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MASTER THESIS

THE USE OF NON-COGNITIVE FACTORS TO IDENTIFY ENGINEERING STUDENTS AT RISK

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Abstract

Introduction: Underprepared students lead to drop out, which in turn leads to economic loss and a shortage of high-level skills. Identifying and supporting students at risk is, therefore, important. As shown by the meta-analysis conducted by Credé and Kuncel (2008), non-cognitive factors (also known as non-intellective factors) such as study habits, emotional intelligence skills, and attitude rival standardized tests and previous grades as predictors of academic performance. The need to also consider non-cognitive factors to protect the investment in engineering education made by the South African society, is therefore essential. It is hoped that if study habits, emotional intelligence skills, and attitudes can be developed, students will be better equipped to navigate the educational landscape. This work provides a machine-learning-based methodology of how to identify students at risk and proposes a series of interventions to enhance study habits, emotional intelligence skills, and attitude.

Methods: A sample of (n = 1439) undergraduate engineering students at TUT completed the risk profiling, administered by the SDS (Student Development and Support) division at TUT, from 2011 to 2015. Students in the sample all wrote a National Examination at the end of Grade 12 to obtain the National Senior Certificate (NSC). The students in the sample were admitted based only on their NSC results. All students in the sample enrolled for a three-year National Diploma in Engineering. The National Diploma comprises two years (four semesters) of theoretical study and one year (two semesters) of industry placement.

The students in the sample completed the Emotional Skills Assessment Process (ESAP) and the Learning and Study Strategies Inventory (LASSI) during the first-year orientation period. Student success was then predicted based on the non-cognitive factors measured during the first-year orientation. The LASSI and ESAP results were used as independent variables. The time students spend at TUT before dropping out from the qualification or graduating with the qualification, and the Credit Accumulation Rates (CAR) of students, were used as dependent variables.

Results: The results obtained showed that some non-cognitive factors, identified during the beginning of the first year, are strongly linked to academic success. Although many factors have an impact on student academic success, the non-cognitive *precursors* to academic efficacy are often overlooked. The results obtained in this study show that interventions focusing on building emotional intelligence competencies, specifically on skills related to Assertion, Time Management, Self-Esteem, Stress Management, Deference, and Change Orientation, might have significant and lasting long-term effects on student success. Further work should focus on the design and delivery of suitable interventions.

Keywords
Non-cognitive factors, At-risk students, Student Success, Undergraduate Engineering studies, Graduation Rates, First-year interventions

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ABBREVIATIONS

CAR: Credit Accumulation Rates
CHE: Council for Higher Education
DHET: Department of Higher Education and Training
ESAP: Emotional Skills Assessment Process
HESA: Higher Education South Africa
HEMIS: Higher Education Management Information System
LASSI: Learning and Study Strategies Inventory
NBTP: National Benchmark Tests Project
NDip: National Diploma
NSC: National Senior Certificate
OECD: Organization for Economic Cooperation and Development
SDS: Student Development and Support
TUT: Tshwane University of Technology
UoT: Universities of Technology

1 INTRODUCTION

1.1 MOTIVATION FOR THIS STUDY

As previously discussed in van Wyk BJ, Hofman WAH et al. (2015)[1], the theory of human capital (Becker 1967, Becker 1967, Becker 2009) forms the starting point for an economic perspective on Education. The length of the study duration in university education is interpreted as the result of individual cost-benefit considerations. Costs and benefits are interpreted in the broadest possible sense so that not just financial but also immaterial arguments, e.g., 'usefulness and satisfaction,' are considered (Oosterbeek and van Ophem 1995). Although cost-benefit considerations are individuals' decisions, the decision is not reached on a purely individual basis. The size and form of the individual's costs and benefits are not only influenced by his or her unique characteristics, e.g., capacities, but the student's social and cultural contexts are also expected to play a role (Brown 2013). For example, the Education professions of the student's parents, as well as the parental income strongly associated with this, are co-determinants for the form and size of the cost-benefit curves (Van den Berg and Hofman 2005). In the so-called cultural theories, a distinction is made between the theoretical conflict vision, in which an individual's social status, race, and gender determine his social position, and the structural fundamentalistic vision (Terenzini and Pascarella 1980, Tinto 2006, Tinto 2007). In this second vision, do not only social status, race, and gender play a role but also individual (psychological) characteristics, such as aptitude, motivation, and effort. Socially acquired skills are also explained by (school) experiences which the individual acquires. In this study, the focus is on the impact of individual non-cognitive factors on study success.

Underprepared students lead to drop out, which in turn leads to economic loss and a shortage of high-level skills. Scott, Yeld et al. (2007) re-iterated the findings of Moleke (2005), who pointed to the fact that high-level skills shortages that have been identified

[1] This work is a continuation of a previous study dealing with *cognitive* factors and school performance: van Wyk BJ, Hofman WAH, Louw I (2015). "Impact of Mathematics and Physics on the Success of South African Engineering Technology Students." International Journal of Engineering Education **31**(4): 1158–1166. The motivation for studying cognitive and *non-cognitive* factors is the same from an economic perspective, and are therefore repeated here.

are clear indicators that the country's needs are not met and that there is a level of mismatch between output and the requirements of the economy.

Various studies have shown that the study duration and success rate vary considerably between countries. While higher education participation rates have risen sharply in many European countries, about one-third of all entrants leave higher Education without completing a degree. Completion grades vary greatly between countries: in some countries only a minority of entrants complete the course; in others almost all do. We observe higher education survival rates ranging from over 80% in the United Kingdom to 55% or less in Austria, France, Portugal and Turkey; in Italy the survival rate is just 35% (Co-operation and Development 2010, Development 2010) . Overall, we observe a third of students in OECD countries to withdraw from higher Education before obtaining a diploma (Co-operation and Development 2010). There are considerable differences in the success rate between various fields of study. The highest success rates are often found in medicine and dentistry courses. The technology sector often falls behind with only moderate or low success rates.

In South Africa, the situation is not better. The Higher Education Management Information System (HEMIS) of the Department of Higher Education and Training (DHET) only recently matured to such an extent that broad undergraduate cohort studies, starting with the 2000 first time entering intake, became possible. Scott, Yeld et al. (2007), in a research report commissioned by the Council for Higher Education (CHE) of South Africa, reported that despite significant improvements in access that there are substantial shortcomings in performance in terms of completion rates. They performed a basic analysis of current student performance patterns using a disaggregation of student data provided by the DHET and argued that systemic responses, such as the reform of core curriculum frameworks, building educational expertise in the sector, and strengthening structures to enforce accountability, are essential for improving outcomes.

As previously referenced by Van Wyk and Basson (2014)[2], Scott, Yeld et al. (2007) showed that the 2000 cohort study conducted by the DHET showed that after five years after of entering (i.e., in 2004), only 30% of the total first time entering student intake graduated, that 14% were still in the system and that 56% left without graduating. Only 54% of the students who enrolled for a four-year professional bachelor's degree in 2000 in Engineering graduated within a five-year period, and 19% were still in the system. Although this is a disturbing overall picture, the picture for engineering students at Universities of Technology (UoTs) is much worse. Only 17% of students who enrolled for a three-year diploma in Engineering in 2000 at non-distance education institutions graduated within a five-year period, and 14% were still in the system. As a developing country, it would be shortsighted to ignore the cost associated with students leaving the system without graduating.

The predictive value of cognitive factors (referred to by Credé and Kuncel (2008) as intellective factors) is well known. Although van Wyk BJ, Hofman WAH et al. (2015) have reported on the significance of using pre-admission cognitive factors such as Grade 12 Mathematics, Science, and English for admission to South African University of Technology (UoT) students, such factors, on their own, are not sufficient to ensure increased graduation rates.

The need to also consider non-cognitive factors (referred to by Credé and Kuncel (2008) as non-intellective factors) in an attempt to protect the investment in engineering education made by the South African society, is therefore not an option anymore. This point of view is supported by Credé and Kuncel (2008), who conducted a meta-analysis and found that constructs such as study habits, skill, and attitude rival standardized tests and previous grades as predictors of academic performance. The logical corollary then is that if study habits, emotional intelligence skills, and attitude can be developed, that students will be better equipped to navigate the educational landscape (Conley 2010).

[2] Similar to cognitive and non-cognitive factors, finding placement in industry for Work Integrated Learning (WIL), is also a factor influencing throughput in the South African context. This has been explored in Van Wyk BJ and Basson SN (2014) *To WIL or not to WIL,* 6th International Conference on Education and New Learning Technologies, Barcelona, Spain, 7-9 July, 5246-5249, and the completion rate statistics presented are also relevant to the current study.

1.2 CHAPTER OVERVIEW

Chapter 2 deals in more detail with the Research Objective, the Research Questions and the Methodology.

Chapter 3 is a review of the relevant literature, focusing on the Emotional Skills Assessment Process (ESAP) and Learning and Study Strategies Inventory (LASSI) questionnaires for assessing non-cognitive (also referred to as non-intellective) factors.

The experimental results are discussed in Chapter 4, including the use of Machine Learning to identify students at risk. A discussion on the implications of the results and recommendations are provided in Chapter 5.

2 OBJECTIVE, QUESTIONS, AND METHODOLOGY

2.1 CHAPTER OVERVIEW

In this Chapter, the Research Objective, Research Questions are stated, and the process that was followed to obtain the reported results is discussed.

