

**Entrepreneurial education and entrepreneurial intention:
Mediated by self-efficacy and moderated by ChatGPT
engagement**

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ABSTRACT

Entrepreneurship is recognised as a global phenomenon for addressing economic and social development challenges particularly in developing nations which face high unemployment. Consequently, fostering entrepreneurial intentions is a key objective for policymakers and Higher Education Institutions (HEI) to increase the level of entrepreneurial behaviour. The rising utility of Generative Artificial Intelligence (GenAI), specifically ChatGPT, offers new opportunities that may transform entrepreneurial pedagogy and student engagement to increase entrepreneurial intentions. However, the impact of GenAI (ChatGPT) on the interrelations among entrepreneurship education, entrepreneurial intentions and entrepreneurial self-efficacy among HEI students in developing economies such as South Africa remains largely unexamined.

The objective of this study was to interrogate the effect of entrepreneurship education on entrepreneurial intentions, mediated by entrepreneurial self-efficacy and moderated by GenAI (ChatGPT) acceptance. Grounded in the Theory of Planned Behaviour (TPB) and Technology Acceptance Model (TAM), the study adopted a quantitative research design using non-probability sampling of South African HEI students. A total of 211 valid online survey respondents were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM).

The study revealed significant correlations among entrepreneurship education, entrepreneurial self-efficacy and entrepreneurial intentions, supporting a significant indirect mediation effect. Furthermore, the direct relationship between entrepreneurship education on entrepreneurial intentions was significantly moderated by acceptance of GenAI (ChatGPT). However, contrary to some literature, the relationship between entrepreneurial self-efficacy and entrepreneurial intentions (mediation path) was negatively moderated by GenAI (ChatGPT), highlighting the delicate behavioural and psychological balance required when integrating transformative technology. This research offers support for integrating TBP and TAM to evaluate behavioural and psychological interactions of GenAI engagement. Furthermore, this research offers cautious and actionable insights for HEI and policymakers who aim to leverage GenAI for the advancement of education and cultivation of entrepreneurial intentions.

Keywords: Entrepreneurship Education, Generative Artificial Intelligence, ChatGPT, Entrepreneurship Intention, Entrepreneurship self-efficacy, Entrepreneurship

PLAGIARISM DECLARATION

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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LIST OF ABBREVIATIONS

AI	Artificial intelligence
AVE	Average Variance Extracted
β	Beta coefficient
BCa	Bias-Corrected and accelerated
CB-SEM	Covariance based structural equation modelling
ChatGPT	Chat Generative Pre-Trained Transformer
CCA	Confirmatory Composite Analysis
CFA	Confirmatory Factor Analysis
CMB	Common method bias
CTA	Confirmatory tetrad analysis
EE	Entrepreneurship education
EI	Entrepreneurial intention
EOU	Ease of use of ChatGPT
ESE	Entrepreneurial self-efficacy
f^2	Effect size
GEM	Global entrepreneurship monitor
GenAI	Generative artificial intelligence
GDP	Gross domestic product
HEI	Higher education institution
HTMT	Heterotrait-monotrait Ratio of Correlations
LM	Linear regression model
M	Mean
MAE	Mean absolute error
NQF	National qualifications framework
PLS-SEM	Partial least squares structural equation modelling
Q^2	Predictive power indicator
R^2	Coefficient determination
RMSE	Root Mean-Square Error
SD	Standard deviation
SEDA	Small enterprise development agency
SEM	Structural equation modelling
SMME	Small, micro and medium sized enterprises
SPSS	Statistical package for social science

TAM	Technology acceptance model
TPB	Theory of planned behaviour
UCGT	Usefulness of ChatGPT
VIF	Variance Inflation Factor

CHAPTER 1: INTRODUCTION TO RESEARCH PROBLEM

1.1 Introduction

Entrepreneurship is recognised as a critical global phenomenon that drives economic and social development as well as reduces unemployment (Global Entrepreneurship Monitor [GEM], 2023; Gieure et al., 2020; Meyer et al., 2022). Consequently, increasing entrepreneurial behaviour is a credible option for alleviating the high levels of unemployment in South Africa, and this may be achieved by increasing the level of entrepreneurial intentions, a proven antecedent of entrepreneurship behaviour (Amani et al., 2024; Debarliev et al., 2022; Nguyen & Nguyen, 2024; L. Wu et al., 2022). Entrepreneurial intention refers to an individual's deliberate mindset that frames their attention and action towards entrepreneurial tasks and new venture creation (Batista-Canino et al., 2024) and understanding what drives this intention is central to this study.

Fostering entrepreneurial intention and capabilities, particularly among students, has become an important objective for higher education institutions, thereby leading to a rise in entrepreneurship education programmes and government investment globally (Batista-Canino et al., 2024; Ramadani et al., 2022). This heightened focus on entrepreneurship education aims to increase the number of individuals with the necessary human capital by investing in knowledge, skills, mindset and self-efficacy to identify and exploit opportunities, thus transforming educational investments into entrepreneurial intentions and behaviours (Kuratko et al., 2021). Despite the investment in entrepreneurship education, South Africa's entrepreneurial activity remains comparatively low relative to other developing nations (GEM, 2025; Meyer et al., 2022; Zwane & Osuigwe, 2024). This reflects a complex link between the investments in human capital captured through entrepreneurship education, and the psychological outcomes manifested in both entrepreneurial intentions and behaviour.

The advent of Artificial Intelligence (AI), particularly Generative Artificial Intelligence (GenAI) has introduced new dimensions to entrepreneurship and education, changing how information is processed, tasks are executed, and how learning occurs (Chalmers et al., 2021; Feuerriegel et al., 2024; Vecchiarini & Somià, 2023). The rapid integration of these emerging technologies is expected to revolutionise approaches for new venture ideation, creation, learning experiences and enhance student engagement by providing capabilities to automate tasks, to improve access to information and to facilitate decision-making (Duong & Vu, 2025; Obschonka et al., 2024; Somià & Vecchiarini, 2024).

Although extant research has studied the direct relationship between entrepreneurship education and entrepreneurial intention as mediated by entrepreneurship self-efficacy, the impact of emerging technologies such as GenAI remains largely unexamined (Duong & Vu, 2025; Xie & Wang, 2025). Furthermore, the integration of GenAI into entrepreneurship education introduced an evolving dimension to entrepreneurial pedagogy that requires enquiry. Despite the growing body of research on GenAI acceptance and adoption, the research on GenAI's intervening effects on the empirically validated relationships between entrepreneurship education, entrepreneurship self-efficacy and entrepreneurial intention within traditional entrepreneurial contexts remains scant (Dwivedi, 2025; Shepherd & Majchrzak, 2022; Uriarte et al., 2025).

As such, this study aimed to address this research gap by employing the theory of planned behaviour (Ajzen, 1991, 2020) and the technology acceptance model (Davis, 1989) to examine the extent to which the acceptance of GenAI tools such as Chat Generative Pre-Trained Transformer (ChatGPT), a prominent GenAI tool, in entrepreneurship education, moderates the relationship between entrepreneurship education and entrepreneurial intention, mediated by entrepreneurship self-efficacy. The understanding of this emerging technology acceptance and adoption may inform effective policy interventions and enhance entrepreneurship activity.

The rest of this chapter expands on the need for the research by outlining the study's background, the research problem, the business as well as the theoretical needs for the study. The research purpose, objectives and scope are also summarised in this section, providing the reader with a clear outline of the research direction.

1.2 Background and Context

1.2.1 Importance of Entrepreneurship

Entrepreneurship is generally defined as the process of identifying, evaluating and exploiting new venture ideation, and thus it promotes the creation of new businesses and entrepreneurial opportunities (Lévesque et al., 2022; Uriarte et al., 2025). The ability to discover and pursue these entrepreneurial opportunities is recognised as one of the symbols of a successful entrepreneur (Zhu et al., 2021). Entrepreneurship research has matured past focusing on identifying standard traits and characteristics that distinguish entrepreneurs and evolved to integrating psychological and behavioural aspects that develop entrepreneurial skills and intentions (Debarliev et al., 2022). As such, understanding how to teach and acquire these fundamental entrepreneurial skills has emerged as a key research area in entrepreneurship and education.

Small, Micro and Medium-sized Enterprises (SMMEs) are considered the bedrock of the South African economy (Small Enterprise Development Agency [SEDA], 2024) as they provide 60% of the labour force employment and contribute 30% to the Gross Domestic Product (GDP). The SMME sector through entrepreneurship, not only fosters economic development, but also nurtures innovation (GEM, 2025; SEDA, 2024). As a result, entrepreneurship plays an important role in achieving the full employment objectives envisioned in the 2030 South African National Development Plan.

Despite South Africa being the most industrialised African country with a vibrant SMME sector, the country still faces one of the world's highest unemployment and youth unemployment rates in particular (Munyati, 2024; Statistics South Africa, 2025). Recent data from Statistics South Africa (2025) further demonstrates this employment challenge, indicating that youth unemployment (ages 15-34 years) has risen from 35.5% in the second quarter of 2015 to 46.1% in the second quarter of 2025; potentially affecting nearly 4.9 million young people. This sharp increase in chronic unemployment reflects the grim reality that erodes the social trust, and negatively impacts the socio-economic needs of the youth, as well as the country's broader economic growth (Azzollini, 2023; Mseleku, 2022). This persistent unemployment, especially among graduates highlights the urgent need to promote entrepreneurial intentions and entrepreneurial activity as a pathway to job creation and poverty alleviation (Zwane & Osuigwe, 2024).

1.2.2 Entrepreneurship education

The findings of the Department of Higher Education and Training's (2017) Entrepreneurship Enabling Task Team established that a significant effort has been made by the South African government to integrate entrepreneurship skills into the curriculum from primary school through to higher education. However, challenges remain in higher education mainly due to a lack of funding and a shortage of qualified faculties to focus on entrepreneurship educational programmes (Department of Higher Education and Training, 2017). Entrepreneurship education is not only intended to increase entrepreneurial intentions, but also to improve the quality of potential entrepreneurs by developing a wide range of skills such as creativity, problem-solving, risk-taking propensity and resilience (Ramadani et al., 2022). These skills help students to become more entrepreneurially orientated and be prepared to endure and navigate the challenges that are inherent in business endeavours, especially those that operate in under resourced environments which are prevalent in most developing nations.

Despite scholars providing the benefits of entrepreneurship education explained through diverse moderating and mediating factors such as culture (Qudsia Yousaf et al., 2022), gender (Ramadani et al., 2022), environment characteristics (Shirokova et al., 2016), self-efficacy (Hsu et al., 2019), competition (L. Wu et al., 2022), and family support (Vu et al., 2025; Xu et al., 2020), entrepreneurship activities are not increasing enough in South Africa.

Notwithstanding the investment in entrepreneurship education, the level of entrepreneurial intentions has notably decreased in South Africa from 11.9% in 2020 to 7.5% in 2023, aligning with the observed decrease in total entrepreneurial activity (GEM, 2023). This resultant decline in entrepreneurial intention is a cause for concern, given the established empirical relationship between entrepreneurship education, entrepreneurial intention and actual entrepreneurial behaviour.

1.2.3 Entrepreneurial intentions

Compounding the aforementioned economic challenges is the notable decline in overall entrepreneurial activity (GEM, 2023). Total entrepreneurial activity in South Africa has declined from 20% in 2021 to 11.1% in 2023, far lower than the Global Entrepreneurship Monitor average of 26.2% and the continental average of 40.1% (GEM, 2023). While the decrease in entrepreneurial activity may be attributed to low economic growth, the entrepreneurial environment in South Africa has also deteriorated, ranking third lowest among the 49 economies surveyed in the Global Entrepreneurship Monitor Report (GEM, 2023). The quality of the entrepreneurial ecosystem which is supported by among other conditions, entrepreneurship education and technological infrastructure, significantly impacts the degree of entrepreneurial intentions (Roos & Botha, 2022).

While entrepreneurship education is considered as a positive influence on entrepreneurial intention, the varying pedagogical approaches across theory and practice have resulted in inconsistent effects on entrepreneurial intentions (Jardim & Sousa, 2023; Ramadani et al., 2022; Taneja et al., 2024). Improving these entrepreneurial intentions is central to changing attitudes and perceptions about entrepreneurship and positioning it as a viable career alternative for students. As GenAI becomes more integrated into entrepreneurship and education, it may offer an opportunity to enhance the efficacy of entrepreneurship education and address the pedagogical deficiencies that lead to inconsistent impacts on entrepreneurial intentions (Chalmers et al., 2021; Fan et al., 2025).

1.2.4 Entrepreneurship self-efficacy

Self-efficacy impacts an individual's confidence and belief in their abilities to manage potential situations; similarly, entrepreneurial self-efficacy is one's belief in their ability to successfully perform entrepreneurial tasks (Ajzen, 1991; Hsu et al., 2019). The development of self-efficacy as defined by Bandura's social cognitive theory, depends on the development of mastery, the influence of role models, as well as the social, physiological and emotional environments the individual is in (Neneh, 2022; Newman et al., 2019). The more specialised and personalised these experiences are, the greater self-efficacy one may develop.

Entrepreneurship education helps to create occupation specific capabilities and opportunities for mastery, thus enhancing entrepreneurship self-efficacy (Ramadani et al., 2022). Depending on the design and structure of the curriculum, it may offer experiential learning to enhance the student's confidence to fulfil entrepreneurship tasks. This increases the perceived behavioural control, a construct that is closely related to entrepreneurship self-efficacy and is linked to entrepreneurial intention and behaviour (Duong & Vu, 2025; Taneja et al., 2024). The use of GenAI in entrepreneurship education has created opportunities for dynamic and interactive learning experiences that accelerate the development of entrepreneurship skills, knowledge and mindsets (Vecchiarini & Somià, 2023). The ability of GenAI to simulate real-world experiences, helps students to analyse data, and provides immediate feedback to students which has created personalised learning experiences that positively influence the development of not only entrepreneurship self-efficacy but also, digital entrepreneurship self-efficacy (Duong et al., 2024; Duong & Vu, 2025; Piperopoulos & Dimov, 2015).

