Doing Things Differently:

Transformation, Innovation and Student Success in CTA and ITC

Tracy Louise Kraus

RGLTRA001

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I hereby declare that I have read and understood the regulations governing the submission of Master of Commerce dissertations, including those relating to length and plagiarism, as contained in the rules of the University, and that this dissertation conforms to those regulations.

SUPERVISOR: Mr. Riley J. Carpenter

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ABSTRACT

The need for racial transformation within the accounting profession has been highlighted in recent years and consequently, efforts have been made by numerous players to further support accounting students pursuing the chartered accountant designation. This research focuses on an innovative postgraduate accounting programme, referred to as a Certificate in Theory of Accounting (CTA), offered by a private higher education institution, CA Connect. The research examines the factors associated with academic success in that programme as well as the subsequent initial professional board exam, known as the Initial Test of Competence (ITC). The variables considered are students' demographic details (age, gender and race), prior academic performance, prior tertiary institution, previous CTA attempts, time lapses between undergraduate and postgraduate study and class format selection. While this research repeats prior work done in public education contexts within the private higher education space, it is also novel, in that it extends prior research by examining several variables which have not been investigated before, neither in the South African context nor abroad. Three logistic regression models were developed, employing both forced entry and hierarchical regression methods. The findings confirm prior research which suggests that previous academic performance is strongly positively associated with future academic success and that race is a key determinant of success, most notably in CTA. Prior tertiary institution and attending full-time, contact classes were also found to be associated with success at CTA level. However, adopting an after-hours, blended learning approach to CTA was found to be associated with success in the ITC. These findings provide further evidence of the need for continued grassroots interventions to allow scholars and students to build upon the strongest possible educational foundation and show a link between the innovations introduced by CA Connect and student success in the ITC.

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KEY ABBREVIATIONS AND TERMS

KEY ABBREVIATIONS

Abbreviation	Full Term	Explanation
APC	Assessment of Professional Competence	Second professional board exam
CAC	CA Connect	Private education provider for students studying towards CA(SA)
CA(SA)	Chartered Accountant (South Africa)	Designation of chartered accountants registered with SAICA
CTA	Certificate in Theory of Accounting	Generic name for postgraduate year of study before professional board exams
SAICA	South African Institute of Chartered Accountants	Accounting professional body
ITC	Initial Test of Competence	First professional board exam
PGDA	Postgraduate diploma in Accounting	A CTA programme
PPE	Public Practice Exam	Forerunner to APC
QE1	Qualifying Exam 1	Forerunner to ITC

KEY TERMS

Term	Definition
Additional factors	Variables included in this research whose influence on academic performance has not been researched extensively or at all in prior literature (namely, prior tertiary institution, previous CTA attempts, time lapses and class selection)
After-hours offering	The portion of the CAC PGDA which employed a blended learning approach, whereby students watched online recordings of daytime lectures in their own time and attended contact tutorial sessions in the evenings
CAC PGDA	The first private, SAICA-accredited CTA, which was offered in partnership by CA Connect and the host institution for the academic years between 2013 and 2017
Class selection	Whether students completed the CAC PGDA on a fully contact basis (i.e. the daytime offering) or via the blended learning approach (i.e. the after-hours offering)
Daytime offering	The portion of the CAC PGDA which followed a traditional, fully contact approach for full-time students
Host institution	The private higher education institution with which CAC partnered to offer the CAC PGDA

Time lapses	Gaps between completion of undergraduate degree and postgraduate studies (i.e. CTA)
Typically researched factors	Variables included in this research whose influence on academic performance has been researched extensively in prior literature (namely, age, gender, race and prior academic performance)
Success in CAC PGDA	Whether the student achieved a pass mark (i.e. 50% or more) in each of the four PGDA subjects and hence, qualified for admission to the ITC
Success in the ITC	Whether the student achieved a pass within their first two attempts at the ITC (i.e. within the first year immediately following successful completion of PGDA)

INTRODUCTION

The chartered accountancy profession in South Africa has long been regarded as arguably one of the most prestigious and, due to the onerous qualification path required, has been an option available mainly to privileged and well-resourced students, who have access to adequate levels of support, financial and otherwise, and the educational foundation necessary to complete the extended process. In recent years, however, there has been a growing awareness of the need to foster racial transformation in the profession, by assisting promising students from a diverse range of ethnicities in pursuing a professional accounting career. This is imperative for the economic stability of the nation as well as to promote equality and rectify the injustices of South Africa's past. Many of the established residential universities across the country have made commendable efforts in this regard. However, with the recent increase of private education providers in this field, which have a higher degree of flexibility and the ability to innovate more rapidly, education providers are thinking in new ways about how best to support students on the path to qualifying as chartered accountants.

This research examines the postgraduate offering of one such private higher education institution by investigating the relationship between student endogenous factors and academic performance, both in the programme itself and at the subsequent initial professional board exam. Research conducted at public universities indicates that prior academic performance and race are strongly associated with academic success, while other factors, such as age and home language, also appear to play a role (Ungerer, Becker, Nieuwoudt, Swart & Wilcocks, 2013). Limited local research on professional exams supports these findings (van Wyk, 2011). International studies suggest that the tertiary institution attended may affect the academic performance of students in professional accounting exams (Rodrigues, Pinho, Bugarim, Craig & Machado, 2018), but until now, it has not been possible to investigate that relationship within the South African context. However, the recent introduction of private education alternatives provides the opportunity to perform such research, as well as to consider a number of other factors not previously researched.

This study uses data obtained directly from a private higher education institution for students attempting its unique postgraduate programme in 2015, 2016 and 2017. The research tests the relationship between academic performance in the programme and subsequent board exam and students' age, gender, race, prior academic performance, prior tertiary institution, previous postgraduate attempts and any time lapses between undergraduate and postgraduate study, as well as whether students studied full-time or after-hours. Logistic regression analysis was employed and both forced entry and hierarchical regression methods were used to provide insight into the impact of the previously unresearched variables. Due to the nature of the available data, three regression models were designed to test the research hypotheses – the first relating to students who were attempting their postgraduate diploma for the first time; the second relating to students who had previously attempted the postgraduate diploma; and the third relating to students who had successfully completed the postgraduate diploma and progressed to the professional board exam.

The results confirm previous research which indicates that prior academic performance is the single strongest indicator of future academic success and that race is strongly associated with academic performance at a postgraduate level, despite the change of context into a private education space. However, the findings of this study suggest that the association between race and academic performance in the board exam is somewhat weaker. Prior tertiary institution attended was found to be significant for students attempting their postgraduate diploma for the first time, however, in contrast to international studies, it was not found to be of significance for students attempting the board exam. Further research may be required to understand why this is the case. Of key importance is the finding that students who study on a full-time, contact basis are more likely to be successful in completing the postgraduate programme, while those who study after-hours, using a blended learning model, are several times more likely to be successful when attempting the board exam.

These findings are important for a number of reasons. Firstly, they provide further evidence that educational interventions by government, NGOs, corporates and financiers seeking to make a meaningful contribution within accounting education space, should aim

to support learners from as early on as possible, as each academic year lays the foundation for the next. Thus, success at a postgraduate and professional exam level relies on a solid grounding in even the initial stages of education. Additionally, the disparities in academic success along racial lines highlight the need for continued efforts to correct the inequalities of South Africa's past. Despite the attempts to widen access and provide support to previously disadvantaged groups in the several decades since the introduction of democracy in 1994, inequalities persist, and it may be time for regulators, investors and communities to think differently about how best to aid racial transformation.

For the private higher education institution which is the subject of this research, the findings suggest that the innovations introduced through its postgraduate programme are contributing to an increase in the number of marginal students qualifying as chartered accountants. The findings also provide some insight into the characteristics associated with students who are likely to achieve academic success and may therefore be useful in assessing applications to the programme and the allocation of available capacity to those students considered most likely to be successful. These insights may also be of value to other higher education institutions offering similar accounting programmes, as well as academics and the profession, in seeking ways to support students who would otherwise be deprived of the opportunity to pursue their accounting qualification.

If access to a professional accounting qualification can be widened to accommodate those previously excluded from participating, through innovations in how programmes are structured and by offering additional support (financial and otherwise), it is hoped that the goal of an equitable society will be more within reach and that all South Africans will be afforded the opportunity to achieve their full potential. It is hoped that this research contributes to achieving that lofty goal.

The remainder of this paper is structured as follows. Firstly, background information essential to understanding the context of this research is presented, along with a more detailed explanation of the purpose of the research. A review of relevant literature is then provided. The subsequent section describes the research method, followed by a

presentation and discussion of the results. Lastly, the limitations of the study are addressed and recommendations for further research are suggested.

BACKGROUND AND PURPOSE

The CA(SA) designation, which indicates that an individual is a chartered accountant of South Africa, has for many years been associated with the highest level of professionalism and multi-disciplinary business expertise (SAICA, 2018f). CAs(SA) routinely occupy important roles in commerce and industry in the South African economy (SAICA, 2014). As per the requirements of the Chartered Accountants Designation Act (Act 67 of 1993), only members of the South African Institute of Chartered Accountants (SAICA) may use the designation (SAICA, 2018b). SAICA is thus entrusted with determining the requirements which prospective CAs(SA) must fulfil before being admitted for membership, as well as overseeing and regulating the profession.

CA(SA) QUALIFICATION PATH

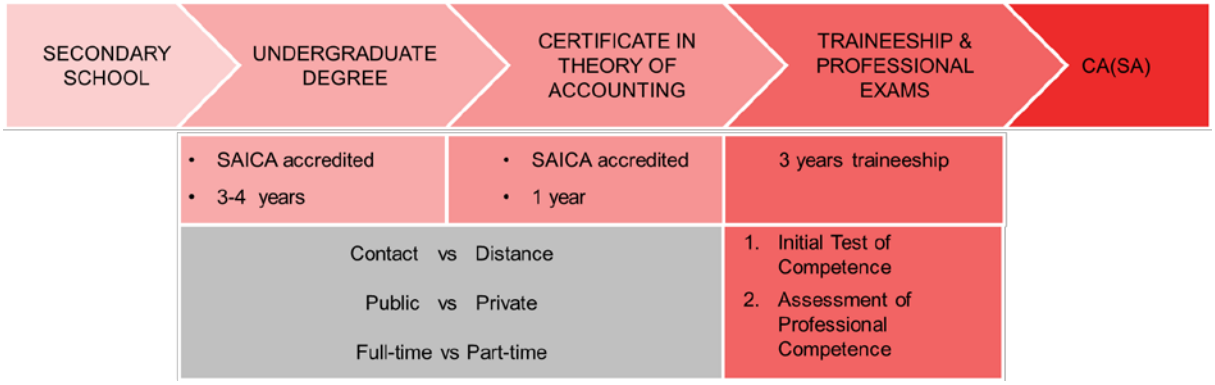

Figure 1: CA(SA) qualification path

(Source: Author's own)

Figure 1 illustrates the SAICA-determined path that an individual must follow in order to qualify as a CA(SA). After completing secondary schooling with sufficiently strong academic results, students complete a SAICA-accredited commerce undergraduate degree of either three or four years (depending on the degree selected), specialising in accounting (SAICA, 2018a). This is followed by a postgraduate qualification, broadly referred to as a Certificate in Theory of Accounting (CTA) (SAICA, 2018a). This is often called a Postgraduate Diploma in Accounting (PGDA) or Honours in Commerce (BCom Hons) (SAICA, 2018e) and has also been through SAICA's stringent accreditation

procedure. As at July 2019, SAICA had accredited 19 undergraduate programmes and 17 CTA programmes (SAICA, 2019a).

A number of options are available to accounting students when selecting where to complete their studies (SAICA, 2018e). Many students study full-time through one of the accredited residential institutions offering contact-based education. Historically, these have mainly been the large public universities, however, in recent years, there has been a rise in the number of private higher education institutions offering equivalent programmes (SAICA, 2019a). Additionally, each year a large cohort of students registers for distance correspondence courses available through the University of South Africa (Unisa) (SAICA, 2019b). Until recently, the latter was the only institution to accommodate students who wished to study on a part-time basis.

While most undergraduate programmes are designed to equip students broadly for commerce-related employment, a CTA programme focuses on the four main subject areas in which CAs(SA) are required to be competent: Financial Reporting (also known as Financial Accounting); Taxation; Management Accounting and Finance (also known as Financial Management); and Corporate Governance and Auditing (SAICA, 2018a). In order to qualify to progress to the professional exams, CTA students are required to pass all four subjects simultaneously (SAICA, 2018a) – i.e. it is not sufficient to pass different subjects in different years.

Students are then required to complete a learnership programme, referred to as a training contract, with a registered training office (SAICA, 2018a). For students who studied full-time, this training contract is typically three years long; for students who studied part-time and therefore began their training contract immediately after high school, learnership is five years (SAICA, 2018a). There are over 700 training offices registered with SAICA (SAICA, 2018d), offering trainees the opportunity to complete their learnership by following either the conventional auditing specialisation, referred to as Training Inside Public Practice (TIPP), or with a financial management specialisation, referred to as Training Outside Public Practice (TOPP) (SAICA, 2018c).

Concurrent with the training contract, students are required to pass two professional exams. Upon successful completion of the CTA, candidates are eligible to sit for the first exam, the Initial Test of Competence (ITC), formerly called Qualifying Exam 1 (QE1) (SAICA, 2018a). This assessment is offered by SAICA in January and June of each year and is typically written in the first year of the training contract (for students who studied full-time) (SAICA, 2018a). Students are afforded six attempts at the ITC (SAICA, 2018a). Should they not successfully pass the exam in three years, they are required to repeat CTA before reattempting. After passing the ITC and completing a minimum of 20 months of learnership, students are eligible to sit for the second professional exam, the Assessment of Professional Competence (APC) (SAICA, 2018a), which was formerly called the Public Practice Exam (PPE). This is offered annually in November by SAICA and is typically written in the second year of the training contract (for students who studied full-time) (SAICA, 2018a).

Upon successful completion of the professional exams and the learnership programme, a candidate is eligible to register with SAICA as a CA(SA) (SAICA, 2018a). Thus, a minimum of seven years is needed for an individual to qualify as a CA(SA) after completing high school.

CA CONNECT PGDA

CA Connect (CAC) was founded as a private educational venture in 2010, with the support of SAICA, to assist students on the path to becoming CAs(SA) (CA Connect, 2018b). The company has prioritised building relationships of genuine care with its students (CA Connect, 2018a). CAC initially offered contact support to students in Unisa's CTA programme in 2010 and 2011. Then, in 2012, CAC was contracted to support the SAICA-accredited PGDA programme at the University of the Western Cape (UWC) (CA Connect, 2018a). In 2013, CAC entered into a partnership with a private higher education institution (the host institution) to offer the first private, SAICA-accredited CTA (which, for ease of reference, will be referred to as the CAC PGDA, despite the fact that the SAICA accreditation was awarded to the host institution) (CA Connect, 2018a). The CAC PGDA began in 2013, initially offering a daytime contact programme for full-time students (CA Connect, 2013).

The CAC PGDA was unique in a number of ways. Firstly, in line with its goal of assisting students who did not meet the CTA entrance requirements of other institutions, the admission policy permitted application to the programme by any student with a SAICA-accredited undergraduate degree (Monash South Africa, 2018). At the time, other institutions often required a minimum average mark in undergraduate studies of 55% or higher in order to be considered eligible for CTA (Murray, 2017). Thus, students hoping to qualify as CAs(SA) who did not meet this threshold would either have to repeat their final undergraduate year in the hopes of achieving the required marks or pursue an alternative career, abandoning their dreams of becoming CAs(SA). With the introduction of the CAC PGDA, however, such students were afforded the opportunity to continue pursuing the CA(SA) designation, without requiring an additional year of study. As a result, applications to the CAC PGDA were received from students with a wide range of SAICA-accredited undergraduate qualifications. Therefore, while it would appear that the CTA classes of most other institutions consisted largely of students who had moved through that university's undergraduate pipeline, the CAC PGDA consisted of students from a diverse range of institutional backgrounds.

Additionally, in 2014, the CAC PGDA introduced an alternative, after-hours course structure which accommodated students who were required to work during regular office hours (CA Connect, 2014). This initiative was revolutionary insofar as it afforded working students the opportunity to engage in a contact CTA programme, whereas previously the only option available to such students would have been to attempt their CTA through the correspondence distance programme offered by Unisa. In the CAC PGDA, a blended learning approach was implemented to accommodate the after-hours cohort of the class – lectures presented to the daytime class were recorded in a user-friendly format and made accessible online for after-hours students to watch in their own time, while contact tutorial sessions[1] were offered in the evening, allowing for personal engagement with lecturers and peers around the course content (CA Connect, 2014).

[1] The CAC PGDA, like many other CTA programmes, made use of both lectures and tutorials to support student learning (CA Connect, 2014). Lectures focused on presenting the main conceptual aspects of a topic to all students in a single large group. Tutorials, in contrast, were smaller sessions, focused on a

At the end of the 2017 academic year, the relationship between CAC and the host institution came to an end and the host institution assumed responsibility for the future running of the PGDA. This research is limited to the years of CAC's involvement at the host institution.

PURPOSE OF THIS RESEARCH

The specifics of the CAC PGDA present the opportunity to research the link between student endogenous factors and academic performance, both in the PGDA and the ITC, which is not available in different contexts. Firstly, it allows for investigation into the relationship between student endogenous factors and academic success, which has been widely researched in public university contexts, within the private education space. Secondly, the unique nature of the programme allows for investigation of the link between additional variables and student performance, which has not previously been possible.

With regard to the first objective, this is the first formal research to be performed on the CAC PGDA and the author was unable to identify any research into the other private SAICA-accredited CTA programmes offered in South Africa. This is unsurprising, as all of these offerings are relatively new entrants to the market, when compared to the established public universities. Therefore, this research appears to be the first to consider the relationship between student endogenous factors, which have been investigated at several public universities, and academic performance within the context of private higher education.

However, this research is able to go a step further and consider variables which may be associated with academic performance which have received little or no research focus in prior literature. This opportunity for further research is a function of both how the CAC PGDA was structured, which is considered unique as described above, as well as the unique cohort of students who were granted access to the CAC PGDA in terms of the unusual entrance requirements.

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particular example, and allowed for more interaction between academic staff and students, as well as practical application and honing of exam technique.

