techniques to provide decision support (Power and Sharda 2007). Quantitative models implemented in a DSS that performs learning analytics functions, present a unique

solution for timeous data processing (Power and Sharda 2007). The implementation of learning analytics in a model-driven DSS will offer advantages to lecturers and students alike, irrespective of their technical capabilities. "Models in a model-driven DSS should provide a simplified representation of a situation that is understandable to a decision maker" (Power and Sharda 2007, 1045). The learning analytics functionality in the progress feedback framework presented in this paper, is therefore provided by a model-driven DSS which uses quantitative mathematical models to manipulate the data.

To evaluate the proposed progress feedback framework, the properties of effective feedback need to be investigated. Researchers generally agree on the conditions under which assessment feedback has a positive effect on learning (Belcadhi 2016; Evans 2013; Krause et al. 2009; Rubel and Jones 2016; Wiggins 2012). Academic progress feedback differs from assessment feedback in that it is based on overall student performance in a module, rather than on individual assignments. The proposed framework was developed according to a qualitative technique proposed by Jabareen (2009) and is model-based because it consists of constructs and variable-dependent models. Evaluation criteria for the proposed framework is a compilation of the conditions established in literature relating to progress feedback, privacy concerns in learning analytics and the behavioural and technical issues concerning a model-driven DSS.

3. Method

This study was performed within the positivistic paradigm for Information Systems as described by Siponen and Tsohou (2018). A combination of qualitative and quantitative data collection methods were used. More specifically, the proposed framework was developed according to an action design research method and applied in a case study at a South African university. The instrument of data collection was a survey in the form of a structured questionnaire. A convenience sampling procedure was used due to students participating voluntarily and anonymously.

4. Progress feedback scenario

In order to identify and integrate the elements relevant to the proposed framework, the academic progress feedback scenario is described and analysed in Section 4.1. The evaluation criteria for the framework, are discussed in Section 4.2.

4.1. Scenario layout and analysis

A lecturer is responsible for facilitating module contact sessions and determining how to grade and pass students. On-campus students are expected to prepare for and attend contact sessions,

study subject material and complete formative assessments like attendance, informal tuition or formally scheduled tests. Assessment grades are entered into a spreadsheet in which students are typically identified by their university numbers. A collection of grades as progress feedback, lacks essential information that students need to improve their learning. Feedback has a positive effect on learning when it reports backwards (provides each student with up-to-date progress reports), upwards (gives the student a goal to work towards) and forward (lists distinct actions for a student to perform towards reaching the goal) (Hattie and Timperley 2007). Therefore, in the proposed framework a DSS performs the data analysis and generates a personalised progress profile for each student, with these three forms of feedback.

A detailed description of the mathematical models and the related algorithm implemented in the DSS, can be found in Van der Merwe et al. ("Mathematical modelling," 2018). The progress profile of a student is generated using all accumulated grades at any current point in time in the semester. The DSS requires certain module specific information from a lecturer to generate an improvement plan for each student. This information includes the type of assessments (*i.e.* class assignments, tuition tests, etc.) as well as the number of assessments in each category. The calculated weighted average participation mark (a student's level of participation in academic activities) is used in conjunction with a layout of the remaining planned assessments for a semester to determine if a student can improve by a specified amount, like 5% (provided by the user). A decision-tree structure is created by the DSS to represent all the possible scenarios that a student can follow for participation in the remaining assessments. For each one of those scenarios, the algorithm calculates a required score per assessment that will result in an increase in the current weighted average participation mark, as provided.

Learning analytics techniques implemented on student data sets, present privacy issues that need attention (Rubel and Jones 2016). An academic ranking that categorises students according to their progress relative to the rest of the class, partially addressed this issue (Van der Merwe et al., "Student ranking," 2016). The method allowed students to compare their progress with that of their peers without actually knowing the grades of the rest of the class.

Feedback can be provided to users by means of any existing platform used for communication of academic information, like an LMS. A student accordingly has several options to consider when proceeding with the semester. A typical student progress profile is shown in Table 1.

Table 1: Personalised academic progress feedback

Current status for student:	12345678	Improvement plan: To improve your current weighted average participation mark by a maximum target of:	
Rank in class:	10/26	5%	
Type of assessment:	Averages:	Required number of assessments:	Required grades:
Attendance	100%	4	100%
Practical assignments	64%	2	86%
Class tests	57%	1	77%
Semester test	73%	N.A.	N.A.
Current minimum participation mark:		Projected minimum participation mark:	
	65%		70%

Apart from the information in Table 1, a lecturer has access to the assessment class averages which can be used to determine fixed weights towards reaching a specific participation mark class average (see Table 2). If, for example, a lecturer wishes to maintain a class average of at least 70% the DSS can calculate the weights required for each assessment type, based on the students' current marks.

Table 2: Feedback provided to a lecturer

Target class participation mark average:		70%
Assessment type:	Current class assessment average:	Weights required to reach target:
Attendance	89%	0,64
Practical assignments	51%	0,12
Class tests	60%	0,12
Semester test	72%	0,12

Participation profiles/semester marks are used as the measure by which students are allowed admission to the final summative assessment/examination. The final module mark is calculated according to a mathematical equation established by the lecturer, by considering the semester mark and that of the final examination.

The outlined scenario presents some challenges. Research indicates that the frequency of academic progress updates are generally unsatisfactory (Carless 2006; Gielen et al. 2010). Students fail to obtain their assignments or grades timeously (Carless 2006) and remain

oblivious to impending failure (Du Toit 2015). Also, lecturers often have trouble identifying at-risk students when trying to process large data sets in a limited amount of time (Van der Merwe et al., "Student ranking," 2016). Feedback should ideally be provided to students and lecturers in time for them to still be able to affect change.

In any teaching-learning environment, the persons responsible have to manage various challenges to facilitate effective feedback. Specific issues and their framework references were identified in this section and will be used for evaluation of the proposed framework. These concerns were translated into framework requirements and are discussed next.

4.2. Requirements of the proposed feedback framework

A framework is a grid with interlinked elements consisting of concepts and/or models that collectively provide comprehensive insight into a phenomenon (Jabareen 2009). Conceptual analysis of the discussed scenario resulted in the identification of the following components: the students, data, a lecturer, a DSS and an LMS for providing feedback. These elements were combined to portray the academic progress feedback scenario discussed in Section 4.1.

Feedback in general should exhibit seven key attributes to be effective (Wiggins 2012). Those relevant to academic progress feedback are timeliness, consistency, being goal-referenced, generic (independent of subject content), personalised and actionable. Utilisation of a DSS facilitates compliance to all of these requirements. Incorporation of a DSS to perform the necessary analytical actions on the data set decreases the amount of required processing time considerably. This allows a lecturer to provide progress feedback consistently and as soon as the assignments are graded. Once the captured data have been processed, feedback should report backwards, upwards and forward to students and lecturers alike. The resulting feedback is actionable because both students and lecturers can subsequently plan and act to affect improvement.

A model-driven DSS allows a non-expert user to set up or manipulate the parameters required to solve the models (Power and Sharda 2007). The models are dependent on the knowledge and experience of the perceiver and will therefore be evaluated for conceptual ease, basic operation and model support (Argent et al. 2006).

In summary, feedback provided to the user should:

- Be provided timely and consistently;
- Protect student privacy while providing an academic ranking; and
- Report backwards, upwards and forward.

Certain semantic models need to be preserved when setting up the concepts and models necessary to provide insight into the described feedback phenomenon. These models and how they are interlinked to epitomise the feedback environment, follow.

5. Development of the academic progress feedback framework

The scenario outlined in Section 4.1 can be categorised into three interlinked phases namely "perform", "analyse" and "report". These phases represent the semantic models that need to be maintained within a feedback framework in order to adhere to the requirements set forth in Section 4.2. A description of the semantic models and their attributes is provided in Section 5.1 followed by how they were integrated into a new feedback framework in Section 5.2.

5.1. Models description

The three phases identified served as the blueprint for developing the framework for personalised academic progress feedback. The "perform" phase involves face-to-face contact between the lecturer and students. An individualised user profile is created for each student which is a structure for modelling and storing information relating to a student's current academic progress and characterises the participation and performance level of a student. The user model therefore portrays a student in terms of a participation level and ranking relative to the rest of the class. This data is categorised as personal, performance and profile information. The captured data is used in the "analyse" phase to generate progress feedback and convert it into an appropriate format. A metadata model describes the entities involved in data generation and the processes of producing, capturing and formatting the data into the structure required for feedback. The metadata model is implemented by means of a DSS because it interacts with a decision maker and applies various different methods to provide information that will support decision-making (Chiu and Huang 2016).

The model-driven DSS implemented as part of the proposed framework, maintains the metadata model so as to generate feedback and format the information into the required form. The DSS implements the mathematical model in Van der Merwe et al. ("Mathematical modelling," 2018) to create a progress profile for each student consisting of:

- A set of all the accumulated marks;
- A dynamically weighted participation mark average calculated from the current marks; and
- An overall student ranking created from the student participation mark averages.

After completion and grading of each new assessment, all of the progress profiles are re-calculated and updated information is provided to the students. As the semester progresses, students have the ability to monitor their academic performance.

In order to provide all the relevant users with personalised (for students) and generic (for a lecturer) feedback in the "report" phase, the strategy and resource(s) need to be appropriate to the given context. These must be maintained in the feedback model. The general ontology between these models for a number of n assessments and m students, is illustrated in Figure 1.