2.2 RESEARCH OBJECTIVES

The main objective of this research is to improve the identification of first-year Tshwane University of Technology (TUT) undergraduate engineering students at risk so that limited resources for interventions could be utilized in a more targeted way. This will be done by predicting success based on the non-cognitive factors measured during the first-year risk assessment, and the time students spend at TUT before dropping out from the qualification or graduating with the qualification, and the Credit Accumulation Rates (CAR) of students.

2.3 RESEARCH QUESTIONS

2.3.1 Which non-cognitive factors contribute most to student success?

2.3.2 What do we learn from investigating relationships between non-cognitive factors measured during the first-year risk profiling, the time students spend in the TUT system before dropping out or graduating, and the Credit Accumulation Rates (CAR) of students?

2.3.3 How can Machine Learning be used to improve the identification of first year engineering students at risk and the support needed by such students?

2.4 RESEARCH POPULATION

A sample of (n = 1439) undergraduate engineering students at TUT completed the risk profiling, administered by the SDS (Student Development and Support) division at TUT, from 2011 to 2015. Since attending the risk profiling during this period was strongly encouraged, but not strictly enforced, the sample is lower than the actual number of first-year students in engineering that joined TUT during this period, but is still considered representative.

Students in the sample all wrote a National Examination at the end of Grade 12 to obtain the National Senior Certificate (NSC). International students and other students who have not followed the NSC curriculum were not included in the sample. The students in the sample were admitted based only on their NSC results.

All students in the sample enrolled for a three-year National Diploma in Engineering. The National Diploma comprises two years (four semesters) of theoretical study and one year (two semesters) of industry placement.

2.5 INDEPENDENT VARIABLES: ESAP AND LASSI CONSTRUCTS

The students in the sample completed the Emotional Skills Assessment Process (ESAP) and the Learning and Study Strategies Inventory (LASSI).

As shown in Table 1, the ESAP, developed by Nelson, Low, and Vela, measures *four* (4) Emotional Intelligence Dimensions and *thirteen* (13) Emotional Intelligence skills. The ESAP contains 213 items. According to the developers, it provides an assessment of personal emotional skills essential to academic success and career excellence (Nelson D. 2003).

1: INTERPERSONAL SKILLS	Assertion
2: LEADERSHIP SKILLS	Comfort
	Empathy
	Decision Making
	Leadership
3: SELF MANAGEMENT SKILLS	Drive Strength
	Time Management
	Commitment Ethic
4: INTERPERSONAL SKILLS	Self Esteem
	Stress Management
POTENTIAL PROBLEMS AREAS	Aggression
	Deference
	Change Orientation

Table 1: ESAP scales https://eilearningsys.files.wordpress.com/2011/08/10-esap-interpretation-intervention-guide.pdf

The LASSI probes the use of learning and study strategies related to skill, will, and self-regulation. The third edition is a 10-scale, 60-item instrument aimed at measuring the thoughts, behaviors, attitudes, and beliefs related to successful learning (Weinstein, Palmer et al. 1987, Weinstein, Schulte et al. 1987, Weinstein, Zimmermann et al. 1988, Weinstein and Palmer 2002). The 10 LASSI scales are listed in Table 2.

Anxiety	Attitude
Concentration	Information Processing
Motivation	Selecting main ideas
Self-testing	Test strategies
Time-management	Using academic resources

Table 2: LASSI Scales https://www.hhpublishing.com/ap/_assessments/LASSI-3rd-Edition.html

2.6 DEPENDENT VARIABLE: ACADEMIC SUCCESS DIMENSIONS

Students are allowed double minimum time before being excluded from academic studies. For a three-year National Diploma (six semesters), students are permitted a maximum of six years (twelve semesters). Unless there is proof of extenuating circumstances, students need to obtain at least 50% of the total credits per year to be re-admitted. If a student, for example, excluded after three years, it implies that less *than 50%* of the credits for the qualification was accumulated during six semesters at TUT. On the other hand, if a student graduates after three years of study, it implies that 100% of the credits were obtained in minimum time (three years or six semesters). Also, even though the maximum time is 12 semesters (6 years), if students can provide proof of extenuating circumstances (illness, psychological problems, financial and family difficulties, etc.) or only has a small number of modules left to complete, more time is usually allowed.

Since the final aim of the study is to prevent students from dropping out, the following convenient measures will be used to measure academic success:

2.6.1 <u>The status of a student after twelve semesters</u>: The minimum time to complete a National Diploma is six semesters. The maximum time allowed is twice the minimum, i.e., 12 semesters. The maximum time is linked to the maximum period that is funded by the DHET. A student's status, i.e., whether a student after or during twelve semesters has 1) *Graduated,* 2) *Dropped Out,* or is still 3) *In System*, is, therefore, a useful measure of success.

2.6.2 The Credit Accumulation Rate (CAR) of a student: N.Dip students governed by NATED 151 regulations need to accumulate 3.0 credits to graduate. The maximum credits a student can therefore accumulate is 0.5 credits per semester or 1.0 credits per year. The average CAR of a student is, therefore, another useful measure of success. We have opted to calculate the CAR per semester. A student that completed in minimum time will have a CAR of 0.5 and a student that completed in maximum time a CAR ≤ 0.25. A CAR < 0.2 is, therefore, a good indicator that a student will not be able to complete the qualification without an intervention.

2.7 ANALYSIS OF THE DATA

MATLAB was used for the analysis of the data to determine if there exist statistically significant relationships between the independent and dependent variables and to investigate if Machine Learning algorithms, such as Bayesian Classification and Neural Networks can be used to identify students at risk.

2.8 CHAPTER CONCLUSION

In this Chapter, the Research Objective, Research Questions are stated, and the process that was followed to obtain the reported results was discussed. Chapter 3 will focus on the Literature Review.

3 LITERATURE REVIEW

3.1 ACADEMIC SUCCESS AND NON-COGNITIVE CONSTRUCTS

As discussed in Van Wyk et al. (2019)[3], the brain actively and continuously adapts at a molecular and neuronal level in the presence of a stressor. Non-academic factors related to resilience can be seen as a pre-requisite for academic performance: For students to be successful, they should have strategies able to withstand a variety of stressors, including negative institutional factors, time and exam pressure, the ability to recover from negative emotional experiences such as failure or poor grades, the ability to stay optimistic and pursue a long-term goal, such as a degree or diploma, as well as financial pressures.

Resilience in an academic context has been explored by many authors: For example, Johnston-Wilder and Lee (2010) defines resilience as a positive approach that allows people to overcome affective barriers presented when learning. They argue that although all types of learning require resilience, that the resilience needed to be successful in mathematics is mainly a consequence of the kind of teaching, the nature of mathematics, and the subjective, albeit pervasive, beliefs about mathematical ability. These findings support the seminal work of Yeager and Dweck (2012) who argue that based on their research, psychological interventions that change the mindset of students (what they believe or are taught about intellectual abilities and social attributes) increase resilience in educational settings. This resonates with the work of Hanson, Austin et al. (2003) who showed that although factors related to educators and educational climate, such as the expectations and attitudes of educators, seem to have

[3] Van Wyk, B. van Wyk, M. and Jacobs, C. (2019). RESILIENCE AS A PRECURSOR TO ACADEMIC SUCCESS. 11th International Conference on Education and New Learning Technologies. EDULEARN19. Palma de Mallorca, Spain, IATED: 5367-5370. This paper investigated the relationship between behaviours such as exercise, sleep, quiteting the mind, eating habits, etc. as measured by the Neurozone™ instrument and academic performance. The discussion here on resilience overlaps with the introduction of this paper.

an influence on academic performance, the educational aspirations of students is to be the most reliable and consistent predictor of academic resilience.

Although some researchers such as Goff (2011) found no significant relationships among stressors, learned resourcefulness (the ability to *regulate emotions and cognitions*), and academic performance from multiple regression analyses on a cohort of nursing students, this does not seem to be the case for younger students. Wong (2008) showed that a higher level of perceived parental involvement, autonomy support, and greater *self-regulation* predicted better educational outcomes for adolescent students.

Social support, in general, seems to enhance academic resilience for both adolescent and university students. In a sample of Latino students, Perez, Espinoza et al. (2009) reported that students who have high levels of *personal and environmental protective factors* such as supportive parents, friends, and participation in school activities, report higher levels of academic success than students with similar risk factors. Wilks (2008) echoed these findings for a group of social work students and published on the moderating role of *social support* in the relationship between academic stressors and resilience.

There is also a significant body of work on socioeconomically-disadvantaged students who are academically successful based on TIMSS (Trends in International Mathematics and Science Study), and Programme for International Student Assessment (PISA) results from developing countries. Erberber, Stephens et al. (2015) reported on the positive relationships between internal resilience assets (physical activity, nutrition, a safe environment), external resilience assets (provided schools, families, communities, and peers), and academic performance across socioeconomically disadvantaged students across countries. The analysis of Ainscow, Chapman et al. (2018) revealed that some developing countries were able to increase the share of resilient students over time as measured by the improvements in the average performance, resulting in a weaker relationship between socio-economic status and performance. They emphasize the role of school policies and practices related to issues such as extra-curricular activities, school disciplinary climate, teacher turn-over, leadership, and classroom climate. These findings are echoed by Sandoval-Hernández and Białowolski (2016) who also analyzed TIMSS results from developing countries and commented on the relationships between student attitude, teacher confidence, language spoken at home, time spent on mathematics at home and differences in resilience between disadvantaged and non-disadvantaged students.