Given CAC's stated goal of assisting marginal students, investigation into the factors contributing to the success of students within the CAC PGDA offers valuable insights into factors relevant to all such students and supports the broader goal of transforming the CA profession. It is more likely for students from less privileged backgrounds to encounter obstacles along the path to qualification due to financial constraints or lack of access to educational support during schooling and previous studies. By offering an innovatively structured programme, CAC attempted to support these students and increase the number of candidates qualifying as CAs(SA) from previously disadvantaged backgrounds. Evidence as to whether these innovations were successful or not offers all institutions involved in accounting education insights into approaches which may be adopted to achieve meaningful transformation outcomes.

Furthermore, insights into which students are more likely to be successful in the PGDA are valuable in refining the student application process related to future programmes run by CAC (and potentially also for equivalent programmes at other institutions considering applications from students outside of their own pipeline). Due to capacity constraints, only a limited number of applicants can be catered for each year at any institution. A clearer understanding of what factors contribute to academic success given the uniqueness of the private education environment can greatly assist in offering places to students with the greatest chances of success, thereby maximising the effectiveness of the programme.

Additionally, the introduction of the after-hours structure in 2014 presents an opportunity to investigate the performance of students in that portion of the CAC PGDA in comparison to those who attended the daytime classes of the course. The after-hours cohort of students on the CAC PGDA represented the only students in the country pursuing the CA(SA) designation on a contact, after-hours programme. Insights into whether this structure was successful are valuable when evaluating both the sustainability of the programme and potential future interventions to assist marginal students. As noted by Byrne and Flood, (2008, p. 203), 'It is clear that the more information educators have regarding factors which are associated with academic success or failure, the better they can support students and advise potential entrants'.

Thus, the primary objective of this research is to investigate the relationship between student endogenous factors, as well as whether students attended the course[2] during daytime or after-hours, and academic success in the CAC PGDA and SAICA's ITC.

[2] This research uses the terms "course" and "programme" interchangeably when referring to the CAC PGDA.

LITERATURE REVIEW

OVERVIEW OF BIGGS' 3P MODEL

Student academic performance in any tertiary course depends on numerous factors. While this can be described in various ways, the model developed by J.B. Biggs, known as the "3P Model", has been used extensively as a framework for researchers in the accounting space (for example, Papageorgiou (2017); Wang (2017); van Rensburg (2016); Pullen, Toerien and Anthony (2013); and Davidson (2002)). The model has also been used further afield - for example, Zhang (2000) and Dart, Burnett, Purdie, Boulton-Lewis, Campbell and Smith (2000) to research educational psychology and Freeth and Reeves (2004) to evaluate interprofessional collaboration.

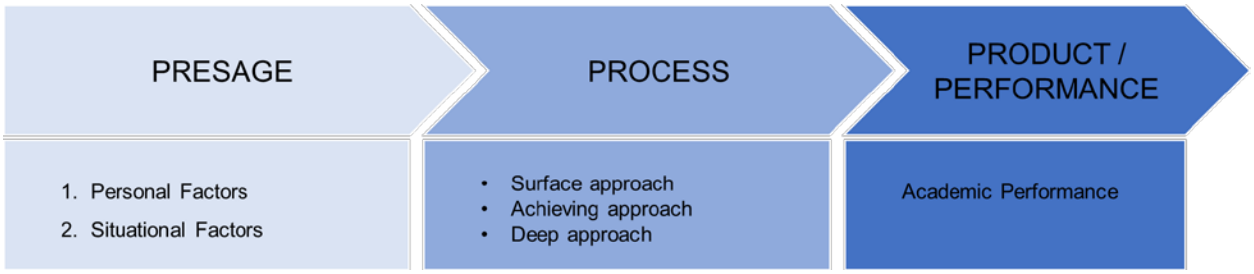

Figure 2: Biggs' 3P model

(Source: Author's own)

As depicted in Figure 2 above, Biggs' 3P model is a general model of student learning, which describes three sets of factors affecting student performance, namely, (i) presage, (ii) process and (iii) product or performance (Biggs, 1985, 1987a, 1987b).

Presage factors are those which are independent of the learning situation. These can be either personal factors, such as intelligence, background, personality and demographics or situational factors, such as subject content and course structure.

Process factors relate to the study approach which students adopt, which is contingent on their motives and strategies for learning. Biggs (1985, 1987b) details three approaches which may be followed: (i) a surface approach, where students seek to perform the minimum amount of work required and often adopt a rote learning strategy; (ii) an achieving approach, where the students' goal is to achieve high marks, often employing

an organised strategy; and (iii) a deep approach, where students are motivated by an intrinsic interest in the material and consequently adopt a strategy of reading widely and building a deep understanding. An achieving strategy may be combined with either a surface or a deep approach, resulting in a hybrid approach. Biggs (1987b) notes that a deep-achieving approach is a characteristic of many successful students.

Finally, when describing the performance or product factors, Biggs (1987b) accepts that performance may be measured in various ways, but that two dimensions consistently apply – cognitive and affective. The cognitive dimension relates to whether students contextualise factual information into a high-level structure or instead focus on the detail of the material content in isolation. The affective dimension describes how the student experiences the learning process – namely, whether it is positive or negative. Positive effects would include enjoying the learning or deriving satisfaction from it, while negative effects would include experiencing boredom or being stretched beyond one's ability.

While the focus of Biggs' work is the learning approach adopted by students and how this can be influenced and assessed by educators, he notes that presage factors are largely responsible for the development of the learning approach adopted (Biggs, 1987b). In other words, factors such as age, language, locus of control, stress and training go a long way to determine which of the three learning approaches a student will apply in their studies, which ultimately impacts on their performance.

APPLICATION OF BIGGS' 3P MODEL

Stated in the language of Biggs' 3P model, the primary objective of this research is to examine the relationship between personal and situational factors on the one hand, and students' academic success in the CAC PGDA and SAICA's ITC on the other. As a result, this study focuses on the presage and performance portions of the Biggs' 3P model, as summarised in Figure 3 below.

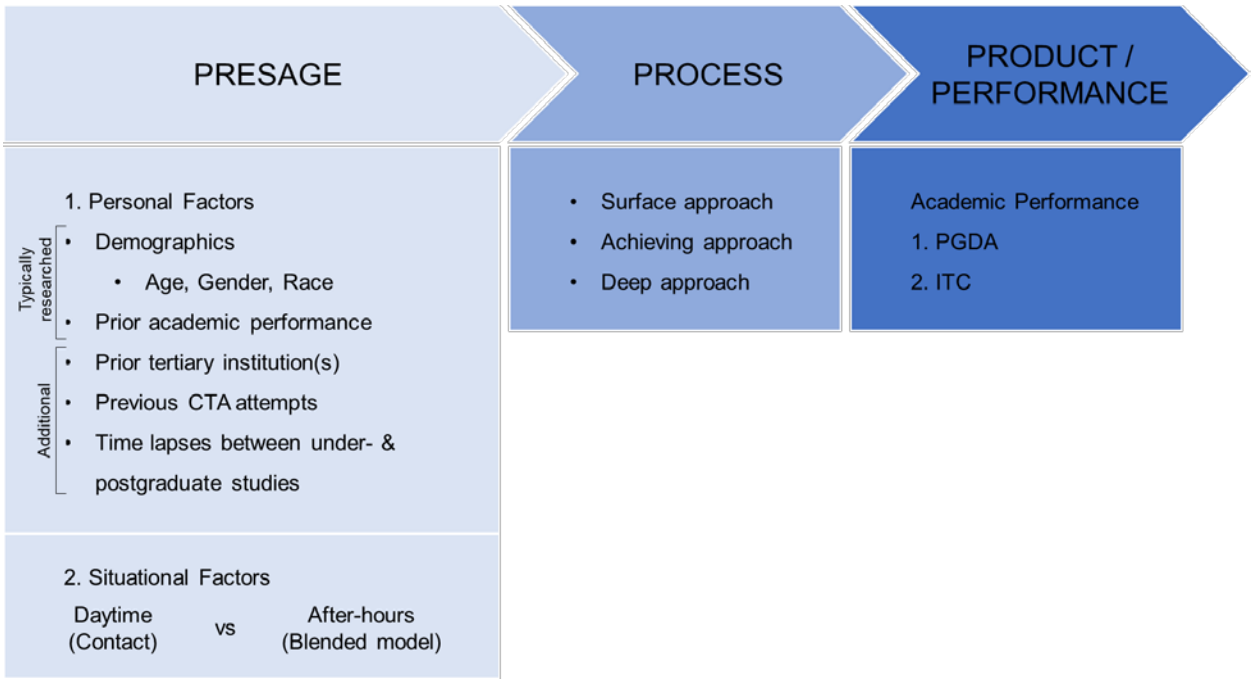

Figure 3: Application of Biggs' 3P model to this research

(Source: Author's own)

Presage factors

As mentioned, the presage factors are those personal and situational factors which are independent of the learning situation. They are thus the factors which students bring with them when enrolling and which exist prior to students' selecting their preferred learning approach for the programme. In the context of this research, personal presage factors include demographic details, such as the student's age, race and gender; prior academic performance; the institutions at which the student completed their previous academic studies; any time lapses in the qualification journey following the student's undergraduate degree; and whether the student had previously attempted CTA. These variables are all considered endogenous factors related to the student. In this study, relevant situational presage factors would notably include whether the student engaged with the PGDA on the daytime or after-hours track (i.e. whether they completed the programme on a fully contact basis or via the blended learning approach), as well as other considerations related to the course structure, which would be common to both tracks.

Performance

The measures used to determine academic success for this research will be student passes in both the PGDA and the ITC, which is in line with the measures most commonly used to determine academic success in similar research (York, Gibson & Rankin, 2015). Specifically, success in the CAC PGDA refers to whether the student achieved a pass mark (i.e. 50% or more) simultaneously in each of the four subjects (and hence, qualified for admission to the ITC). For SAICA's ITC exam, success refers to whether the student achieved a pass within their first two attempts (i.e. within the first year immediately following successful completion of PGDA). As explained in the background, students who are successful in any CTA are not able to enjoy the full benefit of completing that demanding year if they are unable to pass the ITC (and APC thereafter). Thus, an important measure of any CTA programme is the subsequent performance of its passing students in the ITC, particularly in the year immediately following CTA. This is reflected by the fact that SAICA requires all accredited institutions to achieve an 80% pass rate for students attempting the ITC in the first year following their CTA, regardless of whether they completed their postgraduate studies on a full-time or distance basis (SAICA, 2015).

TYPICALLY RESEARCHED PERSONAL PRESAGE FACTORS

In South Africa and internationally, much research has been done on certain student endogenous factors at an undergraduate level and their effect on academic performance. These works have tended to focus on factors such as age, gender, race, home language, whether accounting was selected as a Grade 12 subject, performance in Grade 12 accounting, performance in Grade 12 mathematics and overall Grade 12 performance in assessing which are most closely correlated with successful students. (These factors are referred to as "typically researched factors" in this study.) However, there is relatively little research into factors which predict the academic success of accounting students at a postgraduate level (although this has begun to change in recent years) and the body of literature on performance in the SAICA professional exams is very limited. A summary of this research follows below.

Age

It is apparent that prior research has not applied a uniform or standardised approach to determining age groupings for assessment relative to academic performance (de Hart,

Doussy, Swanepoel, van Dyk, de Clercq & Venter, 2011). However, studies conducted at various South African higher education institutions researching the impact of age on academic performance have largely concluded that younger students outperform those who are older at both undergraduate level (Jansen & de Villiers, 2016; Bokana & Tewari, 2014; Müller, Prinsloo & du Plessis, 2007) and postgraduate level (Steenkamp, 2014; Ungerer *et al.*, 2013; de Hart *et al.*, 2011). Ungerer *et al.* (2013) found that students younger than 25 years of age were 1.6 times more likely to pass CTA at Unisa on their first attempt than older students. A younger age has also been found to be significantly positively correlated with performance in SAICA's and other similar professional exams (Le Roux, 2017; van Wyk, 2011; Roos, 2009). This may be due to the additional family commitments and responsibilities which older students bear (Aboo, 2017; de Hart *et al.*, 2011). In contrast, however, other studies conclude that age does not significantly impact performance at an undergraduate level (Papageorgiou, 2017; Wang, 2017) or that it does so only towards the end of undergraduate studies (Papageorgiou & Halabi, 2014).

A similar pattern emerges from the limited international research performed on the link between age and academic performance. The findings of Koh and Koh (1999) at Nanyang Technological University in Singapore indicate that younger students outperformed their older counterparts in an undergraduate accounting degree. This is corroborated by the findings of Deschacht and Goeman (2015) at KU Leuven in Brussels, Belgium. Younger students have also been shown to perform better in professional accounting exams by Rodrigues *et al.* (2018) in Brazil. In contrast, Guney (2009) found that the older cohort of students included in that study performed better in an accounting undergraduate programme at a university in the United Kingdom while Douglas (2017) found no significant relationship between age and performance in professional accounting exams in Scotland.

In light of the above literature, it is expected that younger students will be found to outperform older students. The related research hypotheses, stated as null hypotheses, are as follows:

Hypothesis 1a: Age is not significantly associated with academic performance in the CAC PGDA.

Hypothesis 1b: Age is not significantly associated with academic performance in SAICA's ITC.

Gender

The findings related to the impact of gender on academic performance in accounting courses and professional assessments are somewhat contradictory in different contexts. Jansen and de Villiers (2016) found that male students outperform female students in undergraduate accounting courses at UWC. This is supported by the findings of Tewari (2015) at the University of Zululand, who noted that males slightly outperformed female students. On the other hand, Wang (2017) and van Rensburg (2016) found that female students were more likely to be successful in undergraduate accounting courses at the University of Cape Town (UCT). Coetzee, Janse van Rensburg and Schmulian (2016) came to a similar conclusion in their study on the comprehension of the International Financial Reporting Standards among undergraduate students at another leading South African university. Similarly, both Le Roux (2017) and Roos (2009) found that females tended to perform better in professional accounting exams. Yet other studies have found no correlation between gender and academic performance at other institutions (Papageorgiou, 2017; Bokana & Tewari, 2014; Papageorgiou & Halabi, 2014; Steenkamp, 2014; de Hart *et al.*, 2011) or in SAICA's professional exams (van Wyk, 2011).

Males were shown to outperform females at an undergraduate level by Koh and Koh (1999) in Singapore and in professional exams by Rodrigues *et al.* (2018) in Brazil. However, Ismail, Mohammed, Ahmad and Yatim (2017) found that females performed better in professional accounting exams in Malaysia, which mirrors the findings of Douglas (2017) in Scotland. Yet, most research abroad has concluded that gender is not significantly correlated with accounting academic performance (Thorpe, Snell, Davey-Evans & Talman, 2017; Byrne, Flood & Griffin, 2014; Guney, 2009; Byrne & Flood, 2008; Doran, Bouillon & Smith, 1991). Byrne and Flood (2008) posit that this may be the consequence of a more gender-balanced world of accounting education.

As a result, it is expected that gender will not be found to be significantly associated with performance in the CAC PGDA and SAICA's ITC. The related research hypotheses are as follows:

Hypothesis 2a: Gender is not significantly associated with academic performance in the CAC PGDA.

Hypothesis 2b: Gender is not significantly associated with academic performance in SAICA's ITC.

Race

Given South Africa's history of apartheid and the disparities in educational opportunities along racial lines which it institutionalised, it is unsurprising that numerous studies have noted significant differences between the academic performance of white students and that of students from other racial groups (Papageorgiou, 2017; Le Roux, 2017; Wang, 2017; van Rensburg, 2016; Bokana & Tewari, 2014; Ungerer *et al.*, 2013). Notably, Ungerer *et al.* (2013) found that white students on Unisa's CTA programme were 2.2 times more likely to pass than Coloured or Indian students and 2.8 times more likely to pass than black students. Sartorius & Sartorius (2013) noted that black students consistently underperformed in QE1 during the period 2005 to 2010 compared to candidates of other racial groupings, although they also found that the performance gap slightly lessened over the period under review. Additionally, Le Roux (2017) found that black candidates were over four times more likely to fail the APC than white candidates. Research by Barac (2015) on the leading causes of failure in the PPE of the first cohort of SAICA's Thuthuka students[3] appears to indicate that lack of workplace readiness and lack of a social support structure played a significant role.

The causes of the noted underperformance of black students relative to students of other racial groupings is a multifaceted and complex issue, rooted in the legacy of Apartheid and influenced by other factors. Consideration of these aspects, while important and

[3] The Thuthuka Education Upliftment Fund (TEUF) was established by SAICA in 2002 with the strategic objectives of growing the number of CAs(SA) and transforming the demographics of the CA profession to align with those of the South African population (SAICA, 2019c). TEUF operates the Thuthuka Bursary Fund, which assists disadvantaged black and Coloured students in qualifying as CAs(SA) (SAICA, 2019c).

worthwhile, is beyond the scope of this research and the data to which it relates. Yet it is noted that Kaburise (2014) states that in the newly democratic South Africa, it was initially assumed that widening access to tertiary education would automatically lead to diverse academic success. However, despite intensive efforts within the first two decades of democracy to widen access at a tertiary level and provide a considerable amount of student funding, student attrition rates remain high and throughput remains low (Kaburise, 2014). Substantial change is only likely once adjustments are made at either end of the tertiary education pipeline, by addressing the deficiencies in the secondary schooling system and ensuring that employment opportunities await successful graduates (Kaburise, 2014).

Internationally, it appears that little research has been done on the link between race and accounting academic performance, which is perhaps indicative of the lack of diversity in other countries in comparison to the rainbow nation of South Africa. Where such research has been performed, the results have been varied and inconclusive (Douglas, 2017; Guney, 2009).

Given the prior research, it is expected that this research will find that white students outperform students from other racial groups. The related null hypotheses are as follows:

Hypothesis 3a: Race is not significantly associated with academic performance in the CAC PGDA.

Hypothesis 3b: Race is not significantly associated with academic performance in SAICA's ITC.