1.2.5 Generative AI

The advancements of AI and GenAI have led to one of the most significant technological evolutions of this era (Redondo-Rodríguez et al., 2024). The ability of large language models such as ChatGPT to generate new and original content, has expanded the usefulness of this emerging technology into powerful dynamic capabilities, which are useful for both individuals and organisations (Shore et al., 2024). The students' adoption of GenAI is primarily influenced by the perceived benefits and strengths of the technology's capability to enhance their learning efficiency; however, this does not necessarily translate into improved actual academic performance (Fan et al., 2025;

Gupta, 2024). This implies that while technology can provide speed and convenience, it does not replace critical thinking and deeper knowledge.

As discussed in the constructs above, the integration of Gen AI tools such as ChatGPT in entrepreneurship education offers new avenues for innovation and holds the potential to strengthen the relationship between entrepreneurship education and entrepreneurial intention (PWC Education, 2023). Therefore, this highlights the need to examine the integration of GenAI tools such as ChatGPT into entrepreneurship education and how this may enhance students' entrepreneurial competencies to operate in both digital and traditional entrepreneurial environments (Duong & Vu, 2025; Somià & Vecchiarini, 2024).

1.3 Research Problem

Extant research posits that entrepreneurship education influences entrepreneurial intention by enhancing self-efficacy, which are both critical antecedents to entrepreneurship behaviour (Debarliev et al., 2022; Nguyen & Nguyen, 2024). However, in the South African context, the relationship between entrepreneurship education and entrepreneurial outcomes remains ambiguous, as evidenced by the low entrepreneurial intention and entrepreneurial activity discussed above. This raises questions about the efficacy of current pedagogical approaches and the necessity to consider potential interventions.

Emerging technologies such as AI and GenAI in particular, offer new opportunities to increase entrepreneurship education's efficacy. The rapid integration of AI and GenAI in both entrepreneurship and education presents an opportunity to foster pedagogical shifts within entrepreneurship education (Chalmers et al., 2021; Uriarte et al., 2025; Zulfiqar et al., 2025). The diverse applications of AI are transforming the approach to entrepreneurship, changing how entrepreneurs originate, develop, design and execute ideas (Chalmers et al., 2021; Uriarte et al., 2025). Despite the broader acceptance and use of GenAI, particularly OpenAI's ChatGPT, the intersection of GenAI acceptance in entrepreneurship education remains under-researched in developing nations such as South Africa (Shepherd et al., 2025; Uriarte et al., 2025; Winkler et al., 2023). Additionally, Obschonka et al. (2024) have also called for more research to advance the academic contributions towards the ethical application of AI across the entrepreneurial lifecycle.

1.4 Significance of Research for Business and Theory (Research Gap)

1.4.1 Business Significance of Research

While entrepreneurship education alone cannot increase entrepreneurship activity, it does, however, empower nascent entrepreneurs with the vital skills and knowledge to navigate the challenging requirements of the modern era entrepreneurship processes (Lyu et al., 2024). The GEM (2023) Report for South Africa highlighted that graduates are more likely to start new ventures than non-graduates, emphasising the value of acquired skills and knowledge. Although the positive influence of entrepreneurship education in forming entrepreneurial intention has been substantiated, the relationship has shown mixed results contingent upon pedagogical approaches (for instance, theoretical versus practical) (Debarliev et al., 2022; Lyu et al., 2024). South Africa's high unemployment rates and low entrepreneurial activity indicate a critical gap in traditional entrepreneurship education.

Moreover, entrepreneurship education's value in developing long-term objective outcomes such as actual entrepreneurial behaviour has also been questioned (Piperopoulos & Dimov, 2015; Wiklund et al., 2025). Given these challenges and the ongoing efforts to enhance the efficacy of entrepreneurship education, this study sought to examine how GenAI can intervene in entrepreneurship education regardless of the specific pedagogies employed to enhance the relationship with entrepreneurial intention.

The democratisation of fundamental information accessible through AI has broadened access to resources and opportunities that can expand access to new venture creation. Although South Africa is developing a national AI policy framework to promote AI adoption across all sectors; the integration of AI and GenAI is not yet ubiquitous in the education sector. This is largely attributable to various challenges such as the digital divide (for instance, unequal access to digital education and technology), resource constraints and insufficient digital infrastructure (Dept Com & Digital Tech, 2024; Kajiita & Kang'ethe, 2025).

As such, the advancements and potential benefits of GenAI observed in developing nations offer an opportunity to improve entrepreneurship education efficacy in South Africa. However, the intersection of AI and particularly GenAI engagement in entrepreneurship education remains under researched in developing nations such as South Africa (Duong & Vu, 2025; Uriarte et al., 2025; Zulfiqar et al., 2025).

1.4.2 Theoretical Significance of Research

The relationship between entrepreneurship education and entrepreneurial intention has been extensively studied over the past decade with most scholars finding a positive relation between the constructs (Amani et al., 2024; Bae et al., 2014; Debarliev et al., 2022; Duong et al., 2024; Fayolle & Gailly, 2015; Nguyen & Nguyen, 2024; Piperopoulos & Dimov, 2015; L. Wu et al., 2022). However, few studies have examined these relationships in the context of GenAI integration.

Despite the pervasive use of AI in modern era, there remains a noticeable gap in literature relating to the theoretical integration required to guide entrepreneurship education practices (Zulfiqar et al., 2025). Recent studies confirm that AI enhanced education can improve students' entrepreneurial mindset and attitudes; however, the contextual factors that influence these effects are not fully understood (Duong & Vu, 2025; Dwivedi, 2025; Nguyen & Nguyen, 2024). Duong and Vu (2025) demonstrated in their research that self-efficacy serves as a critical mediator in the relationship between entrepreneurship education and entrepreneurial intention, although within the setting of digital entrepreneurship. Conversely, Nguyen and Nguyen (2024) identified a negatively moderated relationship between digital entrepreneurship education and digital entrepreneurial intention. This debate of whether digital tools such as GenAI in education act as amplifiers or dampeners of self-efficacy and intentions creates a critical research gap.

While similar studies have employed the Theory of Planned Behaviour (TPB), few have integrated it with the Technology Acceptance Model (TAM) (Ajzen, 1991; Davis, 1989). Zulfiqar et al. (2025) adopted a similar TPB and TAM integration approach to investigate the influence of perceptions regarding the usefulness and ease of use of AI on intention formations. Similarly, this study also employed this meaningful TPB and TAM framework approach; however, it expanded its application by exploring the moderating role of GenAI, particularly the usefulness and ease of use perceptions of Chat GPT on the relationship between entrepreneurship education, entrepreneurial intention, as mediated by entrepreneurship self-efficacy.

Duong and Vu (2025) examined this moderated mediation relationship utilising the Stimulus Organism Response (SOR) framework, wherein entrepreneurship education (i.e., stimulus) influences digital intentions (i.e., response), mediated by digital self-efficacy (i.e., organism) and moderated by GenAI. This current study, however, employed a hybrid approach that integrated the established TPB and TAM framework

applying them in a moderated mediation relationship. This hybrid approach offered a unique theoretical contribution by examining *how* the factors of TAM, specifically ease of use and usefulness alongside perceived behavioural control (TPB), may explain the *pathway* by which GenAI (ChatGPT) moderates general entrepreneurial intentions.

Furthermore, conducting this study in South Africa's developing economy, characterised by the growing acceptance and adoption of AI, addressed the research calls for greater geographical and cultural diversity, as the majority of extant studies have focussed on developing Asian economies or developed nations (Duong & Vu, 2025; Nguyen & Nguyen, 2024; Shepherd et al., 2025; Zulfiqar et al., 2025).

1.5 Research Purpose and Objectives

The purpose of this research was to interrogate how the perceived ease of use and usefulness of GenAI (ChatGPT), analysed as GenAI (ChatGPT) acceptance, moderates the relationship between entrepreneurship education and entrepreneurial intentions, as mediated by entrepreneurship self-efficacy (Amani et al., 2024; Jiatong et al., 2021; X. Wang et al., 2023; L. Wu et al., 2022). Grounded in the theory of planned behaviour and the technology acceptance model, this research aimed to provide insights for education institutions and policymakers to enhance entrepreneurship education efficacy and integrate emerging technologies in a deliberate self-efficacy enhancing manner (Sardi et al., 2025). Ultimately, the study sought to contribute to the increase in entrepreneurial activity by strengthening the students' entrepreneurial intentions to engage in actual entrepreneurship behaviour, thereby reducing high unemployment. This study achieved this purpose by pursuing the following research objectives:

1.5.1 Research Objectives

- A. To examine the direct relationships between entrepreneurship education and entrepreneurial intention.
- B. To examine the direct relationships between entrepreneurship education and entrepreneurial self-efficacy.
- C. To examine the direct relationships between entrepreneurial self-efficacy and entrepreneurial intention.
- D. To examine the mediating role of entrepreneurship self-efficacy in the relationship between entrepreneurship education and entrepreneurial intention.
- E. To examine the moderating effects of GenAI (ChatGPT) acceptance in the relationship between entrepreneurship education and entrepreneurial intention.

- F. To examine the moderating effects of GenAI (ChatGPT) acceptance in the relationship between entrepreneurial self-efficacy and entrepreneurial intention.

1.6 Research Scope

The scope of the research was limited to studying the relationship between entrepreneurship education and entrepreneurial intention. The intervening effects of entrepreneurship self-efficacy and the acceptance of ChatGPT were examined to explain the nature of the relationship between entrepreneurship education and entrepreneurial intention. Furthermore, the study was limited to participants who were enrolled in South African higher education institutions.

1.7 Structure of the Research

The structure of this research developed as follows:

- **Chapter Two:** Includes the literature review of the existing studies relating to the research problem, objectives, purpose of the study and the significance of the study.
- **Chapter Three:** Outlines the hypothesis development and the conceptual model of the study based on the literature review and the research objectives.
- **Chapter Four:** Outlines and defends the methodology and the design of the study.
- **Chapter Five:** Presents the empirical outcomes of the study including the descriptive and inferential statistics results.
- **Chapter Six:** Discusses the results within the context of the literature review.
- **Chapter Seven:** Presents the study's conclusion, implications of the study, limitations and the areas for future research.
- **Appendices:** Present supplementary information that is useful for the study.

1.8 Conclusion

This chapter introduced the reader to the study's background, research problem, the business and academic significance of the research based on the gaps identified in the literature. Additionally, the research purpose, the objectives and the scope of the research were also outlined. Chapter Two outlines the theoretical foundation of the study and the literature review.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Entrepreneurship and education are pillars of economic development, job creation and poverty alleviation for many nations including South Africa (Meyer et al., 2022). The integration of technology and generative artificial intelligence into entrepreneurship and education has transformed the approach to entrepreneurship development and democratised access to entrepreneurial information (Chalmers et al., 2021; Obschonka & Audretsch, 2020; Redondo-Rodríguez et al., 2024). This chapter examined the current discourse surrounding the evolving research on artificial intelligence and generative artificial intelligence within the context of the advancement of entrepreneurial intentions. The review discussed the dynamics of the research constructs and the ensuing relationships between entrepreneurship education, entrepreneurial intention, entrepreneurship self-efficacy, and GenAI acceptance as a precursor to adoption (Mutanga et al., 2024).

Firstly, this chapter analysed the essential literature relevant to the research objectives. The theoretical foundation of the study was the integration of the theory of planned behaviour and the technology acceptance model (Ajzen, 1991, 2020; Davis, 1989). Secondly, the main constructs were defined and their characteristics examined, commencing with entrepreneurship education. Thirdly, entrepreneurial intention was defined and discussed as an antecedent for entrepreneurial behaviour (Amani et al., 2024). Fourthly, entrepreneurship self-efficacy was defined and discussed for its posited role as a mediator in the relationship between entrepreneurship education and entrepreneurial intention (Jiatong et al., 2021). Fifthly, AI with a focus on GenAI was unpacked to examine its influence in entrepreneurship and the aforementioned constructs (Ivanov et al., 2024; Sun & Deng, 2025; Xie & Wang, 2025).

The chapter concluded with insights from the literature regarding the associated relationships between 1.) Entrepreneurship education and entrepreneurial intention, 2.) Entrepreneurship education and entrepreneurial self-efficacy, 3.) Entrepreneurial self-efficacy and entrepreneurial intention, 4.) The mediating role of entrepreneurial self-efficacy and 5.) The moderating role of generative artificial intelligence, particularly ChatGPT acceptance, which was identified in the research gap and was the focus of the study.

2.2 Theory of Planned Behaviour

Entrepreneurial ventures were outcomes of deliberate actions derived from intentions; thus, intention-based models were most effective to understand and predict entrepreneurial actions (Krueger & Carsrud, 1993). The formation of intentions was also influenced by several psychological factors which collectively shaped intentions to act. Over the past four decades, scholars have examined these antecedents of entrepreneurial intentions using diverse theoretical frameworks such as the human capital theory, the entrepreneurial event model and the most prominent one being the theory of planned behaviour (Batista-Canino et al., 2024).

The theory of planned behaviour as a psychological framework, predicted an individual's intention to engage in a specific behaviour based on the following determinants: 1.) Their perceptions and attitudes toward the behaviour 2.) The subjective norms surrounding the behaviour, and 3.) The perceived behavioural control (Ajzen, 2020). Given the difficulties of explaining the complexities of human behaviour across varied situations of voluntary and non-voluntary control, the theory of planned behaviour emerged as a more pragmatic extension of Ajzen and Fishbein's (1977) theory of reasoned action (Ajzen, 1991; Ajzen & Fishbein, 1977; Kautonen et al., 2015; C. Wang et al., 2025).

The theory of reasoned action aimed to explain the relationship between attitudes, intention and behaviour; but although it did establish this link, it had a major limitation which assumed rational reasoning concerning the behaviour and importantly, that the intended behaviour was wholly under an individual's voluntary control (Kufaine, 2024). Furthermore, the theory of reasoned action assumed that intentions would lead to behaviour without accounting for exogenous factors that could change the initial motivation (Hagger et al., 2022; Kufaine, 2024). In reality, attitudes shifted based on many factors (for instance contextual and cognitive) and this could influence initial intentions, and thus initial behaviours to change. These assumptions were insufficient for predicting behaviours where the individual lacked voluntary control or when other non-motivational exogenous factors interfered (Hagger & Hamilton, 2024). As such, the theory of planned behaviour was extended to include perceived behavioural control to account for the model weakness (Ajzen, 1991; Kufaine, 2024). An illustration of the theory of planned behaviour as posited by Ajzen (1991) was included in Figure 1.