For this study, we will only focus on non-cognitive constructs related to *Study Habits, Skills, and Attitudes*. A meta-analysis conducted by Credé and Kuncel (2008) showed that found that factors related to *Study Habits, Skills, and Attitudes* rival standardized tests and previous grades as predictors of academic resilience and performance. Kafka (2016) compiled a comprehensive list of standardized tests that can be used to measure non-cognitive constructs that are widely acknowledged to be essential for success. Carlson, Geisinger et al. (2014) provide information regarding the strengths and limitations of many available instruments. The Emotional Skills Assessment Process (ESAP) and Learning and Studying Strategies Inventory (LASSI) on which this study is based, focus broadly on *Study Habits, Skills, and Attitudes.* The ESAP and LASSI are well-known to the academic and student support communities and are widely used for academic risk assessment and interventions.

3.2 EMOTIONAL SKILLS ASSESSMENT PROCESS (ESAP)

Stottlemeyer (2002) conceptualized a framework for emotional intelligence in Education focused on factors affecting student achievement. Vela Jr (2004) also investigated the role of emotional intelligence in academic achievement. The work of Stottlemeyer (2002) and Vela Jr (2004), which reported significant relationships between emotional intelligence skill scales and academic achievement, laid the foundation for the Emotional Skills Assessment Process (ESAP) evaluation, now a popular instrument for assessing emotional intelligence in an educational setting. Detailed information on how the ESAP should be interpreted is provided by Nelson D. (2003).

ESAP validation studies were carried out in China (Nelson, Jin et al. 2002), Mexico (Triujeque 2009), and in South Africa by Dockrat (2012). These studies showed that although there are differences between cultures and groups, emotional intelligence skills such as drive strength, time management, and commitment seem to be universal predictors of academic achievement.

The ESAP also has value beyond the academic achievement of students: Jani, Shahid et al. (2015) suggested that it could also be used as a tool for predicting the teaching effectiveness of lecturers, and Vivian Tang, Yin et al. (2010) demonstrated correlations between emotional intelligence and leadership practices. Ramos-Villarreal and Holland (2011) derived similar relationships between emotional intelligence and leadership, using the Personal Excellence Map (PEM). Justice and Espinoza (2007) used the ESAP as an instrument to determine skills intervention for beginning teachers to face the challenges of diverse classrooms, and Mishra, Kumar et al. (2016) showed that ESAP constructs such empathy, drive and stress management abilities could be used to predict employability of senior students.

A number of researchers also investigated the effectiveness of emotional intelligence interventions for students: Martinez, Brown et al. (2011) found that although an intervention for first-generation minority students only had a significant effect on assertion scores, students, in general, were of the opinion that an intervention focusing on emotional intelligence skills added value. Choubisa (2011) investigated the effectiveness of an internet skills-based intervention for college students in India, focusing on key emotional intelligence constructs and showed that such interventions have the potential to enhance the wellbeing of students. This is echoed by Love (2014), who reported that emotional intelligence and leadership skills could be improved by incorporating emotional intelligence training as part of a management course, and by Ramos-Villarreal and Holland (2011) who showed that first-year emotional intelligence assessments, such as ESAP, aid in cultivating student resilience by helping them understand their strengths versus weaknesses. As pointed out by Low and Nelson (2006), there is overwhelming evidence for incorporating the development of emotional intelligence and personal skills in university curricula for career success, human development education, and leadership.

3.3 LEARNING AND STUDY STRATEGY INVENTORY (LASSI)

The Learning and Study Strategies Inventory (LASSI) does not only provide diagnostic information about the self-perception of students regarding their study skills and learning orientations, but it also assists educators to design interventions for students to improve their skills, and aids in the prediction of academic achievement (Weinstein, Palmer et al. 1987, Weinstein, Schulte et al. 1987, Weinstein, Zimmermann et al. 1988, Weinstein and Palmer 2002).

Several authors investigated the reliability of the instrument (Albaili 1997, Cano 2006, Flowers, Bridges et al. 2012, Boruchovitch and Santos 2015). Although there seem to be acceptable degrees of consistency and reliability, there are exceptions. Marland, Dearlove et al. (2015) conducted an Australian study on LASSI as an enduring study skills assessment tool. They found a high degree of similarity between scores from the students at two Australian universities but noted that these scores differ considerably from those published in the LASSI manual (Weinstein, Schulte et al. 1987), which led them to question the validity of the instrument. The findings of Marland, Dearlove et al. (2015) contrast with other international studies, such as the Brazilian study conducted by Boruchovitch and Santos (2015), which provided initial evidence of content and construct validity.

Research by authors such as Jordan (2016) , Lawson (2009), and Albaili (1997) may shed some light on discrepancies: Jordan (2016) found that *only* the first-semester Grade Point Average (GPA) correlated significantly with LASSI constructs. Jordan (2016), therefore, questioned the *long-term* correlation between LASSI scores and academic performance. The work of Lawson (2009) also confirmed the usefulness of LASSI as an instrument to predict students at risk during the *first semester*. This links to the results obtained by (Cano 2006), who reported acceptable psychometric properties for his sample of first-year college students. The analysis conducted by Albaili (1997) on low- average- and high-achieving students showed that that low-achieving students scored significantly lower than the average- and high-achieving students. No significant differences were observed between the average- and high-achieving groups on any of the scales. It is therefore reasonable to assume that both timeframe and student type (low-, average- or high-performing) have an influence on results.

The most value gained from subjecting students to the Learning and Study Strategies Inventory (LASSI) should not be to predict whether students are at risk but to design interventions that empower students to excel. Examples include the work of Millikin (2011), who reported higher persistence and graduation rates for students who participated in a student success course designed to address specific barriers common to first-year students. Burkart (2017) designed a specific course aimed at students placed on academic probation that uses LASSI to spark meta-cognitive learning strategies. Structured interventions such as this the *16 Weeks to College Success* (https://he.kendallhunt.com/product/16-weeks-college-success, Burkart (2017)) where students reflect on and discuss how they will apply specific strategies to improve their academic performance, have been proven very successful in helping students succeed.

3.4 CHAPTER CONCLUSION

The relevant literature, focusing on the Emotional Skills Assessment Process (ESAP) and Learning and Study Strategies Inventory (LASSI) questionnaires for assessing non-cognitive (also referred to as non-intellective) factors, was reviewed in this Chapter. Chapter 4 will focus on the Analysis and Results obtained.

4 ANALYSIS AND RESULTS

This chapter focusses on the analysis of the results. Group trends are discussed in Section 4.1. In Sections 4.2 and 4.3, the ESAP and LASSI results are analyzed. In Section 4.4, the use of popular Machine Learning algorithms to predict student success is investigated.

4.1 GROUP TRENDS

Figure 1 to Figure 4 show the group trends for our sample of (n = 1439) undergraduate engineering students at TUT completed the risk profiling, administered by the SDS (Student Development and Support) division at TUT, during 2011 to 2015.

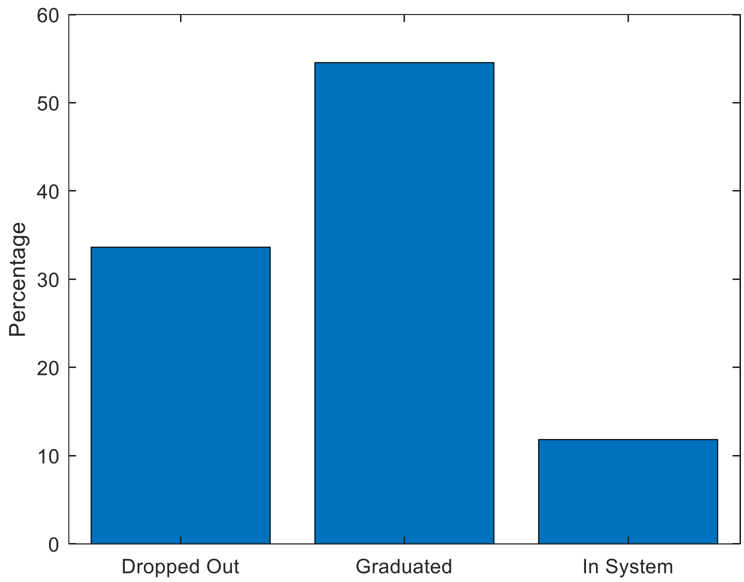

Figure 1: Percentage of Students Graduated, Dropped Out, and still In System

Figure 1 shows that 54.5% of the students graduated after 12 semesters (remember that the minimum time to complete is six semesters), 33.6% dropped out, and 11.8% are still in the system after 12 semesters. The 11.8% of students remaining in the system after 12 semesters (maximum time allowed) are usually those who successfully appealed exclusion based extenuating circumstances (illness, psychological problems, financial problems, or having only a few credits left to complete).

On average, the students dropped out after 4.3 semesters or graduated after 7.34 semesters, but since the distributions are not Gaussian, a more detailed analysis is provided in Figure 2 to Figure 4.