Language

Linked to the impact of race on academic performance is that of home language, as in South Africa, tertiary education is offered in only English and Afrikaans, just two of the nation's 11 official languages (van Wyk, 2011). Prior research suggests that a strong positive correlation exists between academic success and assessment in one's first language (Papageorgiou, 2017; Bokana & Tewari, 2014; Steenkamp, 2014; Swart & Becker, 2014; de Hart *et al.*, 2011). At Unisa, Ungerer *et al.* (2013) found that students assessed in their home language were 30% more likely to pass CTA at their first attempt

than those who were assessed in another language. In contrast, however, numerous studies have found that Grade 12 language marks are not correlated with academic success at university level. This is confirmed in the work of van Rooy and Coetzee-Van Rooy (2015) at the North-West University (NWU), Aboo (2017) at Unisa and Jansen and de Villiers (2016) at UWC. Also at UWC, Pullen *et al.* (2013) found that while having English as a first language was not associated with success for undergraduate students enrolled in management accounting courses, it was of statistical significance for management accounting at PGDA level. They posit that this may be due to the greater requirement for interpretation and application of key principles in unfamiliar scenarios at a postgraduate level, which suggests that home language may be a contributor to success at a postgraduate level even if it does not play a significant role at undergraduate level. Additionally, van Wyk (2011) found a strong positive correlation between students who were successful in the QE1 and those who had Afrikaans or English as their first language and were therefore able to sit the exam in their first language[4].

Interestingly, there is some research which suggests that multilinguism may actually contribute to academic success (Papageorgiou, 2017; Martirosyan, Hwang & Wanjohi, 2015), which may be applicable to many students within the South African context who are fluent in several languages. Also, Rossouw (2018) found that more than a third of undergraduate Afrikaans accounting students would consider changing to English as their language of instruction.

It is noted that there is a distinction between home language and the language selected as a student's first language for Grade 12, although most research appears to use the latter as a proxy for the former. For instance, a student from an isiXhosa home may complete English as a first language in Grade 12; thus, English may be considered their

[4] In light of these findings, van Wyk (2011) suggests that SAICA should consider offering QE1 (i.e. ITC) in isiXhosa and isiZulu, the 'two main black languages' (p.170). However, SAICA recently announced its decision to offer its ITC only in English (i.e. to remove Afrikaans as an alternative) from January 2022, rather than making additional languages available (SAICA, 2018g), given that English is the primary language of business and to avoid unfair preferential treatment of just one of the additional official languages.

first language for the purposes of a study, despite the fact that it would not be representative of their home language.

Due to limitations in the available data, the impact of language on academic success will not be included within the scope of this research. It is noted, however, that with language, as with race, there are important cultural, historical and economic considerations within the South African context which are beyond the scope of this research.

Grade 12 subject selection and results

A number of studies have found that students who took accounting as a subject in Grade 12 outperform their counterparts who did not have accounting as a Grade 12 subject in first-year accounting courses (Papageorgiou & Carpenter, 2019; Papageorgiou, 2017; van Rensburg, 2016; Bokana & Tewari, 2014). This is supported to some extent by similar research done abroad (Byrne & Flood, 2008), although Koh and Koh (1999) and Douglas (2017) did not reach the same conclusion. It should, in any case, be noted that any advantage gained from selecting accounting in high school does not endure beyond the first year of undergraduate study, both in South Africa (Wang, 2017; Jansen & de Villiers, 2016; Papageorgiou & Halabi, 2014) and overseas (Doran *et al.*, 1991), presumably as the content of second- and third-year accounting courses becomes more advanced.

Performance in Grade 12 mathematics has also been found to have a positive correlation with performance in South African undergraduate accounting courses (Wang, 2017; van Rensburg, 2016; Tewari, 2015; Bokana & Tewari, 2014; Papageorgiou & Halabi, 2014; Swart & Becker, 2014). This is supported by Guney (2009) in the United Kingdom, Koh and Koh (1999) in Singapore and Ismail *et al.* (2017) in Malaysia. However, there is evidence to suggest that this correlation also declines towards the end of undergraduate studies and at postgraduate level (Jansen & de Villiers, 2016; Pullen *et al.*, 2013).

Overall performance in Grade 12 has been shown to be strongly correlated with academic success at all levels of tertiary education (Jansen & de Villiers, 2016; Bokana & Tewari, 2014; Pullen *et al.*, 2013). However, van Rooy and Coetzee-Van Rooy (2015) found that Grade 12 results were a strong predictor of success at university only for students who achieved an average of 65% or more. The prediction value of Grade 12 results was much

weaker for students who achieved an average of less than 65% - some of those students went on to perform well at tertiary level, while others did not succeed at all. A possible explanation may be that other, more qualitative factors such as grit, motivation and maturity play a larger role in determining whether more marginal students succeed in their chosen studies.

As Grade 12 subject selection has been shown not to be significantly associated with academic performance at postgraduate level in prior studies, it will be excluded from the scope of this research. Furthermore, overall academic performance in Grade 12 is assumed to be subsumed into the next variable – prior academic performance – and will not be specifically tested.

Prior academic performance

Numerous studies support the conclusion that the single best predictor of academic performance at every level is academic performance in the immediately preceding year of study. This has been found to hold true in South African undergraduate courses (Jansen & de Villiers, 2016; Papageorgiou & Halabi, 2014; Swart & Becker, 2014), postgraduate courses (Steenkamp, 2014; Swart & Becker, 2014; Pullen *et al.*, 2013) and professional exams (Dehrmann, 2013; van Wyk, 2011). Thus, it would appear that the progression requirements applied by most universities are justified, as these tend to consider the most recent academic performance of students in determining whether they qualify to progress. The reason that prior performance is so strongly linked to academic success is likely due to the hierarchical knowledge structure applicable in an accounting context (Myers, 2017).

Additionally, international research supports this conclusion, both at a university level (Archambault & Archambault, 2016; Maksy & Wagaman, 2016; Byrne & Flood, 2008; Koh & Koh, 1999; Doran *et al.*, 1991) and in professional exams (Rodrigues *et al.*, 2018; Douglas, 2017). Lento and Sayad (2015) noted that undergraduate grades were a better predictor of success in professional accounting exams than faculty intuition for students at Lakehead University in Ontario, Canada.

In light of these findings, it is expected that this research will also conclude that prior academic performance is significantly associated with performance in the PGDA and the ITC. As such, the relevant research hypotheses, once again stated as null hypotheses, are as follows:

Hypothesis 4a: Prior academic performance is not significantly associated with academic performance in the CAC PGDA.

Hypothesis 4b: Prior academic performance is not significantly associated with academic performance in SAICA's ITC.

ADDITIONAL PERSONAL PRESAGE FACTORS

Although the influence of the factors discussed above is certainly relevant to this research and will remain within the ambit of the study, the unique opportunity of this research is to investigate the link between academic performance and student presage factors which have not been the subject of other academic work up to this point. There are three such personal presage "additional factors", namely, the institution at which a student's prior tertiary studies were undertaken; whether any time elapsed between the completion of the undergraduate degree and the commencement of CTA; and whether CTA had previously been attempted.

Prior tertiary institution

Most research done in the postgraduate space has focused on students within a single university (such as Papageorgiou (2017), Steenkamp (2014) and Pullen *et al.* (2013)). Where distinctions have been made with regard to undergraduate institution, these have typically involved dividing students into those who progressed through a given university pipeline and those who did not. For instance, in comparing the CTA performance of students at the University of KwaZulu Natal (UKZN), Murray (2017) noted that those who had completed their undergraduate degree at UKZN performed significantly better than those who had done so at another university.

Until now, no research has been done in the context of the CAC PGDA, which presents an opportunity for more detailed comparisons relating to educational background. Although some universities accept students into CTA from other undergraduate

institutions, given its nationwide accessibility, Unisa appears to be the only programme other than the CAC PGDA to accept CTA students from a wide range of undergraduate backgrounds. It would therefore appear to be well positioned to compare the performance of students from different undergraduate institutions. However, most research on accounting programmes at Unisa appears to divide students into those who acquired their undergraduate degree through Unisa and those who did so at other institutions (Swart & Becker, 2014; Ungerer *et al.*, 2013; Sadler & Erasmus, 2005). This is despite the fact that the majority of Unisa CTA students were found to have completed their undergraduate degrees full-time at other institutions (Aboo, 2017). The fact that Unisa provides solely distance education also distinguishes its programmes from those offered by residential universities and adds unique risks and demands to student performance (Aboo, 2017; Ungerer *et al.*, 2013; de Hart *et al.*, 2011).

Nationwide research by Rodrigues *et al.* (2018) in Brazil found a significant positive relationship between students' performance in professional accounting exams and the higher education institution at which they completed their studies. In fact, they found that prior higher education institution was even more strongly correlated with success in the professional exams than prior academic performance. This highlights the value of similar research in a South African context, comparing the performance in CTA and the ITC of candidates across institutions in order to gain a fuller understanding of the factors contributing to success in SAICA's professional exams.

Additionally, with the CAC PGDA it is possible to go one step further and also consider the institution at which students repeating CTA had made their previous attempt. Thus, consideration of undergraduate institution as well as the institution of any previous attempt at CTA is combined into a single variable, prior tertiary institution.

In light of the findings of Rodrigues *et al.* (2018), is it expected that this research will identify that prior tertiary institution will have a significant impact on the likelihood of success in the CAC PGDA and SAICA's ITC.

The related research hypotheses, stated as null hypotheses, are as follows:

Hypothesis 5a: Prior tertiary institution is not significantly associated with academic performance in the CAC PGDA.

Hypothesis 5b: Prior tertiary institution not significantly associated with academic performance in SAICA's ITC.

Previous CTA attempts and Time lapses after undergraduate degree

For students pursuing the CA(SA) designation, the journey is often fraught with obstacles. Non-academic factors, such as geographical location, financial resources and marital status may play a significant role either in aiding or obstructing eventual success (Aboo, 2017; Roos, 2009). Such non-academic factors may result in students taking pauses in their progress along the path to qualification. They may also contribute to poor academic performance, requiring repetition of steps along the way.

The author was unable to identify much research specifically investigating the impact of multiple attempts at CTA or time gaps following completion of undergraduate studies (referred to as "time lapses" in this research) on ultimate academic success in CTA or the ITC within a South African context. However, Pullen *et al.* (2013) found that students attempting UWC's CTA management accounting for the first time were more likely to be successful than those repeating the course. Furthermore, van Wyk (2011) noted a strong negative correlation between the length of time taken to complete both undergraduate and postgraduate studies and performance in QE1. van Wyk (2011) also found that candidates' chances of success in QE1 were the highest at their first attempt and decreased with each additional attempt. This is supported by the findings of Sartorius & Sartorius (2013), who noted that the chances of success in the QE1 were significantly reduced for students attempting the exam a second time or for those who took more than one year to complete CTA or wrote supplementary exams.

Some international studies have noted that the timing of courses may be linked to academic success. Archambault and Archambault (2016) identified a negative correlation between the time taken to complete a sophomore undergraduate course and academic performance in a senior undergraduate course at Marshall University in West Virginia. Surprisingly, Douglas (2017) noted that students who did not progress directly from

university to their training contracts performed better in one of the professional accounting exams in Scotland, though only significantly so in financial reporting.

In summary, it would appear that the longer it takes accounting students to successfully complete any leg of their academic journey, the less likely they are to reach their ultimate goal.

The null hypotheses related to these aspects of this research are as follows:

Hypothesis 6a: Previous CTA attempts are not significantly associated with academic performance in the CAC PGDA.

Hypothesis 6b: Previous CTA attempts are not significantly associated with academic performance in SAICA's ITC.

Hypothesis 7a: Time lapses are not significantly associated with academic performance in the CAC PGDA.

Hypothesis 7b: Time lapses are not significantly associated with academic performance in SAICA's ITC.

From the above, it is apparent that there is limited existing research into the effect of these additional personal presage factors on academic performance, not only in South Africa, but also within an international context. Thus, these key aspects addressed in this research will add to the body of knowledge, thereby assisting all parties involved to better understand student success.

SITUATIONAL PRESAGE FACTORS

Class selection

As mentioned earlier, situational presage factors relevant for this research include whether the student engaged with the CAC PGDA on the daytime or after-hours track (i.e. whether they completed the course on a fully contact basis or via the blended learning approach). This is termed "class selection" in this research.

Asarta and Schmidt (2017, p. 29) offer a helpful summary of the spectrum along which modern educators may be found integrating technology into their courses, thereby adopting a blended learning approach:

> ‘At one end of the spectrum, small bits of online materials are brought into the traditional classroom, playing only a minor role to complement the fully retained face-to-face lecture environment. Such courses are commonly labelled “web enhanced”. At the other end of the spectrum are purely online courses with no face-to-face meetings… Between those two extremes are blended courses.’

The daytime cohort of the CAC PGDA was exposed to a traditional, face-to-face, fully contact environment – this would likely not even be regarded as “web enhanced” according to the Asarta and Schmidt (2017), as there was very little integration of technology into the classroom. However, the after-hours cohort, which viewed all lectures as online recordings and only received in-person contact sessions at tutorials, experienced the course through a blended learning format (CA Connect, 2014). It stands to reason that engagement with the PGDA through differing modes may have an impact on academic performance.

Internationally, a substantial amount of research has been performed on the academic performance of students in traditional learning environments and those exposed to a blended learning approach. Most of these have found no statistically relevant difference (such as, Aly (2016) and Baepler, Walker and Driessen (2014)), while others have noted that blended learning may actually contribute to improved student performance (Vo, Zhu & Diep, 2017). However, when analysing the effect of learning mode against prior academic performance, Asarta and Schmidt (2017) found that while stronger students performed significantly better in a blended learning environment, weaker students performed significantly better in a traditional classroom environment whereas mid-range students’ performance was unaffected. Additionally, although Deschacht and Goeman (2015) found blended learning had no significant effect on exam performance, they did note that there was a negative effect on exam performance in accounting courses in particular. They observe that this may be related to how blended learning was implemented in those particular courses.

Student reasons for selecting the after-hours format over the daytime format may also play a role in determining their eventual academic performance – for example, some full-time students may have selected the after-hours format if they preferred to attend tutorials in the evenings and keep active studying hours free during the day, while working students would have only been able to attend the after-hours format of the programme due to work commitments during the day. Surprisingly, research at Unisa has found that part-time students outperform full-time students at both undergraduate (de Hart *et al.*, 2011) and postgraduate level (Müller *et al.*, 2007). This is supported by Maksy and Wagaman (2016), who found no negative association between working students and academic performance in Pennsylvania.

The research hypotheses related to this aspect are as follows:

Hypothesis 8a: Class selection is not significantly associated with academic performance in the CAC PGDA.

Hypothesis 8b: Class selection is not significantly associated with academic performance in SAICA's ITC.

Other situational presage factors

There were several other aspects of the CAC PGDA which set the programme apart from other CTA programmes available in South Africa at the time. The first was the widespread use of technology to streamline and modernise the education process. For example, a mobile app was developed for students to record lecture and tutorial attendance; all assessments were scanned and marked digitally in a move away from traditional paper-based approaches to marking; and social media was utilised to foster community among each student cohort and with the lecturing staff (CA Connect, 2014). Research by de Hart *et al.* (2011) at Unisa indicates that integration with technology leads to a highly statistically significant improvement in student results and therefore the extensive application of innovative technology in the CAC PGDA is expected to have an effect on student performance.

A second key distinguishing factor of the CAC PGDA was the design and implementation of a mentorship programme, which sought to provide non-academic support to students

on a more individualised basis (CA Connect, 2014). In the initial years of the programme, students were given the opportunity to select a member of staff to act as their mentor; but in 2017, student alumni volunteered their time to mentor PGDA students through the difficult year, sharing insights into helpful studying approaches and providing emotional support and encouragement. As shown by Barac (2015), social support plays an important role in student performance, and therefore it is expected that the mentorship programme would have an impact of student success in the PGDA as well as in the ITC.

However, these factors would be consistent for all PGDA students, regardless of their class selection and thus, this research does not investigate the effect of technology or mentorship on student performance.

RESEARCH METHOD

RESEARCH HYPOTHESES

As stated, the primary objective of this research is to examine the relationship between personal and situational factors and student academic success in the CAC PGDA and SAICA's ITC. Specifically, this research uses logistic regression analysis to test the relationship between students' demographic details (age, gender and race), prior academic performance, prior tertiary institution, previous CTA attempts, time lapses and class selection and their academic performance in the CAC PGDA and SAICA's ITC exam.

A summary of the research hypotheses is provided below.

Hypothesis 1a: Age is not significantly associated with academic performance in the CAC PGDA.

Hypothesis 1b: Age is not significantly associated with academic performance in SAICA's ITC.

Hypothesis 2a: Gender is not significantly associated with academic performance in the CAC PGDA.

Hypothesis 2b: Gender is not significantly associated with academic performance in SAICA's ITC.

Hypothesis 3a: Race is not significantly associated with academic performance in the CAC PGDA.

Hypothesis 3b: Race is not significantly associated with academic performance in SAICA's ITC.

Hypothesis 4a: Prior academic performance is not significantly associated with academic performance in the CAC PGDA.

Hypothesis 4b: Prior academic performance is not significantly associated with academic performance in SAICA's ITC.

Hypothesis 5a: Prior tertiary institution is not significantly associated with academic performance in the CAC PGDA.

Hypothesis 5b: Prior tertiary institution is not significantly associated with academic performance in SAICA's ITC.

Hypothesis 6a: Previous CTA attempts are not significantly associated with academic performance in the CAC PGDA.

Hypothesis 6b: Previous CTA attempts are not significantly associated with academic performance in SAICA's ITC.

Hypothesis 7a: Time lapses are not significantly associated with academic performance in the CAC PGDA.

Hypothesis 7b: Time lapses are not significantly associated with academic performance in SAICA's ITC.

Hypothesis 8a: Class selection is not significantly associated with academic performance in the CAC PGDA.

Hypothesis 8b: Class selection is not significantly associated with academic performance in SAICA's ITC.

DATA ACQUISITION AND PREPARATION

Prior to the commencement of this research, all parties involved (i.e. CAC, the author, her supervisor and UCT) signed a non-disclosure agreement which granted the author permission to use the data concerned, subject to confidentiality requirements. Ethical clearance for the research was also obtained from the UCT Ethics Committee. Following this, the PGDA Programme Coordinator at CAC sent the author several spreadsheets containing the relevant information applicable to the CAC PGDA classes of 2015, 2016 and 2017. The reason for releasing the information for these years largely stemmed from

the fact that CAC had implemented an online application system from 2015 onwards, which generated digital copies of the relevant information. Applications for the CAC PGDA prior to 2015 (i.e. in 2013 and 2014) were paper-based and records were therefore unreliable, incomplete or inaccessible.