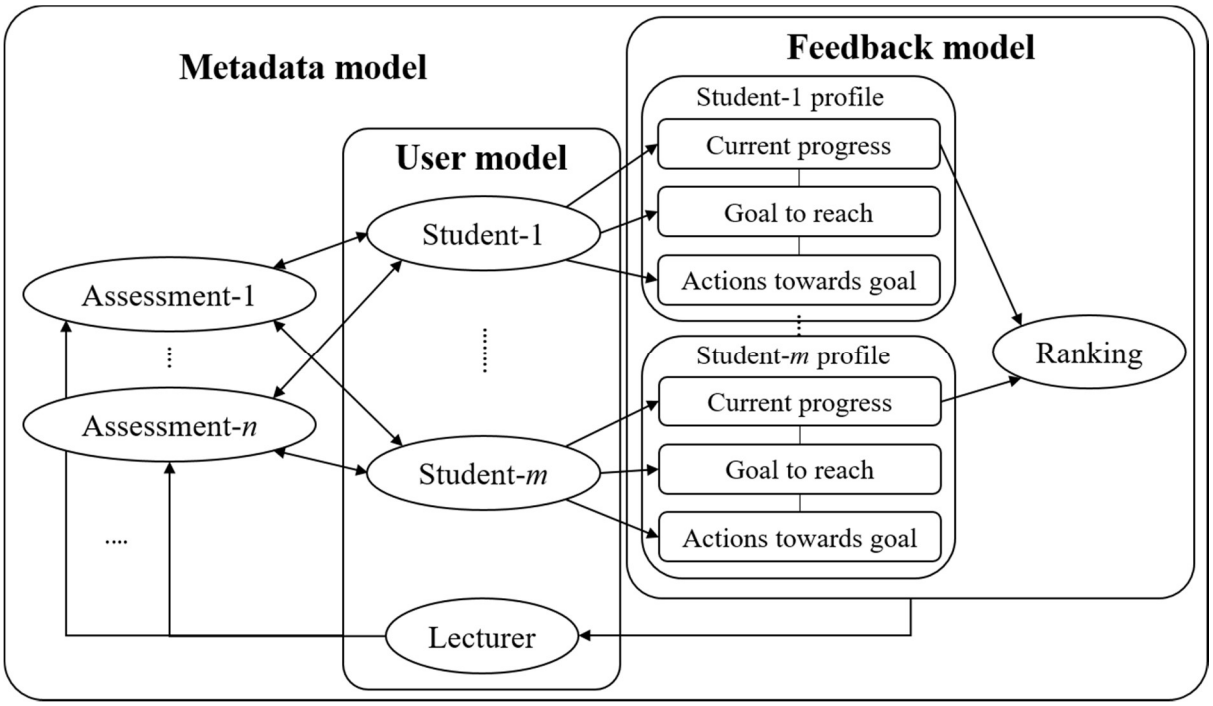

Figure 1: The metadata model

The feedback strategy implemented in the DSS, provides information granularity by presenting progress profiles in terms of a layout of grades that a student achieved for each assessment. LMSs are widely used for communication between a lecturer and students in tertiary education environments but generally lack specific integration of academic feedback to students (Stantchev et al. 2014). A specialised learning management system (SLMS) is ideal for providing feedback to students as it allows a lecturer to use it for data capturing and access to progress profile information (Van der Merwe et al., "A prescriptive," 2018). This will enable a lecturer to identify at-risk students and implement timely interventions to assist them. The use of an SLMS also contributes to the protection of student privacy by requiring authentication before gaining access to individualised student feedback.

In this section, the models and their relationships were discussed for the purpose of recognising the elements needed for the proposed feedback framework. These elements and how they combine to form the new feedback framework, follow in Section 5.2.

5.2. The academic feedback framework

The elements identified for the feedback framework include concepts and models as part of the DSS. Each of these elements provides some contribution towards the feedback framework in terms of ontological (the nature of reality or actual existence and actions), epistemological (the way things work in an assumed reality) and methodological (the process of constructing and assessing information about the performance status of students) assumptions (Jabareen 2009). The elements required for efficient depiction of the three phases identified in the previous section, are shown in Table 3.

Table 3: Concepts/models in the proposed feedback framework

Metadata component	Concept/model	Role in the framework
User model	Data	Ontological
	Student (expectation: academic motivation)	Epistemological
	Student (adaptive conduct)	Methodological
	Student (privacy)	Ontological
	Lecturer (expectation: adaptive conduct)	Epistemological, methodological
Feedback model	DSS	Methodological
	Data	Ontological
	SLMS	Methodological

Frequent academic feedback can improve a student's academic motivation as it reveals the effect of student participation in academic activities. A motivated student exhibits a change in academic conduct. A lecturer also expects to see certain results from the teaching methods employed during contact sessions. Feedback can affirm that these methods are successful and if not, prompt the lecturer to adapt. The elements were synthesised into a theoretical model-based conceptual framework for ranking feedback and is presented graphically in Figure 2.

The framework provides comprehensive insight into the feedback phenomenon in the described teaching-learning environment. It contains the required structures, effectively addresses the issues that were identified and maintains the relevant semantic models. In order to establish whether the framework comprehensively portrays the academic feedback phenomenon, it was implemented at a South African university and evaluated according to the requirements identified in Section 4.2. Framework validation and evaluation is discussed in Section 6.

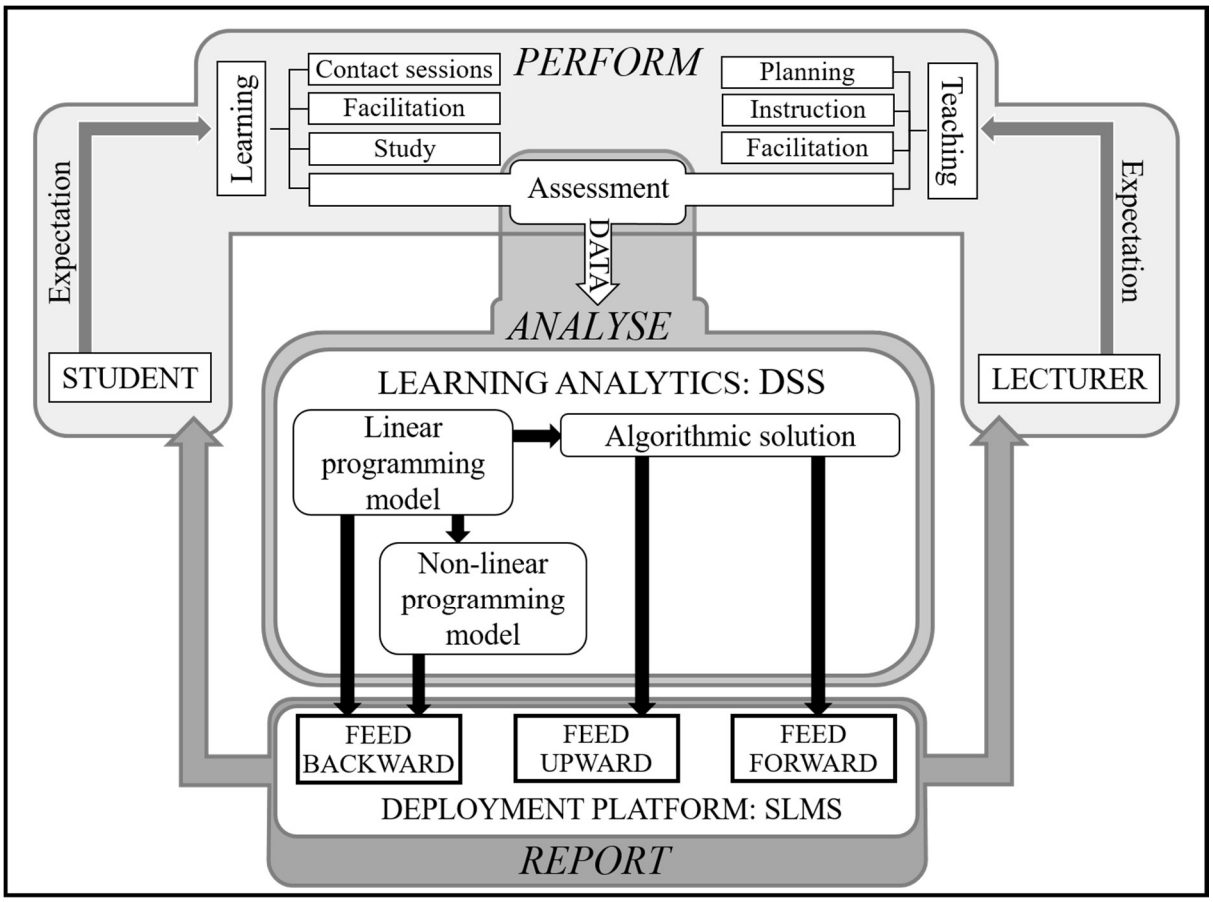

Figure 2: The academic progress feedback framework

6. Evaluation of the proposed feedback framework

The proposed framework is model-based and consists of several interlinked concepts. Validation of the evolving theoretical framework was done by means of peer reviewed presentations at academic conferences in management science (Van der Merwe et al., "Student ranking," 2016); mathematical modelling (Van der Merwe et al., "A mathematical ranking," 2016); operational research (Van der Merwe et al., "A modelling approach," 2017); ICT, society and human beings (Van der Merwe et al., "An early alert," 2017); and education and humanities (Van der Merwe et al., "A prescriptive," 2018).

The qualitative measures for evaluating the DSS include conceptual ease, basic operation and model support. The DSS consists of mathematical models that were designed so that student or lecturer-users can have access to its modelling capabilities without having expert knowledge of the mathematics embedded within. Although the conditions for module completion can vary, the proposed framework utilises the data generated by students as variables rather than set parameters, according to which each student's progress is determined. This means that the progress feedback framework is a generic solution, can be set up according to specific lecturer requirements and be implemented in any module, regardless of the content. The DSS was

created as a standalone computerised system which means further modelling support will only be required for exceptions or special cases.

Formal evaluation of the framework was done by implementation in a third year Computer Science module. The feedback platform used was an existing SLMS used at the university. Students were asked to participate in the three phases along with a lecturer and evaluate the feedback by completing a survey. The constructs employed in the survey (Table 4) were inferred from the criteria set in Section 4.2.

Table 4: Constructs used for framework evaluation

Construct	Factor(s) for evaluation
The implemented feedback framework:	
1. Provides me with frequent feedback throughout the semester.	TC (timely and consistently), ER (efficiency of academic ranking)
2. Keeps me informed on my current academic standing (current marks and level of participation) throughout the semester.	TC, BFU (backwards, forwards and upwards), ER
3. Provides me with effective improvement goals (how much I can still improve on my participation mark)	BFU
4. Effectively provides for specific targets (which assessments to complete with specific marks) that will help me to make informed decisions on how and when to participate in academic activities throughout the semester.	BFU
5. Effectively informs me how I am performing in relation to my peers.	ER
6. Uses my academic data confidentially.	SP (student privacy)
7. Will help me to monitor my progress throughout the semester.	TC, BFU
8. Is easy to understand and interpret.	BFU

The students were invited to show their level of agreement with the posed constructs on a Likert scale ranging from one (totally disagree) to seven (totally agree). In a module with 129 enrolled students, 97 (75%) completed the survey. A level of satisfaction was calculated for each factor by determining the ratio of students who responded with values five through seven. The level

of satisfaction for the frequency and timeliness of the provided feedback (TC), as well as the effectiveness of peer ranking (ER), was 92%.

The students' overall satisfaction with the content of the feedback given (BFU) was 94%, indicating that they felt that the information supplied will help them to improve their academic progress during the semester. Anecdotal evidence from informal class discussions indicated that although their academic rankings provided students with some motivation to improve, they wanted to have access to the detailed grade sets of their peers for comparative purposes. Furthermore, respondents indicated a level of 95% satisfaction with the confidential use of their academic data. Figure 3 shows the averages of all the students' responses, for all the evaluated constructs.