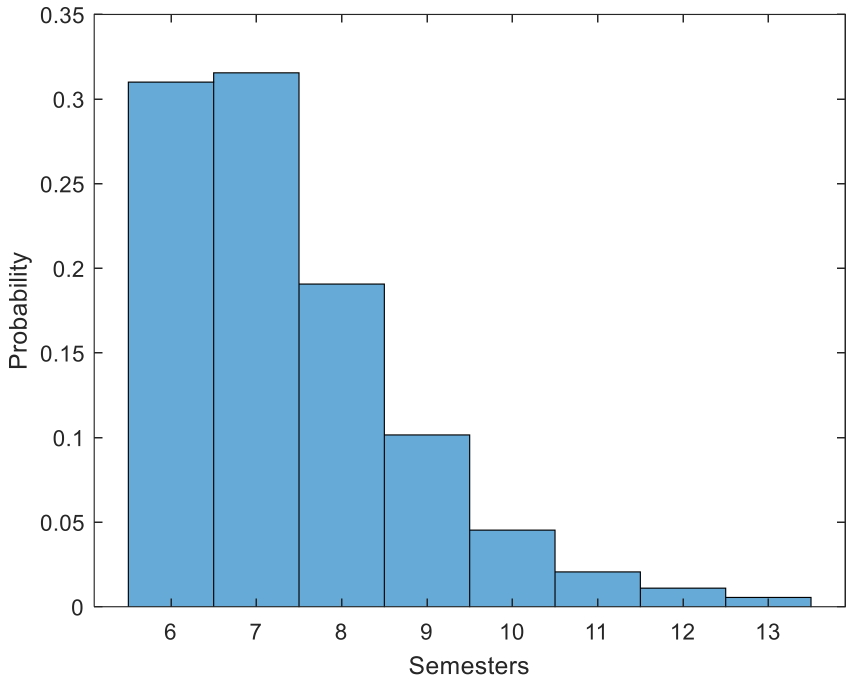

Figure 2: Probability of completing the N.Dip in a given number of semesters for the Graduated group

Figure 2 shows that slightly more than 60% of students who completed the N.Dip, did so in less than *seven* semesters. Slightly less than 20% completed in *eight* semesters, about 10% in *nine* semesters, and the rest (about 10%) in more than nine semesters.

Figure 3 shows that the probability for students in the *Dropped Out* group to leave the system is the highest during the first two semesters and is the highest (more than 26% chance). The probability increases again to more than 30% during semesters 5 to 7, but then exponentially decreases after the sixth semester.

Figure 4 shows the Average *Credit Accumulation Rate* (CAR) for all the students in the sample. The CAR plays an important role in the rest of the analysis and is defined as

$$CAR = \frac{total\ credits\ accumulated}{total\ semesters\ in\ system}.$$

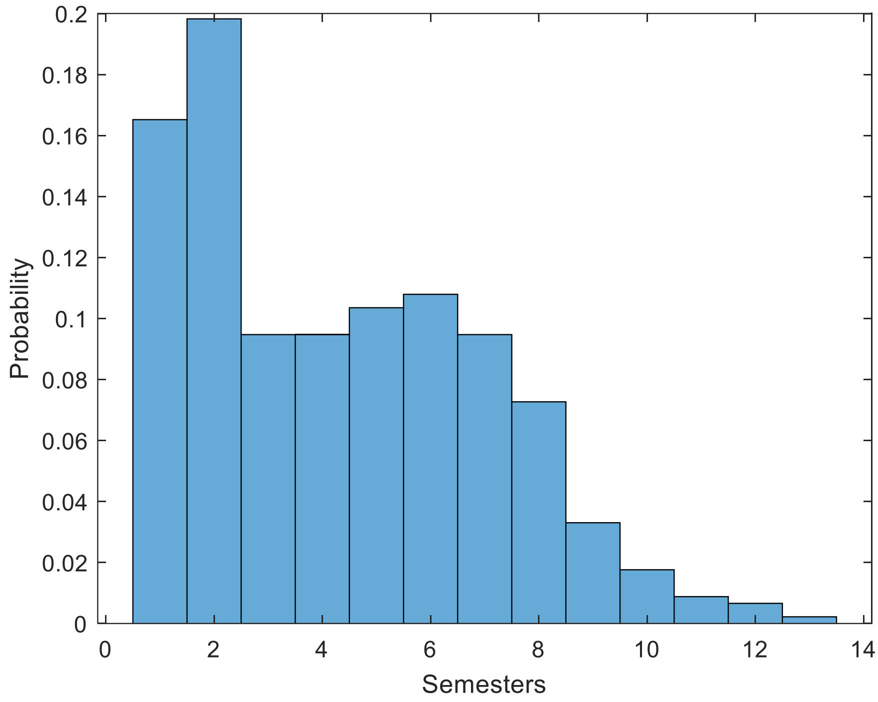

Figure 3: Probability of dropping out during a given semester for Dropped Out group

According to the NATED151 regulations governing the issuing of National Diplomas (N.Dip) in the South African system, a student needs to accumulate 3.0 credits. If the N.Dip is completed in minimum time, i.e., three years, then the CAR for the student will be

$$CAR = \frac{3}{6} = 0.5$$

If the N.Dip is completed in maximum time, i.e., six years or more, then the CAR for the student will be

$$CAR < \frac{3}{12} = 0.25$$

From Figure 4, it is clear that slightly more than 40% of the students in the cohort managed to maintain an average CAR of > 0.4.

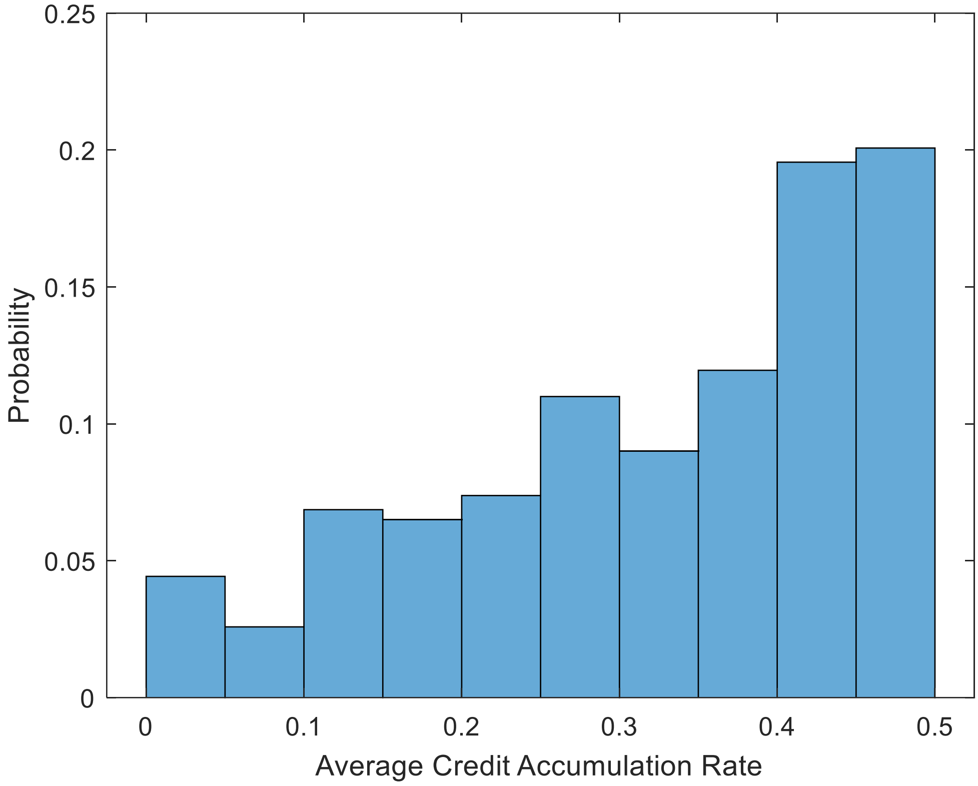

Figure 4: The average credits accumulated per semester for the entire group

MATLAB was used to analyze the data and determine the significance values. The results for the ESAP and LASSI dimensions are shown in the following sections. The aim was to determine if any of the ESAP and LASSI dimensions are significantly different between the Graduated, Dropped Out, and In-System groups, and if there are significant differences between students with different CAR values.

4.2 ESAP RESULTS

Table 3: Comparison of ESAP scale means and standard deviations for first-year college students from Texas A&M and TUT

ESAP Scale	Mean (A&M)	Std. Deviation (A&M)	Mean (TUT)	Std. Deviation (TUT)
Assertion	23.4	5.3	24.0	4.6

Aggression	9.7	6.3	10.0	5.4
Deference	16.6	7.6	17.3	6.4
Comfort	18.2	3.9	17.7	3.2
Empathy	19.0	4.4	18.6	4.0
Decision Making	15.3	4.2	16.4	3.6
Leadership	16.9	4.8	16.7	4.2
Self Esteem	35.3	8.0	36.6	5.8
Stress Management	30.5	11.3	33.1	8.0
Drive Strength	35.2	7.6	38.5	6.3
Time Management	15.3	4.8	17.9	4.3
Commitment Ethic	17.8	4.0	18.3	3.6
Change Orientation	10.0	5.7	10.1	4.8
	N = 760		N = 1355	

(Nelson D. 2003)

Table 3 is a comparison between the means and standard deviations of the ESAP scales of our sample with the standard Texas A&M sample. Table 3 shows that the TUT students in the sample and the Texas A&M students referenced in the ESAP documentation [*https://eilearningsys.files.wordpress.com/2011/08/10-esap-interpretation- intervention -guide.pdf*], exhibit very similar trends (Nelson D. 2003). A standard deviation outlier that perhaps needs further investigation is Stress Management.