The information received from CAC contained the details entered into the online application system by students when applying for the programme (independently validated by CAC for all accepted students) as well as demographic data gathered at the time of enrolment. The information also contained the final marks spreadsheet for each academic year, indicating results for the four core subjects after the outcome of the supplementary exams had been taken into account. Lastly, the information also contained an analysis of the ITC results of students who had successfully passed PGDA. Working backwards from students for whom the marks spreadsheet indicated final PGDA outcomes (i.e. eliminating those students who were either not eligible for final exams in accordance with the programme rules or who had dropped out during the year[5]), relevant information was compiled for each student in each year, using their unique, numeric student number as a reference point. Where missing data points were identified for certain students, the author manually retrieved this information from CAC's online application records, where possible. The three years were then combined into a single spreadsheet. Any identifying particulars (such as name, surname and student number) were then deleted from the dataset and each data point was instead allocated a unique ID number for the purposes of this research.

High-level analysis was performed on the data to ensure that all points were within logical parameters. No application data was available for one student and no enrolment information was available for another two students. Duplicate data relating to one student was also identified. These were therefore removed from the dataset. Additionally, of the

[5] This approach to preparation of the data was employed, as the programme rules applicable in each year included in the study were not consistent. In 2015, all students were eligible to write final exams. However, in 2016, students were divided into those on a 1-year programme and those on a 2-year programme at the beginning of the year and only those on the 1-year programme who achieved a sub-minimum of a certain percent at mid-year were permitted to write final exams. In 2017, students were again divided at the beginning of the year, but all students satisfying the mid-year sub-minimum requirement were permitted to write the final exam. Thus, this study elected to focus on those students who were eligible to write the final exams.

274 students who progressed from the PGDA to the ITC in the three years under review, the ITC results of five candidates were unavailable. This was because four had not attempted the paper for unknown reasons and one had sat for the exam in Zimbabwe and was thus excluded from the available results, which pertain only to South African candidates. These candidates were therefore excluded from the sample relating to the ITC results. Following this, the sample consisted of 777 PGDA students across the three years, of whom 269 progressed to the ITC. The data was then entered into SPSS (IBM Corp., 2017), a statistical analysis software package used extensively in similar research, in order to perform the analyses described below. Testing for complete separation in variables (i.e. where any one independent variable perfectly predicts the outcome variable) was performed to ensure that cases existed in all categories and the coding of the independent variables was adjusted where necessary.

RESEARCH APPROACH

Logistic regression

Given the aim of this research as well as the statistical tests available, logistic regression was selected as the best approach for testing the research hypotheses, applying a significance level (*p*-value) of 0.05, representing a 95% confidence level. According to Field (2009), simple regression is a linear model by which an outcome (or dependent) variable is predicted based on the value of a single predictor (or independent or explanatory) variable. When two or more predictor variables are used to predict the value of the outcome variable, multiple regression is applied (Field, 2009). Logistic regression is an extension of multiple regression which is appropriate when the outcome variable is categorical rather than continuous[6] (Field, 2009; DesJardins, 2001; Hosmer & Lemeshow, 2000). In the context of this research, where the outcome variable is dichotomous (as it relates to academic performance, namely, whether a student passed or failed), the logistic regression applied is referred to as binary logistic regression. This

[6] Categorical variables are made up of different categories (Field, 2009). These variables are referred to as binary or dichotomous, where only two categories exist (e.g. male or female; pass or fail); nominal, where more than two categories exist (e.g. white, black, Coloured or Indian); or ordinal, where multiple categories exist, but can be placed in a logical order (e.g. high, medium, low). In contrast, continuous variables consist of a scale, where each case can be assigned a distinct value (e.g. age; test result) (Field, 2009).

distinguishes it from multinomial logistic regression, where more than two categorical outcomes exist (Field, 2009).

Logistic regression has the benefit of being an ‘extremely flexible and easily used function’ leading to ‘clinically meaningful interpretation’ (Hosmer & Lemeshow, 2000, p. 6). Therefore, it is unsurprising that this technique has been frequently used in higher education research (DesJardins, 2001), particularly in accounting education research (for instance, Rodrigues *et al.,* (2018); Le Roux (2017); Wang (2017); van Rensburg (2016); Lento and Sayad (2015); Bokana and Tewari (2014); Ungerer *et al.,* (2013); and Guney (2009)).

However, one of the challenges associated with logistic regression is the interpretation of the results. The output of a logistic regression model includes the slope coefficient, which represents an estimate of the change in the logarithm of the odds (otherwise referred to as the “log-odds” or “logit”) of the event represented by the dependent variable associated with a one-unit change in the predictor variable, while holding all other variables in the model constant (DesJardins, 2001). As the logit is symmetrical around zero, it provides a preferable building block for regression, depicting the S-shaped curve resulting from the binary outcome of a logistic regression (Pampel, 2000). However, the slope coefficient is unintuitive and difficult to understand (DesJardins, 2001). Thus, it is commonly converted to an odds ratio (OR) by applying the exponential, facilitating easier interpretation. This is because the OR is an indicator of the change in odds resulting from a single unit change in the explanatory variable (Field, 2009). Despite this, when slope coefficients are negative (i.e. when there is a negative relationship between the independent and dependent variable), interpretation of the OR may remain unintuitive, as it will be less than 1. DesJardins (2001) suggests the use of an “inverse odds ratio” (IOR) in these instances. This is found by taking the inverse of the OR included in the output of the logistic regression and allows for interpretation with reference to the base category. For example, if the OR resulting from the logistic regression indicates that males are 0.5 times more likely to pass than females, the IOR ratio is 2 (= 1 ÷ 0.5), indicating that females are twice as likely to pass than males.

Method of regression

When performing logistic regression, several options exist with regard to the manner of including the independent variables into the analysis. Selecting the most appropriate method should be done with the goal of the research in mind (Field, 2009). This research employed hierarchical regression analyses in addition to the conventional forced entry method. The application of these methods of regression in conjunction with each other was used to extract as much insight as possible into the relationship between the explanatory and outcome variables considered in this research.

Forced entry is a method of regression whereby all the explanatory variables are included in the regression simultaneously. This is considered the default or conventional approach to regression analysis (Field, 2009) and has been applied extensively in similar prior research. As such, a forced entry regression method was applied in the initial analysis performed in this research.

In contrast to forced entry, hierarchical regression (sometimes referred to as “block-wise” regression) allows for the inclusion of predictor variables into the regression analysis in a number of meaningful groupings or blocks, with statistical analysis performed at each step (Field, 2009). When utilising hierarchical regression, it is best practice for known predictors to be included in the model first, in the order of their importance in predicting the dependent variable, followed by any new predictors which are being researched (Field, 2009). This allows the researcher to better understand the impact of under-researched variables.

A hierarchical regression method should be distinguished from a stepwise regression method, whereby independent variables are included in (or removed from) the regression analysis, usually by regression software, in an order based entirely on statistical significance (Field, 2009). As pointed out by Berger (2004) and Malek, Berger and Coburn (2007), while it may be tempting to use a stepwise regression method as its use yields a smaller set of predictor variables, this approach has several theoretical shortcomings and should be used with caution. Instead, it is almost always preferable to apply a hierarchical analysis, where the researcher carefully plans the inclusion of the variables in the regression (Berger, 2004).

Furthermore, it is important to note that the order of entry will not affect the final results related to a complete set of variables (Berger, 2004). Thus, following the inclusion of the final block of predictor variables into a hierarchical analysis, the results will mirror those achieved in the forced entry approach. However, at the intermediate steps, the results generated reflect the outcomes of the variables included in the analysis to that point (Berger, 2004). This allows the researcher to isolate the effect of the inclusion of each group of variables.

Underlying assumptions

Several key assumptions underpin logistic regression and it is important that these are not violated when performing the analysis. Therefore, tests relating to each of the following assumptions were performed as part of this research.

Linearity of logit

When performing logistic regression, an underlying assumption exists that there is a linear relationship between the log of the dependent variable and any continuous independent variables (Field, 2009). This assumption may be tested by determining whether the interaction term between any continuous variable and its log transformation is significant when included in the regression analysis (Field, 2009).

Independence of errors

Logistic regression also assumes that cases of data are not related, which is referred to as independence of errors (Field, 2009). In the context of this research, cases do exist where a single individual may be included in the data on multiple occasions, if individual students attempted the CAC PGDA more than once in the timeframe under review, resulting in a violation of this underlying assumption. Thus, where appropriate, a mixed effects logistic regression model, which allows for correlation between data points (Allison, 2011), was utilised to analyse whether the relationships within the data significantly affected the outcome of the testing.

Multicollinearity

In terms of this underlying assumption, it must be ensured that the independent variables included in the model are not highly correlated with each other (Field, 2009). Pearson correlation matrices may be used to assess the correlations between the independent

variables included in the regression, making use of dummy variables where independent variables are categorical (Tabachnick & Fidell, 2014).[7]

However, although a review of the correlation matrices does provide some comfort with regard to potential multicollinearity issues, it may not detect all such issues (Field, 2009). Thus, additional diagnostics may be performed in order to calculate the variance inflation factor (VIF) and tolerance for the variables included in the regression analysis. VIF is an indicator of whether an independent variable has a strong linear relationship with other predictor variables and it has been suggested that VIF values exceeding 10 may be cause for concern with regard to multicollinearity (Field, 2009). Tolerance is the inverse of VIF and hence, values below 0.1 signal collinearity issues (Field, 2009). Additionally, a review of the standard errors in the regression output may be used to obtain additional comfort relating to multicollinearity, as excessive standard errors may be indicative of issues with this assumption (Tabachnick & Fidell, 2014).

Influential cases

For the purposes of this research, Cook's distance was used to identify any potential influential cases exerting undue influence on the models. Cook's distance is a measure of the impact on the regression coefficients if the case in question was omitted and therefore identifies which cases most influence the model (Stevens, 1984). If the Cook's distance of a particular case in the sample exceeds 1, it is generally understood that that case may have undue influence on the model (Field, 2009; Stevens, 1984). Applying this approach is preferable to simply identifying outliers in a model, as outliers do not necessarily unduly influence the regression outcome (Stevens, 1984). Instead, Cook's distance identifies all cases which are influential to the model, regardless of whether they represent outliers or not (Stevens, 1984).

[7] The chi-square test of independence to evaluate associations between the categorical variables was considered in order to assess multicollinearity, but due to the low expected counts in a large proportion of the cells, the results of the chi-squared test may not be valid in this instance. Hence, the Pearson correlation matrices were used instead.

Regression outputs

As already mentioned, the output of a logistic regression model includes the slope coefficient, which is commonly converted to an OR to aid with the interpretation of the results. When slope coefficients are negative, the use of an IOR is used to facilitate interpretation. These measures were used in reporting the outcomes of the regression analyses performed in this research.

Also reported are the -2 log-likelihood (-2LL), Nagelkerke's pseudo-R^2 and the results of the Hosmer-Lemeshow goodness-of-fit test. The -2LL is a measure of the unexplained variance in the model and therefore, larger measures of this metric indicate a more poorly fitting model, as more unexplained observations increase the deviance associated with the model (Field, 2009). Nagelkerke's pseudo-R^2 is a measure of the fit of the model, adjusted from the R^2 commonly used in linear regression for application to logistic regression (Field, 2009). The result varies between 0 and 1 and is reported on a percentage basis, with 0% indicating that none of the observed variance is predicted by the model and 100% indicating that the model perfectly predicts all the observed variance in the sample. Finally, the Hosmer-Lemeshow goodness-of-fit test assesses how effectively the model describes the outcome variable (Hosmer, Taber & Lemeshow, 1991). The null hypothesis associated with this test is that the model is a good fit for the data and therefore a significant *p*-value result would indicate that the model is a poor fit for the data (Hosmer, Sturdivant & Lemeshow, 2013).

RESEARCH DESIGN

Due to the nature of the data available, it became apparent that to test the research hypotheses, three regression models would be necessary – two related to academic success in the CAC PGDA (i.e. portion "a" of each hypothesis) and one related to academic success in SAICA's ITC (i.e. portion "b" of each hypothesis). This necessity resulted from the fact that the online application model only required students to enter their most recent academic results when applying for the CAC PGDA. Therefore, for students who were progressing to the PGDA following completion of their undergraduate degree, the data captured by the online application model related to their final undergraduate year and would therefore comprise pass marks. However, for students

who had already attempted CTA at least once, the data captured by the online application model related to their most recent CTA attempt, which would have been unsuccessful (as the student was applying to reattempt CTA). It would therefore represent an overall fail mark.

As a result, the analysis regarding academic success in the PGDA was performed separately for those students who were attempting their CTA for the first time (Model 1) and for those who were attempting it a subsequent time (Model 2). All students who successfully completed the PGDA and progressed onto the ITC were included in the sample for Model 3, regardless of whether they had previously been included in Model 1 or Model 2 for the purposes of PGDA testing. The relationship between the testing models as well as how they link to the two portions of each hypothesis, is represented graphically in Figure 4 below.

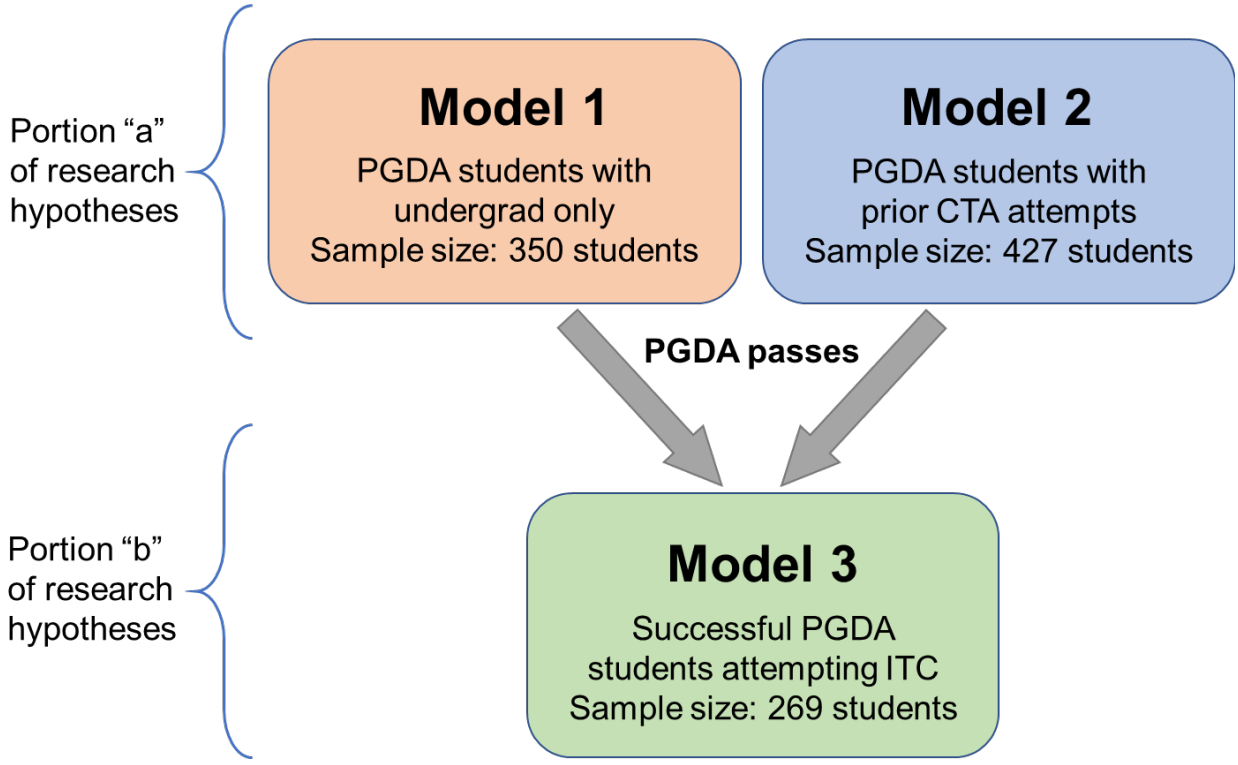

Figure 4: Relationship between testing models and research hypotheses (Source: Author's own)

Dependent variable

The dependent variable for each of the three models was academic success at the relevant level. The measure used to assess academic success for the CAC PGDA (Models 1 and 2) was whether the student achieved a pass mark (i.e. 50% or more) simultaneously in each of the four subjects (hence qualifying for admission to the ITC). For SAICA's ITC exam (Model 3), it was whether the student achieved a pass within their first two attempts (i.e. within the first year immediately following successful completion of PGDA). Thus, the dependent variable for each model was binary (pass or fail), justifying the selection of a logistic regression analysis approach.

Table 1: Frequency statistics relating to dependent variable for Models 1, 2 and 3

		Model 1		**Model 2**		**Model 3**	
Dependent Variable		PGDA result		PGDA result		ITC result	
	Coded	**n**	**%**	**n**	**%**	**n**	**%**
Fail	0	240	68.6	263	61.6	39	14.5
Pass	1	110	31.4	164	38.4	230	85.5
Total		**350**	**100.0**	**427**	**100.0**	**269**	**100.0**

Independent variables[8]

The independent variables are those factors which, as discussed in the literature review, may be associated with the dependent variable, namely, academic success. All non-binary categorical independent variables were coded such that the first category contained the largest number of cases when considering the total PGDA sample.

Hypothesis 1: Age

In order to obtain the students' age during the PGDA, students' date of birth, as indicated at enrolment, was compared to the PGDA year for which they had enrolled. The result was then coded as an ordinal variable as follows: students aged between 23 and 24 were coded as "0"; between 25 and 26 as "1"; between 27 and 29 as "2"; older than 29 as "3";

[8] It is noted that interaction effects between independent variables may exist where two or more predictor variables have a combined effect on the outcome variable (Field, 2009). However, the assessment of these interaction effects is beyond the scope of this research.

and younger than 23 as “4”. The coding for this variable was applied to all three regression models.