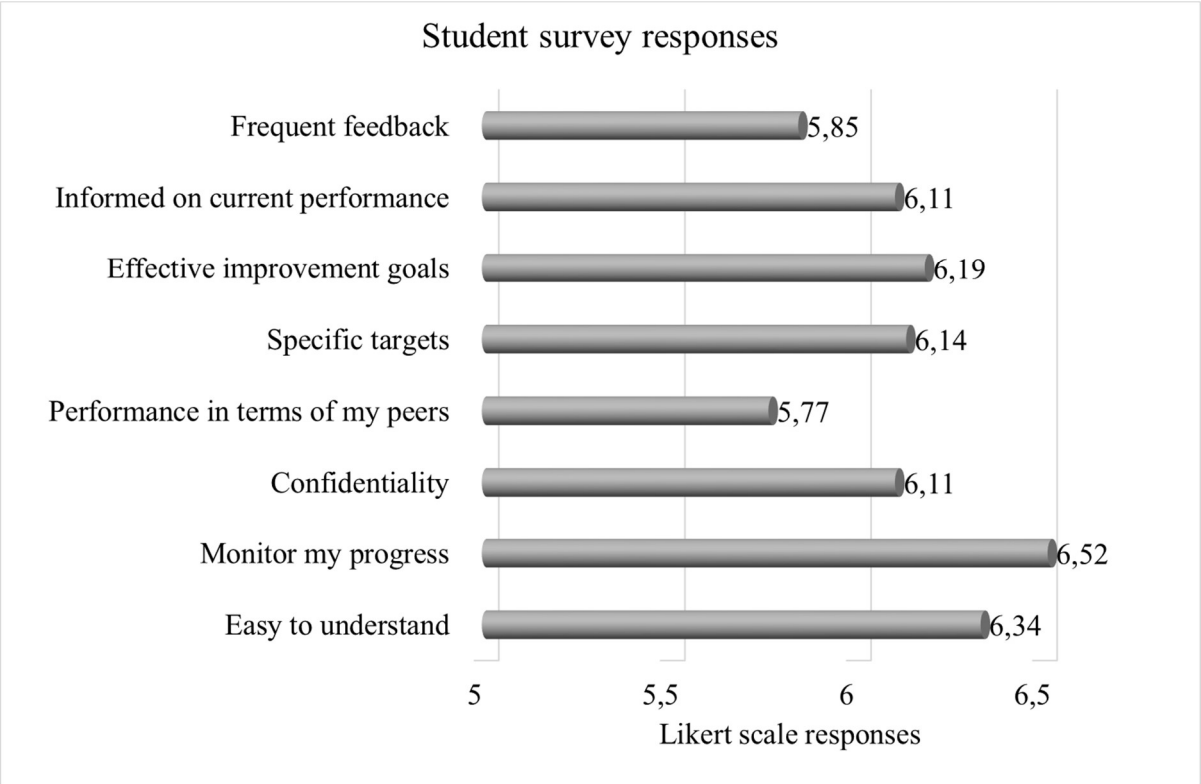

Figure 3: Student satisfaction regarding feedback content

Section 6 started with an outline on the validation of the proposed feedback framework by means of presentations of the evolving concepts at academic conferences, followed by a brief reference to the evaluation of the mathematical models implemented in the DSS in terms of qualitative measures established by Argent et al. (2006). The section concluded in a discussion on the formal evaluation of the feedback framework as implemented in a tertiary education setting. Section 7 consists of a layout of specific and more general contributions of this study to the field of educational feedback.

7. Discussion

One of the major success factors towards improvement in the learning process in tertiary education is effective academic feedback. Research has also shown that in order to be considered a leader in teaching, lecturers and institutions need to efficiently incorporate technology in their teaching regimes (Newman and Scurry 2015). An academic feedback framework was proposed that provides insight into the changing tertiary education environment. This study offers goal specific contributions and some more general contributions.

7.1. Specific contributions

The proposed framework provides timely feedback in a dynamic teaching-learning environment. The feedback contains up-to-date progress reports, individual goals to reach to affect improvement as well as distinct actions to perform towards reaching the set goals. A progress report consists of a compilation of the grades a student achieved during a semester, an updated minimum participation mark and a ranking position for that student in relation to the rest of class. The improvement goals (feed upwards) contribute towards improved learning in that students can change their approaches towards learning by following the steps suggested (feed forward). The structure of these performance reports is in contrast to the traditional manner of providing students with only their latest assessment grades and contributes towards improving student motivation.

Implementation of the proposed framework improves module management by lecturers. Academic feedback is provided timely, leaving lecturers with more time to spend on expanding their teaching regimes and providing facilitation for hard-to-master subject content. Lecturers have access to student progress information which can help them identify at-risk students and implement interventions early in a semester.

Although the framework was evaluated in a contact program, it has the potential to improve the management of online courses. Such courses are generally operated by means of LMSs on the Internet. An SLMS was demonstrated in this study to be the ideal deployment platform of the proposed framework. The feedback framework successfully integrates existing concepts with new approaches to efficiently address the dynamic nature of the evolving teaching-learning environment.

7.2. General contributions

The proposed academic feedback framework successfully integrates concepts and models to describe the intricacies of educational feedback. For this purpose, a combination of the

qualitative methods proposed by Jabareen (2009) and Argent et al. (2006) were applied. These studies were also used to set up appropriate evaluation criteria for the developed framework.

The proposed framework effectively supports the goal of improving student achievement in an evolving teaching-learning environment and assisting lecturers with early identification of at-risk students. The provided feedback can also be used to identify subject content that students have not fully mastered.

Implementation of the framework will contribute on an institutional level to the quality and accuracy of learning statistics. The framework also contributes to the field of learning analytics by using a DSS to perform the data processing. The DSS can be implemented as an educational tool so that users with no mathematical modelling knowledge can operate it, ensuring dynamic, timely and up-to-date academic performance feedback in many modules.

The proposed framework will help to improve communication between institutions and students, so too in online programs. By providing feedback that is relevant to their learning progress, an institution can positively influence the students' motivation towards their studies. Implementation of the proposed framework in South African universities will therefore help to improve student retention which in turn can improve the overall quality of graduates.

8. Conclusions

The aim of this study was to propose an academic feedback framework for improving the learning standard of tertiary education in South Africa. For this purpose, recent research relating to feedback, learning analytics and DSSs were investigated to form a greater understanding of the environment and how it is changing. The concepts and models relevant to this environment were identified, categorised and integrated to create the proposed feedback framework. Academic presentations served as validation of the evolving theory and the framework was evaluated by means of implementation in a case study.

As the DSS analyses academic data, the need for further research into improving student data privacy, exists. Therefore, the platform for mass deployment of the framework for many modules within an institution and the access measures used to authenticate its users, must be reliable and conform to the requirements for the protection of personal privacy. Research and development regarding privacy issues and the use of LMSs for the proposed framework as well as investigation into the success of mass framework deployment at a South African university, serves as future work.

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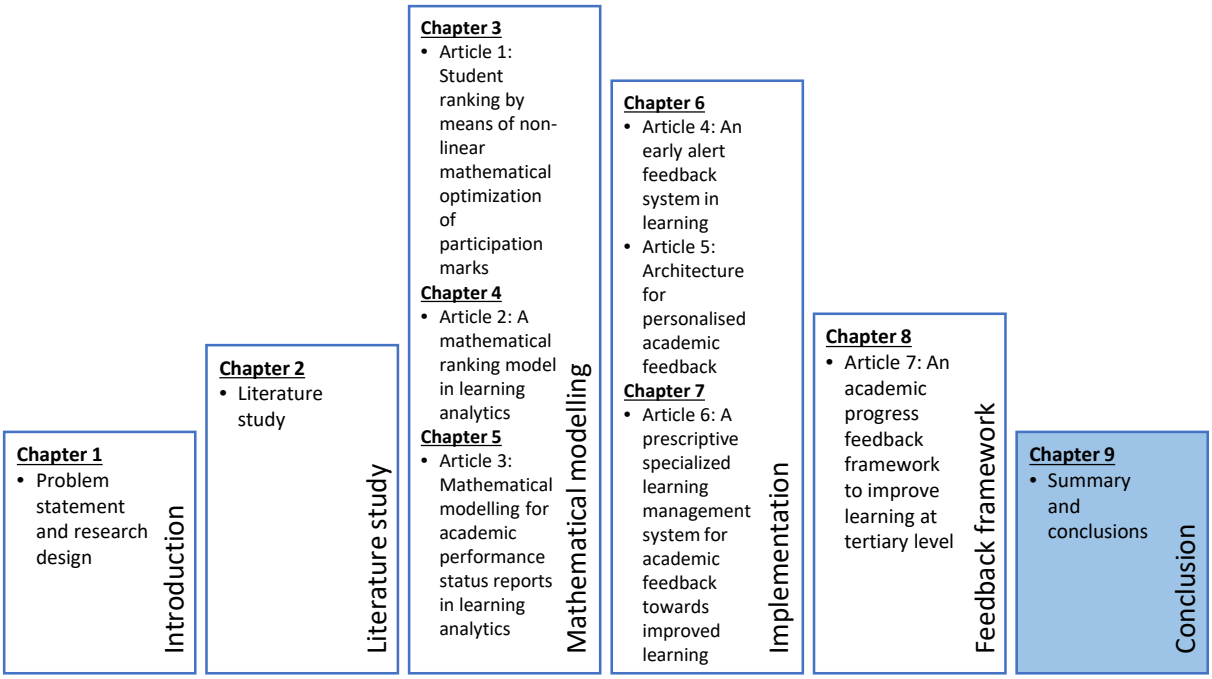
Chapter 9

Summary and conclusions



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9.1. Introduction

Chapter 9 is the final and concluding chapter of this thesis. A synopsis of the study is presented, followed by a description of how the research objectives were achieved. A summary of the research contributions is provided. Some limitations are discussed followed by possible continuation projects of this work.

9.2. Synopsis of the study

This thesis consists of nine chapters. The first chapter served as an introduction to the study and briefly outlined the research design. This was succeeded by a chapter that contained a review and some examples of recent research in the areas within the problem context. Seven papers were then presented, three as part of mathematical modelling, another three to describe work done on the implementation of the models and a final one to describe the development and evaluation of the academic performance feedback framework.

Chapter 1 served as introduction to the study through some background on the academic feedback environment and the resulting problem statement, research objectives and research methodology of this study. In the aim to answer the question: "*Can a model-based conceptual framework be developed for comprehensive academic performance feedback towards improved learning?*" these secondary research questions were formulated:

- What is the current state of academic performance feedback in education?
- Can mathematical modelling be utilised to facilitate an improved approach for creating comprehensive academic performance status reports?
- What are the components and composition required for successful implementation of the academic performance status reports generated by the mathematical models?
- How can the modelling approach for creating academic performance feedback be implemented to improve learning?
- What are the concepts and models required for an effective academic performance feedback framework?

The main aim of the study therefore was to *propose* an academic performance feedback framework that utilises mathematical modelling techniques in order to facilitate an enhanced feedback approach for improved learning. The secondary research questions translated into these objectives:

- To *conduct* a thorough literature survey of recent research on the relevant fields;
- To *formulate* mathematical programming models for improved approaches towards calculating participation profiles and student rankings and creating comprehensive academic performance status reports;
- To *establish* the architecture required for an electronic demonstrator of the mathematical modelling approach, in the form of a computerised early-alert feedback system;
- To *implement* and *evaluate* the academic performance feedback system as part of a specialised learning management system; and
- To *validate* the concepts and models for the improved academic performance feedback framework, in accordance with requirements established from literature and a pilot study.

Chapter 2 pursued the first objective of *conducting* a literature survey. It was dedicated to reviewing literature and providing summaries on recent research studies performed in the fields of academic performance feedback, learning analytics, mathematical modelling and framework development. The subsequent chapters contained papers with their own literature sections, so therefore the literature review in Chapter 2 assumed an abridged form. The secondary research question on the current state of academic performance feedback in education, was answered.