Table 4 displays that when the ESAP scales of the *Graduated* sub-group, is compared with the lumped *Dropped Out,* and *In-System* sub-groups in the TUT sample, there are not many statistically significant differences. Only four ESAP scales, i.e., Time Management, Self-Esteem, Assertion, and Aggression, have *p*-values < 0.05.

Table 4: [Graduated] vs [Dropped Out & In System] *ESAP scales*
https://eilearningsys.files.wordpress.com/2011/08/10-esap-interpretation-intervention-guide.pdf

Group	ESAP scale	*p*-value
LEADERSHIP SKILLS	Comfort	0.82795
	Empathy	0.194507
	Decision Making	0.857025
	Leadership	0.776396
SELF MANAGEMENT SKILLS	Drive Strength	0.916378
	Time Management	0.042221
	Commitment Ethic	0.586858
INTERPERSONAL SKILLS	Self Esteem	0.030754
	Stress Management	0.717827
	Assertion	0.002861
POTENTIAL PROBLEMS AREAS	Aggression	0.024756
	Deference	0.108473

	Change Orientation	0.126692

Table 5 displays that of the ESAP scales of the lumped *Graduated* and *In-System* sub-groups, is compared with the *Dropped Out* sub-group in the TUT sample that different statistically significant differences show up. Only two ESAP scales, i.e., Empathy and Decision Making, have *p*-values < 0.05.

Table 5: [Graduated & In System] vs [Dropped Out] *ESAP scales*
https://eilearningsys.files.wordpress.com/2011/08/10-esap-interpretation-intervention-guide.pdf

Group	ESAP scale	*p*-value
LEADERSHIP SKILLS	Comfort	0.423844
	Empathy	0.028354
	Decision Making	0.031064
	Leadership	0.431889
SELF MANAGEMENT SKILLS	Drive Strength	0.776759
	Time Management	0.064469
	Commitment Ethic	0.570468
INTERPERSONAL SKILLS	Self Esteem	0.161342
	Stress Management	0.960846
	Assertion	0.08398

POTENTIAL PROBLEMS AREAS	Aggression	0.051638
	Deference	0.283955
	Change Orientation	0.298333

Since not much in terms of targeted areas for intervention could be inferred from Table 4 and Table 5, the differences between students with different CAR values were investigated. The results are shown in Table 6. Table 6 shows that for a CAR of 0.1, 95 students in the sample has a CAR < 0.1 denoted as Below Threshold (BT), and that 1251 students have a CAR > than 0.1, denoted as Above Threshold (AB). Consider a CAR of 0.5 as another example: The BT and AT values for a CAR of 0.5 are 1084 and 262, respectively.

GROUP	ESAP scale	*Credit accumulation rate*				
		0.1	0.2	0.3	0.4	0.5
		Classification group sizes (AT ≥ above CAR threshold, BT < below CAR threshold)				
		BT: 95 AT: 1251	BT: 276 AT: 1070	BT: 525 AT: 821	BT: 809 AT: 537	BT: 1084 AT: 262
		p-values (Wilcoxon rank-sum)				
LEADERSHIP SKILLS	Comfort	0.27113	0.63382	0.28783	0.23687	0.43850
	Empathy	0.32642	0.14674	0.19065	0.54175	0.35809
	Decision Making	0.82987	0.91038	0.98519	0.01479	0.00873
	Leadership	0.87897	0.89388	0.67613	0.00677	0.16909

SELF MANAGEMENT SKILLS	Drive Strength	0.06656	0.13694	0.13068	0.00574	0.00013
	Time Management	0.00212	0.00658	0.01014	0.05128	0.04252
	Commitment Ethic	0.08769	0.04108	0.01926	0.00145	0.01298
INTERPERSONAL SKILLS	Self Esteem	0.75969	0.40373	0.87436	0.58036	0.49382
	Stress Management	0.26733	0.51244	0.18464	0.40098	0.00297
	Assertion	0.65175	0.03744	0.00409	0.01964	0.00304
POTENTIAL PROBLEMS AREAS	Aggression	0.22642	0.79581	0.93140	0.85811	0.17315
	Deference	0.51333	0.03383	0.00205	0.14068	0.10140
	Change Orientation	0.34754	0.05338	0.00654	0.00754	0.00192

Table 6: ESAP scales https://eilearningsys.files.wordpress.com/2011/08/10-esap-interpretation-intervention-guide.pdf

Some interesting trends, to our knowledge not reported elsewhere in the literature, are shown in Table 6:

- Nine ESAP dimensions, i.e., Decision Making, Leadership, Drive Strength, Time Management, Commitment Ethic, Stress Management, Assertion, Deference, and Change Orientation, have *p-values* < 0.05 at a specific a CAR or across all CARs (see Time Management for example).
- It is evident that on the one end of the spectrum where CAR = 0.5, that differences in the AT and BT groups are remarkably different, but that statistically significant differences either fade or completely disappear as we move towards the other end of the spectrum where CAR = 0.1. Time Management, Commitment Ethic, and Assertion are good examples.
- Designing interventions that focus on Decision Making, Leadership, Drive Strength, Time Management, Commitment Ethic, Stress Management, Assertion,

Deference, and Change Orientation dimensions might improve academic performance.

4.3 LASSI RESULTS

Table 7 displays that when the LASSI scales of the *Graduated* sub-group, is compared with the lumped *Dropped Out* and *In-System* sub-groups in the TUT sample, Table 8 shows the LASSI scales of the lumped *Graduated* and *In-System* sub-groups, compared with the *Dropped Out* sub-group. Unfortunately, these comparisons have not exposed any statistically significant differences.

Table 7: [Graduated] vs [Dropped Out & In System] LASSI Scales
https://www.hhpublishing.com/ap/_assessments/LASSI-3rd-Edition.html

LASSI scale	*p*-value
Anxiety	0.216579
Attitude	0.12147
Concentration	0.051229
Information Processing	0.910706
Motivation	0.063
Selecting main ideas	0.179263
Self-testing	0.905765
Test strategies	0.07139
Time-management	0.067954

Using academic resources	0.107969

Table 8: [Graduated & In System] vs [Dropped Out] LASSI Scales
https://www.hhpublishing.com/ap/_assessments/LASSI-3rd-Edition.html

LASSI scale	*p*-value
Anxiety	0.725475
Attitude	0.489463
Concentration	0.202421
Information Processing	0.476702
Motivation	0.064843
Selecting main ideas	0.700171
Self-testing	0.280818
Test strategies	0.69455
Time-management	0.076079
Using academic resources	0.21877

Since not much in terms of targeted areas for intervention could be inferred from Table 7 and Table 8, the differences between students with different CAR values were investigated. The results are shown in Table 9. Similarly to Table 6, Table 9 shows that for a CAR of 0.1, 95 students in the sample has a CAR < 0.1 denoted as Below Threshold (BT), and that 1251 students have a CAR > than 0.1, denoted as Above Threshold (AB). Similarly, for a CAR of 0.5: The BT and AT values for a CAR of 0.5 are 1084 and 262, respectively.

LASSI scale	*Credit accumulation rate (CAR)*				
	0.1	0.2	0.3	0.4	0.5
	Classification group sizes (AT ≥ above CAR threshold, BT < below CAR threshold)				
	BT: 95 AT: 1251	BT: 276 AT: 1070	BT: 525 AT: 821	BT: 809 AT: 537	BT: 1084 AT: 262
	p-values (t-test and Wilcoxin rank sum)				
Anxiety	0.56790	0.76759	0.15999	0.03214	0.00325
Attitude	0.02512	0.02590	0.00535	0.00385	0.00005
Concentration	0.21732	0.00907	0.00051	0.00079	0.01936
Information Processing	0.13346	0.96048	0.42423	0.17630	0.01480
Motivation	0.00358	0.00003	0.00001	0.00000	0.00000
Selecting main ideas	0.54959	0.38907	0.08545	0.10869	0.01200
Self-testing	0.19539	0.22781	0.11462	0.22049	0.11557
Test strategies	0.10598	0.04118	0.00771	0.00050	0.00002
Time-management	0.10006	0.00023	0.00020	0.00069	0.00117
Study Aids	0.41990	0.49120	0.28230	0.23975	0.64969

Table 9: LASSI Scales https://www.hhpublishing.com/ap/_assessments/LASSI-3rd-Edition.html

Similarly, as for the ESAP analysis, some interesting trends, to our knowledge not reported elsewhere in the literature, are shown in Table 9:

- Eight LASSI dimensions, i.e., Anxiety, Attitude, Concentration, Information Processing, Motivation, Selecting Main Ideas, Test Strategies, and Time-Management, have *p-values* < 0.05 at a specific a CAR or across all CARs (see Time Management for example, which was also flagged in the ESAP results).

- It is obvious that on the one end of the spectrum where CAR = 0.5, that differences in the AT and BT groups are remarkably different, but that statistically significant differences either fade or completely disappear as we move towards the other end of the spectrum where CAR = 0.1. Attitude and Motivation are good examples.

Designing interventions that focus on Anxiety, Attitude, Concentration, Information Processing, Motivation, Selecting Main Ideas, Test Strategies, and Time-Management, might improve academic performance.