The inclusion of perceived behavioural control, which referred to how easy or difficult an individual perceived a specific behaviour based on their experience, skills or any

exogenous factors they anticipated (Hagger et al., 2022), was crucial for developing a more robust theoretical model. Perceived behavioural control captured a distinguishing factor to explain behaviours where perhaps the motivational attitudes (such as attitudes and social norms) were low, but the individual's self-belief was high. Such scenarios were synonymous with entrepreneurial contexts, where motivations alone are not sufficient to lead to behaviour (Batista-Canino et al., 2024).

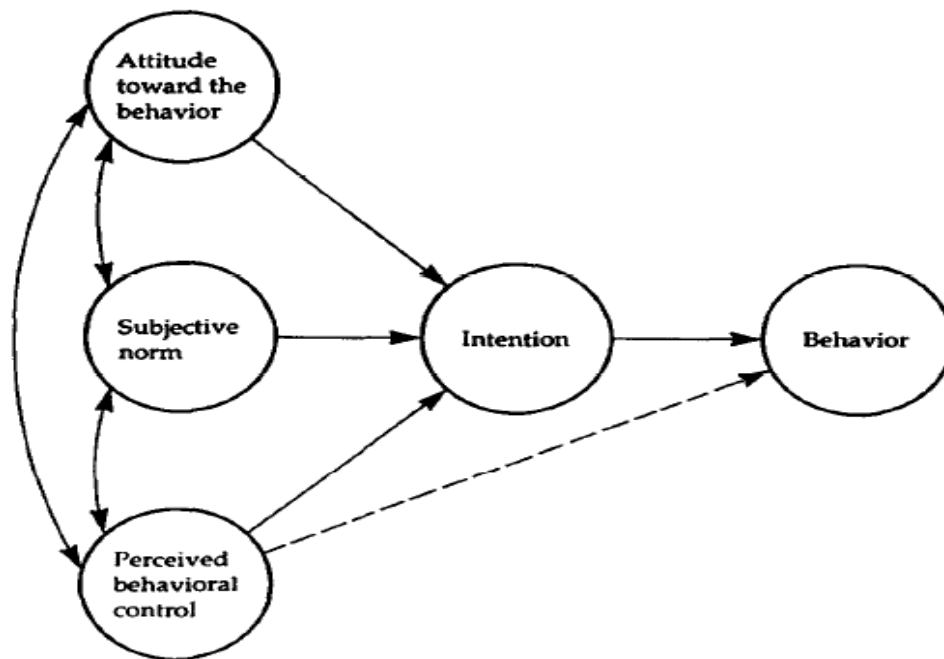


Figure 1: Theory of Planned Behaviour

(Ajzen, 1991)

Additionally, perceived behavioural control also served as a direct link between intentions and behaviours, given that it would endorse the effort and persistence that was required to achieve the intended behaviour (Krueger & Carsrud, 1993). Therefore, if a student had a high perceived behavioural control towards entrepreneurship based on the skills, knowledge and mindset imparted upon them through their education, they could be inclined to act entrepreneurially even as their motivations decreased with time. Hagger and Hamilton (2024) supported this view in a recent longitudinal study which found that only perceived behavioural control remained stationary overtime, whereas the other motivations showed reduced influence over time. Thus, understanding what drove perceived behavioural control was central to the study.

Since its inception, the theory of planned behaviour has served as a robust theoretical framework for predicting intentions and behaviours across diverse disciplines and it has

become the most commonly used theoretical framework for studying intentions (Bayona-Oré, 2023; Kautonen et al., 2015; Krueger & Carsrud, 1993). Within the entrepreneurship discipline, the theory has been used to examine various antecedents and intervening constructs of entrepreneurial intention and behaviour, including GenAI adoption (Duong et al., 2024; Habibi et al., 2024; Kumar et al., 2025; Udeozor et al., 2025; C. Wang et al., 2025; Zulfiqar et al., 2025). The natural extension of the theory of planned behaviour to technology was anticipated given that it had a close relation to another well studied theory, the technology acceptance model, which was also rooted in the theory of reasoned action (Zaineldeen et al., 2020).

A central foundation to the theory of planned behaviour was that the intentions formed through three motivational beliefs were the closest and most significant predictors of behaviour (Ivanov et al., 2024). These three motivational beliefs and attitudes that anchored as antecedents of intention are discussed in detail below.

2.2.1 Attitudes towards the behaviour

This concept captured the positive and negative beliefs as well as the attitudes an individual possessed towards a certain behaviour (Zulfiqar et al., 2025). In the context of entrepreneurship, if the individual believed that entrepreneurship was desirable from their own perspective, the intention to act entrepreneurially would be greater. These attitudes could be altered by other exogenous factors such as education or experiences that positively frame the outcomes or reduce the perceived consequences of actions (Taneja et al., 2024).

Entrepreneurship education's ability to alter mindsets by influencing cognitive and behavioural aspects through theoretical and practical learning positioned it well to form positive attitudes towards entrepreneurship in students and society (Jiatong et al., 2021; Kuratko et al., 2021). Furthermore, the use of GenAI in education and entrepreneurship made entrepreneurial behaviour more appealing given the information resource accessibility which GenAI provided. The GenAI tools helped to automate tedious tasks and processed vast amounts of data with speed which helped students make informed decisions. Through making complex entrepreneurial tasks more manageable and useful, this fostered greater positive attitudes towards venture creation (Vecchiarini & Somià, 2023; Zulfiqar et al., 2025).

Although previous studies have found that the antecedents of TPB "jointly explained 59% of the variation of intention" (Kautonen et al., 2015, p.668), more recent studies by

Hagger and Hamilton (2024) indicated that the predictive strengths of 'attitudes to behaviour' and the 'social norms' reduced over time, relative to the influence exerted from 'perceived behavioural control' on the intention to behaviour link.

2.2.2 Social norms

Social norms represented the perceived views of important or influential people around an individual (Udeozor et al., 2025). They captured the impact of how other views (family, friends, colleagues etc.) influenced an individual's beliefs or attitudes towards a behaviour. If a student believed that important people around them viewed entrepreneurship positively, they were likely to have stronger entrepreneurial intentions (Rauch & Hulsink, 2015). Likewise, if the people around them viewed the use of GenAI positively, they were likely to have positive intentions towards technology acceptance and adoption (Zulfiqar et al., 2025).

Other people's perceptions could be more influential than an individual's own attitudes, as demonstrated by Chai et.al (2020), who found that the subjective norms of secondary students impacted their attitudes and intentions to use AI, despite their neutral attitudes towards technology. These results made sense given that secondary students were more likely to be impressionable by those around them, and thus more impacted by social norms in forming their intentions (Chai et al., 2020).

2.2.3 Perceived behavioural control

As discussed above, perceived behavioural control was the crucial component that distinguished the theory of planned behaviour from its roots of the theory of reasoned action. Perceived behavioural control was a construct that was similar to Bandura's (1977) perceived self-efficacy, which was defined as the belief in one's capabilities to perform tasks (Taneja et al., 2024). Similarly, entrepreneurial self-efficacy was an occupational derivative of self-efficacy that manifested perceived behavioural control, which had been shown to significantly influence entrepreneurial intention and entrepreneurial behaviours (Amani et al., 2024; Newman et al., 2019; L. Wu et al., 2022). Drawing from the theory of planned behaviour, this study focussed on examining perceived behavioural control as the anchor determinant for entrepreneurial intention development. Perceived behavioural control had two components: self-efficacy (perceived ease or difficulty of performing behaviour) and controllability (perceived control over influencing variables of the particular behaviour) (Ajzen, 2020). As such, self-efficacy was best suited to examine how the outcomes of education facilitated entrepreneurial intentions in the context of GenAI acceptance (Zulfiqar et al., 2025).

Therefore, this study specifically focussed on entrepreneurial self-efficacy as the primary mediating variable between entrepreneurship education and entrepreneurial intention.

Furthermore, the rising research interest in the role of AI and GenAI within entrepreneurship and education, necessitated a robust theoretical approach (Tarisayi, 2024). Given the prevalence of ChatGPT as one of the fastest growing technologies, being the only one to reach 100 million users within two months, the study was motivated to interrogate its influence (Kumar et al., 2025; Tarisayi, 2024). To adequately consider the behavioural motivations that influence entrepreneurial intentions in the context of emerging technologies, applying the 'perceived attitudes towards the behaviour' articulated in the technology acceptance model and the 'perceived behavioural control' articulated in the theory of planned behaviour was most suitable for the study (Ivanov et al., 2024; C. Wang et al., 2025; Zulfiqar et al., 2025). This integration of the theory of planned behaviour and the technology acceptance model ensured a comprehensive coverage of the core psychological motivations and attitudes that influenced entrepreneurial intentions in the context of emerging technologies.

2.3 Technology Acceptance Model

The rapid growth and development in technology and AI resulting in what was now termed as the "second machine age" (Obschonka & Audretsch, 2020, p.4) has resulted in individuals having to adapt and adopt emerging technologies more frequently. With AI infiltrating many sectors of the economy such as education, business, health and mining, it was expected to drive economic development for nations that have the greatest adoption (Redondo-Rodríguez et al., 2024). As such, the theories and models that explained the mechanisms that led to increased adoption of these emerging technologies became important to research (Zaineldeen et al., 2020).

One such theory was the technology acceptance model which was a highly influential theory used to explain and predict individuals' acceptance or resistance of new technology (Davis, 1989; Sharma et al., 2025). The model was developed as an adaptation of the theory of reasoned action (Ajzen & Fishbein, 1977). The technology acceptance model aimed to explain the determinants of user acceptance, focussing on the attitudes and beliefs that shaped individuals' intention. These determinants were 1.) Perceived usefulness and 2.) Perceived ease of use (Davis, 1985; 1989; Zaineldeen et al., 2020).

2.3.1 Perceived usefulness

Perceived usefulness refers to the extent to which an individual considers technology useful to enhance their performance (Gupta, 2024). In the entrepreneurial education context, this referred to a student's belief that using a GenAI tool like ChatGPT would be useful to improve efficiency, productivity and new venture ideation processes (Bell & Bell, 2023; Sun & Deng, 2025; Xie & Wang, 2025). Recent studies have shown that when individuals perceive technology to be useful, they would have higher intentions to adopt it even if it was not perceived to be easy to use (Abaddi, 2023; Sharma et al., 2025). This implied that perceived usefulness was a stronger determinant with a direct link to behavioural intention towards adoption than perceived ease of use discussed below.

2.3.2 Perceived ease of use

Perceived ease of use referred to the extent to which an individual believed that they could utilise new technology with minimal difficulty (Gupta, 2024; Zaineldeen et al., 2020). In the context of GenAI, this construct captured how easy it was for a student to engage GenAI tools such as ChatGPT for their learning or entrepreneurial benefit. Furthermore, the theory model posited that perceived ease of use had an indirect effect on acceptance behaviour through perceived usefulness. As such, when students found technology easy to use, the more useful it could be perceived (Al-Dokhny et al., 2021; Davis, 1985, 1989).

Additionally, the perceived ease of use construct was also conceptually aligned with the self-efficacy construct, where a judgement of an individual's perceived ease of use of the technology was linked to their internal perceptions of control (Davis, 1989). This perception of control encouraged the acquisition of AI skills or literacy in the context of GenAI acceptance (Al-Dokhny et al., 2021; C. Wang et al., 2025). However, while perceived ease of use focussed on the individual's internal evaluation of usability, it did not not consider the explicit external factors such as, access to resources, training or infrastructure. Such external factors and others are addressed in the perceived behavioural control construct of the theory of planned behaviour (Ahmed et al., 2020; Ajzen, 1991). This conceptual distinction highlighted the motivation for integrating technology acceptance model and theory of planned behaviour in the current study, to capture internal perceptions of usability and external factors influencing behavioural intention in technology enabled entrepreneurship education (see Section 2.4).

Recent research by Gupta (2024) claimed that traditional technology models such as the technology acceptance model were not suitable for assessing the acceptance and adoption of intelligent technology that does not require human intervention, such as GenAI. Notwithstanding that fact of limited human intervention, however, the author failed to acknowledge the importance of the human ingenuity that developed the algorithms that enabled the automation; and thus, needed to have developed attitudes and behaviours towards the initial acceptance and adoption of emerging technologies. Despite this criticism, the technology acceptance model has been widely adopted and used to examine the intentions to accept and adopt new technologies and thus it was employed in this study together with the theory of planned behaviour to ensure a more comprehensive framework (Al-Dokhny et al., 2021; Sharma et al., 2025; Strzelecki, 2023). A depiction of the technology acceptance model has been included in Figure 2, and it also reflects the mediated role of perceived usefulness (Zaineldeen et al., 2020).

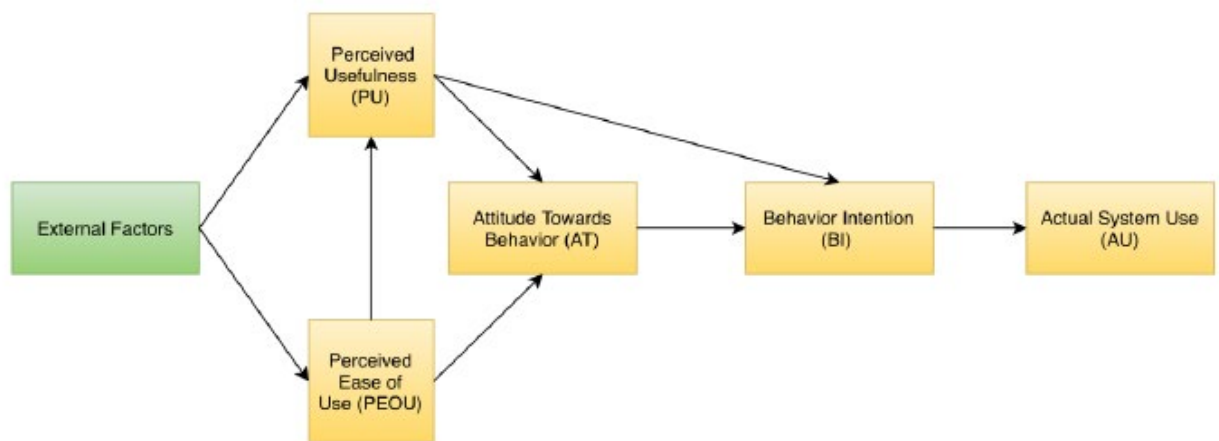


Figure 2: Technology Acceptance Model

(Zaineldeen et al., 2020)

2.4 Integration of Theory of Planned Behaviour and the Technology Acceptance Model

Though few studies have done so, integrating the theory of planned behaviour and the technology acceptance model offered a more comprehensive framework for understanding a user's intention to adopt a new technology in the context of entrepreneurial intention development (Ivanov et al., 2024; Sharma et al., 2025; Strzelecki, 2023; Zulfiqar et al., 2025). While both models were powerful on their own, they had distinct limitations that were effectively addressed when the theories were combined (Zulfiqar et al., 2025).