The second objective was achieved in Chapters 3 to 5. Mathematical programming models were *formulated* to find improved approaches for calculating participation profiles and student rankings and creating comprehensive academic performance status reports. These chapters served to describe the progress in developing mathematical modelling techniques to optimise the calculation of participation marks (measure of student participation in academic activities). A non-linear programming model was formulated and solved to calculate the participation marks of students and to create an academic ranking. This work was presented in Chapter 3 as a paper titled *Student ranking by means of non-linear mathematical optimization of participation marks*. As part of this paper, an existing method for average participation mark calculation and student ranking, was evaluated. Use of the non-linear programming model provided significant improvements on this method by eliminating the need for time-intensive manual calculations. The resulting student ranking correlated favourably with that obtained in the existing method. It was found that although the non-linear model optimised participation mark calculation and ranking, the method did not provide students with targets towards improving their academic performance.

The development of mathematical models in the ongoing effort to improve the calculation of student participation profiles, was continued in Chapter 4. A paper titled *A mathematical ranking model in learning analytics* was presented in which a multi-stage mathematical class ranking model was implemented. The model applied the Pareto optimality principle to determine an efficiency score for each student based on their academic performance. The students were then sorted into classes of similar ranking, according to dominance. An outputs-only based data envelopment analysis model was then used to calculate targets for students to advance to a higher class of academic efficiency. The model utilised in this approach provided improvements in learning analytics through the creation of a student output efficiency class-ranking as well as calculating individualised improvement targets for each student. Unfortunately, this approach did not use similar weight distributions for the categories contributing to the efficiency scores of all the students. Furthermore, implementation of the class-ranking method for a large number of students was impractical.

In order to address the issues identified in the methods evaluated in Chapters 3 and 4, improvements were made and presented in Chapter 5. The paper titled *Mathematical modelling for academic performance status reports in learning analytics* started with some background on an existing empirical method, *benchMark*, as well as the approaches discussed in the preceding two chapters. A linear programming model was presented as improvement on the participation mark calculation methods of *benchMark* and was a modified version of the non-linear programming model presented in Chapter 3. Correlation between the student ranking resulting from the linear programming model and that of its non-linear programming predecessor, was very good. In the paper, a decision tree algorithm for determining improvement targets for an individual student, was also presented. The resulting output could be obtained in a relatively short time and conformed to all of the requirements for academic feedback to be effective. An additional non-linear programming model was also presented which could assist lecturers in selecting the weights for participation mark

calculation that would result in a required participation mark class average. The models discussed in the paper in Chapter 5 provided some valuable contributions to the field of academic performance feedback but needed to be implemented in a software application for use by non-experts in mathematical modelling. Upon completion of Chapter 5, the secondary research question of whether mathematical modelling can be utilised to optimise the creation of academic performance status reports, was successfully answered.

The third objective was achieved in Chapter 6. Towards *establishing* the architecture required for an electronic demonstrator of the mathematical modelling approach, papers were presented here that addressed the concerns relating to implementation and use of the mathematical ranking models discussed in the preceding chapters. Chapter 6 contained two papers. The paper, titled *An early alert feedback system in learning*, described how the non-linear programming model (Chapter 3) and the class-ranking model (Chapter 4) were put into operation in a computer system and evaluated as part of a pilot study. This paper served to determine which components were needed to implement such models in a software application. The second paper in Chapter 6 was titled *Architecture for personalized academic feedback*. This paper implemented the improved mathematical models (Chapter 5) and illustrated how the required components could be combined into an electronic system. A preliminary version of the system was also evaluated. The paper answered the research question relating to the components required and their composition for successful implementation of the academic performance status reports generated by the mathematical models.

Chapter 7 comprised of a paper titled *A prescriptive specialized learning management system for academic feedback towards improved learning*. This paper achieved the fourth objective of *implementing* and *evaluating* the academic performance feedback system as part of a specialised learning management system. It represented the culmination of the groundwork performed in Chapter 6 and addressed the secondary research question of how the modelling approach could be implemented to improve learning. The results from evaluating the electronic system and the composition of the components established in the previous two papers, were regarded as the guidelines towards creating a specialised learning management system (SLMS). The SLMS implemented the improved mathematical models to dynamically create student academic performance feedback and was deployed parallel to an existing feedback approach, in a tertiary education environment. The SLMS was evaluated in a field test which provided some valuable insights to be considered for development of an academic performance feedback framework in tertiary education.

In Chapter 8, the manuscript, *An academic progress feedback framework to improve learning at tertiary level* was presented. This paper represents achievement of the final objective of this study: *validation* of the concepts and models for the improved academic performance feedback framework. It started with an outline of the problem regarding student retention rates at universities in the South African environment. A model-based academic performance feedback framework was consequently developed in an effort to address the problem. It was believed that implementation of the framework would yield an intrinsic self-monitoring

responsibility among students. The feedback scenario in the tertiary education environment was described and analysed with the intention of identifying the elements necessary for the framework. These elements, together with the requirements for feedback to be effective, were considered when creating the framework for academic performance feedback. The framework consisted of concepts and models, with a decision support system included as a learning analytics supplemental tool. The resulting framework was implemented and evaluated in a tertiary institution in South Africa. Evaluation criteria were established from literature as well as from work presented in the preceding papers in this thesis. An overall feedback content satisfaction of 94% was determined, among other results, which were also reported in the manuscript. Insight into the evolving nature of academic performance feedback was inferred and reported. The manuscript in Chapter 8 therefore answered the final secondary research question. The framework was consequently created, proposed and evaluated in a course presented at a tertiary institution. With the preceding chapters addressing the secondary objectives of this study and providing the important information and results towards development of the framework, Chapter 8 constitutes achievement of the final secondary objective as well as the primary aim of this study.

9.3. Contributions of the study

The main contribution of this study is the development of a novel academic performance feedback framework. The framework contributes to tertiary education through the utilisation of mathematical ranking models to facilitate improved techniques to create comprehensive academic performance feedback. The feedback conforms to the requirements as established in literature, in that it feeds backwards (reports the current performance status of a student), forwards (individualised targets that will lead to reaching the improvement goals) and upwards (provides discrete goals which will result in improvement).

An outputs-only data envelopment analysis model was used to create a student class-ranking by categorising students according to their output efficiency (academic achievement). This method provides the unique contribution to mathematical ranking models by using the principle of Pareto optimality to sort students into classes of similar academic efficiency, irrespective of the weighted average of their grades. As far as can be ascertained, this approach has not been used for ranking students in the past. Further contributions offered by using mathematical modelling techniques, include the following:

- *Timely and dynamic feedback process*: The feedback generation process was improved to such an extent that it can be done immediately after assessment grading, allowing timely and dynamic feedback throughout the course of a semester.
- *Feedback consistency:* By eliminating the manual calculation of student grades, feedback can be generated as often and consistently as required by a lecturer. The models further support the creation of these comprehensive academic performance reports for classes with large groups of students.
- *Complete feedback*: The information contained in the feedback reports is complete and addresses the requirements for feedback to be effective towards improvement.

Accordingly, students have the unique opportunity to monitor their academic performance from an early stage in the semester and initiate actions towards improving, if required. They will also have a future-time perspective on how their participation in academic activities will influence their grades.

A novel academic ranking approach was developed that allows students to compare their performance to that of their peers without compromising student privacy. This new contribution is especially significant because it leads to additional advantages like self-assessment which also improves student self-efficacy and -motivation.

In creating a software application to provide early alert feedback, the innovative contribution of integrating the elements required for implementation of the mathematical models in a system that conforms to specific criteria, was made. The architecture included the three main elements namely students, lecturer and computer system, and also provided valuable insight into the learning analytics substructure of the system.

The incorporation of the feedback architecture into a software application contributed to the development of a contemporary SLMS for its deployment. The SLMS was developed for the specific purpose of providing individualised and dynamic academic performance feedback. Due to its specialised nature, it further contributes to SLMS development strategies in that it was developed to conform to the criteria for satisfaction as a learning management system as well as those of an action-recommender system.

The SLMS further offers a valuable contribution to the field of learning analytics by combining mathematical models with an algorithmic approach to form a prescriptive analytics engine. This form of learning analytics enables a student to get perspective on specific activities to perform in the near-future to improve learning. Students who have access to such specialised information, can affect change early in a semester and avoid course discontinuance. Combined with the availability of student rankings to a lecturer who can timely identify at-risk students, this provides a significant contribution towards improving student retention at tertiary institutions.

The proposed academic performance feedback framework extends the following important contributions:

- *Improvement of module management*: Implementation of mathematical modelling techniques to perform mass calculation of participation marks and speedy creation of the academic feedback reports, leaves lecturers with more time for expanding their teaching regimes and providing facilitation for hard-to-master subject content. As the framework was deployed in an SLMS, it also has the potential to improve the management of online courses. Such courses are generally operated by means of LMSs on the Internet. The feedback framework successfully integrates existing concepts with new approaches to efficiently address the dynamic nature of the evolving teaching-learning environment.

- *New framework development approach*: An important contribution to framework development approaches was made through the integration of concepts and models to describe the intricacies of dynamic tertiary educational feedback. A new framework development approach was pursued, grounded in techniques for conceptual framework development and supplemented by qualitative methods for developing a model-driven decision support system.
- *Quality and accuracy of learning*: The feedback generated by the mathematical models upon implementation of the framework, can also be used to identify subject content that students have not yet fully mastered. It will therefore further contribute on an institutional level to the quality and accuracy of learning statistics.
- *Accurate decision support in learning analytics*: The framework contributes to the field of learning analytics through the use of a decision support system to perform the data processing. It can be implemented as an educational tool so that users with no mathematical modelling knowledge can operate it, ensuring dynamic, timely and up-to-date academic performance feedback in many modules.
- *Improved and accurate communication*: By providing feedback that is relevant to the learning progress of students, an institution can positively influence the students' motivation towards their studies. Such improved communication also extends to online programs which in turn can improve the overall quality of graduates.

9.4. Limitations and directions for future research

The papers presented in this thesis, systematically focussed on the aim and objectives stated in Chapter 1. Issues identified upon completion of a paper were addressed in subsequent chapters. The remaining limitations provide direction for future research and include the following:

- The mathematical ranking models were implemented in the SLMS as fixed models. Modifications to allow lecturer users to modify the models for specific purposes, can further improve the usefulness of these models and offers scope for more research.
- Students have indicated the need to be able to compare the grades they obtained for individual assessments to those of their peers. The current form of the framework only creates an academic ranking for the participation marks generated for students at any time during a semester. This limitation can be addressed by using the methods established in this work to create rankings for individual assessments, rather than publishing assessment grades of students.
- The academic performance feedback framework was implemented for evaluation in the form of an SLMS at interface level. Student privacy can be further protected through implementation of the feedback framework at server level. This will compel user authentication at institutional level and provide more user statistics data.
- For the proposed framework to be effectively utilised, it needs to be available from any device. Further development in terms of implementation on different operating systems for mobile devices, may serve for further research.