4.4 USING MACHINE LEARNING ALGORITHMS TO PREDICT STUDENT PERFORMANCE

Computer-based training and computer-aided instruction were supplemented by intelligent systems more than three decades ago (Beck, Stern et al. 1996). Luckin, Holmes et al. (2016) makes a strong case for the use of AI in the development of adaptive learning environments that are flexible, inclusive, personalized, engaging, and effective. Conati, Porayska-Pomsta et al. (2018) put forward a convincing case for constructing Artificial Intelligence (AI) models of learners' cognition and emotions to support human learning and teaching. AI ventures that improve anything from student learning to teacher training to school management will have a profound effect on the future of education (Hao 2019).

Given the popularity of Machine Learning, a sub-division of Artificial Intelligence is gaining in Education, it is worthwhile to investigate how accurate popular Machine Learning algorithms can predict student performance using *only* LASSI and ESAP results. Applying Bayesian classification to the LASSI and ESAP results are explored in Section 4.4.1, and Neural Network classification is explored in Section 4.4.2.

4.4.1 BAYESIAN CLASSIFICATION USING ESAP AND LASSI

In this section, using the classical Naïve Bays classifier to predict student performance is explored. This type of classifier assumes that observations have a multivariate Gaussian distribution given class membership, but the predictor or features composing the observation are independent. MATLAB was used to train the model, and after training, posterior probabilities are used to predict class membership. Half the data was used for training the model, and after training, the remaining data were used to test the prediction accuracy of the model.

Table 10 displays the result for predicting if a sample belongs to the *Graduated* sub-group, or the lumped *Dropped Out* and *In-System* sub-groups. Although the overall accuracy is 62.62%, it is clear that the *Dropped Out,* and *In-System* classification ability of the system is severely deficient, and using such a system to predict whether a student will Drop Out is too inaccurate to be of any practical value.

Table 10: [Graduated] vs [Dropped Out & In System]

	Graduated: 440 Dropped Out & In System: 237
Overall Correctly Classified (%)	62.62
Graduated correctly classified (%)	91.81
Dropped Out and In System correctly classified (%)	8.43

Table 11 displays the result for predicting if a sample belongs to the lumped *Graduated* and *In-System* sub-groups, or the lumped *Dropped Out* sub-group. Although the overall accuracy is only 52.7%, it is clear that the *Dropped Out* classification ability of the system significantly improved when compared to Table 10. Although there is an overall improvement in performance, using such a system to predict whether a student will Drop Out is still too inaccurate to be of any practical value.

Table 11: [Graduated & In System] vs [Dropped Out]

	Graduated & In System: 361 Dropped Out: 316
Overall Correctly Classified (%)	52.73
Graduated and In-System correctly classified (%)	70.08
Dropped Out correctly classified (%)	32.91

Using Bayesian classification to predict the CAR thresholds are shown in Table 12. This approached yielded more useful results. As can be seen in Table 12, using results in the intersection of two predictions may have more practical value:

- We can correctly predict 87.77% of students that have a CAR of 0.2 or more.
- We can accurately predict 84.6% of students who will have a CAR < 0.5
- We can correctly predict 65.59% of students who will have a CAR < 0.4
- Using the intersection of AT and BT predictions can, therefore, be used to identify students who will need additional support. We can also use these predictions to establish the intensity of the support.

Table 12: Credit Accumulation Rate Prediction (without re-substitution)

	Credit Accumulation Rate (CAR)				
	0.1	0.2	0.3	0.4	0.5
	Classification group sizes *(AT ≥ above CAR threshold, BT < below CAR threshold)*				
	BT: 47 AT: 625	BT: 138 AT: 535	BT: 262 AT: 410	BT: 404 AT: 268	BT: 542 AT: 131
Overall Correctly Classified (%)	92.90	74.59	56.42	59.67	73.55
AT correctly classified (%)	99.68	**87.77**	66.82	50.91	28.88
BT correctly classified (%)	4.16	22.62	40.44	**65.59**	84.68

It was found that PCA feature transformation on the ESAP and LASSI scales do not improve the performance of the Bayesian Classifier, not when considering all the Principle Components, or when considering only the 20 most significant Principle Components.

4.4.2 NEURAL NETWORK CLASSIFICATION USING ESAP AND LASSI

In this section, using a simple Neural Network classifier to predict student performance is explored. A Neural Network is a network composed of artificial neurons for solving Artificial Intelligence (AI) problems. MATLAB was used for implementation. As shown in Figure 5, a network with five hidden layers and one output layer, trained using Leveberg-Marquardt parameter optimization and the Mean Squared Error as a cost function, was used. The best overall performance was obtained when using five hidden layers. Figure 6 is an example of training performance, showing that the best Mean Squared Error was obtained after 11 Epochs when training to predict for a CAR > 0.3.

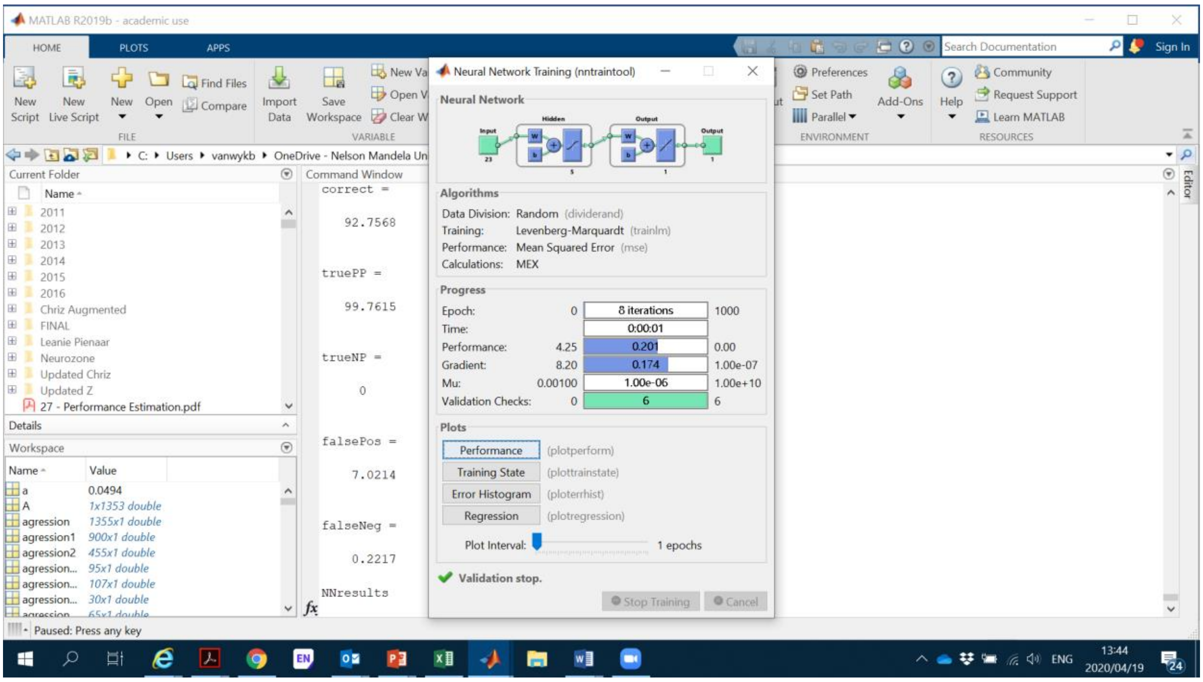

Figure 5: MATLAB Neural Network Implementation

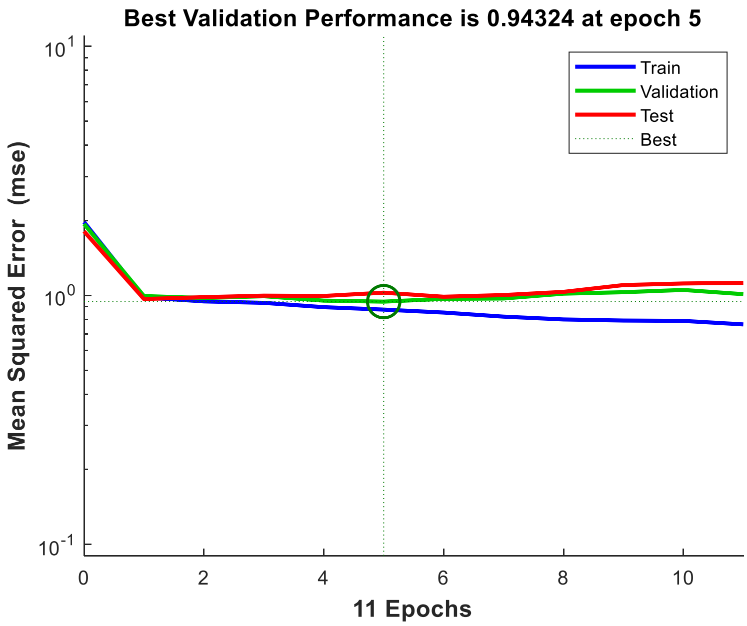

Figure 6: 0.3 CAR

Table 13 displays the result for predicting if a sample belongs to the *Graduated* sub-group, or the lumped *Dropped Out* and *In-System* sub-groups. Although the overall accuracy is only 55.6%, it is clear that even though the system is fairly accurate to predict the *Graduated* group, it is significantly less accurate for the lumped *Dropped Out* and *In-System* sub-groups.

Table 14 shows the results if the Graduated and In-System sub-groups are lumped, but the results are not accurate enough for any practical significance.