Though both models had their roots in the theory of reasoned action, the technology acceptance model had similar limitations of the assumption of volitional control, which was addressed in the theory of planned behaviour through the addition of perceived behavioural control (Zaineldeen et al., 2020). Technology acceptance model, however, was able to explain the user's perception of technology with greater specificity than the theory of planned behaviour which was more general. Furthermore, integrating it with the theory of planned behaviour compensates for the missing perceived behavioural control which not only considers internal but external control factors unlike the perceived ease of use construct of the technology acceptance model (Ahmed et al., 2020; Zaineldeen et al., 2020).

Combining the models was particularly useful for educational and entrepreneurial contexts. The students' intentions to use GenAI like ChatGPT were not influenced only by perceived ease of use and usefulness (referred to as attitudes for behaviour) of ChatGPT, but also by their perceived confidence in their abilities to use the technology (such as perceived behavioural control) (Duong et al., 2024; Ivanov et al., 2024; Kumar et al., 2025; Sharma et al., 2025; Zulfiqar et al., 2025). Therefore, an integration resulted in a robust framework to interpret human behaviour and predict intentions when employing technology (Zaineldeen et al., 2020; Zulfiqar et al., 2025).

2.5 Entrepreneurship Education

2.5.1 *Entrepreneurship education definition*

Kuratko (2005) documented the historic evolution of entrepreneurship education, where the first Master of Business Administration specialising in entrepreneurship was developed by the University of Southern California in 1971. Since then, entrepreneurship and entrepreneurship related courses have been offered throughout the world (Kuratko, 2005; Martin et al., 2013). Entrepreneurship education is broadly defined as a range of pedagogical methods designed to develop entrepreneurial human capital investment that result in human capital assets such as skills, knowledge, mindsets and attitudes towards new venture creation (Martin et al., 2013; Unger et al., 2011). Carpenter and Wilson (2022) also defined it as any program or process that developed entrepreneurial skills and attributes. Ultimately, entrepreneurship education was about the improvement of individuals' competencies to achieve new venture creation, as opposed to broader business management skills (Hägg & Gabrielsson, 2020; Lackéus, 2020).

To address high unemployment and improve economic growth conditions, governments in numerous countries, including South Africa, have invested in entrepreneurship education and entrepreneurship learning initiatives to develop human capital assets such as skills and mindsets for self-employment (Fayolle & Gailly, 2015; Lyu et al., 2024; Meyer et al., 2022; Udeozor et al., 2025; Zwane & Osuigwe, 2024). As such, entrepreneurship education was acknowledged for playing a vital role in; developing entrepreneurs, fostering innovation and developing entrepreneurial intention (Amani et al., 2024; Debarliev et al., 2022).

2.5.2 Entrepreneurship education pedagogies

Entrepreneurship education was delivered through diverse pedagogical approaches, broadly distinguished between theoretical-orientated and practical-orientated programmes (Gabrielsson et al., 2020; Hägg & Gabrielsson, 2020; Lyu et al., 2024; Piperopoulos & Dimov, 2015). The theoretical-orientated programmes content was mainly focussed on entrepreneurship theory, business plan writing and management skills, often taught through teacher-centred methods such as case study, guest speakers etc. (Lyu et al., 2024; Piperopoulos & Dimov, 2015). Practical-orientated programmes, however, focussed on content that was geared towards new venture creation which included ideation, innovation negotiation, and business venture evaluation (Fayolle & Gailly, 2015; Lyu et al., 2024; Piperopoulos & Dimov, 2015; Udeozor et al., 2025). These were taught through hands on methods such as simulations, in-field experiences, role-playing, mentorship and networking with other entrepreneurs (Lyu et al., 2024).

Furthermore, a commonly used pedagogical framework to distinguish entrepreneurship classified entrepreneurship education as either education *about* entrepreneurship, education *for* entrepreneurship, or education *in* entrepreneurship (Hägg & Gabrielsson, 2020; Piperopoulos & Dimov, 2015; Rauch & Hulsink, 2015). Education *about* entrepreneurship was primarily focussed on imparting theoretical knowledge about the features and processes of entrepreneurship (Piperopoulos & Dimov, 2015; Rauch & Hulsink, 2015). Education *for* entrepreneurship aimed to provide practical skills and knowledge to create and operate new ventures, while education *in* entrepreneurship was aimed at improving existing human capital assets for those who were already entrepreneurs (Piperopoulos & Dimov, 2015; Rauch & Hulsink, 2015).

Studies have found that diverse pedagogical approaches created divergent entrepreneurship education outcomes, making it challenging to objectively assess the

efficacy of entrepreneurship education (Cui & Bell, 2022; Debarliev et al., 2022; Hägg & Gabrielsson, 2020; Lyu et al., 2024; Udeozor et al., 2025). For instance, Piperopoulos and Dimov (2015) found that practical-oriented entrepreneurship education enhanced entrepreneurial self-efficacy, which in turn had a stronger influence on entrepreneurial intention. This was further supported by Lyu et al. (2024) who observed that practical-based pedagogy influenced opportunity identification more than exploitation, whereas the latter was more influenced by theoretical-based pedagogy.

Despite the pedagogical distinctions, several studies (Alakaleek et al., 2023; Jiatong et al., 2021; Nabi et al., 2017; Soomro & Shah, 2022) have treated entrepreneurship education as a uniform construct given that there was a lack of consensus on the justification for endorsing particular pedagogical approaches above others (Hägg & Gabrielsson, 2020; Wiklund et al., 2025). Moreover, recent studies (Chaker & Dellagi, 2023; Chaker & Jarraya, 2021) have found that combined methods for teaching *about* and *for* entrepreneurship education were more effective over theoretical or practical only orientated programmes (Lyu et al., 2024). While theory-orientated only programmes foster cognitive understanding of entrepreneurship, they may fail to adequately translate knowledge into action. Conversely, practise-oriented only programmes may focus excessively on contextual entrepreneurial skills without developing entrepreneurship conceptual depth that is transferable to different contexts (Fayolle & Gailly, 2015; Lyu et al., 2024). Thus, the effectiveness of any pedagogy therefore depends on methods and approaches that bridge cognition and action.

These findings collectively suggest that pedagogy affects intention indirectly through development of self-efficacy and thus perceived behavioural control (X. Wang et al., 2023). In South Africa's resource constrained higher education system, experimental only models may be unsustainable without digital intervention that can replicate aspects of experimental mentoring required to develop self-efficacy at scale (Meyer et al., 2022; Zwane & Osuigwe, 2024). As such, the literature remains ambiguous on whether entrepreneurship can truly be taught (theoretical-orientated) or only experienced (practical-orientated) (Gabrielsson et al., 2020). This unresolved tension underpins the need to investigate how technology integration such as ChatGPT could bridge the two perspectives. Therefore, this current study assessed entrepreneurship education as a composite construct integrating cognitive and experiential aspects whose impact is channelled through self-efficacy and moderated by GenAI acceptance.

2.5.3 *Entrepreneurship education and technology*

Given the diverse styles of learning and contexts that influenced entrepreneurial mindsets, attitudes, self-efficacy and intention, the scholarly discourse calls for more innovative, effective and practical integrating approaches to bridge the gap between education, intention and behaviour (Chaker & Dellagi, 2023; Chaker & Jarraya, 2021; Lyu et al., 2024; Nabi et al., 2017; Ratten & Usmanij, 2021; Rauch & Hulsink, 2015; Tran et al., 2024). “Entrepreneurship cannot be a field that succumbs to stagnation. It must recognize and apply technologies in the educational setting” (Kuratko, 2005, p. 588). The rise of advanced technologies such as AI and GenAI presented unique opportunities to address the longstanding challenges of entrepreneurship education (Nguyen & Nguyen, 2024; Ratten & Usmanij, 2021).

Leveraging GenAI tools such as ChatGPT could create more consistent, scalable and effective learning environments that bridged the best of both theory and practice (Bell & Bell, 2023). Generative artificial intelligence tools could infuse experiential learning in traditional theoretical orientated programmes by helping students to brainstorm business ideas, simulate entrepreneurial activities such as customer service interactions and fundraising (Sun & Deng, 2025). This integration could improve self-efficacy and address the shortcomings of theoretical orientated programmes as identified by Lyu et al. (2024), Piperopoulos and Dimov (2015), as well as by Tran et al. (2024).

2.6 Entrepreneurial Intention

2.6.1 *Entrepreneurial intention definition*

Entrepreneurial intention was considered as a key foundation of entrepreneurship research because, intention was regarded as the best precursor of deliberate behaviour such as new business creation (Ahmed et al., 2020; Batista-Canino et al., 2024; Krueger & Carsrud, 1993; Liñán & Chen, 2009). Entrepreneurial intention, a social psychology construct, was the cognitive state preceding action. Saoula et al. (2025) posited that entrepreneurship intention was a mindset that kept one determined to pursue entrepreneurial ventures. Acknowledging the commitment and effort required to take action, Shirokova et al. (2016) defined it as an individual's commitment to start a business. More recently, Taneja et al. (2024) defined entrepreneurial intention as the willingness and determination to see new venture creation processes through to the end. This study therefore adopted the definition of entrepreneurial intention as the deliberate mindset and resolve to engage in new business creation. Therefore, fostering

entrepreneurial intention particularly among higher education students, was considered essential for economic development, innovation and reducing unemployment (Duong et al., 2024; Iddris, 2025; Lyu et al., 2024; Nowiński et al., 2019; Onjewu et al., 2021; Udeozor et al., 2025).

Given its critical role in funnelling new venture creation, a rich body of literature spanning over 50 years has been dedicated to examining and understanding entrepreneurial intention's antecedents and moderators with a significant focus on the role of the theory of planned behaviour and entrepreneurship education in creating intentions (Bae et al., 2014; Batista-Canino et al., 2024; Fayolle & Gailly, 2015; Gieure et al., 2020; Kautonen et al., 2015; Lv et al., 2021; Neneh, 2022; Piperopoulos & Dimov, 2015; Taneja et al., 2024; L. Wu et al., 2022).

2.6.2 Entrepreneurial intention antecedents

As discussed in Section 2.2., the formation of entrepreneurial intention can be examined by a number of intention-based models with the most prominent one being theory of planned behaviour (Batista-Canino et al., 2024; Krueger & Carsrud, 1993). Sniehotta et al. (2014) cautioned against the over reliance on the theory given its limitations to consider, among others, beliefs which can predict behaviours independently of the intentions of the model. While the theory of planned behaviour assumes stable attitudes, the ever-evolving digital context created situational intentions which called for interrogating intention formation where technology was integrated in cognition. Despite their calls to retire the theory for more innovative and contextually relevant theories, the theory of planned behaviour continues to be one of the most effective intention-based models used in behavioural research (Ajzen, 2015; Conner, 2015; Hagger, 2015).

Given the pertinent role that entrepreneurial intentions played in new venture creation, it was often judged as the outcome of entrepreneurship education, although Onjewu et al. (2021) advised against this narrow view of entrepreneurship education. As alluded to in the above sections, the antecedents of entrepreneurial intention are influenced by the pedagogical approaches and efficacy of entrepreneurship education (Gabrielsson et al., 2020; Lyu et al., 2024; Taneja et al., 2024; Udeozor et al., 2025). Despite consensus that education fosters intention, some studies reported negative effects implying that awareness of entrepreneurial risks could dampen intentions (Oosterbeek et al., 2010). These contradictions highlighted the psychological costs of realism in entrepreneurship education. These mixed outcomes suggested that education may not influence intention directly, but mainly transferred its outcomes through shaping self-

efficacy, which was strengthened when learning environments reinforced perceived control (Zhao et al., 2025).

While the theory of planned behaviour relationships has been widely used to explain entrepreneurial intention, it does not fully account for contextual and demographic antecedents that may interact with psychological factors. Other situational variables such as past experiences with startup ventures have also been shown to negatively influence intentions where failures were encountered (Malebana & Mothibi, 2023). Similarly, family support and access to financial capital could lead to mixed effects on entrepreneurial intentions, where high financial capital and family support have been shown to decrease entrepreneurial behaviour (Xu et al., 2020). Furthermore, perceptions of gender inequalities have also negatively impacted some female student's entrepreneurial self-efficacy intentions (Vu et al., 2025). These findings show that entrepreneurial intention is not only a function of cognitive antecedent but is also shaped by broader social contexts which could be relevant for the fragmented South African context.

Furthermore, the antecedents of entrepreneurial intention as proposed by the theory of planned behaviour could be subject to change in digitally mediated environments. In learning settings that integrated GenAI tools, for instance, perceived behavioural control could strengthen as students experience the efficiency of technology that automates complex entrepreneurial tasks (Duong et al., 2024; Zulfiqar et al., 2025). These dynamics point to the need to interrogate entrepreneurial intention within GenAI integrated learning environments where theory of planned behaviour relationships could be reshaped (Dwivedi, 2025). As such, this study responds to the empirical inconsistencies in the entrepreneurship education and entrepreneurial intention literature by examining entrepreneurial self-efficacy as a mediating pathway and GenAI acceptance as a contextual moderator within the theory of planned behaviour and technology acceptance model framework.

2.7 Entrepreneurship Self-efficacy

2.7.1 Entrepreneurship self-efficacy definition

Entrepreneurship self-efficacy was a critical construct in entrepreneurship research that was acknowledged for its ability to distinguish entrepreneurship from business management characteristics (Chen et al., 1998; Hsu et al., 2019). Chen et al. (1998) found that an individual's belief in their own capacity for risk-taking, innovation and a high internal locus of control distinguished them from managers or non-founders.