9.5. Conclusion

Chapter 9 is the final chapter of this thesis. The chapter presented a synopsis of the study and showed how the research objectives had been achieved. In conclusion, limitations of the study and how they present directions for future research opportunities, were outlined.

Appendix A

Additional conference presentations arising from this study

The following oral presentations emanated from this research:

- A. van der Merwe, J. V. du Toit, H. A. Kruger, “Mathematical contributions to influence performance in tertiary education” Presented at the *45th ORSSA Annual Conference*, Stellenbosch, South Africa, 11-14 September 2016.
- A. van Der Merwe, J. V. Du Toit, H. A. Kruger, 2017. “Affecting performance in tertiary education by means of mathematical modelling” Presented at the *21st Conference of the International Federation of Operational Research Societies (IFORS2017)*. Quebec, Canada. 17-21 July 2017.
- A. van der Merwe, H. A. Kruger, J. V. du Toit, “A modelling approach to improve learner performance” Presented at the *46th ORSSA Annual Conference*, Champagne Sports Resort Drakensberg, South Africa, 10-13 September 2017.
- A. van der Merwe, H. A. Kruger, J. V. du Toit, 2018. “A decision tree algorithm towards a dynamic academic improvement plan” Presented at the *47th ORSSA Annual Conference*, CSIR Pretoria, South Africa, 16-19 September 2018.

Appendix B

Additional information: Chapter 3

B. Guidelines for authors

In accordance with the rules of the North-West University, it is a requirement to include author guidelines for papers presented in a thesis. This appendix contains the author guidelines for the paper titled *Student ranking by means of non-linear mathematical optimization of participation marks* which was presented as Chapter 3 and published in *Lecture Notes in Management Science*, the proceedings of the *8th International Conference on Applied Operations Research*.

The author guidelines were obtained from the following URL:
http://orlabanalytics.ca/lnms/authors.htm.

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Appendix C

Additional information: Chapter 4

C. Guidelines for authors

In accordance with the rules of the North-West University, it is a requirement to include author guidelines for papers presented in a thesis. The author guidelines for the paper portrayed in Chapter 4 which was titled *A mathematical ranking model in learning analytics*, and presented at the *16th International Conference on Computational and Mathematical Methods in Science and Engineering*.

The author guidelines were obtained from the following URL:
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3.

4. References

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Appendix D

Additional information: Chapter 5

D. Guidelines for authors

In accordance with the rules of the North-West University, it is a requirement to include author guidelines for papers presented in a thesis. The paper titled *Mathematical modelling for academic performance status reports in learning analytics* and presented in Chapter 5, was published in the peer reviewed journal, *ORiON*.

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According to the Harvard standard, literature citations in the text should proceed by listing the relevant author's name and the year of publication (*e.g.* "An optimal solution exists (Dantzig 1963)." or "According to Dantzig (1963) an optimal solution exists."). Additional information, such as page numbers, chapter numbers, theorem numbers, *etc.*, may be given directly after the date, separated by a comma (*e.g.* "An optimal solution exists (Dantzig 1963, p. 69)." or "According to Dantzig (1963, p. 69) an optimal solution exists."). For literture citations involving two authors, both authors' names should be listed, separated by an amprasand (*e.g.* "An optimal solution exists (Dantzig & Wolfson 1967, Theorem 4.2)." or "According to Dantzig & Wolfson (1967, Theorem 4.2) an optimal solution exists."). For literture citations involving more than two authors, only the first author's name should be listed in conjunction with the phrase "*et al.*" (*e.g.* "An optimal solution exists (Dantzig, *et al.* 1972, p. 3)." or "According to Dantzig, *et al.* (1972, p. 3) an optimal solution exists."). In cases of more than one bibliography entry per author per year, small alphabetical characters should be used to distinguish between references (*e.g.* "An optimal solution exists (Dantzig 1965b)." or "According to Dantzig (1963b) an optimal solution exists.").

According to the Vancouver standard literature citations in the text should proceed by listing the number of the relevant bibliography entry (*e.g.* “An optimal solution exists [7].” or “According to Dantzig [7] an optimal solution exists.”). Additional information, such as page numbers, chapter numbers, theorem numbers, *etc.*, may be given directly after the citation number, separated by a comma (*e.g.* “An optimal solution exists [7, p. 69].” or “According to Dantzig [7, p. 69] an optimal solution exists.”). For literature citations involving two authors, both authors’ names may be listed, separated by an amprasand (*e.g.* “An optimal solution exists [9, Theorem 4.2].” or “According to Dantzig & Wolfson [9, Theorem 4.2] an optimal solution exists.”). For literature citations involving more than two authors, only the first author’s name may be listed in conjunction with the phrase *et al.* (*e.g.* “An optimal solution exists [10,§3].” or “According to Dantzig *et al.* [10, §3] an optimal solution exists.”).

References
Books should be listed in the bibliography by including the surnames and initials (without punctuation) of all authors and/or editors (IN SMALL CAPITALS), the date of publication, the title (*in italics*, using small letters only, the only exceptions being the first word of the title and proper nouns), the edition (if second or higher), the publisher, the city of publication (followed by the official two-letter abbreviation of the state for cities in the United States — no country names should be listed), and the relevant pages cited (if appropriate), such as in the examples below:

[1] DANTZIG B, 1963, *Linear programming and extensions*, 2nd Edition, Princeton University Press, Princeton (NJ).

[2] GENDREAU M, LAPORTE G & POTVIN J-Y, 2002, *Metaheuristics for the capacitated vehicle routing problem*, pp. 129–149 in TOTH P & VIGO D (EDS.), *The vehicle routing problem*, SIAM, Philadelphia (PA).

Journals should be listed in the bibliography by including the surnames and

initials of all authors (IN SMALL CAPITALS), the date of the issue, the title of the relevant paper (*in italics*), the title of the journal (not abbreviated), the volume (and issue/part) number (**in bold face**), and the pages of the relevant paper, such as in the following example:

[3] NORESE MF & TOSO F, 2004, *Group decision and distributed technical support*, International Transactions in Operational Research, **11(4)**, pp. 395 –417.

Online resources should be listed in the bibliography by including the surnames and initials of the web page designer (if known, IN SMALL CAPITALS), the date of construction of the web page (if known), the title of the web page (if known, *in italics* — this is typically found in the title bar at the very top of the web page), an indication that it is an online reference, the date on which the site was accessed, and the URL (`in true type or courier fonts`), such as in the example below.

[4] SKIENA SS, 1997, *The algorithm design manual*, [Online], [Cited September 9th, 2004], Available from `http://www2.toki.or.id/book/algdesignmanual/index.ht`

Theses and dissertations should be listed in the bibliography by including the surnames and initials of the author, the date, the thesis (or dissertation) title, the university where the thesis (or dissertation) was submitted and the city in which the university is situated, such as in the example below [5]. An example of an unpublished technical report [6] is also shown below.

[5] VUMBI AI, 2003, *Algorithmic complexity*, MSc Thesis, University of Stellenbosch, Stellenbosch.

[6] HAMMING R, 1956, *On the amount of redundancy required to correct information errors*, (Unpublished) Technical Report TR 1956-371, Bell Laboratories, Murray Hill (NJ).

An example of the format in which an unpublished conference paper should be listed in the bibliography is given in [7] below, whilst an example of the bibliography listing format of a paper published in conference proceedings is shown in [8] below.

[7] LACOMME P, PRINS C & RAMDANE-CHERIF W, 2002, *Fast algorithms for general arc routing problems*, Paper presented at the 16th Triennial Conference of the International Federation of Operations Research Societies, Edinburgh.

[8] WILKINSON C & GUPTA SK, 1969, *Allocating promotional effort to competing activities: A dynamic programming approach*, Proceedings of the 5th Triennial Conference of the International Federation of Operations Research Societies, Venice, pp. 419–432.

The bibliography should be arranged in alphabetical order, according to first author surnames.

Note that although authors may use either the Harvard standard or the Vancouver standard (consistently) for citation purposes in the text, all references in the bibliography are expected to adhere to the guidelines above — irrespective of which citation standard is utilised by authors. A more comprehensive list of referencing examples are available in ps and pdf.

SUBMISSION PREPARATION CHECKLIST

As part of the submission process, authors are required to check off their submission's compliance with all of the following items, and submissions may be returned to authors that do not adhere to these guidelines.

1. The file containing my manuscript is a pdf file or an MS Word file.
2. My manuscript adheres to the requirements for a blind submission - *i.e.* (i) I have deleted the names and affiliations of all authors from the manuscript, and (ii) I have removed all author identification from the properties of the submission file.
3. I have prepared an accompanying cover letter to the editor in which the names, affiliations and contact details of all authors of the manuscript are listed in the order in which they should eventually appear in the paper, if accepted, and I will upload this cover letter when making my submission online.
4. My manuscript includes an abstract of approximately 300 words in the case of submissions made in English, or of approximately 1000 words in the case of submissions made in another language (and in the latter case I also include an English abstract of approximately 300 words).
5. My manuscript includes a list of keywords, and I have used the official list of keywords, unless the inclusion of a keyword not in that list is absolutely necessary.

6. All mathematical formulae and expressions in my manuscript form part of sentences (and hence include punctuation, but are not preceded by colons). [Merely check this box, if your manuscript does not include mathematical formulae.]
7. I have typeset all mathematical formulae and expressions in text lines where possible, the only exceptions being formulae that are so bulky that that they would force increased line spacing if included in the text, or formulae that have to be numbered for further referencing. [Merely check this box, if your manuscript does not include mathematical formulae.]
8. I have referenced all numbered mathematical formulae and expressions in my manuscript - *i.e.* there are no dangling formulae. [Merely check this box, if your manuscript does not include mathematical formulae.]
9. I have typeset all Latin abbreviations or phrases, such as *e.g.*, *i.e.*, *et al.*, *vice versa*, *etc.* in italics. [Merely check this box, if your manuscript does not include Latin phrases or abbreviations.]
10. In the case of having used MS Word to prepare my manuscript, I have ensured that all mathematical formulae and expressions were typeset using Microsoft Equation Editor - *i.e.* I have not merely typeset mathematical formuale as italicised text. [Merely check this box, if your manuscript does not include mathematical formulae.]
11. I have used either a full stop or a comma consistently throughout my manuscript as decimal separator. [Merely check this box, if your manuscript does not include decimal numbers.]
12. I have numbered figures and tables consecutively, using separate numbering sequences - *i.e.* Table 1, Table 2, Figure 1, Table 3, Figure 2 ... instead of Table 1, Table 2, Figure 3, Table 4, Figure 5 ... [Merely check this box, if your manuscript does not include figures or tables.]
13. I have provided each figure and table with a detailed caption, ending in a full stop. [Merely check this box, if your manuscript does not include figures or tables.]
14. I have included all figures and tables approximately where they should appear in the text - *i.e.* not on separate pages or at the end of the manuscript. [Merely check this box, if your manuscript does not include figures or tables.]
15. I have referenced all figures and tables in my manuscript - *i.e.* there are no dangling figures or tables. [Merely check this box, if your manuscript does not include figures or tables.]
16. I have numbered all theorems, algorithms and other numbered environments consecutively, using separate numbering sequences - *i.e.* Theorem 1, Theorem 2, Algorithm 1, Corollary 1, Algorithm 2 ... instead of Theorem 1, Theorem 2, Algorithm 3, Corollary 4, Algorithm 5 ... [Merely check this box, if your manuscript does not include theorems, algorithms or other numbered environments.]
17. I have referenced all theorems, algorithms and other numbered environments in my manuscript - *i.e.* there are no dangling figures or tables. [Merely check this box, if your manuscript does not include theorems, algorithms or other numbered environments.]
18. I have consistently followed either the Harvard-like standard (author date) or the Vancouver-like standard (Author [reference number]) of referencing throughout my manuscript.
19. I have arranged the bibliography in alfabetical order (and NOT in the order cited in the main text).
20. I have followed the instructions for typesetting entries in the bibliography (as shown in the extended set of referencing examples), including punctuation and font options (small caps for author names, italics for reference titles and bold face for journal volume numbers).
21. I have cited all references in the bibliography from the main text - *i.e.* there are no dangling references.