Table 13: [Graduated] vs [Dropped Out & In System]

	Graduated: 440 Dropped Out & In System: 237
Overall Correctly Classified (%)	55.58
Graduated correctly classified (%)	72.49
Dropped Out and In-System correctly classified (%)	35.28
False positives (%)	29.41
False negatives (%)	15.00

Table 14: [Graduated & In System] vs [Dropped Out]

	Graduated & In System: 361 Dropped Out: 316
Overall Correctly Classified (%)	68.36
Graduated correctly classified (%)	88.97
Dropped Out and In-System correctly classified (%)	27.69
False positives (%)	24.31

False negatives (%)	7.31

Table 15: Neural Network CAR prediction

	Credit Accumulation Rate (CAR)				
	0.1	0.2	0.3	0.4	0.5
	Classification group sizes (AT ≥ above CAR threshold, BT < below CAR threshold)				
	BT: 95 AT: 1251	BT: 276 AT: 1070	BT: 525 AT: 821	BT: 809 AT: 537	BT: 1084 AT: 262
Overall Correctly Classified (%)	92.97	**80.63**	64.30	60.97	80.11
AT correctly classified (%)	100	**97.40**	94.08	54.39	1.84
BT correctly classified (%)	0	15.21	17.33	**65.42**	99.72

Using a Neural Network to predict the CAR thresholds are shown in Table 15. Similar to Naïve Bayes classification, this approach yielded more useful results. As can be seen in Table 15 using results in the intersection of two predictions have more practical value:

- We can correctly predict 97.4% of students who will achieve a CAR > 0.2.
- We can accurately predict 65.42% of students will achieve a CAR < 0.4
- As shown in Table 15, using the intersection of AT and BT predications can, therefore, be used to predict which students will need additional support. We can also use these predictions to establish the intensity of the required support.

As shown in Table 16, we found that similar to the Bayesian Classifier, PCA feature transformation on the ESAP and LASSI scales do not improve the performance of the Neural Network performance when considering all the Principle Components, or when considering only the 20 most significant Principle Components. Each principal component is a linear combination of the original ESAP and LASSI variables (scales), and the principal components are orthogonal to each other (forming an orthogonal basis for the space of the data), so there is no redundant information.

Table 16: PCA Dimensionality Reduction

Overall Correctly Classified (%)	*Credit Accumulation Rate (CAR)*				
	0.1	0.2	0.3	0.4	0.5
	Classification group sizes (AT ≥ above CAR threshold, BT < below CAR threshold)				
	BT: 95 AT: 1251	BT: 276 AT: 1070	BT: 525 AT: 821	BT: 809 AT: 537	BT: 1084 AT: 262
20 Principle Components	93.2003	**79.6009**	63.1929	59.6452	76.4228
10 Principle Components	92.9786	**79.8965**	62.6016	54.9150	80.0443

4.5 CHAPTER CONCLUSION

This Chapter focused on the analysis of our data. Group trends were discussed in Section 4.1. The ESAP and LASSI results were analyzed in Sections 4.2 and 4.3, respectively, and in Section 4.4, the use of Bayesian Analysis to predict student success was investigated. From the results, it is clear that non-cognitive factors do play a role in success, that the most salient factors can be identified, and that students most in need of interventions can be identified.

5 DISCUSSION AND RECOMMENDATIONS

In this Chapter, we will discuss our results based on the results obtained in Chapter 4 and the Research Questions stated in Section 2.3. Recommendations for implementation and future work are given before some concluding remarks are made.

5.1 RESEARCH QUESTION I

Research Question	Which non-cognitive factors contribute most to student success?
Discussion	Eight LASSI dimensions, i.e., Anxiety, Attitude, Concentration, Information Processing, Motivation, Selecting Main Ideas, Test Strategies, and Time-Management, have *p-values* < 0.05 at a specific CAR, or across all CARs. Nine ESAP dimensions, i.e., Decision Making, Leadership, Drive Strength, Time Management, Commitment Ethics, Stress Management, Assertion, Deference, and Change Orientation, have *p-values* < 0.05 at a specific a CAR or across all CARs. The non-cognitive factors contributing most to student success can, therefore, be identified.
Practical relevance	As is currently done, request students to complete the LASSI and ESAP instruments during the first few weeks upon arrival. What should be developed is a longitudinal system of interventions replacing the single feedback session for first-years currently in place. Ideally, a compulsory time-tabled weekly engagement with first-year students is needed.

5.2 RESEARCH QUESTION II

Research Question	What do we learn from investigating relationships between non-cognitive factors measured during the first-year risk profiling and the time students spend in the TUT system before dropping out or graduating?
Discussion	From Table 4 and Table 7 is clear that if only the categories Graduated, Dropped-Out and In-System are used, that the relationship between the non-cognitive factors identified during risk profiling is not that clear. However, when considering Table 6 and Table 12, it is evident that on the one end of the spectrum where CAR = 0.5, that differences in the AT and BT groups are remarkably different, but that statistically significant differences either fade or completely disappear as we move towards the other end of the spectrum where CAR < 0.25. There is a direct relationship between CAR and Graduation or Drop Out (i.e., a student with a CAR of 0.5 will graduate in minimum time, and a student with a CAR of <0.25 will be excluded (Drop Out).
Practical relevance	The CAR can be used as a measure to *direct available resources to students needing it most*. Students with a CAR < 0.35 should, therefore, receive targeted interventions and counseling. Areas such as Anxiety, Attitude, Concentration, Information Processing, Motivation, Selecting Main Ideas, Test Strategies, Time-Management, Decision Making, Leadership, Drive Strength, Commitment Ethic, Stress Management, Assertion, Deference, and Change Orientation could be tailored for interventions.

5.3 RESEARCH QUESTION III

Research Question	What recommendations can be made to improve the identification of first-year engineering students at risk and the support provided to such students?
Discussion	From Sections 4.4.1 and 4.4.2, it is clear that we can use Machine Learning, specifically Neural Networks, to identify: • We can correctly predict 97.4% of students who will achieve a CAR > 0.2. • We can correctly predict 65.42% of students will achieve a CAR < 0.4 • As shown in Table 15, using the intersection of AT and BT predictions can, therefore, be used to predict which students will need additional support. We can also use these predictions to establish the intensity of the required support.
Practical relevance	Persist with the LASSI and ESAP instruments during the first few weeks upon arrival for first-year students, and use a Neural Network, trained on the LASSI and ESAP variables. Initially, direct limited resources for non-cognitive interventions towards students in the CAR < 4 bands. From the second year onwards, CAR values on their own could be used to focus resources and interventions where needed most.

5.4 RECOMMENDATIONS

5.4.1 Recommendation 1: First-Year Assessments

The results clearly show that non-cognitive factors, identified during the beginning of the first year, are strongly linked to academic success. It is recommended that as is currently done, that students complete the LASSI and ESAP evaluations as soon as possible after joining the university, ideally during the first month after arrival. Identifying areas of development as early as possible enable the roll-out of *targeted* and *individualized* pre-emptive student interventions and support.

Table 17 (derived from *Table 9*) shows the most salient LASSI scales, ranked from most to least important on a scale from 1-10 (for a CAR of 0.5). Such a ranking elucidates the most salient areas in need of development.

LASSI Scale	Rank
Anxiety	5
Attitude	3
Concentration	8
Information Processing	7
Motivation	1
Selecting main ideas	6
Self-testing	9
Test strategies	2
Time-management	4
Study Aids	10

Table 17: Ranked LASSI scales

Similarly the most salient ESAP scales, ranked from most to least important on a scale from 1-13 (for a CAR of 0.5) are shown in Table 18 (derived from *Table 6*).

LEADERSHIP SKILLS	Comfort	12
	Empathy	11

	Decision Making	5
	Leadership	9
SELF MANAGEMENT SKILLS	Drive Strength	1
	Time Management	7
	Commitment Ethic	6
INTERPERSONAL SKILLS	Self Esteem	13
	Stress Management	3
	Assertion	4
POTENTIAL PROBLEMS AREAS	Aggression	10
	Deference	8
	Change Orientation	2

Table 18: Ranked ESAP scales

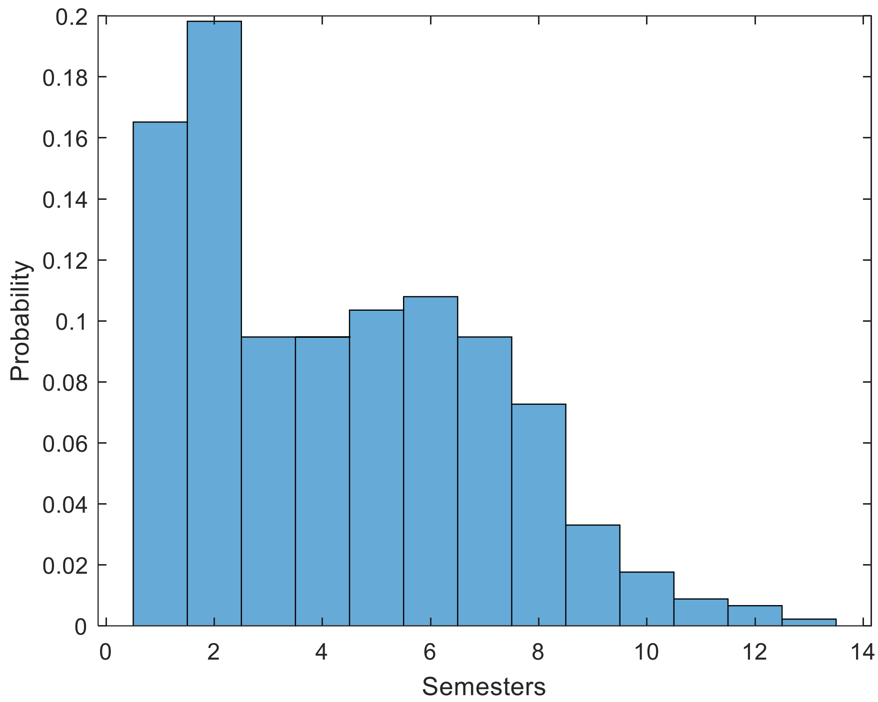

Figure 7: Probability of dropping out during a given semester for Dropped Out, group

From Figure 3 (repeated for clarity in this section), it is clear that the combined probability of dropping out during the first two semesters is > 0.28, and higher than for any subsequent semester. Since nearly 30% ($p > 0.28$) of the student population in the study dropped out during the first year, any intervention to mitigate this figure will have a positive effect on the overall graduation rate.