Similarly, Newman et al. (2019), defined entrepreneurship self-efficacy as self-belief in an individual's abilities to perform and achieve entrepreneurial tasks. This paper adopted the definition of entrepreneurial self-efficacy from Newman et al. (2019), particularly as it related to students in higher education who may not have capacity to understand the risk appetite for entrepreneurship but could develop self-efficacy through education and interactions with technology.

2.7.2 *Entrepreneurship self-efficacy antecedents*

Entrepreneurship self-efficacy reflected one's perceived skills and competence to succeed in business ventures, which was essential to develop lasting intentions to persevere through challenging entrepreneurship environments (Jiatong et al., 2021). Entrepreneurship self-efficacy was rooted in Bandura's social cognitive theory, which posited that self-efficacy was developed from a combination of social context, observation and replication of desired behaviours (Newman et al., 2019). Entrepreneurship self-efficacy was an occupation-specific self-efficacy that was influenced by mastery experiences of entrepreneurship. Mastery could be developed through current entrepreneurship or prior entrepreneurship experiences, vicarious learning through role modelling and observation of other successful entrepreneurs, social persuasion developed through positive feedback from educators, mentors and others, and the management of the physiological or emotive states that come with entrepreneurial challenges (Chen et al., 1998; Neneh, 2022).

This diverse range of antecedents implied that entrepreneurship self-efficacy was a dynamic and fluid construct based on the prevailing context, and the South African context could derive different entrepreneurship self-efficacy. Entrepreneurship self-efficacy's outcomes varied from individual to firm-level, which together lead to entrepreneurial intentions and ultimately entrepreneurial behaviours (Hsu et al., 2019; Newman et al., 2019). The firm-level outcomes developed self-efficacy for entrepreneurial processes that result in greater economic impact, such as venture creation, innovation and job creation (Newman et al., 2019). At an individual level, entrepreneurship self-efficacy developed psychological capabilities to develop essential attributes which were required for entrepreneurs such as mental resilience, opportunity recognition and positively framing trust in one's judgment (Newman et al., 2019). These attributes were required to deal with challenges that were inevitable in entrepreneurship. As such, entrepreneurship self-efficacy therefore enabled the pathway to entrepreneurial intention (Jiatong et al., 2021; X. Wang et al., 2023; L. Wu et al., 2022).

2.8 Artificial Intelligence

AI has emerged as a leading technology transforming the approach to entrepreneurship, impacting how entrepreneurs originate, develop, design and implement ideas (Chalmers et al., 2021; Mannuru et al., 2023; Uriarte et al., 2025). AI refers to computer systems or models capable of performing tasks that mimic human intelligence, such as language processing, pattern recognition and problem solving (Feuerriegel et al., 2024; Kajiita & Kang'ethe, 2025; Lévesque et al., 2022). AI is a computer science concept that dates back to the 1950's when scientists were trying to build computers that simulated human intellectual capabilities (Lévesque et al., 2022; Obschonka & Audretsch, 2020; Redondo-Rodríguez et al., 2024).

AI was developed through many decades of neural language model development, which led to the development of foundational technology for GenAI and pre-trained language models, which were the structures of the current GenAI models (Feuerriegel et al., 2024). With the innovation of the transformer architecture which was a self-attention mechanism that was able to weigh the importance of input data, it propelled the development of large language models that could predict subsequent words based on previous ones, thus enabling the generative capacity of creating new coherent text (referred to as generative artificial intelligence) (Feuerriegel et al., 2024; T. Wu et al., 2023).

2.8.1 Generative artificial intelligence (ChatGPT)

Generative artificial intelligence, a subset of AI, comprised of algorithms and network structures capable of generating new and creative content such as text, audio, images and videos (Feuerriegel et al., 2024). This capability of GenAI marked a profound shift in technology content creation and production that was previously exclusive to human intelligence. The impact of GenAI can be noted in the wide acceptance and adoption of pre-trained models, specifically OpenAI's ChatGPT. Launched in November 2022, it became one of the most highly adopted consumer applications in history, reaching five million users within five days, and 100 million users within two months, relative to Facebook and X who took ten months and two years respectively to reach one million users (Kumar et al., 2025; Tarisayi, 2024; T. Wu et al., 2023). As an intelligent chatbot that was able to provide detailed responses based on a user's personalised prompts, ChatGPT has reshaped how humans perceive and interact with machines (T. Wu et al., 2023).

The democratisation of AI has profoundly reshaped the entrepreneurial and education environment enabling access to information resources that could augment access to new venture creation and various other opportunities (Chalmers et al., 2021; Vecchiarini & Somià, 2023). For entrepreneurs, GenAI could help drive innovation, automate complex tasks, conduct complex data analysis and predict market trends from big data processing, thus offering a competitive edge even to smaller under resourced companies (Dwivedi, 2025; Mutanga et al., 2024). Entrepreneurship educators could leverage the technology to enhance the educational experience through personalised learning paths, faster feedback and digital collaborative environments; supporting entrepreneurial tasks such as business model development, market analysis and pitch developments (Bell & Bell, 2023; Fan et al., 2025; Vecchiarini & Somià, 2023; Zulfikar et al., 2025).

Despite the revolutionary potential of GenAI to increase employment by improving digital literacy, providing access to information and automating tasks; Chalmers et al. (2025) cautioned against the negative effects of AI relating to ethical considerations towards the abuse of powerful data capabilities to further deepen inequalities (Kajiita & Kang'ethe, 2025; Mannuru et al., 2023). The fears of "AI colonialism" promoting "isolation and individualization, technology addiction and increasing inequality" (Kajiita & Kang'ethe, 2025, p.140) remain inhibitors of broad AI adoption in developing nations. From an education perspective, academics feared the lack of critical thinking development with students' overreliance on the technology leading to surface level learning and plagiarism (Bell & Bell, 2023; Fan et al., 2025; Tarisayi, 2024; Zhai et al., 2024; Zhang & Xu, 2025). Furthermore, the tendency of generative artificial intelligence to produce incorrect outputs at times called hallucinations was also a concern, given it relies on algorithms to make probabilistic outputs. This made its reliability questionable for academic purposes and thus needed to be used with scepticism and caution (Feuerriegel et al., 2024). Despite some of these limitations, the potential benefits of the technology far outweighed the cons, with some forecasts expecting GenAI to drive global GDP up by 7% (estimated \$7 trillion) over the next decade (Feuerriegel et al., 2024; Kumar et al., 2025). Collectively, these studies suggest that the role of GenAI can provide pedagogical shifts in education that could strengthen student's self-efficacy and thus foster higher intentions.

2.9 Main Relationships

2.9.1 *Entrepreneurial education and entrepreneurial intention*

One of the most studied outcomes of entrepreneurship education is entrepreneurial intention (Shirokova et al., 2016; Taneja et al., 2024). The relationship between entrepreneurship education and entrepreneurial intention was central to the literature on entrepreneurship (Bae et al., 2014; Taneja et al., 2024; Vu et al., 2025). Entrepreneurial intention was a psychological phenomenon that was a vital predictor of new venture creation behaviour, and thus critical for entrepreneurship and education research (Batista-Canino et al., 2024; Kautonen et al., 2013). The relationship between entrepreneurship education and entrepreneurial intention was shaped by complex interactions that were influenced among others, by education pedagogy (Lyu et al., 2024; Piperopoulos & Dimov, 2015), human capital assets (Martin et al., 2013; Skorodzyevskiy et al., 2025), student characteristics (Ramadani et al., 2022; Shirokova et al., 2016) and contextual environments (Shirokova et al., 2016).

The entrepreneurship education environment was recognised for initiating and transforming student development and behaviour (Batista-Canino et al., 2024). Consequently, entrepreneurship education enhanced perceived behavioural control through increased theoretical knowledge and practical training on entrepreneurship practices (for instance, business model canvassing, market research, funding or idea pitching, etc.), which built skills, confidence and self-efficacy to act entrepreneurially (Qudsia Yousaf et al., 2022; Taneja et al., 2024). Furthermore, entrepreneurship through its various pedagogies, exposed and connected nascent entrepreneurs to other established entrepreneurs' communities and mentors which established other psychosocial antecedents of intentions such as behavioural attitudes and subjective norms (Kautonen et al., 2015; Qudsia Yousaf et al., 2022; Udeozor et al., 2025; Xie & Wang, 2025).

Though several studies have found a positive relationship between entrepreneurship education and entrepreneurial intention (Martínez-Gregorio et al., 2021; Nabi et al., 2017; Onjewu et al., 2021; Ramadani et al., 2022) for students, the results have been inconsistent. Divergent pedagogical approaches that resulted in inconsistent outcomes, the compulsory nature of some entrepreneurship education courses and prior exposure of some students to entrepreneurship could deter students from future entrepreneurial intentions (Debarliev et al., 2022; Fayolle & Gailly, 2015; Oosterbeek et al., 2010; Piperopoulos & Dimov, 2015; von Graevenitz et al., 2010). Despite these

inconsistencies, however, entrepreneurship education was considered as a significant contributor to entrepreneurial intentions because it provided fundamental skills and knowledge for entrepreneurial behaviour (Batista-Canino et al., 2024).

2.9.2 Entrepreneurship education and entrepreneurship self-efficacy

Entrepreneurship education through its multifaceted pedagogical approaches provides a learning environment where students could develop and practise entrepreneurial skills. This in turn develops their self-confidence to perform entrepreneurial tasks resulting in higher entrepreneurial self-efficacy (Chen et al., 1998; Nowiński et al., 2019). As discussed in Section 2.2 of this document, entrepreneurial self-efficacy was conceptually aligned with Bandura's (1977) perceived self-efficacy and Ajzen's (1991) perceived behavioural control. Entrepreneurship education serves as the pathway for the development of entrepreneurial knowledge, skills and ultimately for entrepreneurial self-efficacy (Amani et al., 2024; Newman et al., 2019).

According to the social cognitive theory, an individual's self-efficacy was developed through four pathways being mastery, role modelling, social persuasion and one's emotional states (Chen et al., 1998; Zhao et al., 2005). Though entrepreneurial self-efficacy could be developed outside of entrepreneurship education through work experiences, mentorship relationships, and role models (Newman et al., 2019); entrepreneurship education, however, provided the opportunity to develop all four pathways through a resourced and structured environment that accelerates the self-efficacy development process (Duong & Vu, 2025).

Moreover, the type of education approach (pedagogy) also mattered, where traditional or theoretical focussed classroom teaching was criticised for not including enough education *for* entrepreneurship that focused on experiential learning (Ndlovu et al., 2025). Pedagogical approaches that incorporated experiential learning and practical activities were noted to be effective in developing personalised and reflective learning, and thus positively influenced entrepreneurial self-efficacy (Ahmed et al., 2020; Chaker & Dellagi, 2023; Chaker & Jarraya, 2021; Piperopoulos & Dimov, 2015; Taneja et al., 2024). On the other hand, a recent study from Nguyen and Nguyen (2024) found that in the digital context, the relationship between entrepreneurship education and entrepreneurial self-efficacy was negative perhaps due to the increased awareness of the challenges which digital entrepreneurship education revealed. This outlined the need for further enquiry of this direct relationship in different contexts.

2.9.3 *Entrepreneurial self-efficacy and entrepreneurial intention*

Entrepreneurial self-efficacy is a key antecedent of entrepreneurial intentions through the manifestation of perceived behavioural control, which is the belief that one is capable of the said behaviour (Amani et al., 2024; Newman et al., 2019; X. Wang et al., 2023). As such, individuals and students who believed they had the skills to spot opportunities, handle the risks and succeed, thus a high entrepreneurial self-efficacy could perceive greater control over the entrepreneurial process leading to stronger entrepreneurial intentions (Batista-Canino et al., 2024; Newman et al., duo 2019; Roos & Botha, 2022). The relationship between entrepreneurial self-efficacy and entrepreneurial intention also had boundary conditions that influenced it, such as social support (Neneh, 2022). Interestingly, the influence of entrepreneurial self-efficacy on entrepreneurial intention was highest when social support was lower, which explained why entrepreneurs with pioneering ideas succeeded without social support, because they had a high resolve and self-belief in their abilities to be resourceful and successful with their novel ideas. Conversely, when social support was high, entrepreneurial intentions could be higher regardless of the level of entrepreneurial self-efficacy (Neneh, 2022).

Furthermore, other factors that influenced the antecedents of entrepreneurial self-efficacy such as education, prior experiences and overconfidence could lower the relationship between the two constructs (Newman et al., 2019). The negative effects associated with education and prior experiences could reduce both entrepreneurial self-efficacy and intentions. In addition, the more students became aware of the negative realities of entrepreneurship, the more it led to disillusionment and thus resulted in lower entrepreneurial intentions (Nguyen & Nguyen, 2024; Oosterbeek et al., 2010). The rise in technology use influences the development of entrepreneurial self-efficacy through new learning experiences, which also influences the interactions of the constructs in novel ways (Duong & Vu, 2025; Winkler et al., 2023; Xie & Wang, 2025). Given these changing boundary conditions, there is room for more exploration of the relationship between entrepreneurial self-efficacy and entrepreneurial intention (Duong & Vu, 2025).

2.9.4 *Mediating role of entrepreneurial self-efficacy*

Entrepreneurship self-efficacy is recognised in literature for its ability to intervene between entrepreneurship education and entrepreneurial intentions (Jiatong et al., 2021; Taneja et al., 2024; Zhao et al., 2005). As such, entrepreneurship education influenced the students' entrepreneurial intentions primally by building cognitive abilities

and psychological confidence to perform entrepreneurial tasks. Entrepreneurship education programmes were created to build students' attitudes and competencies towards entrepreneurship, which was achieved through a combination of theoretical and practical orientated approaches (Martínez-Gregorio et al., 2021; Nabi et al., 2017; Saoula et al., 2025). The vast number of pedagogical approaches used in education resulted in different aspects of entrepreneurial self-efficacy being developed; however, where theoretical and practical pedagogical approaches were combined, it resulted in greater skills, self-efficacy and intentions (Chaker & Dellagi, 2023; Chaker & Jarraya, 2021; Lyu et al., 2024).