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SUNJournals Help

Appendix E

Additional information: Chapter 6

E.1. Guidelines for authors: Article 4

In accordance with the rules of the North-West University, it is a requirement to include author guidelines for papers presented in a thesis. The first of two papers in Chapter 6, titled *An early alert feedback system in learning*, was presented at the *ICT, Society and Human Beings* track of the 11th *Multi Conference on Computer Science and Information Systems, 2017*.

The author guidelines for this journal were obtained from the following URL: https://www.conf-system.org/confman_ict2017/guidelines.asp.

MCCSIS 2017 LISBON, PORTUGAL 20 - 23 JULY MULTI CONFERENCE ON COMPUTER SCIENCE AND INFORMATION SYSTEMS

Home | Co-located events | Contacts

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- Commitees
- **Submissions**
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- Registration / Rates
- Social Event
- Venue / Hotel Info
- Travel
- Sponsors
- Location
- Publication Ethics Statement
- Previous Editions (2016-2008)
- Guidelines
- Previous Keynotes

Submissions

The following instructions for submissions must be followed for any contribution sent. Please read them carefully and use the Word template we provide. Then, use the **Electronic Submission System** to submit your paper.

Important notes:
– The submitted work must be a complete work. No abstracts please. Use the template we provide here but with the initial submission please REMOVE the author details from the paper (i.e. name, university or company information and address, as well as any acknowledgements that may lead to information about the authors).

– The submitted paper or poster file must be submitted anonymously (without any references to author affiliation).

– This conference has defined a maximum limit of 3 submissions per author (including co-authored papers). Please note that Submissions beyond this limit will not be considered.

– Images cannot have text along the side of it in the main body of the text. However, if two images fit next to each other, these may be placed next to each other to save space.

Instructions for Submissions

These guidelines include complete descriptions of the fonts, spacing, and related information for producing your submission.

Paper Size: A4

Margins:	Top:	3,3 cm
	Bottom:	4 cm
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	Right:	2,5 cm
	Header:	1,5 cm
	Footer:	2,5 cm

Do NOT Use footers, headers and page numbers.

Title: The title should be centered in 16pt Times New Roman, boldface, all capitalized and paragraph spacing after 24pt.

Authors: The Authors name should be centered in 11pt Times New Roman.

Affiliation: The Affiliation should be centered italicized in 9pt Times New Roman.

Abstract: Use the word ABSTRACT as the title, in 9 pt Times New Roman, boldface, paragraph spacing before 42pt and paragraph spacing after 6pt. The abstract is to be in 9pt Times New Roman and justified.

Keywords: Use the word KEYWORDS as the title, in 9 pt Times New Roman, boldface, paragraph spacing before 18pt and paragraph spacing after 6pt. The keywords are to be in 10pt Times New Roman and justified.

Main Text: Type your main text in 10 pt Times New Roman and justified. Please do not place any additional blank line between paragraphs. The second paragraph and subsequent paragraphs should be indented first line 0,5 cm.

Program listings or program commands in the text are normally set in typewriter font, e.g., CMTT9 or Courier.

First-order Headings: For example, "1. HEADING", should be 13pt Times New Roman, boldface, paragraph spacing before 24pt, paragraph spacing after 12pt, flush left and all capitalized. Use a period (".") after the heading number, not a colon.

Second-order Headings: For example, "1.1 Heading", should be 13pt Times New Roman, boldface, initially capitalized, flush left, paragraph spacing after 12pt and paragraph spacing before 12pt. Do not use a period (".") after the heading number.

Third-order Headings: For example, "1.1.1 Heading", should be 11pt Times New Roman, boldface, initially capitalized, flush left, paragraph spacing after 6pt and paragraph spacing before 6pt. Do not use a period (".") after the heading number.

Do NOT Use more than three levels of heading.

Footnotes: Use footnotes sparingly (or not at all!) and place them at the bottom of the page on which they are referenced. Use 8pt Times New Roman, justified. To help your readers, avoid using footnotes altogether and include necessary peripheral observations in the text (within parentheses, if you prefer, as in this sentence).

Figures and Tables: All figures and tables should have caption. Figure and table captions should be 9pt Times New Roman. Initially capitalize only the first word of each figure caption and table title. Figures and tables must be numbered separately. For example "Figure 1. Text here", "Table 1. Text here". Figure captions are to be centered below the figures with paragraph spacing after 6pt and paragraph spacing before 6pt. Table titles are to be centered above the tables, paragraph spacing after 6pt and paragraph spacing before 6pt.

References: The references must be listed alphabetically. References should be 9pt Times New Roman, justified, indentation hanging 0,5 cm and paragraph spacing after 2pt.

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E.2. Guidelines for authors: Article 5

The second paper reported in Chapter 6, titled *Architecture for personalised academic feedback*, was presented at the *Education & Humanities* track at *The WEI International Academic Conference, 2018*.

The author guidelines for this journal were obtained from:
https://www.westeastinstitute.com/educationconferenceinvienna/#Style_Guidelines

International Academic Conference on Education & Humanities and Social Sciences (WEI-EHSS 2018) at Vienna University, Austria, April 17-19, 2018

Publication

Abstracts and full articles will be published in the proceedings entitled WEI International Academic Conference Proceedings, in electronic format (ISSN 2167-3179 USA).

Full-length manuscripts may be published in

-Journal of WEI Business and Economics(JWEIBE) (ISSN 2166-7918 USA)
-West East Journal of Social Sciences(WEJSS) (ISSN 2168-7315 USA)

The review process for the journals is slower and more demanding in its standards. Although both the proceedings and journals are refereed, research that meets the refereed standards for the conference and the proceedings may not meet the refereed standards for the journals.

Style Guidelines

For proposals/abstracts, your submissions should not exceed 1500 words. Include your name, institute affiliation, mailing address, and email address for all authors.

For full papers to appear in our conference proceedings, your manuscript should be saved as a Microsoft Word-compatible file. Text should be formatted for 8.5 x 11 inch paper, single-spaced at 10 points, with one inch margins and left justified. We generally follow American Psychological Association (APA) guidelines. Your submission should contain the following:

- Name, institute affiliation, mailing address, and email address for all authors
- Paper title
- Abstract
- Keywords
- Introduction
- Body of paper
- Tables, figures, etc. in their proper position in the paper (if applicable)
- Conclusion
- Brief biography of each author (one paragraph, no more than 100 words)
- References

Topics for Education Conference

Topics include, but are not limited to:

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- E-Learning
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- Health Education
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- History
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- Interdisciplinary Studies
- International Education
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- Religious Studies
- Science Education
- Secondary Education
- Social Sciences
- Sociology
- Special Education
- Spirituality
- Sport Science
- Teacher Education
- Teaching Method
- Tourism
- Urban Studies

Top

Appendix F

Additional information: Chapter 7

F. Guidelines for authors

In accordance with the rules of the North-West University, it is a requirement to include author guidelines for papers presented in a thesis. The paper presented in Chapter 7 was titled *A prescriptive specialized learning management system for academic feedback towards improved learning* and published in the peer reviewed journal, *Journal of Computer* Science.

The author guidelines for this journal are available at:
http://thescipub.com/journals/jcs/instructions.

Science Publications

Journal of Computer Science

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- Manuscript Types
- Online Submission
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When reporting experiments on human subjects, authors should indicate whether the procedures followed were in accordance with any ethical standards set by a governing committee responsible for human experimentation (ie, if applicable, a university review board) and with the Helsinki Declaration of 1975, as revised in 2000. If doubt exists whether the research was conducted in accordance with the Helsinki Declaration, the authors must, in a separate document, explain the rationale for their approach, and, if presented before a review body, demonstrate that the institutional review body explicitly approved the doubtful aspects of the study.

Studies using human subjects are required to state in the manuscript that all human subjects were provided with the approved informed consent.

When reporting experiments on animals, indicate whether the institutions or the National Research Councils guide for, or any national law on, the care and use of laboratory animals was followed.

Manuscript Preparation

Journal Template

The manuscript should be written in clear, concise and grammatically correct English. It is recommended that you ask colleagues to read over your paper prior to submission to ensure it is of a high standard and conforms to a high level of scientific writing.

Download the LaTex Template Download the Microsoft Word Template

Order of Manuscript

The manuscript should be presented in the following order.

Title Page

This should contain the title of the contribution and the names and addresses of the authors. The full postal address, e-mail address, telephone and facsimile number of the author who will receive correspondence and check the proofs should be included.

Running Head

The running head or short title is the shortened version of your manuscript title. Not only does this help identifying your manuscript during the evaluation process, it also acts as the manuscript title on the journal homepage providing information at a glance for people who are reading the journal.

Abstract

All manuscripts must include a brief but informative Abstract. It should not exceed 300 words and should describe the scope, hypothesis or rationale for the work and the main findings. The abstract should allow the reader to quickly have a clear idea about the rational for the work, the experiments conducted and the results of those experiments before reading the rest of the manuscript. Both common and scientific names should be included; the authorities are not given if they appear in the title. References to the literature and mathematical symbols/equations should not be included.

Keywords

Key words (3-5) should be provided below the Abstract to assist with indexing of the article.

Introduction

The Introduction should briefly indicate the objectives of the study and provide enough background information to clarify why the study was undertaken and what hypotheses were tested.

Materials and Methods

This section should be concise but provide sufficient detail of the material used and equipment and the procedure followed to allow the work to be repeated by others.

Results

Results should be presented in a logical sequence in the text, tables and figures. Repetitive presentation of the same data in tables and figures should be avoided. The results should not contain material appropriate to the Discussion. All tables, graphs, statistical analyses and sample calculations should be presented in this section.

Discussion

The results should be discussed in relation to any hypotheses advanced in the Introduction. Comment on results and indicate possible sources of error. Place the study in the context of other work reported in the literature. Only in exceptional cases should the "Results and Discussion" sections be combined. Refer to graphs, tables and figures by number. This helps tie the data into the text in a very effective manner. Authors should also take future research and limitations into account in the Discussion section.

Conclusion

The main conclusions of the experimental work should be presented. The contribution of the work to the scientific community and its economic implications should be emphasized.