As was recently proposed by the Student Development and Support division at TUT, a progressive development will be to move from two assessments for *Profiling* to a comprehensive *Metacognitive Assessment Process*, comprising a battery of assessments. Additional instruments that could be included in such a battery are:

5.4.1.1 Neurozone® Brain Performance Diagnostic

As mentioned by Van Wyk (2019), many factors influence academic success, and much has been published on institutional factors, learning styles, teaching styles, and various cognitive and non-cognitive factors. Van Wyk (2019) took a different approach and investigated the influence of brain-body system drivers related to resilience as measured by the Neurozone® Brain Performance Diagnostic (Neurozone® 2017), on academic performance. A significant positive correlation was found between academic achievement and brain-body system drivers related to resilience. Since brain-body system drivers such as exercise, sleep, silencing the mind (meditation), social safety, collective creativity, etc. as defined by Neurozone®, have all been shown to enhance resilience (Neurozone® 2017), it then becomes imperative for academic institutions to facilitate the cultivation of these behaviors in order to increase the probability of academic success.

5.4.1.2 Dweck Mindset Instrument

According to Dweck (2008) the belief inherent in a growth versus fixed mindset may be a key factor in individual success in education and other areas of life. Dweck (2012) is of the view that if one believes that intelligence is fixed and immutable, one's motivation to improve intelligent behavior, such as academic achievement, would be lessened. The Dweck Mindset Instrument is a 16-item measure that assesses how students view their intelligence .

5.4.1.3 The Grit Scale

Duckworth, Peterson et al. (2007) investigated the importance of a single noncognitive trait, namely grit, on achievement. They defined grit as 'perseverance and passion for long-term goals' and found grit accounted for an average of 4% of the variance in success outcomes, including educational attainment. The Grit questionnaire designed by Duckworth, Peterson et al. (2007) has 8 items and demonstrated incremental predictive validity of success measures over and beyond IQ and conscientiousness.

5.4.1.4 The Hardiness Scale

Hardiness is a personality style associated with resilience, good health, and performance under stressful conditions. Bartone (2007) developed and verified a hardiness scale using only 15 items. The Hardiness Scale, originally popular for gauging the hardiness of military recruits, also have value in an educational setting, to complement other resilience measures.

5.4.1.5 The Wellness Questionnaire for Higher Education

Gradidge and De Jager (2011) designed the Wellness Questionnaire for Higher Education (WQHE), a self-report measure that was developed in a South African context. The WQHE comprises 119 questions, and feedback is generated in relation to six domains of wellness, namely Physical Wellness, Career Wellness, Intellectual Wellness, Environmental Wellness, Social Wellness, Emotional Wellness, and Spiritual Wellness.

5.4.2 Recommendation 2: Longitudinal Life Skills Intervention for First Years

Despite the fact that the students in the sample completed the LASSI and ESAP evaluations, *they have only been given a single feedback session*, during which the LASSI and ESAP reports were explained, and some guidance on how to address the problem areas were given. Based on the results, specifically the fact that nearly 30% dropped out during the first two semesters, the need for a different approach is obvious. What should be developed is a longitudinal system of interventions replacing the single feedback session for first-years currently in place. Ideally, *compulsory credit-bearing time-tabled weekly engagements with first-year students are needed*, systematically focusing on the following five areas:

- LEADERSHIP SKILLS
- SELF MANAGEMENT SKILLS
- INTERPERSONAL SKILLS
- STUDY SKILLS
- PROBLEM AREAS (such as Aggression, Change Orientation and Deference)

Based on past experience, students do not attend interventions if they are not credit-bearing. Integrating such interventions in a credit-bearing 15 week Life Skills module should be considered. Instead of developing customized material for such a module, existing off the shelve interventions could be used.

Possibilities for off-the-shelve solutions include:

5.4.2.1 16 Weeks to College Success

Burkart (2017b) designed a *16 Weeks to College Success* course aimed at students placed on academic probation that uses LASSI-based constructs to spark meta-cognititve learning strategies. Interventions where students reflect on and discuss how they will apply specific strategies to improve their academic performance have been proven very successful in helping students succeed (Burkart 2017).

5.4.2.1 LifeXchange Self-Management

The LifeXchange (2018) Self-Management course comprises 16 units and focuses on topics related to motivation, success, planning, mindsets, assertiveness, authority, change, goal setting, work-life balance, etc. It is a course developed within the South African context, addressing the unique challenges of previously disadvantaged participants. It can be completed online and is accompanied by a workbook containing a variety of individual and group activities. It has been piloted with a small sample of engineering students at TUT during 2019, and the majority of the students in the sample provided positive feedback.

5.4.2.1 TUT Life Skills Module

The Student Development and Support (SDS) division at TUT has developed an introductory four week (one hour per week for four weeks) Life Skills module. Students are introduced to self-management, emotional intelligence, health and wellness, and financial management. The focus is on developing well-rounded, emotionally mature, and socially responsible students who want to contribute positively to the country. Blended and self-directed learning are used to encourage students to take control of their own learning experiences via competency-based assessments that focus on skills practice and refinement. Further refining and supplementing this module to deepen the contents with additional materials to span a semester (15 weeks), is also an alternative to be considered.

5.4.3 Recommendation 3: Continued Interventions for Struggling Students

From Sections 4.4.1 and 4.4.2, it is clear that we can use Machine Learning, specifically Neural Networks, to identify:

- We can correctly predict 97.4% of students who will achieve a CAR > 0.2 (finish within minimum time)
- We can correctly predict 65.42% of students will achieve a CAR < 0.4 (finish in double the time or longer, or drop-out)

These predictions could, therefore, flag students who might need additional support beyond the weekly class sessions. These predictions could also be used to establish the intensity of the required support.

It is recommended that limited resources are initially directed towards one-on-one interventions for students in the *CAR < 0.35* bands. From the second year onwards, CAR values on their own could be used to focus resources and interventions where needed most, i.e., use the CAR as a measure to *direct available resources to students needing it most*. *Students with a CAR < 0.35 should, therefore, receive continued targeted interventions and counseling, not only during the first year but also during subsequent years.*

5.4.3.1 The Utrecht Work Engagement Scale

It might be useful during subsequent years also administer the *Utrecht Work Engagement Scale (UWES)* to determine levels of academic engagement and burnout. Work engagement is considered as the positive opposite of burnout. Specifically, Schaufeli and Bakker (2003) define work engagement "as a positive, fulfilling, work-related state of mind that is characterized by vigor, dedication, and absorption." Schaufeli (2006) adapted it to the university context and contained 14 items that serve as an empirical measure of vigor, dedication, and absorption. Students who are assessed as falling into a risk range should be referred to a practitioner for personal counseling or to a study practitioner for assistance with learning and study strategies assistance.

5.5 CONCLUSION

As previously mentioned, a number of researchers, such as Martinez, Brown et al. (2011) and Choubisa (2011) investigated the effectiveness of emotional intelligence interventions for students. Although the results of these studies showed different degrees of success, students, in general, were of the opinion that an intervention focusing on emotional intelligence skills added value and those skills-based interventions for college students, focusing on key emotional intelligence constructs have the potential to enhance the wellbeing of students. In Low, Lomax et al. (2004), there is overwhelming evidence for incorporating the development of emotional intelligence and personal skills in university curricula for career success, human development education, and leadership.

It is claimed that the Learning and Study Strategies Inventory (LASSI) does not only provide diagnostic information about the self-perception of students regarding their study skills and learning orientations, but also assist educators in designing interventions for students to improve their skills, and aids in the prediction of academic achievement (Weinstein, Palmer et al. 1987, Weinstein, Schulte et al. 1987, Weinstein, Zimmermann et al. 1988, Weinstein and Palmer 2002).

The results obtained showed that some non-cognitive factors, identified during the beginning of the first year, are strongly linked to academic success. Although many factors have an impact on student academic success, the non-cognitive *precursors* to academic efficacy are often overlooked. Although preliminary, the results obtained in this study show that interventions focusing on building emotional intelligence competencies, specifically on skills related to Assertion, Time Management, Self-Esteem, Stress Management, Deference, and Change Orientation, might have significant and lasting long-term effects on student success. Further work should focus on the design and delivery of suitable interventions.

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