The nature of mediation by entrepreneurial self-efficacy has not been consistent. In some studies, entrepreneurial self-efficacy facilitated full mediation between the relationship of entrepreneurial education and entrepreneurial intention, while in others the mediation was only partial (Jiatong et al., 2021; X. Wang et al., 2023; L. Wu et al., 2022; Zhao et al., 2005; Zhang & Chen, 2024). This suggested that the role of entrepreneurship education was to maximise entrepreneurial self-efficacy to foster entrepreneurial intentions. This also implied that entrepreneurial education could still inspire intentions through other means not directly linked to human capital investment (for instance, creativity) or other antecedents of entrepreneurial self-efficacy (Jiatong et al., 2021; Zhang & Chen, 2024). This variability in the mediation findings suggests that the mediation role is highly contextual and could derive a different mediation in the South African context that is characterised by high unemployment and perhaps has differing motives for entrepreneurship behaviour.

2.9.5 Moderating role of generative intelligence (ChatGPT)

The transformative potential of GenAI in broader entrepreneurship processes provides an opportunity to amplify entrepreneurship education's impact (Obschonka & Audretsch, 2020). The acceptance and adoption of GenAI in education provides opportunities to offer personalised learning tailored to the students' needs, addressing the challenges of the resource constraints experienced in higher education, enabling more effective use of the educators' time (Bell & Bell, 2023; Vecchiarini & Somià, 2023). Through big-data processing and deep learning capabilities, GenAI could augment new venture formation processes by providing immediate feedback on business proposals, ideation quality, and overall writing coherence, thereby developing the students' skills with immediacy (Chalmers et al., 2021). However, in developing nations where there was a lack of digital literacy, lack of representative datasets with sufficient language

diversity, existing inequalities and infrastructure challenges; the integration of AI in education could further heighten the digital divide (Al-kfairy et al., 2024; Ivanov et al., 2024; Kajjita & Kang'ethe, 2025; Mannuru et al., 2023).

Notwithstanding the challenges, using GenAI could facilitate more experiential learning, thus allowing students to explore and apply theoretical knowledge, which could close the gap between the divergent outcomes of varying pedagogical approaches (Ivanov et al., 2024; Taneja et al., 2024; Vecchiarini & Somià, 2023; Zulfiqar et al., 2025). As such, the experiential learning opportunities offered through the acceptance of GenAI tools such as ChatGPT potentially enhanced the efficacy of entrepreneurship education, thereby strengthening the relationship with entrepreneurial self-efficacy and entrepreneurial intention (Duong et al., 2024; Duong & Vu, 2025; Jo, 2023).

The reasons students and educators use GenAI tools such as ChatGPT have been the subject of several recent studies (Duong et al., 2024; Niloy et al., 2024). These studies found that self-learning opportunities, efficiency of the platform, immediate feedback, human-like interactions, and the largely free cost of the technology were among the key factors influencing adoption (Niloy et al., 2024; Sardi et al., 2025). Nevertheless, ethical concerns related to artificial intelligence plagiarism and platform hallucinations were some of the factors which have caused apprehension for adoption (Al-kfairy et al., 2024; Tarisayi, 2024; Zhang & Xu, 2025). Despite this, a recent study by Duong et al. (2024) found that the adoption of ChatGPT improved digital entrepreneurial self-efficacy, AI skills and the digital entrepreneurial intention of students based in Vietnam. However, ChatGPT is not only being used for digital entrepreneurship purposes but also for non-digital entrepreneurship endeavours, as such, its ability to influence general entrepreneurial self-efficacy, and general entrepreneurial intention has been unresearched, and is thus the subject of this current study (Duong & Vu, 2025; Uriarte et al., 2025; Zulfiqar et al., 2025).

2.10 Conclusion

This chapter discussed the current discourse in the literature relating to the key constructs of the study namely, entrepreneurship education, entrepreneurial intentions, entrepreneurial self-efficacy, and GenAI (ChatGPT) acceptance, emphasising the theoretical underpinnings posited within these relationships. The literature highlighted that although the transformative potential of GenAI in enhancing entrepreneurship education, and influencing entrepreneurial intention outcomes was acknowledged, few studies have tested the moderation effects of this technology outside of digital contexts.

Neither have similar studies to the researcher's knowledge been conducted in the global south. The following chapter outlines the hypotheses that empirically tested the research objectives within the South African context, and it presents the conceptual model of this study.

CHAPTER 3: RESEARCH HYPOTHESES DEVELOPMENT

3.1 Entrepreneurship Education and Entrepreneurial Intention

Entrepreneurship education enhances human capital through its development of the necessary entrepreneurship skills, mindsets, knowledge and attitudes (Bae et al., 2014; Martin et al., 2013; Taneja et al., 2024). The human capital theory posits that those with higher human capital assets are likely to perform better than those without, thus entrepreneurship education is an investment that increases the human capital assets that influence higher entrepreneurial intentions (Bae et al., 2014; Martin et al., 2013; Skorodziyevskiy et al., 2025). Entrepreneurship education provides knowledge about creativity, ideation, opportunity recognition, business creation and management, which all develop skills and mindsets for new venture creation (Iwu et al., 2021; Lyu et al., 2024; Taneja et al., 2024). This has resulted in numerous studies finding positive relations between the constructs which has led many governments and education institutions to invest in entrepreneurship education (Martínez-Gregorio et al., 2021; Nabi et al., 2017; Onjewu et al., 2021; Ramadani et al., 2022).

Despite the positive associations, Oosterbeek et al. (2010) found that although entrepreneurship education increased knowledge, this did not translate to skills and resulted in negative effects on entrepreneurial intentions. Further, Piperopoulos and Dimov (2015) also found that theoretically-orientated entrepreneurship courses led to lower entrepreneurial intentions due to the emphasis on management skills which highlight challenges within entrepreneurship. Practical-orientated education in the same study; however, was found to lead to higher intentions. This finding is also supported by Debarliev et al. (2022) who also found similar associations between formal and non-formal education, which highlights the need for more practical-orientated entrepreneurship education. Consequently, the above discussed arguments necessitated the following hypothesis:

H₁: Entrepreneurship education positively and significantly influences entrepreneurial intention.

3.2 Entrepreneurship Education and Entrepreneurial Self-efficacy

Research has increasingly suggested entrepreneurship education as a key factor in developing entrepreneurial confidence, implying that entrepreneurial self-efficacy is a critical outcome of entrepreneurship education (Chen et al., 1998; Nowiński et al., 2019). Research has shown that entrepreneurial education has a positive influence on

entrepreneurial self-efficacy (Amani et al., 2024; Jiatong et al., 2021; Newman et al., 2019). Studies by Soomro and Shah (2022), X. Wang et al. (2023) and Zhao et al. (2005) conducted in different environmental contexts found that the students who participate in entrepreneurship education report higher entrepreneurship confidence and abilities, which are attributes of entrepreneurship self-efficacy. This is also supported by the systematic reviews by Newman et al. (2019) and Zulfiqar et al. (2025) who also found that entrepreneurship education enhanced the entrepreneurial self-efficacy of students from high school to postgraduate levels.

However, the path between entrepreneurship education and entrepreneurial self-efficacy is not consistently directly positive. Despite the benefits of immediate feedback that is afforded in a structured programme, negative experiences within entrepreneurship education such as consistent failure may reduce confidence and self-efficacy (Howell, 2021; Nabi et al., 2018). Furthermore, though previous studies found gender disparities with regards to entrepreneurial self-efficacy (Shinnar et al., 2014; Vu et al., 2025), recent studies have not found statistically significant differences between the genders' entrepreneurial self-efficacy's (Ramadani et al., 2022). This implies that entrepreneurship education may be beneficial for all individuals, thus leading to the following hypothesis:

H₂: Entrepreneurship education positively and significantly influences entrepreneurial self-efficacy.

3.3 Entrepreneurial Self-efficacy and Entrepreneurial Intention

A vast body of literature confirms that entrepreneurial self-efficacy is a significant predictor of entrepreneurial intention (Amani et al., 2024; Chen et al., 1998; Duong & Vu, 2025; Neneh, 2022; Newman et al., 2019; Shahab et al., 2019; Taneja et al., 2024; L. Wu et al., 2022; Xie & Wang, 2025). Studies across varying contexts and populations including students and working adults, frequently found that those with higher confidence in their entrepreneurial skills were more likely to peruse venture creation (Ahmed et al., 2020; Debarliev et al., 2022; Lyu et al., 2024). These findings are consistent with the findings of the theory of planned behaviour and the social cognitive theory which posit that a higher perceived behavioural control and related self-efficacy could lead to higher entrepreneurial intentions (Ajzen, 1991; 2020). Perceived behavioural control as one of the three antecedents of entrepreneurial intentions is conceptually equivalent to entrepreneurial self-efficacy, as such, the studies by Hagger et al. (2022) and Hsu et al. (2019) found that entrepreneurial self-efficacy did positively

influence entrepreneurial intentions; however, there are boundary conditions that influence this relationship (Amani et al., 2024).

Hsu et al. (2019) highlight that a person's perceived personal fit with entrepreneurship may negatively influence entrepreneurial self-efficacy particularly when entrepreneurship may not align to the personal financial needs of the potential entrepreneur. In developing economy contexts such as South Africa, where entrepreneurship may be driven by necessity as opposed to passion, financial personal needs may lead to a poor perceived personal entrepreneurship fit and negatively associate entrepreneurial self-efficacy to entrepreneurial intention (Neneh, 2022). Therefore, given the mixed results of extant research, there is still room for further empirical investigation of entrepreneurial self-efficacy and entrepreneurial intention relationship, which this study aimed to contribute to. As such, this study aimed to test the following hypothesis:

H₃: Entrepreneurial self-efficacy positively and significantly influences entrepreneurial intention.

3.4 Mediation Role of Entrepreneurial Self-efficacy

The relationship between entrepreneurship education and entrepreneurial intention has been shown to be mediated by entrepreneurial self-efficacy, which enforces self-belief in the acquired skills and knowledge to perform entrepreneurial tasks successfully (Jiatong et al., 2021; X. Wang et al., 2023; L. Wu et al., 2022). The theory of planned behaviour which this study anchored on, posits that entrepreneurial self-efficacy by manifesting one's perceived behavioural control, acts as a critical antecedent of entrepreneurial intention (Amani et al., 2024; Newman et al., 2019). Several studies have supported the mediation role of entrepreneurial self-efficacy including Amani et al. (2024) who found that entrepreneurial self-efficacy significantly mediated between entrepreneurship education and entrepreneurial intention, and this was stronger in a supportive entrepreneurial environment. Furthermore, Xie and Wang (2025) found that entrepreneurial self-efficacy also mediated between GenAI integrated entrepreneurship education and entrepreneurial intention, and when the university environment was dynamic, it positively influenced this relationship even more. However, Jiatong et al. (2021) found a partial mediating role, where entrepreneurial self-efficacy also served as a partial mediator for entrepreneurial mindset and creativity. This indicates an inconsistent relationship that could be further examined in a different context to test the

strength of the relationship. Consequently, based on the theoretical understanding and the extant empirical studies on entrepreneurial self-efficacy, this study proposed:

H₄: Entrepreneurial self-efficacy significantly mediates the relationship between entrepreneurship education and intention.

3.5 Moderation Role of Generative AI

The rapid emergence of GenAI like ChatGPT created a paradigm shift in several sectors, including entrepreneurship and education (Fosso Wamba et al., 2025; Kumar et al., 2025). GenAI presented both transformative opportunities and challenges, acting as a significant moderating construct that reshaped the relationship between entrepreneurship pedagogy, student psychology and entrepreneurial outcomes (Bell & Bell, 2023; Xie & Wang, 2025).

GenAI tools potentially transform pedagogy offering personalised and agile learning experiences that are responsive to the dynamic entrepreneurial environments simulated in safe, risk-free environments, thereby enhancing students' entrepreneurial self-efficacy and intentions (Vecchiarini & Somià, 2023; Xie & Wang, 2025; Zulfiqar et al., 2025). Furthermore, a recent study by Xie and Wang (2025) showed that GenAI integration in entrepreneurship education resulted in a significant positive influence on students' self-efficacy by tackling complex tasks through GenAI (Jo, 2023; Mutanga et al., 2024; Zulfiqar et al., 2025). Despite its potential, the concerns about GenAI reducing students' critical thinking capabilities and problem-solving abilities could negatively influence and weaken the empirical relationships between entrepreneurship education, entrepreneurial self-efficacy and entrepreneurial intention (Zhai et al., 2024). Moreover, other challenges related to data fairness and bias (Al-kfairy et al., 2024), accuracy of outputs (Feuerriegel et al., 2024), copyright issues (T. Wu et al., 2023) and equitable access to GenAI tools remain factors that dampen the moderation of the GenAI participationally ChatGPT (Gwagwa et al., 2020; Kajjita & Kang'ethe, 2025; Mannuru et al., 2023).

The technology acceptance model (Davis, 1989; Zaineldeen et al., 2020) provided a theoretical lens to study the likelihood of acceptance of emerging technology such as ChatGPT through its two antecedents; perceived usefulness of the technology and the perceived ease of use of the technology (Davis, 1989; Jo, 2023). Based on the observations from Duong et al. (2024) and Niloy et al. (2024), the perceived usefulness of ChatGPT seemed high, and the ease of use also seemed high based on ChatGPT

being “the most rapidly adopted consumer product in history” (Winkler et al., 2023, p.580). This historic adoption rate made its applicability in the South African context a suitable case to interrogate. As such, this study proposed the following:

H₅: GenAI (ChatGPT) acceptance positively moderates the relationships between entrepreneurship education and entrepreneurial intention.

H₆: GenAI (ChatGPT) acceptance positively moderates the relationships between entrepreneurial self-efficacy and entrepreneurial intention

3.6 Research Conceptual Model

Figure 3 illustrates the research conceptual model reflecting the research objectives and the supporting literature. The study aimed to interrogate the direct relationships between entrepreneurship education, entrepreneurial self-efficacy and entrepreneurial intention as well as the interfering effects of the acceptance of emerging technologies such as GenAI, specifically ChatGPT, and entrepreneurial self-efficacy on these relationships.