Table 2: Frequency statistics relating to the age variable for Models 1, 2 and 3

		Model 1		Model 2		Total sample		Model 3	
	Coded	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**
Ages 23 to 24	0	179	51.1	95	22.2	274	35.3	106	39.4
Ages 25 to 26	1	73	20.9	118	27.6	191	24.6	60	22.3
Ages 27 to 29	2	26	7.4	109	25.5	135	17.4	43	16.0
Age 30 and older	3	21	6.0	100	23.4	121	15.6	32	11.9
Age 22 and younger	4	51	14.6	5	1.2	56	7.2	28	10.4
Total		**350**	**100.0**	**427**	**100.0**	**777**	**100.0**	**269**	**100.0**

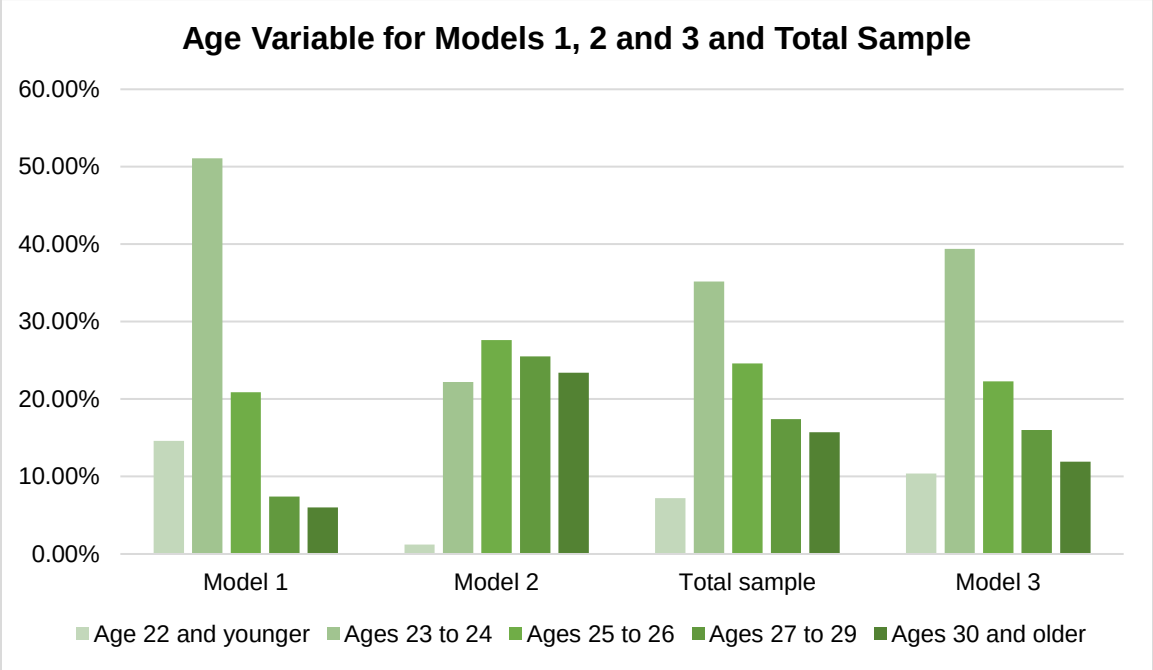

Figure 5: Bar chart of age variable for Models 1, 2 and 3 and total sample

Figure 5, which orders the age categories from youngest to oldest, illustrates that the students contained in Model 1 tended to be younger than those grouped into Model 2. Specifically, of the students included in Model 1, 65.5% were 24 or younger, compared to only 23.4% in Model 2. Instead, in Model 2, the number of students was more evenly

spread across the latter categories with the majority of students (i.e. 53.1%) falling between the ages of 25 and 29. This makes sense, as the students included in Model 2 had previously attempted CTA unsuccessfully, adding years to their educational journey, while those included in Model 1 were progressing directly from their undergraduate studies.

Hypothesis 2: Gender

For this dichotomous variable, females were coded as "0" while males were coded as "1". This coding was applied to all three regression models.

Table 3: Frequency statistics relating to the gender variable for Models 1, 2 and 3

		Model 1		Model 2		Total sample		Model 3	
	Coded	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**
Female	0	202	57.7	220	51.5	422	54.3	144	53.5
Male	1	148	42.3	207	48.5	355	45.7	125	46.5
Total		**350**	**100.0**	**427**	**100.0**	**777**	**100.0**	**269**	**100.0**

From the above, it is apparent that females represented the majority of students included in all three models, though this was most pronounced in Model 1.

Hypothesis 3: Race

The race categories applied for the purposes of this research are black, white, Indian and Coloured, broadly following the categories delineated by Stats SA when preparing demographic information relating to the South African population (Stats SA, 2018). Students self-declared their race when applying for the CAC PGDA.

Within this nominal variable, black South African students, who represented more than half of the total sample, were coded as "0", white students as "1" and Indian students as "2" for all models. For Model 1 Coloured students were coded as "3" while all other races were coded as "4". This final category consisted mainly of students from other African nations, as well as one Asian student. However, for Models 2 and 3, in order to ensure that cases existed in all potential categories, it was necessary to merge Coloured students with students from other races in a final category.

Table 4: Frequency statistics relating to the race variable for Models 1, 2 and 3

		Model 1		Model 2		Total sample		Model 3	
	Coded	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**
Black	0	199	56.9	236	55.3	435	56.0	123	45.7
White	1	96	27.4	106	24.8	202	26.0	94	34.9
Indian	2	37	10.6	59	13.8	96	12.3	35	13.0
Coloured	3	14	4.0	-	-	32	4.1	-	-
Other	3/4	4	1.1	26	6.1	12	1.5	17	6.3
Total		**350**	**100.0**	**427**	**100.0**	**777**	**100.0**	**269**	**100.0**

Hypothesis 4: Prior academic performance

As previously mentioned, the information captured via the online application model relating to prior academic performance differed depending on whether applicants had previously attempted CTA or not. When applying for admission to the CAC PGDA, students were required to input the marks from their most recent academic year for each of the four core subjects into the online model. The average of these four marks, equally weighted, was calculated for each student in the sample and used in Models 1 and 2 as a measure of prior academic performance. Thus, for Model 1, the measure of prior academic performance was the student's average mark in the final year of their undergraduate degree (i.e. a pass mark), while for Model 2, it was the average mark related to the student's most recent previous CTA attempt (i.e. an overall fail mark). For Model 3, the measure of prior academic performance was the average mark obtained in the CAC PGDA prior to progressing to the ITC (i.e. a pass mark).

Using the most recent measure of prior academic performance available is in line with prior research, which indicates that the single best predictor of academic performance at every level is academic performance in the immediately preceding year of study, as discussed in the literature review (for example, Papageorgiou and Halabi (2014); Steenkamp (2014); Swart and Becker (2014); and Dehrmann (2013)).

No coding of this variable was necessary, as it was a continuous variable and could be incorporated into the regression analysis as such.

Table 5: Descriptive statistics relating to the prior academic performance variable for Models 1, 2 and 3

	Model 1	Model 2	Model 3
Measure of prior performance	Average undergrad mark	Average CTA mark	Average PGDA mark
Mean	58.028	44.678	54.138
Standard Deviation	6.457	4.981	3.253

Hypothesis 5: Prior tertiary institution

For the purposes of Model 1, prior tertiary institution relates to the undergraduate institution which the student attended. This nominal variable was coded as indicated in Table 6 below. All students progressing to the ITC from the CAC PGDA had completed their CTA at the same institution and therefore there was no variation within that portion of the sample in terms of the institution of their successful CTA. Thus, for Model 3, prior tertiary institution also relates only to undergraduate institution attended.

Table 6: Frequency statistics relating to the prior tertiary institution variable for Models 1 and 3

		Model 1		Model 3	
	Coded	**n**	**%**	**n**	**%**
Unisa	0	62	17.7	50	18.6
University of Johannesburg	1	49	14.0	34	12.6
Monash South Africa	2	75	21.4	47	17.5
University of Pretoria	3	60	17.1	39	14.5
University of the Witwatersrand	4	22	6.3	28	10.4
North-West University	5	12	3.4	13	4.8
University of Cape Town	6	21	6.0	16	5.9
Other	7	49	14.0	42	15.6
Total		**350**	**100.0**	**269**	**100.0**

A breakdown of the ‘Other’ category for this variable for Models 1 and 3 (coded “7”) is provided below.

Table 7: Frequency statistics relating to 'Other' category of the prior tertiary institution variable for Models 1 and 3

	Model 1		Model 3	
	n	%	n	%
University of Stellenbosch	17	34.7	14	33.3
University of the Western Cape	15	30.6	9	21.4
University of KwaZulu Natal	3	6.1	6	14.3
University of the Free State	9	18.4	5	11.9
Rhodes University	2	4.1	6	14.3
Nelson Mandela University	2	4.1	1	2.4
University of Limpopo	0	0.0	1	2.4
University of Fort Hare	1	2.0	0	0.0
Other	0	0.0	0	0.0
Total	**49**	**100.0**	**42**	**100.0**

For the purposes of Model 2, which includes students who had previously attempted CTA, prior tertiary institution takes into account both the undergraduate institution which they attended as well as the institution of their most recent CTA attempt. Given that multiple combinations of institutions existed within this variable, it was coded according to the most frequently observed combinations, as indicated in Table 8 below.

Table 8: Frequency statistics relating to the prior tertiary institution variable for Model 2

		Model 2	
	Coded	n	%
Monash South Africa CTA with different undergraduate degree	0	199	46.6
Unisa CTA with different undergraduate degree	1	91	21.3
Unisa undergraduate degree and CTA	2	43	10.1
Monash South Africa undergraduate degree and CTA	3	27	6.3
Other single institution	4	57	13.3
Other multiple institutions	5	10	2.3
Total		**427**	**100.0**

The ten students included in the 'Other multiple institutions' category (coded "5") had attended combinations of various institutions across their undergraduate and postgraduate studies. A breakdown of the 'Other single institution' category for this variable for Model 2 (coded "4") is shown in Table 9 below.

Table 9: Frequency statistics relating to 'Other single institution' category of the prior tertiary institution variable for Model 2

	Model 2	
	n	**%**
University of North-West	17	29.8
University of Johannesburg	14	24.6
University of the Witwatersrand	12	21.0
University of Cape Town	6	10.5
University of Stellenbosch	2	3.5
University of the Western Cape	2	3.5
Rhodes University	2	3.5
University of KwaZulu Natal	1	1.8
University of Pretoria	1	1.8
Total	**57**	**100.0**

Hypothesis 6: Previous CTA attempts

The number of previous CTA attempts was relevant only to Models 2 and 3, as students in Model 1 had not previously attempted CTA. Due to the nature of the data available, this variable was coded as a categorical variable, rather than inputted as a continuous variable and was coded for the purposes of Model 2 as shown in Table 10 below.

Table 10: Frequency statistics relating to the previous CTA attempts variable for Model 2

		Model 2	
	Coded	**n**	**%**
1 previous CTA attempt	1	205	48.0
2 previous CTA attempts	2	99	23.2
3 previous CTA attempts	3	69	16.2
4 previous CTA attempts	4	33	7.7
5 previous CTA attempts	5	12	2.8
More than 5 previous CTA attempts	6	9	2.1
Total		**427**	**100.0**

Due to the smaller sample size included in Model 3 and to ensure that cases existed in all coded categories, this variable was coded slightly less granularly for Model 3, as indicated in Table 11 below.

Table 11: Frequency statistics relating to the previous CTA attempts variable for Model 3

		Model 3	
	Coded	**n**	**%**
No previous CTA attempt	0	108	40.1
1 previous CTA attempt	1	86	32.0
2 previous CTA attempts	2	40	14.9
3 previous CTA attempts	3	19	7.1
More than 3 previous CTA attempts	4	16	5.9
Total		**269**	**100.0**

Hypothesis 7: Time lapses

For the purposes of Model 1, it was fairly straightforward to assess whether students had encountered any time lapses between their undergraduate and postgraduate studies, as the completion year of their undergraduate degree was captured by the online application model. Therefore, any time lapses were calculated by comparing the PGDA year for which they enrolled with the year in which they completed their undergraduate degree.

The result was coded as a categorical variable, rather than inputted into the analysis as a continuous variable. This is because very few students had gaps of more than two years between the completion of their undergraduate degree and their first attempt at CTA. The most significant time lapses were 17 years, 14 years and nine years, each only applicable to one student. For the purposes of Model 1, this variable was coded as indicated in Table 12 below.

Table 12: Frequency statistics relating to the time lapses variable for Model 1

		Model 1	
	Coded	**n**	**%**
No time lapse	0	290	82.9
1-year time lapse	1	43	12.3
2-year time lapse or more	2	17	4.9
Total		**350**	**100.0**

For the purposes of Model 2, accounting for the years since completion of students' undergraduate studies was more complex. Although it was possible to calculate the time between the PGDA year for which they had enrolled and the year in which they had completed their undergraduate degree in the same manner as performed for Model 1, for students with multiple previous CTA attempts, the data available did not indicate the years in which all the attempts had taken place. Therefore, for Model 2, this variable was treated as dichotomous and assessed only whether there were unaccounted-for years between the completion of a student's undergraduate degree and the PGDA year in which they enrolled. This was done by subtracting the number of previous CTA attempts from the number of years since the completion of undergraduate studies. For students with more than five previous CTA attempts, it was assumed that they had attempted CTA six times for the purposes of this calculation. The same approach was also applied in including this variable into Model 3.

The observed frequency related to time lapses for Models 2 and 3 is indicated in Table 13 below.

Table 13: Frequency statistics relating to the time lapses variable for Models 2 and 3

		Model 2		Model 3	
	Coded	**n**	**%**	**n**	**%**
No unaccounted-for years	0	223	52.2	184	68.4
At least 1 unaccounted-for year	1	204	47.8	85	31.6
Total		**427**	**100.0**	**269**	**100.0**

Hypothesis 8: Class selection

Whether students engaged with the CAC PGDA on the daytime or after-hours track was identified from their online application. Although it is possible that students later changed their selection, corroborating their actual class attendance was not possible and therefore reliance was placed on the data captured via the online application model. For this dichotomous variable, students who engaged with the PGDA on the daytime track were coded as “0” while those who engaged with it on the after-hours track were coded as “1”. This coding was applied to all three regression models.

Table 14: Frequency statistics relating to the class selection variable for Models 1, 2 and 3

		Model 1		Model 2		Total sample		Model 3	
	Coded	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**
Daytime	0	253	72.3	129	30.2	382	49.2	157	58.4
After-hours	1	97	27.7	298	69.8	395	50.8	112	41.6
Total		**350**	**100.0**	**427**	**100.0**	**777**	**100.0**	**269**	**100.0**

From the above, it is apparent that although the split between the daytime and after-hours students is roughly even in the total sample, there is a marked difference between the class selection of the majority of students in Models 1 and 2. Over 70% of students attempting CTA for the first time selected to attend the contact, daytime portion of the programme. However, almost the same proportion of students who had previously attempted CTA selected the after-hours option, making use of the blended learning model

adopted there. This may indicate that more of the students repeating CTA were working and were therefore unable to attend daytime classes.

RESULTS

Before assessing the findings for each research hypothesis, it is necessary to review the results of the three models included in the analysis. This is because each model tests several hypotheses and none of the hypotheses is tested in full by a single model. Therefore, what follows is first a discussion of the results of the logistic regression analysis performed on each model, as well as the assumption testing performed, followed by an assessment of how the results relate to the hypotheses and prior research findings.

MODEL 1: PGDA STUDENTS WITH UNDERGRAD ONLY

To begin with, a regression analysis was run using the forced entry method, including all independent variables relevant to this model, namely, age, gender, race, prior academic performance (i.e. average mark for the four core subjects in final year of undergraduate degree), prior tertiary institution (i.e. undergraduate institution), time lapses and class selection. The variable relating to previous CTA attempts was excluded from this model as, by definition, all of the students included in this model were attempting CTA for the first time. The outcome of this model ($\chi 2 = 101.878$, df = 20, $p < 0.001$), as shown in Table 15 below, indicated that race ($p = 0.002$), prior academic performance ($p < 0.001$), prior tertiary institution ($p = 0.004$) and class selection ($p = 0.021$) were all statistically significant at a 95% confidence level in predicting success in the PGDA and that the model correctly classified the PGDA outcome related to 75.7% of students. This is a marked increase from the classification accuracy of 68.6% before taking into account any of the identified variables, which results from simply predicting that all students fail the PGDA, given that this was the most common outcome in the sample.

Table 15: Model 1 logistic regression results

Variable	B	*p*-value	SE	OR	IOR
Constant	-11.836	<0.001	2.293		
H1: Age		0.264			
Ages 25 to 26	-0.361	0.406	0.435	0.70	1.43
Ages 27 to 29	-1.504	0.074	0.842	0.22	4.50
Age 30 and older	-0.366	0.649	0.803	0.69	1.44
Age 22 and younger	0.465	0.230	0.388	1.59	
(base = Ages 23 to 24)					
H2: Gender					
Male	-0.007	0.980	0.291	0.99	
(base = Female)					
H3: Race		0.002			
White	1.271	<0.001	0.343	3.57	
Indian	-0.020	0.970	0.550	0.98	1.02
Coloured	0.922	0.172	0.676	2.52	
Other	2.498	0.054	1.298	12.16	
(base = Black)					
H4: Prior academic performance	0.172	<0.001	0.035	1.19	
H5: Prior tertiary institution		0.004			
University of Johannesburg	-0.048	0.947	0.725	0.95	1.05
Monash South Africa	-0.109	0.839	0.539	0.90	1.12
University of Pretoria	1.819	0.003	0.607	6.16	
University of the Witwatersrand	1.160	0.172	0.850	3.19	
North-West University	-0.106	0.914	0.980	0.90	1.11
University of Cape Town	1.627	0.030	0.751	5.09	
Other	1.468	0.024	0.649	4.34	
(base = Unisa)					
H7: Time lapses		0.106			
1-year time lapse	0.820	0.048	0.414	2.27	
2-year time lapse or more	0.731	0.314	0.726	2.08	
(base = No time lapse)					

H8: Class selection						
	After-hours	-1.024	0.021	0.445	0.36	2.79
	(base = Daytime)					
Model statistics:						
	-2LL	333.863				
		χ^2 = 101.878, df = 20, p < 0.001				
	Nagelkerke's R^2	35.5%				
	Hosmer-Lemeshow test	χ^2 (8) = 4.337, p =0.826				
	Classification accuracy	75.7%				

A further regression analysis was then performed on the variables included in Model 1 using a hierarchical regression approach. As previously noted, when using hierarchical regression, it is best practice for known predictors to be included in the model first, in the order of their importance in predicting the dependent variable, followed by any new predictors which are being researched (Field, 2009). Therefore, the variables identified as “typically researched” in the literature review (i.e. age, gender, race and prior academic performance) were included in the model as a first block and then the “additional factors” (i.e. prior tertiary institution, time lapses and class selection) were included in a separate, second block to isolate the improvement in the model attributable to each set of variables. The outcome of this regression is included in Appendix A, Step 2 and indicated that each set of factors made a highly statistically significant contribution to the development of the model. However, the improvement of the classification accuracy of the model appeared largely attributable to the “typically researched” variables, as it increased to 75.4% (from the baseline of 68.6%) following the inclusion of the variables in block 1. It then increased to 75.7% once the “additional factors” included in block 2 had been included.