Acknowledgment

The source of financial support must be acknowledged. Authors must declare any financial support or relationships that may pose conflict of interest in the covering letter submitted with the manuscript. Technical assistance may also be acknowledged.

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The authors should acknowledge the funders of this manuscript and provide all necessary funding information.

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References

It is the Authors responsibility to ensure that the information in each reference is complete and accurate. Only published and "in press" references should appear in the reference list.

Tables

Tables should be self-contained and the data should not be duplicated in figures. Tables should be numbered consecutively. Each table should be presented on a separate page with a comprehensive but concise legend above the table. Tables should be double-spaced and vertical lines should not be used to separate columns. Column headings should be brief, with units of measurement in parentheses. All abbreviations should be defined in footnotes. Use superscript letters (not numbers) for footnotes and keep footnotes to a minimum. *, **, *** should be reserved for P values.

Figures

Only necessary illustrations should be included. All illustrations (line drawings and photographs) are classified as figures. Figures should be cited in consecutive order in the text. Figures should be sized to fit within the column or the full text width. Line figures should be supplied as sharp, black and white or color diagrams, drawn with a computer graphics package. Photographs should be sharp and magnifications should be indicated on photographs using a scale bar. Graphics should be supplied as high-resolution (at least 300 d.p.i.) electronic files. Digital images supplied as low-resolution cannot be used and will not be accepted. The legend should incorporate definitions of any symbols used and all abbreviations and units of measurement should be explained so that the figure can be understood without reference to the text.

Abbreviation and Units

SI units as outlined in the latest edition of Units, symbols and Abbreviations: A Guide for Medical and Scientific Editors and Authors (Royal Society of Medicine Press, London), should be used wherever possible. Statistics and measurements should always be given in figures; except where the number begins the sentence. When the number does not refer to a unit measurement, it is spelt out, except where the number is greater than nine. Use only standard abbreviations. The word Figure should be shortened to Fig. unless starting a sentence.

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Appendix G

Additional information: Chapter 8

G. Guidelines for authors

In accordance with the rules of the North-West University, it is a requirement to include author guidelines for papers presented in a thesis. The author guidelines for the paper presented in Chapter 8, which was submitted and being peer reviewed at the time of submission of this thesis, in the *Africa Education Review*.

The author guidelines for this journal were obtained from the following URL: https://www.tandfonline.com/action/authorSubmission?show=instructions&journalCode=raer20.

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Style Guide: Chicago Manual of Style, Author-Date

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1. Guidelines for Technical Preparation of Manuscript

Layout
General
Submit manuscripts electronically as **Microsoft Word** files.

All graphic material has to be positioned at the correct place in the text and should be of a good quality. Do not add supplementary files with graphic content.

Manuscripts must be presented as: A4 pages; normal margins; 12pt Times Roman; 1.5 line spacing.

Add a line break (enter key) between all paragraphs. Do not apply paragraph styles (hanging indents, automatic spacing after or before, etc.).

Proofing language must be set as UK English (colour—not color; travelled—not traveled; organise; organisation; organising—not -ize).

Do not type double spaces anywhere; not between words, at the end of sentences or after colons.

Type hard spaces (shift + control + space bar) when phrases are preferred to be presented as a unit, e.g.10_000; Vol. 1 (2):_22–21.

Articles should be between 5 000 and 6 000 words in length (including references).

Make sure you follow the guidelines for ensuring a blind peer review.

Present an abstract of not more than 250 words. Abstracts should not contain any footnotes or citations. Do not type the abstract in italics.

Below the abstract, please provide 5–8 keywords for indexing (only proper nouns should be capitalised). Distinguish between keywords/phrases with a semicolon, e.g. Pentecostal; hymnal records; migration; southern regions of Africa.

Authors should include their affiliation or ORCID below their name, after the title of the article.

Book reviews
Please note the format and order of information required:

Oxford Dictionary of Journalism <Book title in italics>
Tony Harcup <Book author name(s) and surname>
Oxford University Press. 2014.Oxford Quick Reference. xiv + pp. 368.
<Publisher, date, series and number of pages>
ISBN: 978-0-0000000-1 <ISBN>,
https://doi.org/10.1093/acref/9780199646241.001.0001 <DOI>

Reviewed by Rod Amner <Reviewer details>

orcid.org/0000-0000-0000-0000 <ORCiD>
Rhodes University, School of Journalism and Media Studies, South Africa
<Affiliation: Institution, Department, Country>
r.amner@ru.ac.za <email address>

Style
Do not use the ampersand (&) anywhere in the text or citations; use "and" instead.

In text, emphasise words by using italics only sparingly. Italicisation should otherwise be reserved for titles and words from a language other than that of the text.

Italicised words/phrases in another language are glossed by an equivalent word/phrase in the language of the text in single inverted commas placed in parentheses, e.g. *indoda* ("a man"). Words well-known in South African English are set as roman, for example, "lobola," "ubuntu," "indaba."

Words/terms that need to be singled out as being "borrowed" from another author/source may be placed in double inverted commas.

Titles of standalone publications must be in headline style (significant words are capitalised) and in italics when typed in the text. Titles of articles are placed between "double inverted commas." Also see citation guidelines for examples.

Acknowledgements
Acknowledgements appear at the end of the article, should be brief, and recognise sources of financial and logistical support and permission to reproduce materials from other sources. Save a copy of documentation granting such permission. Adherence to copyright rules remains each author's sole responsibility.

Footnotes
Footnotes with references in Arabic numbers (1, 2, 3—do not use i, ii, iii) are allowed on condition that these are limited to essential notes that enhance the content without impeding the fluent reading of the article.

Footnotes are typed in 10pt. font and single spacing; hanging indent.

A note number should generally be placed at the end of a sentence or at the end of a clause. The number normally follows a quotation. Relative to other punctuation, the number follows any punctuation mark except for the dash, which it precedes.
Examples are:
"This," wrote George Templeton Strong, "is what our tailors can do." [1]

The bias was apparent in the Shotwell series [2] —and it must be remembered that Shotwell was a student of Robinson's.

Though a note number normally follows a closing parenthesis, it may on rare occasion be more appropriate to place the number inside the closing parenthesis—if, for example, the note applies to a specific term within the parenthesis:

(In an earlier book he had said quite the opposite.) [3]

Men and their unions, as they entered industrial work, negotiated two

things: young women would be laid off once they married (the commonly acknowledged "marriage bar" [4]), and men would be paid a "family wage."

Endnotes are not allowed.

Footnotes **do not replace the alphabetical list of references** at the end of the text. References in notes are regarded as text references and not bibliographic information.

Quotations
When quoting from a source, use "double inverted commas".

To quote within a quote, use 'single inverted commas'.

When quoting more than five lines, indent. Do not print indented text in italics and do not use quotation marks. A citation after the indented quote follows after a full stop, e.g. According to the report the council will discuss the matter at the next council meeting to be held on 5 January 2017. (Smit 2002, 1)

When quoting within an indented quotation, use double inverted commas.

Final full stops and commas are placed inside the quotation mark.

Colons and semicolons are placed outside of quotation marks.

Question and exclamation marks are only placed inside quotation marks if they form part of the quoted material:
Do you know if she is "accredited"?

He asked: "Are you accredited?"

When adding notes to a quote or changing a quotation, use square brackets, e.g. [own translation/emphasis]/[t]oday.

Numbers
In text, numbers one to nine are in words; numbers 10 and above are in digits.
At the start of a sentence all numbers are in words.

In parentheses, all numbers are in digits; as for numbers of tables, figures and chapters.

When in text, percentages (below 10) are in words—seven per cent; above 10 are digits—22 per cent/13.5 per cent.

Decimals—e.g. 7.5 per cent—are always in digits (also in text).

Use the % sign in parentheses and per cent in text.

Chicago prefers 122nd and 123rd (with an n and an r) over 122d and 123d.
The letters in ordinal numbers should not appear as superscripts (e.g., 122nd and **NOT** ~~122nd~~).
Examples:
Gwen stole second base in the top half of the first innings.
The restaurant on the forty-fifth floor has a splendid view of the city.
She found herself in 125th position out of 360.

Equations
Use Mathtype for display and inline equations, but not for single variables. Single variables should be inserted into the text as Unicode characters.

Abbreviations
Abbreviations that begin and end on the same letter as the word, do not get a full stop (Mr/Dr/Eds), but note Ed./Rev.

Degrees: (Preferably without any punctuation)
BA; DPhil; MSc

Ellipsis
Use the ellipsis when indicating that text has been left out in the middle of a quoted sentence—preferably not at the start or end of the sentence. It is a given that text has been left out preceding and following your quote.

Insert spaces before and after the ellipse.

Use only three full stops for an ellipse (A full stop is added before an ellipsis to indicate the omission of the end of a sentence, unless the sentence is deliberately incomplete. Similarly, a full stop at the end of a sentence in the original is retained before an ellipsis indicating the omission of material immediately following the full stop.)

E.g.
In May 1862, two new missionaries, Endeman and Albert Nachtigal, joined Grützner and Merensky. … It was decided that Endeman and Grützner continue working. … The latter two eventually established the mission station Botshabelo … which later would play an important role in the Ba-Kopa history.

Dashes
The unspaced em-dash (—) is used (Alt 0151).

An unspaced en-dash (–) (Alt 0150), NOT A HYPHEN (-), is used to indicate ranges (e.g. of numbers or page numbers: 15–21).

Initials:
One initial: Steyn, P. 2009.
Multiple initials
Steyn, P. R. G. 2009. (spaces between initials)
Steyn, P. R. G., R. T. Robbins and W. R. N. Boshoff. 2011.

Capitalisation of personal names
Names and initials of persons, real or fictitious, are capitalised. The reference lists in some journals (especially in the **natural sciences**) always use initials **instead of given names**. A space should be used between any initials.
Examples are:
Jane Doe
George, S. McGovern
P. D. James
M. F. K. Fisher

Acronyms
Give the full name when first mentioned (with acronym in parentheses),

thereafter use the acronym uniformly and consistently:
Unisa; CSIR; HSRC; Sabinet/SABINET

et al.
et al. (not italics) Never use in the reference list.
When citing a text with four+ authors, use only the first author's name followed by "et al." in text, but list all authors in the reference list.

Tables and figures
Table headings appear above the tables and are numbered.
E.g. **Table 1:** Our Table

Figure captions appear below the figures and are numbered.
Captions of figures other than artworks should be short and descriptive.

Include cited authors in the reference list.

Supply the source below the table or figure, if material is copyrighted.

Captions of **artworks** should include, in the following order:
Figure 1 Artist, title (date). Medium/support, metric dimensions. Name of collection, city of collection, other collection information such as "gift of …", accession number (copyright or credit-line information in parentheses).

Credit lines of artworks should include all elements specified in the letter of permission from the rights holder, institution and/or photographer.
Examples:
Figure 1: Sandro Botticelli, *Primavera* (ca. 1482). Tempera on panel, 203 x 315 cm. Galleria degli Uffizi, Florence (photograph provided by Scala / Art Resource, New York).