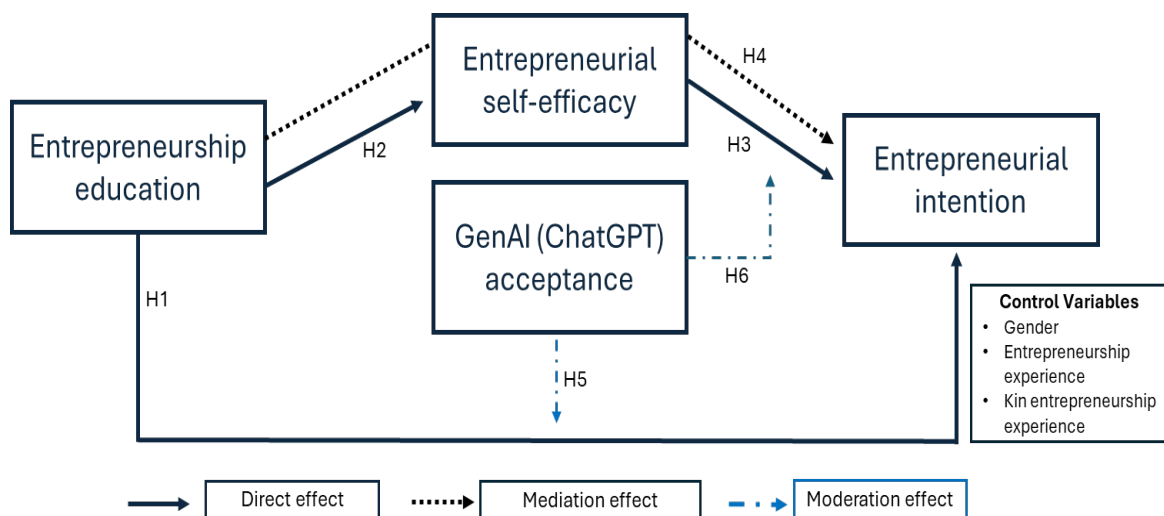


Figure 3: Conceptual moderated mediation model

Source: Author’s own (2025)

3.7 Conclusion

This chapter presented the hypothesis development leading from the literature. The moderated mediation conceptual model was also presented, indicating the essential relationships that were tested through the research methodology and their outcomes presented in the results in Chapter Five. The study focused on testing the direct relationships between entrepreneurship education, entrepreneurial self-efficacy and

entrepreneurial intention, as well as the indirect relationship mediated by entrepreneurial self-efficacy. Lastly, the moderating effect of the perceived ease of use and usefulness of ChatGPT, assessed as GenAI (ChatGPT) acceptance, was examined to understand how it influenced the educational environment and entrepreneurial self-efficacy and intention development. The next chapter outlines the research methodology and the design of the study that tested the hypothesised model.

CHAPTER 4: RESEARCH METHODOLOGY AND DESIGN

4.1 Introduction

This chapter provides an overview of the research methodology and the design choices the researcher adopted to examine the hypothesised relationships that were identified from extant research. This study aimed to understand whether entrepreneurship education positively influenced entrepreneurial intentions, as mediated by entrepreneurial self-efficacy, and whether GenAI acceptance measured through perceived ease of use and usefulness of GenAI (ChatGPT) moderated these existing relationships. Among others, the research philosophy, approach and design choices are discussed in the sections that follow, and the chapter concluding with the limitations of the research.

4.2 Research Methodology

4.2.1 Research Philosophy

The philosophical approach of a study is concerned with the fundamental beliefs the researchers possess about the nature of reality and knowledge development which ultimately shapes their research design (Batista et al., 2024). Several research philosophies exist, each with distinct ontological, epistemological and axiological considerations (Saunders & Lewis, 2018). This study followed the postpositivist philosophy with an ontological stance that was aligned with objective critical realism, which viewed the underlying social or physical environments, and its causal relationships as largely separated and independent of the human participants (Creswell & Creswell, 2017; Holden & Lynch, 2004). Similar to natural scientists, the postpositivist epistemology derives knowledge scientifically based on objective facts without human interpretation or bias (Alharahsheh & Pius, 2020; Creswell & Creswell, 2017; Holden & Lynch, 2004).

This postpositivist research approach was suitable given the current study's objectives of understanding preexisting relationships that had been identified from the literature reviewed in Chapter Two and Three. This study aimed to examine the intervening relationships between entrepreneurship education and entrepreneurial intention based on objective measures which had been empirically tested in the literature studies (Duong & Vu, 2025; Jiatong et al., 2021; Xie & Wang, 2025; Zhao et al., 2005). This philosophical approach is aligned to prior studies that had studied similar constructs employing deductive approaches and similar methodological choices, further substantiating the suitability of this philosophy (Batista et al., 2024).

4.2.2 Approach to theory development

Positivism is associated with the hypothetico-deductive model of science, a scientific method that focuses on generating testable hypothesis and thoroughly tests them through observations or experiments (Park et al., 2020). The deductive approach entails testing theoretical hypothesis using methodologies that were designed specifically to enable generalisability and replicability of the testing (Saunders & Lewis, 2018). As postulated by Creswell and Creswell (2017), in quantitative research, theory provides an explanation for the observed relationships amongst variables. As such, the deductive approach relies on existing scientific studies to draw testable hypothesis, which would either be supported or refuted (Holden & Lynch, 2004; Maula & Stam, 2020; Park et al., 2020).

Therefore, this study followed a deductive approach, as it relied on the theoretical propositions (hypotheses) underpinned by the prominent and widely accepted theory of planned behaviour and the technology acceptance model to examine the hypothesised relationships between entrepreneurship education and entrepreneurial intention, as mediated by entrepreneurial self-efficacy and moderated by GenAI acceptance (Gupta, 2024; Hagger et al., 2022; Hagger & Hamilton, 2024; Ivanov et al., 2024; Kautonen et al., 2013; 2015; Zaineldeen et al., 2020). Moreover, this study did not extend or build new theories as required for an inductive approach to theory development, it merely integrated existing theories applied in a new context (Saunders & Lewis, 2018). This was a suitable approach, as the study tested the theoretical propositions foregrounded in the aforementioned literature review (Dorobantu et al., 2024).

4.2.3 Methodological choice

There are varying research methodologies which enable various philosophical approaches to be tested, and these include quantitative, qualitative and mix methods (Saunders & Lewis, 2018). As suggested by Holden and Lynch (2004), research should not be determined by the methodology, but by the research philosophy which should lead the methodology. As such, the methodological choice that was chosen for the current study was the mono-method quantitative approach which is aligned with the postpositivist philosophy (Alharahsheh & Pius, 2020; Holden & Lynch, 2004; Saunders & Lewis, 2018). The quantitative research methodology requires an objective and systematic approach to test variables that are postulated from theory to explain cause and effect relationships that describe the objective nature of reality (Bloomfield & Fisher, 2019; Park et al., 2020). This approach requires gathering quantitative data using

objective measures, and testing hypothesis using statistical analysis to make inferences about the population of interest (Bloomfield & Fisher, 2019; Köhler et al., 2017).

Given the research objectives of the current study that aimed to examine the degree of association between the direct, intervening and moderating relationships of entrepreneurship education, entrepreneurial intention, entrepreneurial self-efficacy and GenAI (ChatGPT) acceptance, the correlational quantitative design was suitable for use due to its effectiveness in gathering independent survey data to test the hypothesised theoretical perspectives (Bloomfield & Fisher, 2019; Creswell & Creswell, 2017). Scientific rigour is the hallmark of the quantitative research design, and researchers need to aim to maintain transparency and control in their studies to ensure replicability and generalisability (Köhler et al., 2017; Maula & Stam, 2020). As such, the current study derived the hypothesis to be tested from existing theories and used validated measures to collect numeric data through online surveys, ensuring independence throughout the process.

The online survey was the only method that was used to gather data, making this study a mono-method quantitative one (Saunders & Lewis, 2018). Though it appears that the study could have benefited from a mixed method approach to interrogate the nuanced effects of rapidly emerging technologies such as GenAI; however, AI as a technology is not a novel phenomenon and has been studied before using established theories such as the technology acceptance models (Crompton & Burke, 2023; Uriarte et al., 2025; Zaineldeen et al., 2020). Moreover, the constrained timeframe of the research necessitated a mono-method quantitative strategy.

4.2.4 Purpose of research design

The current study employed a descripto-explanatory research design given that both descriptive and inferential statistics were used to explore and understand the relationships between the main constructs of the study (Batista et al., 2024; Saunders & Lewis, 2018). The study aimed to explore the associations between entrepreneurship education, entrepreneurial self-efficacy, entrepreneurial intention as well as ChatGPT acceptance, and the dual approach allowed initial description of the research context using the descriptive statistics, followed by examining the relationships between the constructs using inferential statistics. This design was suitable for the research objectives, as it described real phenomena based on the existing causal relationships identified from the literature.

4.2.5 Research strategy

The research strategy is the approach the researcher employs to gather data that enables them to answer the research questions (Somià & Vecchiarini, 2024). The research strategy for the current study was a survey strategy using an online questionnaire consisting of the measurements outlined in Section 4.3.4 of this document. The survey is the most widely used strategy for studying entrepreneurship phenomena as it enabled the measurement of complex constructs using multi-item scales (Maula & Stam, 2020). The survey involves a systematic collection of perception data from a large diverse sample, and online surveys are best suited for cross-sectional data collection (Siva et al., 2019).

The main objective of survey sampling is to enable reliable and accurate generalisations about the population of interest (Creswell & Creswell, 2017; Maula & Stam, 2020). Despite the wide use of surveys, X. Wang et al. (2023) caution against using survey sampling methods that are not representative and biased and rather encouraged more probabilistic sampling techniques. Although surveys have faced criticism of non-responsiveness biases and common method biases, the time and resource constraints necessitated the use of this strategy herein (Bloomfield & Fisher, 2019; Maula & Stam, 2020; Wegner, 2020).

4.2.6 Time horizon

A cross-sectional study was conducted, collecting data at a single point from the population. This time horizon was suitable, as the aim of the current study was not to establish novel causal relationships but to interrogate and understand established relationships between the constructs, and thus, a longitudinal study was not necessitated (Bono & Mcnamara, 2011). Furthermore, though Maula and Stam (2020) were calling for more longitudinal studies in entrepreneurship research, they did concede that typical studies in entrepreneurship were based on cross-sectional survey designs, supporting the current study's approach. Lastly, the time constraints of the current study necessitated a cross-sectional study (Creswell & Creswell, 2017; Maula & Stam, 2020; Saunders & Lewis, 2018).

4.3 Research Design

4.3.1 Population

The population of a research study is the complete set of members that share common characteristics which are central to the study (Saunders & Lewis, 2018). The suitable population identified for the current study focussing on entrepreneurship education was

students enrolled in Higher Education Institutions (HEIs) in South Africa. Data from the Global Entrepreneurship Monitor (2023) indicated that at least 15.1% of South Africa's entrepreneurs had at least an undergraduate tertiary education (GEM, 2023). Inferring from this data, it implied that the students enrolled at HEIs were inherently positioned to engage in entrepreneurship education, which could lead to entrepreneurial intention and entrepreneurial behaviours (Bae et al., 2014; Batista et al., 2024).

Several studies that examined similar constructs have also included students (such as middle, high school, undergraduate and postgraduate students) in their population and sample designs (Amani et al., 2024; Duong & Vu, 2025; Newman et al., 2019; Ramadani et al., 2022; L. Wu et al., 2022; Zulfiqar et al., 2025). HEI students represented the ideal population, as they were the primary recipients most impacted by the pedagogical approaches, including the integration of GenAI tools like ChatGPT (Duong & Vu, 2025; Xie & Wang, 2025; Zulfiqar et al., 2025). Students who were not predisposed to entrepreneurial intentions due to associations with entrepreneurs or their own past entrepreneurship experiences, were at a formative stage where entrepreneurial self-efficacy and entrepreneurial intentions could develop and grow (Malebana & Mahlaole, 2023). As such, students were most likely to be responsive to pedagogical and technological interventions, thereby providing insights into how technological engagement might influence entrepreneurial outcomes (L. Wu et al., 2022).

This current study aimed to follow a similar approach, as it tested similar entrepreneurship phenomena. It, however, narrowed down its population to focus on students enrolled in public and private HEIs that offered business management and/or commerce and/or entrepreneurship courses in South Africa. According to the Department of Higher Education and Training's (2023) statistics on post education training in South Africa, there are approximately 131 private HEI and 26 public HEIs in South Africa consisting of 11 general universities, nine comprehensive universities and six universities of technology. The estimated number of students enrolled in 2023 at both public and private HEIs was approximately 1 358 169 (Department of Higher Education and Training, 2023).

4.3.2 Unit of analysis

The target of the population was students enrolled in public and private HEI in South Africa studying qualifications that offer either compulsory or elective business management and/or commerce and/or entrepreneurship courses or modules within their chosen academic studies (referred to as entrepreneurship-related courses). The

focus of the research was to examine how the acceptance of GenAI ChatGPT in entrepreneurship education enhanced the students' entrepreneurial self-efficacy and influenced entrepreneurial intention (Duong et al., 2024; Strzelecki, 2023). As such, the unit of analysis for this study was the individual students who provided responses on their own psychological perceptions, experiences and behaviours about entrepreneurship education, the perceived ease of use, and the usefulness of ChatGPT in entrepreneurship education.

4.3.3 Sampling method and size

4.3.3.1 Sampling method

It is an accepted research practice that a study could collect data from a sub-group of a population, given that it is often impracticable and costly to collect data from the full population (Köhler et al., 2017; Saunders & Lewis, 2018). Though the exact number of HEIs in the sample could be approximated, the exact current number of students per institution was indefinable. Student enrolment was a constantly moving target due to graduations, dropouts and midyear changes (Department of Higher Education and Training, 2023). Consequently, the necessary sampling frame was inconsistent and unknown, thus rendering probability sampling unachievable for this study despite its preference for generalisability (Maula & Stam, 2020). As such, non-probability sampling methods were necessary for the study; however, the implications meant that statistical inference to the wider population was constrained (Saunders & Lewis, 2018).