To further investigate which variables accounted for the greatest improvement in the model, a third, even more granular hierarchical regression analysis was run. In this final version of Model 1, the “typically researched” variables where separated into two sets of variables – demographic information (i.e. age, race and gender) and prior academic performance. Division of the variables was done in this manner as prior research strongly indicates that prior academic performance is the single best predictor of future academic

performance, and it was therefore expected that it would have the single largest impact on the development of the model. As such, prior academic performance was included in the regression first, with demographic information included as a second block of variables. As there is little or no prior research on the impact of the "additional factors", it was difficult to identify a way to meaningfully group these variables into categories. Hence, they were each included in this final regression in three separate blocks, from most to least significant (Field, 2009), as indicated from the initial output of Model 1 (i.e. first, prior tertiary institution; second, class selection; and third, time lapses). Thus, the final model contained five blocks of variables, the results of which are summarised in Appendix A, Step 3.

As indicated by these results, the classification accuracy of the model is at its highest level (i.e. 76.3%) when just prior academic performance, age, gender, race and prior tertiary institution are entered as variables. Although the inclusion of class selection reduces the classification accuracy somewhat, this variable is statistically significant to the model and helps to explain the variance in the model, as evidenced by the increase in Nagelkerke's pseudo-R^2 and decrease in -2LL in Block 4. Additionally, the inclusion of time lapses, while not statistically significant to the model, meaningfully increased the model's ability to accurately predict passing students, while again increasing the variance explained by the model.

MODEL 2: PGDA STUDENTS WITH PRIOR CTA ATTEMPTS

As with Model 1, an initial logistic regression analysis was run including all independent variables relevant to this model, namely, age, gender, race, prior academic performance (i.e. average mark for the four core subjects in the most recent CTA attempt), prior tertiary institution (i.e. a combination of undergraduate and prior postgraduate institution), previous CTA attempts, time lapses and class selection. The outcome of this model ($\chi 2$ = 104.436, df = 21, $p < 0.001$), as shown in Table 16 below, indicates that race (p = 0.015), prior academic performance ($p < 0.001$) and class selection ($p < 0.001$) were found to be highly statistically significant in predicting success in the PGDA and that the model correctly classified the PGDA outcome of 72.8%, notably improving this from the 61.6% classification accuracy prior to consideration of the identified variables. It is

interesting to note that in contrast to the results of Model 1, prior tertiary institution was not of statistical significance in this model.

Table 16: Model 2 logistic regression results

Variable	B	*p*-value	SE	OR	IOR
Constant	-9.032	<0.001	1.373		
H1: Age		0.604			
Ages 25 to 26	-0.149	0.668	0.346	0.86	1.16
Ages 27 to 29	-0.201	0.603	0.385	0.82	1.22
Age 30 and older	-0.494	0.268	0.446	0.61	1.64
Age 22 and younger	1.317	0.271	1.197	3.73	
(base = Ages 23 to 24)					
H2: Gender					
Male	0.143	0.548	0.239	1.15	
(base = Female)					
H3: Race		0.015			
White	0.846	0.003	0.280	2.33	
Indian	0.711	0.046	0.357	2.04	
Other	0.435	0.352	0.468	1.55	
(base = Black)					
H4: Prior academic performance	0.202	<0.001	0.030	1.22	
H5: Prior tertiary institution		0.212			
Unisa CTA with different undergrad	-0.445	0.211	0.356	0.64	1.56
Unisa undergrad and CTA	-0.515	0.232	0.431	0.60	1.67
Monash South Africa undergrad and CTA	0.803	0.086	0.467	2.23	
Other single institution	-0.135	0.715	0.370	0.87	1.14
Other multiple institutions	0.485	0.514	0.743	1.62	
(base = Monash South Africa with different undergrad)					

H6: Previous CTA attempts - Model 2			**0.736**			
	2 previous CTA attempts	0.117	0.703	0.307	1.12	
	3 previous CTA attempts	-0.097	0.802	0.387	0.91	1.10
	4 previous CTA attempts	0.540	0.272	0.491	1.72	
	5 previous CTA attempts	-0.534	0.544	0.881	0.59	1.71
	More than 5 previous CTA attempts	0.698	0.44	0.905	2.01	
	(base = 1 previous CTA attempt)					
H7: Time lapses						
	At least 1 unaccounted-for year	0.025	0.926	0.275	1.03	
	(base = No unaccounted-for years)					
H8: Class selection						
	After-hours	-1.164	<0.001	0.278	0.31	3.21
	(base = Daytime)					
Model statistics:						
	-2LL	464.349				
		χ^2 = 104.436, df = 21, p < 0.001				
	Nagelkerke's R^2	29.5%				
	Hosmer-Lemeshow test	χ^2 (8) = 10.120, p =0.257				
	Classification accuracy	72.8%				

Once again, hierarchical regression analysis was employed in order to break down the contribution made to the model by the various independent variables. An initial separation of the independent variables into those considered “typically researched” and the “additional factors” was applied, with those supported by the findings of prior research included first (Field, 2009). The outcome of this regression is summarised in Appendix B, Step 2. The results indicate that each set of factors made a statistically significant contribution to the development of the model. However, the improvement of the classification accuracy of the model once again appeared largely attributable to the “typically researched” variables, as it increased to 69.6% (from the baseline of 61.6%) in block 1 and then to 72.8% in block 2, once the “additional factors” had been included.

A final hierarchical regression was performed on Model 2, once again delving into further detail as to the specific variables contributing to the improved classification accuracy indicated in previous iterations. As with the analysis performed on Model 1, the "typically researched" variables were divided into two categories – those relating to demographic data (i.e. age, race and gender) and prior academic performance, with prior academic performance included in the model first as before. The "additional factors" applied in this model were also divided into two categories – class selection, the only additional factor shown to be of statistical significance in the initial regression, was entered into the model first, while those which had been shown to not be of statistical significance (i.e. prior tertiary institution, previous CTA attempts and time lapses) were grouped together and added to the model in a final block. Thus, this construction of Model 2 was performed in four blocks, the results of which are summarised in Appendix B, Step 3.

Examination of these results reveals that once again, prior academic performance was a key contributing factor to the model's ability to correctly classify students' ultimate PGDA result. Specifically, while it somewhat dilutes the prior model's ability to correct classify failing students, it results in over 40% of passing students being correctly classified. The addition of demographic factors and class selection both make statistically significant improvements to the model, enhancing its predictive power. The inclusion of prior tertiary institution, previous CTA attempts and time lapses in block 4 also notably improves the model's ability to classify passing students and increases the variance explained by the model (as shown by the increase in Nagelkerke's pseudo-R^2), despite not being of statistical significance. Ultimately the model correctly classifies 83.3% of failing students and 56.1% of passing students, while accounting for approximately 30% of the variance in the outcome.

MODEL 3: SUCCESSFUL PGDA STUDENTS ATTEMPTING ITC

Once again, a regression analysis for this model was run, factoring in all of the relevant independent variables. These were age, gender, race, prior academic performance (i.e. average mark for the four core subjects in the CAC PGDA), prior tertiary institution (i.e. undergraduate institution), time lapses and class selection. Given that the overall pass rate for the sample in the ITC was 85.5%, simply predicting that all students would pass

would lead to a classification accuracy of 85.5%. This is a relatively high standard, higher than either of those achieved by Model 1 or Model 2, even after accounting for the influence of the independent variables. Thus, it was noted that further improvement of classification accuracy would likely be limited.

Upon running the model initially ($\chi 2 = 65.452$, df = 22, $p < 0.001$), it was noted that classification accuracy increased marginally to 87.7% and that only prior academic performance ($p < 0.001$) and class selection ($p = 0.015$) were identified as individually statistically significant variables, as shown in Table 17 below. Interestingly, race ($p = 0.056$) was not identified as statistically significant in this model at a significance level of 0.05, unlike in Models 1 and 2. However, it would have been considered significant at a slightly lower significance level of 0.1.

Table 17: Model 3 logistic regression results

Variable	B	*p*-value	SE	OR	IOR
Constant	-18.040	0.001	5.322		
H1: Age		0.227			
Ages 25 to 26	-0.267	0.682	0.652	0.77	1.31
Ages 27 to 29	0.159	0.855	0.869	1.17	
Age 30 and older	1.245	0.241	1.061	3.47	
Age 22 and younger	-1.319	0.072	0.734	0.27	3.75
(base = Ages 23 to 24)					
H2: Gender					
Male	0.556	0.228	0.461	1.74	
(base = Female)					
H3: Race		0.056			
White	1.406	0.015	0.578	4.08	
Indian	1.414	0.071	0.785	4.11	
Other	0.649	0.492	0.945	1.91	
(base = Black)					
H4: Prior academic performance	0.353	<0.001	0.099	1.42	

H5: Prior tertiary institution			**0.162**			
	University of Johannesburg	1.342	0.119	0.860	3.83	
	Monash South Africa	0.538	0.516	0.828	1.71	
	University of Pretoria	1.830	0.015	1.312	24.66	
	University of the Witwatersrand	1.830	0.060	0.972	3.24	
	North-West University	0.645	0.561	1.108	1.91	
	University of Cape Town	1.097	0.291	1.039	3.00	
	Other	0.386	0.618	0.774	1.47	
	(base = Unisa)					
H6: Previous CTA attempts			0.322			
	1 previous CTA attempt	-0.898	0.151	0.625	0.41	2.45
	2 previous CTA attempts	-1.597	0.076	0.901	0.20	4.93
	3 previous CTA attempts	-1.580	0.119	1.012	0.21	4.85
	More than 3 previous CTA attempts	-0.225	0.856	1.237	0.80	1.25
	(base = No previous CTA attempts)					
H7: Time lapses						
	At least 1 unaccounted-for year	-0.867	0.099	0.526	0.42	2.38
	(base = No unaccounted-for years)					
H8: Class selection						
	After-hours	1.419	0.015	0.584	4.13	
	(base = Daytime)					
Model statistics:						
	-2LL	157.228				
		χ^2 = 65.452, df = 22, p < 0.001				
	Nagelkerke's R^2	38.4%				
	Hosmer-Lemeshow test	χ^2 (8) = 8.018, p =0.432				
	Classification accuracy	87.7%				

As before, hierarchical regression was performed, initially dividing the independent variables into those referred to as “typically researched” and as “additional factors” unique to this research. This analysis is summarised in Appendix C, Step 2, again revealing that each set of variables made a highly statistically significant contribution to the model. However, it is interesting to note that the “typically researched” factors alone did not

improve the classification accuracy of the model from the baseline and that the increase noted in the first regression was wholly attributable to the “additional factors” introduced through this research.

The final step in analysing Model 3 was to once again perform a more granular hierarchical regression analysis. A similar approach to that applied to Model 2 was adopted here. Thus, the final regression divided the “typically researched” variables into demographic-related variables and prior academic performance and “additional factors” into non-significant variables (i.e. prior tertiary institution, previous CTA attempts and time lapses) and class selection. This resulted in four separate categories of variables to be included in the model in a blockwise fashion. In accordance with the guidance provided for hierarchical regression analysis by Field (2009), prior academic performance was entered as the first block. Class selection (the only other variable of statistical significance) was added as the second block. Demographic variables were added as a third block, while non-significant “additional factors” were included as the fourth and final block of variables. The results of this analysis are summarised in Appendix C, Step 3.

Although inclusion of the “typically researched” variables did not result in an improvement in the overall classification accuracy of the model from the baseline when considered together in the previous version of the model, when considered alone, prior academic performance did improve the ability of the model to correctly classify failing students. This improved the overall classification accuracy of the model, as shown in block 1. Although the incorporation of class selection in block 2 marginally reduced classification accuracy, this variable made a statistically significant contribution to the model. It also increased the variance explained by the model, as evidenced by the increase in Nagelkerke’s pseudo-R^2 and the reduction in -2LL. In block 3, when age, gender and race were included, it is noteworthy that the result for the Hosmer-Lemeshow test for goodness-of-fit was statistically significant ($p = 0.028$), indicating that the model was not a good fit for the data, despite the improvement noted in classification accuracy, particularly with regard to failing students. However, once the “additional factors” were incorporated into the model in block 4, the Hosmer-Lemeshow test result returned to non-significant levels ($p = 0.432$) leading to the acceptance of the related null hypothesis that the model was a good fit, while

classification accuracy was further improved. The final result was that the model correctly classified almost 36% of failing students and 96.5% of passing students while accounting for approximately 38.4% of the variance in the outcome.

However, as discussed below, a number of influential cases were identified in Model 3. Further investigation of these, as well as a summary of the results of the model excluding these cases, is included below in the discussion on influential cases.

ASSUMPTION TESTING

Detailed below are the results of the additional diagnostics performed to test whether each of the three models satisfied the assumptions underpinning logistic regression.

Linearity of logit

For the purposes of this research, each model contained only one continuous independent variable, namely, prior academic performance. Thus, the regression was rerun for each model including an interaction term between the appropriate measure of prior academic performance and the log of that variable. In all cases, the result was found to be not significant (Model 1: $p = 0.649$; Model 2: $p = 0.997$; Model 3: $p = 0.898$), indicating that the assumption of linearity of the logit was satisfied with regard to the measures of prior academic performance included in the models.

Independence of errors

Given the nature of the research design, the independence of errors was not considered to be a concern for Models 1 and 3, as it was only possible for individual students to be included in those models once. It was therefore accepted that the data points were not correlated with each other. However, for Model 2, the independence of errors assumption was violated, as it was possible for individual students to contribute multiple data points to the data set. For instance, a student may have enrolled for the CAC PGDA in 2015 after attempting CTA previously at another institution and, after failing in that year, enrolled once again in 2016 or 2017 or both. In such a case, the same student would be included in Model 2 numerous times. Review of the data showed that multiple data points existed for 71 students included in Model 2.

Rather than deleting the additional data points generated by the subsequent PGDA attempts of returning students to overcome this issue, Model 2 was also run as a mixed effects logistic regression model, which is a theoretically more correct approach for the data included in that model (Allison, 2011). The output of this analysis compared to that of the binary logistic regression analysis is presented in Appendix E. It shows that the output of the two regression analyses revealed no marked differences in the findings – the same predictor variables were identified as significant and the relationships between the independent variables and the outcome variable, as well as the odds ratios associated with the independent variables, were found to be similar for both approaches. Furthermore, the estimate of the random effect at the case level of the mixed effects logistic regression model was small (σ_u^2= 0.372; SE = 0.363) and not significant (Z = 1.025; *p* = 0.305), indicating that the difference between the two logistic regression approaches was not substantial. However, it is worth noting that the mixed effects logistic regression model achieved correct classifications in 78.7% of cases, which is a notable improvement on the classification accuracy of the previous version of Model 2.

Multicollinearity

In order to assess the correlations between the independent variables included in each model, dummy variables were created for all categorical variables, including the reference categories, and Pearson correlation matrices were drawn for Models 1, 2 and 3. Examination of these matrices revealed no correlation coefficients approaching or greater than 0.9 and therefore, it does not appear that any of the variables were highly correlated (Field, 2009).

Additional diagnostics were run in order to calculate the VIF and tolerance for the variables included in each of the models. The collinearity statistics related to each model are included in Appendix F and reveal that for all variables in all three models, the VIF and tolerance values were well within acceptable ranges. Furthermore, review of the standard errors in the regression reveals that none appeared inflated or excessively large. Thus, it appears reasonable to conclude that the independent variables were measuring different factors and that the assumption of multicollinearity was not violated.

Influential cases

As mentioned, Cook's distance was used to identify any potential influential cases exerting undue influence on the models. If the Cook's distance of a particular case in the sample exceeds 1, then it is generally understood that that case may have undue influence on the model (Field, 2009; Stevens, 1984).

For Models 1 and 2, none of the cases in the sample had a Cook's distance of 1 or greater and therefore, it was concluded that no cases were unduly influencing the model. However, for Model 3, six cases were identified with a Cook's distance of more than 1 (ranging between 1.064 and 1.783). Investigation of these cases did not reveal any immediately apparent indication that they represented outliers to the sample. However, it was noted that in all six cases, the student had previously attempted CTA (i.e. had been included in the sample used for Model 2) and had failed the ITC. Thus, all six cases were included in the portion of the sample representing failing students, which represented only 14.5% of the sample for Model 3. Apart from these factors, the cases in question differed with regard to the other independent variables – ages ranged between 24 and 34; three students were male and three were female; three were black, one was white, two were Indian; two had previously attended Unisa, two had previously attended the University of the Witwatersrand and one each had attended NWU and the University of Pretoria; two had time lapses within their studies and four did not; and four attended the after-hours classes, while two attended the daytime classes.

Removal of these influential cases from the dataset based solely on the fact that they were considered influential was not appropriate (Hosmer *et al.*, 1991). Instead further investigation was required in order to determine the appropriate approach (Field, 2009). Specifically, Stevens (1984, pp. 343-344) recommends the following:

> 'Those points which are flagged as influential by Cook's distance need to be examined carefully to determine whether they should be deleted from the analysis. If there is reason to believe that these cases arise from a process different from that for the rest of the data, then the cases should be deleted… If none of these appears to be the case, two analyses – one with the influential cases in and one with those cases deleted – could be reported to emphasise the impact of these few points on the analysis.'

Investigation revealed that there is no reason to believe that the six cases with a Cook's distance of more than 1 included in Model 3 resulted from a process other than that applied to the remainder of the sample. Therefore, there did not appear to be any justification for removal of these cases from the dataset. Additionally, as these cases were previously included in Model 2 and were not flagged as influential in the testing performed on that model, it stands to reason that they were valid cases, despite the influence which they exerted in the context of Model 3.

However, in line with the guidance provided by Stevens (1984), the analysis of Model 3 was rerun excluding these cases, the results of which can be found in Appendix G. As noted in the original version of Model 3, prior academic performance ($p = 0.001$) and class selection ($p = 0.008$) were found to be of statistical significance. However, race, which previously was only significant for $p = 0.1$, was found to be of statistical significance in this version of the model, with a p-value equal to 0.033. Additionally, gender, which was not previously considered significant, resulted in a p-value of 0.058, which would be considered significant at a confidence level of 90%. Comparisons between the model fit and classification accuracy statistics related to the original version of Model 3 and that excluding the influential cases are presented in Table 18 below.