Figure 2: Roman sarcophagus, *Death of Meleager* (3rd century CE). Detail. Musée du Louvre, Paris (photograph © James Smith, Rome).

Figure 3: Alfred Stieglitz, *Equivalent* (1925–1927). Gelatin silver print, 11.7 x 9.2 cm. The Museum of Modern Art, New York, anonymous gift (© 2009 Estate of Alfred Stieglitz/Artists Rights Society (ARS), New York).

If a scan is used from e.g. a catalogue, this must be indicated by means of an exact reference: Figure 4: Pieter Brueghel the Elder, *The Misanthrope* (1568). Tempura on canvas, 86 x 85 cm. Signed and dated: 'BRVEGEL 1568'. Museo e Gallerie Nazionali di Capodimonte, Naples, catalogue number 585 (reproduced from Martin 1978, figure 37).

Include cited authors in the reference list.

Supply the source below the table or figure, if material is copyrighted.

Linguistic examples in series
Series of linguistic examples **have to** be presented neatly (**as borderless tables**). Individual examples should only be numbered if they are discussed with reference to that number in the article's body text. Such numbering should occur consecutively.
The example numbers should be in parentheses and placed next to the left-hand margin.
Numbered examples may be contrasted or compared to one another by using alphabetical numbering for purposes of contrast and comparison.
If numerous examples are necessary to substantiate a specific point, an

appendix may appear at the end of the article.
For the presentation of interlinear glosses, please refer to the Leipzig Glossing Rules (https://www.eva.mpg.de/lingua/resources/glossing-rules.php)

2. Citation Guidelines: Chicago Author-Date
In text:
Within the body of your text, citations are indicated in parentheses with the **author's surname, publication date**, and **page number** (if needed, as when quoting direct words), **e.g. (Smith 2012, 45).**

Citations are placed within the text where they offer the least resistance to the flow of thought, frequently just before a mark of punctuation.

Single-author citations: If the author's name appears in the text it is not necessary to repeat it, but the date should follow immediately:
Malan (2014, 4) refers to this ...

Single author with two or more works in the same year:
(Gray 2009a; 2009b)

One publication with two or three authors:
... contested by Smith and Jones (2013, 16). Also (Smith and Jones 2013, 16)

Multiple publications:
... venture failed (Bergin 2009; Chance 2008, 14–17).

When citing multiple publications/authors do so alphabetically (Louw 2010a, 3; Ncube 2008, 77; Zeiss 1993, 4).

Multiple-author (three+ authors) publications with the same initial surname and same year of publication—shorten titles:
(Coe et al., "Media diversity," 2001) and (Coe et al., "Social media," 2001)

No page numbers are needed if citing a text on the Internet, e.g. academic freedom (Smith 2014), unless page numbers are available:

When citing a secondary source:
... greater good (Mullins as quoted in Khan 2014, 6).
Mullins (as quoted in Khan 2014, 6) argues ...

Blogs are only referenced in-text.

References: (See examples below)
Use the heading: References.

Only list sources actually referred to in the text.

<u>Authors</u>
List authors alphabetically. Use surnames, first names (if known) and initials.
NB: Although full first names are used in the examples in this document, it is also acceptable to use authors' initials only, as long as one system is used consistently in a given article.

The entries are additionally sorted by the work's date of publication (oldest to newest).

Do not use a dash to replace author names.

If no author or editor, order alphabetically by title (corresponding with text citation).

A single-author entry precedes a multi-author entry beginning with the same surname.

Successive entries by two+ authors, where the first author is the same, are alphabetised by co-authors' surnames.

Titles
Use headline-style capitalisation in titles and subtitles of works and parts of works such as articles or chapters (i.e., *Biology in the Modern World: Science for Life in South Africa*). Capitalise significant words and proper nouns.

Use headline-style capitalisation for titles of journals and periodicals (i.e., *Journal of Social Activism*).

Titles of stand-alone publications are typed in italics when used in text: *Evangelism and the Growth of Pentecostalism in Africa*.

Compound sources
Source within another source: Smit, R. 2012. "Where to Now?" In Climate Change in the Next Decade, edited by S. Y. Tovey and T. Rosti, 200–234. Pretoria: Van Schaik.

Treat pamphlets, reports, brochures and freestanding publications (such as exhibition catalogues) as books. Give sufficient information to identify the document.

Electronic references (**NB:** The text reference must correspond with the **alphabetical reference list**)
Author's surname, name and initials (if available); title of article/publication. website address (URL):
Macdonald, Fiona. 2017. "The Extraordinary Life of the 1920s Lady Gaga." BBC Culture, September 20. Accessed October 6, 2017. http://www.bbc.com/culture/story/20170920-the-extraordinary-life-of-the-19th-century-lady-gaga.

Personal communications, letters, conversations, emails, interviews, recordings may be listed separately in the reference list.

Omit: Inc., Co. Publishing Co. etc. from the name of the publisher.

Journals
Parentheses with issue number: When volume and issue number are used, the issue number is placed in parentheses.
Example: Morasse, Sébastien, Helga Guderley, and Julian J. Dodson. 2008."Paternal Reproductive Strategy Influences Metabolic Capacities and Muscle Development of Atlantic Salmon (Salmo salar L.) Embryos." *Physiological and Biochemical Zoology* **81 (4): 402–13.**

When only an issue number is used, it is not enclosed in parentheses. Example: Meyerovitch, Eva. 1959. "The Gnostic Manuscripts of Upper Egypt." *Diogenes*, no. 25, 84–117.

Archival material/manuscript collections
When citing archival material in the author-date style, it is unnecessary to use n.d. (no date) in place of the date. Dates of individual items should be mentioned in the text, when applicable:
(in the reference list) Egmont Manuscripts. Phillipps Collection. University of Georgia Library.
Kallen, Horace. Papers. YIVO Institute for Jewish Research, New York.
(in text) Oglethorpe wrote to the trustees on January 13, 1733 (Egmont Manuscripts), to say ...
Alvin Johnson, in a memorandum prepared sometime in 1937 (Kallen Papers, file 36), observed that ...
If only one item from a collection has been mentioned in the text, however, the entry may begin with the writer's name (if known). In such a case, the use of n.d. may become appropriate:
Dinkel, Joseph. n.d. Description of Louis Agassiz written at the request of Elizabeth Cary Agassiz. Agassiz Papers. Houghton Library, Harvard University.
(Dinkel, n.d.)

Examples (For full list of examples see http://www.chicagomanualofstyle.org/tools_citationguide/citation-guide-2.html)

R: Reference list
T: Text citation

Books

One author
R: Pollan, Michael. 2006. The Omnivore's Dilemma: A Natural History of Four Meals. New York: Penguin.
T: (Pollan 2006, 99–100).
Two or three authors
R: Ward, Geoffrey C., and Ken Burns. 2007. The War: An Intimate History, 1941–1945. New York: Knopf.
T: (Ward and Burns 2007, 52).
Four or more authors, list all of the authors in the reference list; in the text, list only the first author, followed by et al. ("and others"):
R: Barnes, L. A., A. M. Harcombe, P. B. Rall, and W. Grové. 2010. Unisa Press: An Illustrated History. Pretoria: Unisa Press.
T: (Barnes et al. 2010).
Editor, translator, or compiler instead of author
R: Lattimore, Richmond, trans. 1951. The Iliad of Homer. Chicago: University of Chicago Press.
T: (Lattimore 1951, 91–92).
Editor, translator, or compiler in addition to author
R: García Márquez, Gabriel. 1988. Love in the Time of Cholera. Translated by Edith Grossman. London: Cape.
T: (García Márquez 1988, 242–55).
Chapter or other part of a book
R: Kelly, John D. 2010. "Seeing Red: Mao Fetishism, Pax Americana, and the Moral Economy of War." In Anthropology and Global Counterinsurgency, edited by John D. Kelly, Beatrice Jauregui, Sean T. Mitchell, and Jeremy Walton, 67–83. Chicago: University of Chicago Press.
T: (Kelly 2010, 77).
Chapter of an edited volume originally published elsewhere (as in primary sources)

R: Cicero, Quintus Tullius. 1986. "Handbook on Canvassing for the Consulship." In Rome: Late Republic and Principate, edited by Walter Emil Kaegi Jr. and Peter White. Vol. 2 of University of Chicago Readings in Western Civilization, edited by John Boyer and Julius Kirshner, 33–46. Chicago: University of Chicago Press. Originally published in Evelyn S. Shuckburgh, trans. 1908. The Letters of Cicero, vol. 1. London: George Bell & Sons.
T: (Cicero 1986, 35)

Preface, foreword, introduction, or similar part of a book

R: Rieger, James. 1982. Introduction to Frankenstein; or, The Modern Prometheus, by Mary Wollstonecraft Shelley, xi–xxxvii. Chicago: University of Chicago Press.
T: (Rieger 1982, xx–xxi)

Book published electronically

If a book is available in more than one format, cite the version you consulted. For books consulted online, list a URL and include an access date. If no fixed page numbers are available, you can include a section title or a chapter or other number.
R: Austen, Jane. 2007. Pride and Prejudice. New York: Penguin Classics. Kindle edition.
T: (Austen 2007)
R: Kurland, Philip B., and Ralph Lerner, eds. 1987. The Founders' Constitution. Chicago: University of Chicago Press. http://press-pubs.uchicago.edu/founders/ (accessed January 1, 2012).
T: (Kurland and Lerner, chap. 10, doc. 19)

Journal articles

Article in a print journal

In the text, list the specific page numbers consulted, if any. In the reference list entry, list the page range for the whole article.
R: Weinstein, Joshua I. 2009. "The Market in Plato's Republic." Classical Philology 104 (4): 439–58. https://doi.org/10.1086/650979.
T: (Weinstein 2009, 440)

Article in an online journal

Include a DOI (Digital Object Identifier) if the journal lists one. Do not put a full stop after the DOI—A DOI is a permanent ID that, when appended to https://doi.org/ in the address bar of an Internet browser, will lead to the source. If no DOI is available, list a URL and provide an access date.
R: Kossinets, Gueorgi, and Duncan J. Watts. 2009. "Origins of Homophily in an Evolving Social Network." American Journal of Sociology 115: 405–50. https://doi.org/10.1086/599247.
T: (Kossinets and Watts 2009, 411)

Other sources

Book review

R: Kamp, David. 2006. "Deconstructing Dinner." Review of The Omnivore's Dilemma: A Natural History of Four Meals, by Michael Pollan. New York Times, April 23, Sunday Book Review. Accessed January 1, 2012. http://www.nytimes.com/2006/04/23/books/review/23kamp.html
T: (Kamp 2006)

Thesis or dissertation

R: Choi, Mihwa. 2008. "Contesting Imaginaires in Death Rituals during the Northern Song Dynasty." PhD diss., University of Chicago.
T: (Choi 2008)

Paper presented at a meeting or conference

R: Adelman, Rachel. 2009. "'Such Stuff as Dreams are Made On': God's Footstool in the Aramaic Targumim and Midrashic Tradition." Paper presented at the annual meeting for the Society of Biblical Literature,

New Orleans, Louisiana, November 21–24.
T: (Adelman 2009)

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