Table 18: Comparison of Model 3 results including and excluding influential cases

	Original version	Excluding influential cases
χ^2 - model	65.452	87.356
Significance	<0.001	<0.001
-2LL	157.228	111.311
Nagelkerke pseudo-R^2	38.4%	53.3%
Hosmer-Lemeshow test *p*-value	0.432	0.766
Correct classifications	87.7%	90.5%
Fail	35.9%	45.5%
Pass	96.5%	97.0%

From the table above, it is clear that exclusion of the influential cases identified in the original model improved all measures of model fit as well as classification accuracy. However, these results should be interpreted with caution. As mentioned, no valid justification for the removal of influential cases exists and therefore, their deletion in pursuit of a better statistical fit for the model would be inappropriate. Further, analysis of the model excluding the influential cases revealed an additional six influential cases in that model, five of which related to students who failed the ITC. This may indicate that, given the relatively high pass rate in the ITC among the cases in the sample, instances of students who failed the ITC bore a greater impact on the outcome of the model. Ultimately, removing all students who failed the ITC from the sample would have led to the simplest and best-fitting model. However, such a model would be of little theoretical or practical use. Thus, this research favours the output of the original model, while noting that application of the results beyond the given sample may be limited.

INTERPRETATION OF RESULTS

Appendix D contains a side-by-side summary of the results related to each variable for the initial step of each of the models included in this research (i.e. all variables entered as a single block, using a forced entry approach) and provides a helpful reference for the discussion below.

Hypothesis 1: Age

Age, the first of the typically researched personal presage factors considered in this research, was not found to be of statistical significance with regard to academic performance in any of the models produced in this research. This is in contrast to the findings of Jansen and de Villiers (2016), Steenkamp (2014), Ungerer *et al.* (2013) and van Wyk (2011), amongst others. However, it supports the more recent research of Papageorgiou (2017) and Wang (2017). Despite this, the odds ratios related to this hypothesis appear to support the general conclusion noted in prior research that younger students tend to outperform older students.

Therefore, the null hypotheses that age is not significantly associated with academic performance (i.e. Hypotheses 1a and 1b) are not rejected.

Hypothesis 2: Gender

In line with the findings of Papageorgiou (2017), Byrne *et al.* (2014), Papageorgiou and Halabi (2014) and van Wyk (2011), amongst others, no significant correlation was noted between gender, another typically researched personal presage factor, and academic performance, either for the CAC PGDA or SAICA's ITC. As suggested by Byrne and Flood (2008), this may be the result of a more gender-balanced world of accounting education, which is also evidenced by the fact that females outnumbered males in each model. As a result, the null hypotheses that gender is not significant associated with academic performance (i.e. Hypotheses 2a and 2b) are not rejected.

Hypothesis 3: Race

Race was found to be of statistical significance with regard to academic performance in CTA, as evidenced by the results of Models 1 and 2. Notably, the results of Model 1 indicated that white students were more than 3.5 times more likely to pass CTA than black students, among students who had not yet previously attempted CTA, at a high significance level ($p < 0.001$). Amongst students who had previously attempted CTA, the results of Model 2 indicated that white students were 2.33 times, Indian students 2.04 times and students of other racial groups 1.55 times more likely to pass CTA than their black colleagues. These enormous disparities support the findings of Papageorgiou (2017), Le Roux (2017), Ungerer *et al.* (2013) and Bokana and Tewari (2014), highlighting that there is still much work to be done in the accounting profession to address the disparities in opportunity which exist along racial lines in South Africa. It is worth noting that although many black students would likely be considered to come from previously disadvantaged backgrounds, this would not necessarily be the case for all students within that racial grouping. Further research would be required in order to understand the implications of this.

In Model 3, which related to students attempting SAICA's ITC, the *p*-value associated with the race variable was 0.056, which means that race was found to be not significant at a significance level of 0.05. However, the result is very close to this cut-off and would be considered significant at a slightly lower 90% confidence level. Here, once again, white students were found to significantly outperform their black counterparts ($p = 0.015$), being

more than four times more likely to pass the ITC. This closely aligns with the findings of Le Roux (2017) related to performance in SAICA's second board exam, the APC.

Consequently, Hypothesis 3a, that race is not significantly associated with academic performance in the CAC PGDA, is rejected. However, applying a significance level of 0.05, Hypothesis 3b, that race is not significantly associated with academic performance in SAICA's ITC, is not rejected.

Hypothesis 4: Prior academic performance

In all three models, prior academic performance (the fourth and final typically researched personal presage factor in terms of this research's application of the Biggs' 3P model) was found to be highly positively correlated with academic success ($p < 0.001$ in all three instances). Hence, null Hypotheses 4a and 4b, relating to the association between prior and current academic performance, are consequently rejected. This finding strongly supports the findings of much prior research, including Rodrigues *et al.* (2018), Papageorgiou and Halabi (2014), Steenkamp (2014), Dehrmann (2013), Pullen *et al.* (2013), van Wyk (2011) and Swart and Becker (2014). It also adds further weight to the claim that the single best predictor of academic success is academic performance in the immediately preceding year of study. Furthermore, this finding highlights the need for meaningful support to be offered to scholars and students to achieve their academic potential as early as possible, as each academic year lays the foundation for the next. This research focused on a point of the culmination of many years of education for students and success in these final steps towards qualification as CAs(SA) may depend on the building blocks put in place as far back as early childhood. Therefore, interventions need to be considered not only at this late stage but also throughout the entire educational process in order to foster the highest levels of achievement possible.

Hypothesis 5: Prior tertiary institution

Moving on to the additional personal presage factors considered in this research, prior tertiary institution was found to be highly significant ($p = 0.004$) in Model 1, relating to PGDA students who had not previously attempted CTA. Thus, it would appear that undergraduate institution attended plays an important role in determining success in the PGDA for these students. Specific relationships found to be significant related to students

who had attended the University of Pretoria, UCT and other institutions; those students were found to be 6.16 times, 5.09 times and 4.34 times more likely to pass the CAC PGDA than students who had completed their undergraduate degree at Unisa. While the “Other” category consists of a collection of institutions, both the University of Pretoria and UCT have historically been regarded as well-resourced, premium residential institutions. The success of students from those institutions in the CAC PGDA, even after they had left their undergraduate institution, points to the benefit of strong educational foundations in future success, though other factors (such as teaching philosophy and approach) are likely to also play a role.

Interestingly, however, the relationship between prior tertiary institution and academic performance in the PGDA for students who had previously attempted CTA or in the ITC for students who had successfully completed the CAC PGDA was not found to be statistically significant. This stands in contrast to the findings of Rodrigues *et al.* (2018) in Brazil and suggests that other factors, such as prior exposure to the CTA content, may play a stronger role in contributing to student academic success following an initial attempt at CTA. In order to better understand the relationship between prior tertiary institution and success in the ITC, it would be beneficial to conduct additional research on all candidates writing the ITC to compare the results of those who progressed through a single university pipeline with those who changed academic institution during their studies. It would also be useful to compare the performance of candidates who successfully completed their CTA at CAC with those from other institutions.

Therefore, null Hypothesis 5a, that prior tertiary institution is not significantly associated with academic performance in the CAC PGDA, is partially rejected (for students who were attempting CTA for the first time – i.e. Model 1) and partially not rejected (for students who had previously attempted CTA – i.e. Model 2). Hypothesis 5b, relating to the association between prior tertiary institution and academic performance in SAICA’s ITC, is not rejected.

Hypothesis 6: Previous CTA attempts

Neither Model 2 nor Model 3 found a significant relationship between academic performance and previous CTA attempts, the second additional personal presage factor

addressed by this research. Hypotheses 6a and 6b are therefore not rejected. However, the odds ratios included in the results of Model 3 indicate that students who successfully completed CTA in a single attempt were several times more likely to be successful in the ITC than those who required multiple attempts at CTA. This would support the observation in the literature review that the longer it takes accounting students to successfully complete any leg of their academic journey, the less likely they are to reach their ultimate goal.

Hypothesis 7: Time lapses

No significant relationships between time lapses and student performance were noted in any of the models. Consequently, Hypotheses 7a and 7b relating to this additional personal presage factor are not rejected. However, the odds ratio resulting from Model 3 (which would be considered statistically significant at a 90% confidence level) indicates that students who had no unaccounted-for years in their journey to the ITC were more than two times more likely to pass the board exam than those who had a time lapse of at least one year. Once again, this highlights how delays along the qualification path negatively impact students' chances of ultimately qualifying as CAs(SA).

Hypothesis 8: Class selection

All three models found class selection to be significant in determining academic performance – however, very interestingly, as the only situational presage factor in the context of this research, the nature of the impact of class selection depends on the measure of academic performance. In PGDA, both Models 1 and 2 found that students who attended daytime sessions were more likely to pass than those who attended after-hours classes (Model 1: 2.79 times more likely; Model 2: 3.21 times more likely). However, for performance in the ITC, Model 3 found that students who had attended the after-hours classes were 4.13 times more likely to pass than those who had attended the daytime classes.

These results indicate that students who engaged with the CAC PGDA on a fully contact, daytime basis were more likely to pass that course but that students who attended the blended, after-hours offering were much more likely to pass SAICA's ITC. The improved performance of the after-hours students in the ITC may be the result of several factors or

a combination of factors. Potential explanations may be that perhaps a blended learning approach fostered self-teaching and self-management skills in these students, allowing them to better prepare for the ITC while working, whereas students who had engaged with the fully contact version of the programme were less equipped to prepare for the ITC by themselves once the structured instruction of CTA had ended. Perhaps the move from full-time studies to a work environment (i.e. the start of their training contracts) strongly negatively influenced the academic performance of students who had previously attended daytime classes. Other potential reasons also exist. Further research would be required to investigate the specific underlying causes of the relationship noted here. However, these findings support those of de Hart *et al.* (2011) and Müller *et al.* (2007) at Unisa which suggest that part-time students outperform full-time students. They moreover suggest that the innovative approach to offering a CTA programme as implemented by CAC was effective in assisting students to be successful in the ITC.

In light of these results, null Hypotheses 8a and 8b relating to the association between academic performance and class selection, are rejected.

LIMITATIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

As with all such work, this research is subject to a number of limitations, which provide opportunities for additional research in the future. To begin with, this research has focused on the results related to one, uniquely-structured PGDA programme and while this uniqueness presented the opportunity to conduct research not previously possible, it simultaneously calls into question the applicability of the findings to other contexts. The replication of this research at other institutions, as far as possible, would provide insights as to whether the findings of this research could be transferable to other CTA programmes.

Similarly, this study is limited to the ITC performance of students progressing to the board exam from a single institution. Given that this research has found that the additional factors considered (i.e. prior tertiary institution, previous CTA attempts, time lapses and class selection) make a meaningful contribution to explaining student success, further research into the effect of these factors for all candidates attempting the ITC, similarly to the work of Rodrigues *et al.* (2018), could provide interesting and surprising results.

The factors contributing to academic success included in this research are limited to those detailed in the preceding chapters. However, numerous other factors could play a role and would present interesting opportunities for further work to be done. For example, factors such as language, schooling and Grade 12 subject selection (including, but not limited to, whether mathematics and accounting were selected as subjects) have been researched in the past and have been shown to influence academic performance at undergraduate level (Papageorgiou, 2017; Jansen & de Villiers, 2016; Swart & Becker, 2014). Further research may therefore consider whether these factors contribute to academic performance in CTA and the ITC. Additionally, there are many historical, cultural, social and economic factors associated with race and language in the South African context and these, as well as their impact on academic performance, have not been addressed by this research.

Additionally, several aspects unique to the CAC PGDA, notably, the integration with technology and the mentorship programme, were considered beyond the scope of this

study. However, future research may show that they play a key role in supporting academic success. Within the context of this research, selection of the after-hours option was used as a proxy for indicating that students were attempting the CAC PGDA on a part-time basis. As noted, this may not necessarily be the case, as full-time students may have opted for the after-hours class selection for a number of reasons. Additional data and research would be required to specifically assess how the performance of working students who study part-time differs from that of full-time students within the context of the CAC PGDA. Additional data would also be required in order to research the impact of attending a board preparation course prior to attempting ITC, if any, on performance in that exam – the impact of such courses was not considered by this research.

From a statistical testing perspective, the interaction effects between independent variables were considered beyond the scope of this research but may offer insights as to the relationships between the factors contributing to student's academic performance and aid in the development of a parsimonious model. Further research may also take the findings of this study one step further by developing predictive models of student performance. This could be done by deleting variables which do not account for significant portions of variance in each of the proposed models and by formulating equations to predict individual student outcomes (Osborne, 2000).

Due to the nature of the data received and the manner in which it was cleaned, a survivorship bias was introduced into the data, as students who were not eligible to write final exams in 2016 and 2017 were excluded from the sample. Thus, the impact on the models of some of the weakest students has been excluded. Inclusion of these limited cases may affect the results of the study.

Finally, the role of other, more qualitative factors such as grit, motivation, locus of control, attitude, maturity and study approach, in determining academic success was considered beyond the scope of this research. Study approach, in particular, as it relates to the "process" element of the Biggs' 3P model which has attracted much research in the past, is likely to play a significant role in determining whether students are successful in their

academic pursuits or not. However, a better understanding of these relationships would provide valuable insights to educators.

CONCLUSION

This research investigated the determinants of success for students pursuing the CA(SA) designation through a less conventional route. While many CA(SA) candidates remain at a single university for the duration of their studies, this is not possible for many students who are forced to change tertiary institution. This could potentially be due to failing to meet university progression requirements, because of changes in life circumstances which render residential studies impossible or due to financial constraints, among other factors. The introduction of the CAC PGDA offered a unique and innovative option for such students, many of whom would be considered marginal. The introduction of a blended learning approach sought to contribute to the racial transformation of the accounting profession by allowing working CTA students to access contact education for the first time.

The primary objective of this research, framed through the lens of Biggs' 3P model, was to examine the relationship between personal and situational factors and student academic success in the CAC PGDA and SAICA's ITC. Specifically, this research used logistic regression analysis to test the relationship between several typically researched factors (namely, age, gender, race and prior academic performance), as well as several additional variables (namely, prior tertiary institution, previous CTA attempts, time lapses and class selection), and students' academic performance in the CAC PGDA and SAICA's ITC exam. Three regression models were developed to accomplish this – the first relating to students attempting CTA for the first time; the second relating to students who had previously attempted CTA; and the third relating to students who successfully passed the CAC PGDA and went on to attempt SAICA's ITC. A hierarchical regression method was employed within each model in conjunction with the conventional forced entry method to further investigate the contribution made to the statistical models by those variables which had not been researched in the past.

In line with the findings of prior research performed at public universities, this study confirmed that prior academic performance, a typically researched personal presage factor, appears to be the single strongest predictor of future academic success within the

context of the CAC PGDA, a private offering. The findings also confirmed existing South African research indicating that race is a key determinant of success, although this study suggests that race is more significantly linked to success in CTA than in the ITC. Both of these findings highlight the need for continued interventions at a grassroots level to foster equal access to education in South Africa and correct the institutionalised inequalities of the past and that some determinants of academic success within the context of higher education are similar in the public and private spaces.

With regard to the additional personal and situational presage variables which this research considered, hierarchical regression indicated that these factors make a meaningful contribution to the regression models in all instances. Surprisingly, prior tertiary institution was found to be of significance only for students attempting their CTA for the first time, which is in contrast to findings of similar research abroad (Rodrigues *et al.,* 2018). Further research would be required to provide insight into why this is the case. Also of note, class selection was found to be statistically significant in each model. However, very interestingly, the impact of that selection depends on the measure of academic performance, as students attending daytime, contact classes are more likely to be successful in the PGDA while students attending after-hours classes and following a blended learning approach are more likely to be successful in the ITC. The success of the latter suggests that the innovations introduced by the CAC PGDA have aided marginal students in qualifying as CAs(SA) and have effectively supported transformation of the profession.

In conclusion, all students seeking to qualify as CAs(SA) face an onerous qualification path. But for some, the journey is fraught with even greater challenges when progression from one phase to another is hindered. The onus is on educators to utilise the insights and technology at their disposal to offer meaningful interventions and innovations. It is hoped that this research will assist educators and higher education institutions to design programmes differently to better support accounting students, thereby aiding transformation.

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APPENDICES

APPENDIX A: MODEL 1 TESTING OUTPUT

Step 1: All variables included

	Block 0	Block 1
Variables		All
χ^2 - model		101.878
***p*-value**		<0.001
-2LL		333.863
Nagelkerke psuedo-R^2		35.5%
Hosmer-Lemeshow test *p*-value		0.826
Correct classifications	68.6%	75.7%
Fail	100.0%	90.0%
Pass	0.0%	44.5%

Step 2: Typically researched vs additional factors

	Block 0	Block 1	Block 2
Variables		Typically researched	Additional
χ^2 - model		64.895	101.878
***p*-value**		<0.001	<0.001
χ^2 - step		64.895	36.983
***p*-value**		<0.001	<0.001
-2LL		370.846	333.863
Nagelkerke psuedo-R^2		23.8%	35.5%
Hosmer-Lemeshow test *p*-value		0.603	0.826
Correct classifications	68.6%	75.4%	75.7%
Fail	100.0%	92.5%	90.0%
Pass	0.0%	38.2%	44.5%

Step 3: Final hierarchical regression

	Block 0	Block 1	Block 2	Block 3	Block 4	Block 5
Variables		Prior academic performance	Age, Gender, Race	Prior tertiary institution	Class selection	Time lapses
χ^2 - model		28.111	64.895	92.773	97.392	101.878
***p*-value**		<0.001	<0.001	<0.001	<0.001	<0.001
χ^2 - step		28.111	36.784	27.879	4.619	4.485
***p*-value**		<0.001	<0.001	<0.001	0.032	0.106
-2LL		407.630	370.846	342.967	338.349	333.863
Nagelkerke psuedo-R^2		10.8%	23.8%	32.7%	34.1%	35.5%
Change in Nagelkerke psuedo-R^2			13.0%	8.9%	1.4%	1.4%
Hosmer-Lemeshow test *p*-value		0.119	0.603	0.745	0.647	0.826
Correct classifications	68.6%	73.1%	75.4%	76.3%	75.1%	75.7%
Fail	100.0%	94.6%	92.5%	92.1%	90.4%	90.0%
Pass	0.0%	26.4%	38.2%	41.8%	41.8%	44.5%

APPENDIX B: MODEL 2 TESTING OUTPUT

Step 1: All variables included

	Block 0	Block 1
Variables		All
χ^2 - model		104.436
***p*-value**		<0.001
-2LL		464.349
Nagelkerke psuedo-R^2		29.5%
Hosmer-Lemeshow test *p*-value		0.257
Correct classifications	61.6%	72.8%
Fail	100.0%	83.3%
Pass	0.0%	56.1%

Step 2: Typically researched vs additional factors

	Block 0	Block 1	Block 2
Variables		Typically researched	Additional
χ^2 - model		70.586	104.436
***p*-value**		<0.001	<0.001
χ^2 - step		70.586	33.849
***p*-value**		<0.001	0.001
-2LL		498.198	464.349
Nagelkerke psuedo-R^2		20.7%	29.5%
Hosmer-Lemeshow test *p*-value		0.934	0.257
Correct classifications	61.6%	69.6%	72.8%
Fail	100.0%	84.0%	83.3%
Pass	0.0%	46.3%	56.1%

Step 3: Final hierarchical regression

	Block 0	Block 1	Block 2	Block 3	Block 4
Variables		Prior academic performance	Age, Gender, Race	Class selection	Prior tertiary institution, Prior CTA attempts, Time lapses
χ^2 - model		48.251	70.586	93.603	104.436
***p*-value**		<0.001	<0.001	<0.001	<0.001
χ^2 - step		48.251	22.335	23.017	10.832
***p*-value**		0.000	0.004	<0.001	0.457
-2LL		520.533	498.198	475.181	464.349
Nagelkerke psuedo-R^2		14.5%	20.7%	26.7%	29.5%
Change in Nagelkerke psuedo-R^2			6.2%	6.0%	2.8%
Hosmer-Lemeshow test *p*-value		0.967	0.934	0.406	0.257
Correct classifications	61.6%	68.1%	69.6%	71.2%	72.8%
Fail	100.0%	84.8%	84.0%	84.4%	83.3%
Pass	0.0%	41.5%	46.3%	50.0%	56.1%

APPENDIX C: MODEL 3 TESTING OUTPUT

Step 1: All variables included

	Block 0	Block 1
Variables		All
χ^2 - model		65.452
***p*-value**		<0.001
-2LL		157.228
Nagelkerke psuedo-R^2		38.4%
Hosmer-Lemeshow test *p*-value		0.432
Correct classifications	85.5%	87.7%
Fail	0.0%	35.9%
Pass	100.0%	96.5%

Step 2: Typically researched vs additional factors

	Block 0	Block 1	Block 2
Variables		Typically researched	Additional
χ^2 - model		40.455	65.452
***p*-value**		<0.001	<0.001
χ^2 - step		40.455	24.997
***p*-value**		<0.001	0.023
-2LL		182.225	157.228
Nagelkerke psuedo-R^2		24.8%	38.4%
Hosmer-Lemeshow test *p*-value		0.393	0.432
Correct classifications	85.5%	85.5%	87.7%
Fail	0.0%	7.7%	35.9%
Pass	100.0%	98.7%	96.5%

Step 3: Final hierarchical regression

	Block 0	Block 1	Block 2	Block 3	Block 4
Variables		Prior academic performance	Class selection	Age, Gender, Race	Prior tertiary institution, Prior CTA attempts, Time lapses
χ^2 - model		25.197	30.684	44.792	65.452
***p*-value**		<0.001	<0.001	<0.001	<0.001
χ^2 - step		25.197	5.487	14.108	20.660
***p*-value**		<0.001	0.019	0.079	0.056
-2LL		197.483	191.997	177.888	157.228
Nagelkerke psuedo-R^2		15.9%	19.1%	27.2%	38.4%
Change in Nagelkerke psuedo-R^2			3.2%	8.1%	11.2%
Hosmer-Lemeshow test *p*-value		0.900	0.559	0.028	0.432
Correct classifications	85.5%	85.9%	85.1%	86.2%	87.7%
Fail	0.0%	26.0%	26.0%	15.4%	35.9%
Pass	100.0%	100.0%	99.1%	98.3%	96.5%

APPENDIX D: SIDE-BY-SIDE SUMMARY OF MODEL RESULTS

	Model 1 - Step 1					Model 2 - Step 1					Model 3 - Step 1				
Variable	**B**	***p*-value**	**SE**	**OR**	**IOR**	**B**	***p*-value**	**SE**	**OR**	**IOR**	**B**	***p*-value**	**SE**	**OR**	**IOR**
Constant	-11.836	<0.001	2.293			-9.032	<0.001	1.373			-18.040	0.001	5.322		
H1: Age		0.264					0.604					0.227			
Ages 25 to 26	-0.361	0.406	0.435	0.70	1.43	-0.149	0.668	0.346	0.86	1.16	-0.267	0.682	0.652	0.77	1.31
Ages 27 to 29	-1.504	0.074	0.842	0.22	4.50	-0.201	0.603	0.385	0.82	1.22	0.159	0.855	0.869	1.17	
Age 30 and older	-0.366	0.649	0.803	0.69	1.44	-0.494	0.268	0.446	0.61	1.64	1.245	0.241	1.061	3.47	
Age 22 and younger	0.465	0.230	0.388	1.59		1.317	0.271	1.197	3.73		-1.319	0.072	0.734	0.27	3.75
(base = Ages 23 to 24)															
H2: Gender															
Male	-0.007	0.980	0.291	0.99		0.143	0.548	0.239	1.15		0.556	0.228	0.461	1.74	
(base = Female)															
H3: Race		0.002					0.015					0.056			
White	1.271	<0.001	0.343	3.57		0.846	0.003	0.280	2.33		1.406	0.015	0.578	4.08	
Indian	-0.020	0.970	0.550	0.98	1.02	0.711	0.046	0.357	2.04		1.414	0.071	0.785	4.11	
Coloured	0.922	0.172	0.676	2.52											
Other	2.498	0.054	1.298	12.16		0.435	0.352	0.468	1.55		0.649	0.492	0.945	1.91	
(base = Black)															
H4: Prior academic performance	0.172	<0.001	0.035	1.19		0.202	<0.001	0.030	1.22		0.353	<0.001	0.099	1.42	
H5: Prior tertiary institution - Models 1 and 3		0.004										0.162			
University of Johannesburg	-0.048	0.947	0.725	0.95	1.05						1.342	0.119	0.860	3.83	
Monash South Africa	-0.109	0.839	0.539	0.90	1.12						0.538	0.516	0.828	1.71	

	University of Pretoria	1.819	0.003	0.607	6.16						1.830	0.015	1.312	24.66	
	University of the Witwatersrand	1.160	0.172	0.850	3.19						1.830	0.060	0.972	3.24	
	North-West University	-0.106	0.914	0.980	0.90	1.11					0.645	0.561	1.108	1.91	
	University of Cape Town	1.627	0.030	0.751	5.09						1.097	0.291	1.039	3.00	
	Other	1.468	0.024	0.649	4.34						0.386	0.618	0.774	1.47	
	(base = Unisa)														
H5: Prior tertiary institution - Model 2								0.212							
	Unisa CTA with different undergrad						-0.445	0.211	0.356	0.64	1.56				
	Unisa undergrad and CTA						-0.515	0.232	0.431	0.60	1.67				
	Monash South Africa undergrad and CTA						0.803	0.086	0.467	2.23					
	Other single institution						-0.135	0.715	0.370	0.87	1.14				
	Other multiple institutions						0.485	0.514	0.743	1.62					
	(base = Monash South Africa with different undergrad)														
H6: Previous CTA attempts - Model 2								0.736							
	2 previous CTA attempts						0.117	0.703	0.307	1.12					
	3 previous CTA attempts						-0.097	0.802	0.387	0.91	1.10				
	4 previous CTA attempts						0.540	0.272	0.491	1.72					
	5 previous CTA attempts						-0.534	0.544	0.881	0.59	1.71				
	More than 5 previous CTA attempts						0.698	0.44	0.905	2.01					
	(base = 1 previous CTA attempt)														

H6: Previous CTA attempts - Model 3												0.322			
1 previous CTA attempt											-0.898	0.151	0.625	0.41	2.45
2 previous CTA attempts											-1.597	0.076	0.901	0.20	4.93
3 previous CTA attempts											-1.580	0.119	1.012	0.21	4.85
More than 3 previous CTA attempts											-0.225	0.856	1.237	0.80	1.25
(base = No previous CTA attempts)															
H7: Time lapses - Model 1		0.106													
1-year time lapse	0.820	0.048	0.414	2.27											
2 year time lapse or more	0.731	0.314	0.726	2.08											
(base = No time lapse)															
H7: Time lapses - Models 2 and 3															
At least 1 unaccounted-for year						0.025	0.926	0.275	1.03		-0.867	0.099	0.526	0.42	2.38
(base = No unaccounted-for years)															
H8: Class selection															
After-hours	-1.024	0.021	0.445	0.36	2.79	-1.164	<0.001	0.278	0.31	3.21	1.419	0.015	0.584	4.13	
(base = Daytime)															
Model statistics:															
-2LL	333.863					464.349					157.228				
	χ^2 = 101.878, df = 20, p < 0.001					χ^2 = 104.436, df = 21, p < 0.001					χ^2 = 65.452, df = 22, p < 0.001				
Nagelkerke's R^2	35.5%					29.5%					38.4%				
Hosmer-Lemeshow test	χ^2 (8) = 4.337, p =0.826					χ^2 (8) = 10.120, p =0.257					χ^2 (8) = 8.018, p =0.432				
Classification accuracy	75.7%					72.8%					87.7%				

APPENDIX E: MODEL 2 BINARY VERSUS MIXED EFFECT LOGISTIC REGRESSION

		Model 2 - Binary Logistic					Model 2 - Mixed Effect Logistic				
Variable		**B**	***p*-value**	**SE**	**OR**	**IOR**	**B**	***p*-value**	**SE**	**OR**	**IOR**
Constant		-9.032	<0.001	1.373			-8.999	<0.001	1.419		
H1: Age			0.604					0.623			
	Ages 25 to 26	-0.149	0.668	0.346	0.86	1.16	-0.132	0.713	0.360	0.88	1.14
	Ages 27 to 29	-0.201	0.603	0.385	0.82	1.22	-0.191	0.636	0.403	0.83	1.21
	Age 30 and older	-0.494	0.268	0.446	0.61	1.64	-0.499	0.285	0.466	0.61	1.65
	Age 22 and younger	1.317	0.271	1.197	3.73		1.358	0.278	1.251	3.89	
	(base = Ages 23 to 24)										
H2: Gender											
	Male	0.143	0.548	0.239	1.15		0.154	0.539	0.250	1.17	
	(base = Female)										
H3: Race			0.015					0.022			
	White	0.846	0.003	0.280	2.33		0.857	0.004	0.294	2.36	
	Indian	0.711	0.046	0.357	2.04		0.708	0.061	0.376	2.03	
	Other	0.435	0.352	0.468	1.55		0.432	0.379	0.491	1.54	
	(base = Black)										
H4: Prior academic performance		0.202	<0.001	0.030	1.22		0.202	<0.001	0.031	1.22	
H5: Prior tertiary institution			0.212					0.211			
	Unisa CTA with different undergrad	-0.445	0.211	0.356	0.64	1.56	-0.509	0.171	0.371	0.60	1.66
	Unisa undergrad and CTA	-0.515	0.232	0.431	0.60	1.67	-0.567	0.200	0.442	0.57	1.76
	Monash South Africa undergrad and CTA	0.803	0.086	0.467	2.23		0.794	0.107	0.491	2.21	

	Other single institution	-0.135	0.715	0.370	0.87	1.14	-0.175	0.650	0.385	0.84	1.19
	Other multiple institution	0.485	0.514	0.743	1.62		0.443	0.565	0.770	1.56	
	(base = Monash South Africa with different undergrad)										
H6: Previous CTA attempts			0.736					0.731			
	2 previous CTA attempts	0.117	0.703	0.307	1.12		0.172	0.589	0.318	1.19	
	3 previous CTA attempts	-0.097	0.802	0.387	0.91	1.10	-0.055	0.892	0.403	0.95	1.06
	4 previous CTA attempts	0.540	0.272	0.491	1.72		0.592	0.248	0.512	1.81	
	5 previous CTA attempts	-0.534	0.544	0.881	0.59	1.71	-0.489	0.593	0.915	0.61	1.63
	More than 5 previous CTA attempts	0.698	0.440	0.905	2.01		0.749	0.431	0.946	2.11	
	(base = 1 previous CTA attempt)										
H7: Time lapses between undergrad and CTA											
	At least 1 unaccounted-for year	0.025	0.926	0.275	1.03		0.042	0.884	0.287	1.04	
	(base = No unaccounted-for years)										
H8: Class selection											
	After-hours	-1.164	<0.001	0.278	0.31	3.21	-1.166	<0.001	0.290	0.31	3.22
	(base = Daytime)										
Model statistics:											
	-2LL	464.349					1969.585				
	Classification accuracy	72.8%					78.7%				

APPENDIX F: COLLINEARITY STATISTICS

Model 1

	Tolerance	VIF
Age	.967	1.034
Gender	.946	1.057
Race	.921	1.085
Prior academic performance	.855	1.170
Prior institution	.817	1.223
Time lapses	.924	1.082
Class selection	.861	1.162

Model 2

	Tolerance	VIF
Age	.641	1.560
Gender	.969	1.032
Race	.959	1.043
Prior academic performance	.957	1.045
Prior institution	.960	1.042
Prior CTA attempts	.688	1.453
Time lapses	.793	1.260
Class selection	.855	1.169

Model 3

	Tolerance	VIF
Age	.911	1.097
Gender	.953	1.049
Race	.958	1.044
Prior academic performance	.952	1.050
Prior institution	.932	1.073
Prior CTA attempts	.711	1.407
Time lapses	.851	1.175
Class selection	.763	1.311

APPENDIX G: MODEL 3 TESTING OUTPUT, EXCLUDING INFLUENTIAL CASES

Step 1: All variables included

	Block 0	Block 1
Variables		All
χ^2 - model		87.356
***p*-value**		<0.001
-2LL		111.311
Nagelkerke psuedo-R^2		53.3%
Hosmer-Lemeshow test *p*-value		0.766
Correct classifications	87.5%	90.5%
Fail	0.0%	45.5%
Pass	100.0%	97.0%

Variable	B	*p*-value	SE	OR	IOR
Constant	-22.160	0.001	6.719		
H1: Age		0.066			
Ages 25 to 26	-0.785	0.314	0.779	0.46	2.19
Ages 27 to 29	-0.865	0.409	1.048	0.42	2.38
Age 30 and older	2.153	0.174	1.585	8.61	
Age 22 and younger	-1.790	0.041	0.875	0.17	5.99
(base = Ages 23 to 24)					
H2: Gender					
Male	1.083	0.058	0.571	2.95	
(base = Female)					
H3: Race		0.033			
White	1.451	0.031	0.671	4.27	
Indian	3.089	0.017	1.294	21.96	
Coloured					
Other	0.247	0.833	1.174	1.28	
(base = Black)					
H4: Prior academic performance	0.430	0.001	0.128	1.54	

H5: Prior tertiary institution						
	University of Johannesburg	1.130	0.392	0.994	3.10	
	Monash South Africa	0.685	0.256	0.970	1.98	
	University of Pretoria	20.894	0.480	5597.648	1186135694.00	
	University of the Witwatersrand	3.599	0.019	1.538	36.56	
	North-West University	1.305	0.703	1.562	3.69	
	University of Cape Town	1.285	0.286	1.204	3.61	
	Other	0.240	0.792	0.911	1.27	
	(base = Unisa)					
H6: Previous CTA attempts			0.810			
	1 previous CTA attempt	-0.560	0.444	0.731	0.57	1.75
	2 previous CTA attempts	-1.230	0.286	1.153	0.29	3.42
	3 previous CTA attempts	-0.204	0.873	1.277	0.82	1.23
	More than 3 previous CTA attempts	-0.253	0.868	1.151	0.78	1.29
	(base = No previous CTA attempts)					
H7: Time lapses between undergrad and CTA						
	At least 1 unaccounted-for year	-1.276	0.054	0.662	0.28	3.58
	(base = No unaccounted-for years)					
H8: Class selection						
	After-hours	2.092	0.008	0.788	8.10	
	(base = Daytime)					
Model statistics:						
	-2LL	111.311				
		χ^2 = 87.356, df = 22, p < 0.001				
	Nagelkerke's R^2	53.3%				
	Hosmer-Lemeshow test	χ^2 (8) = 4.925, p =0.766				
	Classification accuracy	90.5%				

Step 2: Typically researched vs additional factors

	Block 0	Block 1	Block 2
Variables		Typically researched	Additional
χ^2 - model		49.263	87.356
***p*-value**		<0.001	<0.001
χ^2 - step		49.263	38.093
***p*-value**		<0.001	<0.001
-2LL		149.404	111.311
Nagelkerke psuedo-R^2		32.2%	53.3%
Hosmer-Lemeshow test *p*-value		0.563	0.766
Correct classifications	87.5%	87.5%	90.5%
Fail	0.0%	12.1%	45.5%
Pass	100.0%	98.3%	97.0%

Step 3: Final hierarchical regression

	Block 0	Block 1	Block 2	Block 3	Block 4
Variables		Prior academic performance	Class selection	Age, Gender, Race	Prior tertiary institution, Prior CTA attempts, Time lapses
χ^2 - model		26.547	35.797	57.982	87.356
***p*-value**		<0.001	<0.001	<0.001	<0.001
χ^2 - step		26.547	9.250	22.185	29.374
***p*-value**		<0.001	0.002	0.005	0.003
-2LL		172.12	162.870	140.685	111.311
Nagelkerke psuedo-R^2		18.1%	24.0%	37.3%	53.3%
Change in Nagelkerke psuedo-R^2			5.9%	13.3%	16.0%
Hosmer-Lemeshow test *p*-value		0.905	0.931	0.768	0.766
Correct classifications	87.5%	87.8%	87.1%	89.4%	90.5%
Fail	0.0%	30.0%	30.0%	27.3%	45.5%
Pass	100.0%	100.0%	99.1%	98.3%	97.0%