Purposive and snowball sampling (referred to as non-probability sampling methods) was employed in the study to obtain the required number of responses to enable sufficient statistical power. The purposive sampling method was used as the researcher selected initial participants based on their judgement of who would be able to answer the research questions, specifically students in entrepreneurship-related courses familiar with GenAI (Köhler et al., 2017; Saunders & Lewis, 2018). The snowball sampling method was used to expand the sample, acknowledging the challenge in identifying suitable research participants across multiple institutions in South Africa (Saunders & Lewis, 2018). While the primary objective of non-probability sampling approach was not statistical inference to the entire student population, it was crucial for accessing the specific target group (Cornesse et al., 2020). Despite this limitation, however, the quantitative methodology required statistical rigour (Köhler et al., 2017; Maula & Stam, 2020). As such, to address internal validity, the study mitigated the risk of Type II errors (such as the probability of accepting false null hypotheses) by

accounting for the statistical power required for Structural Equation Modelling (SEM), which was the chosen method of analysis as further discussed in Section 4.3.10.2 of this document (McQuitty, 2004). The level of statistical significance for this study was set at 5%, based on a 95% confidence interval. To mitigate the inherent potential sampling bias in purposive and snowballing techniques, the results of the analysis were carefully considered, and generalisability was interpreted within the context of the inherent limitations of non-probability sampling methods. (McQuitty, 2004; Saunders & Lewis, 2018).

The researcher relied on personal networks to identify initial purposive participants for the study and employed a snowballing approach to expand the sample. Though these methods were efficient for reaching the target sample, they introduced potential bias due to the likelihood of shared similar characteristics (Saunders & Lewis, 2018). To maximise the number of respondents, the participants were also sourced from social media platforms such as LinkedIn, WhatsApp, Tik Tok, Instagram and university pages on Facebook. Furthermore, online university social communities, professional commercial associations with chapters at universities (for instance, Association of Black Securities and Investment Professionals) and the email lists the researcher had access to were used for snowball sampling.

To mitigate the risk of unsuitable participants, prequalification questions were included to ensure participants were students registered in HEIs within South Africa who were enrolled in programmes that offered elective or compulsory entrepreneurship-related courses and were also familiar with GenAI tools like ChatGPT. Furthermore, to maximise representation and mitigate self-selection bias risk, the survey was distributed to students exposed to elective or compulsory entrepreneurship-related courses across a wide field of academic studies. However, it was acknowledged that students with prior entrepreneurship experience may hold stronger pre-existing interests in entrepreneurship, which were controlled for in the interpretation of the results (Debarliev et al., 2022; Malebana & Mahlaole, 2023).

4.3.3.2 Sampling size

The sample size aimed to reach similar levels as other comparable studies that had tested similar constructs, that is populations of higher learning students or using the SEM analysis (Pan & Lu, 2022; Soomro & Shah, 2022; L. Wu et al., 2022; Xie & Wang, 2025; Zulfikar et al., 2025). As posited by McQuitty (2004), sample size determination has to be assessed prior to data collection, taking into consideration the desired level

of statistical power. The recommended statistical power of 0.80 for social science research was adopted (McQuitty, 2004). While the general power calculation for a complex model would have required a minimum sample size of 56 if the degrees of freedom were 400; the researcher adhered to the general guideline to never use a sample size below 100 (McQuitty, 2004).

Furthermore, though some researchers have relied on the traditional rule of thumb suggesting that a target “sample size to indicator ratio should be 5:1 or 10:1” (Strzelecki, 202, p.5148), this study attempted to secure between 150 to 200 valid responses based on the four constructs and lower degrees of freedom based on a 29-item questionnaire (excluding demographic questions). This provided a conservative margin for the power of the model to detect hypothesised effects. Moreover, to account for potential invalid responses, the researcher aimed to collect more responses than the minimum target range. Although larger sample sizes increase the statistical power of individual path detection, the normality of the data was assessed using appropriate descriptive statistics and was not solely based on sample size, while recognising that very large sample sizes could make model fits tests like Chi-Square test overly sensitive (due to too much power) (Collier, 2020; McQuitty, 2004).

4.3.4 Measurement instrument

The survey online questionnaire was used as the measurement instrument in this study. Survey data was systematically collected to answer ‘what’, ‘who’, ‘where’, ‘how much’ and ‘how many’ questions about the research phenomenon (Batista et al., 2024). Measurement is important for social science research as it enables the assessment of abstract concepts that can only be approximated through proxy variables (Hair et al., 2019a).

The theoretical perspectives of the theory of planned behaviour and the technology acceptance model were operationalised through four constructs (referred to as latent variables): entrepreneurship education, entrepreneurial self-efficacy, entrepreneurial intention and GenAI ChatGPT acceptance (which was measured through perceived ease of use and usefulness). The latent variables were measured using validated scales employed in prior empirical studies, as detailed below (Amani et al., 2024). The items included in the study are included in the questionnaire found in Appendix A of this document.

Demographic information was collected which included information on gender, age, education background, entrepreneurship experience and the type of academic study. The information on gender, prior entrepreneurship experience and kin entrepreneurship experience was used as the control variables in the structural modelling (Malebana & Mahlaole, 2023; Shinnar et al., 2014; Vu et al., 2025; Xu et al., 2020). The demographic information was also coded to enable statistical analysis.

The types of data measured in this survey included a combination of nominal (demographic items) and ratio data (such as age) for questions 1 to 11 excluding the prequalification's questions. Questions 12 to 40 measured latent variable questions using 7-point Likert scales which provided equidistant attributes to approximate interval scale measurement. This enabled the data to be used for inferential statistical analysis (Hair et al., 2017a).

4.3.4.1 Independent variable

To measure the independent variable, the study used the "Assessment Tools and Indicators for Entrepreneurships Education (ASTEE)" (Moberg et al., 2014, p.4) measurement tool developed by Moberg et al. (2014) and applied in a study by Debarliev et al. (2022). ASTEE was established by the European Commission to develop and standardise the measurement of human capital assets acquired through human capital investments (such as entrepreneurial education), which included knowledge, mindsets and skills (Debarliev et al., 2022). The tertiary-level questionnaire was adopted as the study measured higher education students. This study used a 7-point Likert scale (1 = very strongly disagree to 7 = very strongly agree) which included items that approximate entrepreneurship education by measuring entrepreneurial mindset (three items), entrepreneurial attitudes (two items) and entrepreneurial knowledge (three items) (Moberg et al., 2014). The measurement items were assessed in the empirical study to have a Cronbach alpha of 0.837 to 0.952 (Debarliev et al., 2022). The current study also assessed its own internal consistency for all the variables within the study's context, of which the results are presented in Chapter Five.

4.3.4.2 Dependent variable

The latent dependent variable entrepreneurial intention was operationalised through six items measured on a 7-point Likert scale from the EIQ developed by Liñán and Chen (2009). This widely used scale was grounded in the literature of the theory of planned behaviour applied to entrepreneurship (Liñán & Chen, 2009; Lyu et al., 2024). The

measurement items were assessed in the empirical study to have a Cronbach alpha range of 0.776 to 0.953 (Liñán & Chen, 2009).

4.3.4.3 Mediator variable

To measure the mediator variable, the manifestation of entrepreneurial self-efficacy as discussed in the literature was operationalised through six items measured on a 7-point Likert scale, measuring perceived behavioural control from the Entrepreneurial Intention Questionnaire (EIQ) developed by Liñán and Chen (2009). The use of Likert scales enabled subjective perceptions and intentions to be quantified, thus making them valuable for assessing psychological constructs (Simba et al., 2024). The measurement items were assessed in the empirical study to have a Cronbach alpha range of 0.776 to 0.953 (Liñán & Chen, 2009).

4.3.4.4 Moderator variable

To measure the moderator variable through ChatGPT's acceptance which was operationalised through perceived usefulness and perceived ease of use, the study used eight items measured on a 7-point Likert scale from the technology acceptance model (Davis, 1989). Following a similar approach from the recent study by Strzelecki (2023), placeholder words were adapted to ChatGPT and 'jobs' adapted to studies. The measures indicated high reliability with a Cronbach alpha of 0.97 and 0.91 for perceived usefulness and perceived ease of use respectively (Davis, 1989). Furthermore, to measure the engagement of ChatGPT, one item measured on a 7-point Likert scale was used from Strzelecki (2023).

4.3.5 Data gathering process

4.3.5.1 Ethical Clearance considerations

Ethical clearance was applied for from the ethics committee of the University of Pretoria Gordon Institute of Business School (GIBS). Ethical clearance was received from the committee on the 22nd of July 2025 and pilot data was collected from the 1st of August 2025. A consent clause was included in the data collection form which informed participants of their anonymity, confidentiality and right to withdraw from the study at any time.

4.3.5.2 Phase one: Pilot Testing

Following ethical clearance approval, the pilot data was gathered from a structured self-administered questionnaire developed in Google Forms. The form consisted of 40 questions (demographic and items) that were asked in English, and each questionnaire

was expected to take 10min to 15min to complete. Saunders and Lewis (2018) emphasise the importance of conducting pilot testing when using questionnaires to collect data to ensure respondents do not encounter issues with completion and mistakes are not overlooked.

The pilot phase was open between the 1st of August 2025 to the 9th of August 2025. The questionnaire was distributed to 15 participants in the pilot phase of which nine completed and provided feedback. Feedback was received related to the design and flow of the questionnaire following the pre-qualification questions. The feedback included adding a progress bar to the survey, including definitions for the construct's entrepreneurial education, entrepreneurial self-efficacy and entrepreneurial intention to avoid confusion and data missing at random. Furthermore, proposals were also made to separate the demographic question related to the entrepreneurship history, into separate questions related to the participants own historical entrepreneurship experience and the entrepreneurship experience of others related to them. The actual time to complete the survey was an average of five to eight minutes; however, the time indication was left at 10 to 15 minutes for the main study to remain conservative. Once all the feedback was addressed, the main study was made available to the broader sampling frame as discussed in the section below.

4.3.5.3 Phase two: Main study data collection

The final online questionnaire was developed on Google Forms and included qualifying questions that served as a gateway to completing the questionnaire. These questions focussed on qualifying current students enrolled in South African HEI; students who were familiar with GenAI (Incl. ChatGPT), and students who were exposed to entrepreneurship related courses (such as compulsory or elective business management and/or commerce and/or entrepreneurship courses or modules) in their field of study. Demographic information (such as, age, gender, HEI institution, previous experience with entrepreneurship, and affiliation to entrepreneurs) was collected to establish context, to understand the participants, and also to identify the data to be used as control variables (Köhler et al., 2017).

The online link was made available between the 11th of August 2025 and the 8th of September 2025. The link was distributed using purposive sampling and it was shared through emails, social media pages (LinkedIn, Instagram, TikTok, and Facebook university pages) and the WhatsApp groups that the researcher had access to. The message that was distributed with the link included a short description of the ideal profile

of the target participant, as well as the confidentiality and anonymity of the study. Online surveys enable a wider distribution; however, the researcher also encouraged participants to identify and share with other qualifying participants through snowball sampling.

Moreover, the researcher conducted onsite visits to local HEIs to encourage participation and reached out to previous faculty members from her alma marta to encourage their students to participate in the survey during lectures. The researcher continuously posted reminders throughout the various platforms to increase the rate of responses. The data gathering process was tracked throughout the process which resulted in a total of 291 respondents, of which 80 were excluded from the final data for failing pre-qualification questions including the pilot data responses. The final dataset included 211 respondents, and it was analysed using the data analysis procedures included in the sections below.

4.3.6 Confidentiality and storage

The data that was collected was downloaded from Google forms and transferred to a password protected drive where only the researcher had access. The anonymous data will be stored for the minimum required period of 10 years.

4.3.7 Data cleaning and coding

The collected data was cleaned for any anomalies, including missing values. The measurement items were assessed for negatively phrased items which were then reverse coded. One measurement item (EE4) relating to the entrepreneurship education construct was reverse coded to improve the statistical quality of the data collected (Weijters & Baumgartner, 2012). Following the cleaning of the data, the data was encoded to provide descriptive statistical analysis (mean, standard deviation and normality) for summarising the data using International Business Machines Corporation's (IBM) Statistical Package for the Social Sciences (SPSS) 30, while inferential statistical analysis for hypothesis testing was conducted using SmartPLS 4.0.

4.3.8 Missing data

Notwithstanding low response rates, missing data presents a challenge that researchers using self-administered questionnaires have to address for statistical analysis (Allison, 2002; Krosnick, 1999). Allison (2002) and Collier (2020) highlight that data could be missing for various reasons, including respondents forgetting to answer or omitting questions (missing completely at random), respondents opting not to

respond based on other variables in the study (missing at random), or respondents refraining from responding due to the available response options (missing not at random). To minimise this eventuality, the questionnaire was designed to force respondents to complete a question before moving to the next. However, this did not stop a respondent from leaving the questionnaire if they wanted to, as communicated in the consent statements.

Furthermore, according to Hair et al. (2021), PLS-SEM is robust at handling missing data provided that it is within 5% missing per indicator, alternatively the researcher would need to delete missing data. A total of 291 responses were collected at the close of the survey; however, 80 respondents did not meet the target respondent qualifying criteria (missing not at random) and thus more than 50% of the questionnaire was not completed. As such, these respondents were deleted, leaving a final sample of 211 respondents with no missing data.

4.3.9 Outliers

Though outliers affect non-parametric data less severely than parametric, they still need to be considered as they could lead to biased results. Outliers are extreme data points that could distort the results of the analysis of the study (Hair et al., 2017a). They result from data errors or extreme valid responses and are to be assessed within the context of the study objectives. According to Aguinis et al. (2013), rank methods such as the box plots and stem leaf plots could be used to assess outliers for non-parametric data. Furthermore, Tabachnick and Fidel (2013) suggest the use of z-score analysis to identify values that fall beyond ± 3 . 29 as outliers to possibly be removed. This study employed the box and stem leaf plots available in IBM SPSS to assess for outliers as reported in Chapter Five, Section 5.2.3.

4.3.10 Data analysis approach

4.3.10.1 Descriptive statistical analysis

Descriptive statistics provide a summary of the data, offering insights into the data's central tendency, variability and distribution (Saunders & Lewis, 2018). They were crucial for the initial understanding of the data before engaging in complex inferential analyses especially when dealing with the variables related to be entrepreneurial intentions and self-efficacy (Xie & Wang, 2025). The demographic information was organised into categorical data across gender, education level, prior and kin entrepreneurship experience. This data was analysed using frequency and graphs. Mean scores and standard deviations were commonly reported to describe responses

of Likert-scales. Similarly, this current study followed a similar approach reporting on the mean, standard deviation, skewness and kurtosis of the data (Soomro & Shah, 2022; Udeozor et al., 2025). The study used the IBM's SPSS 30 to perform the descriptive and normality analysis for the dataset.

4.3.10.2 Statistical analysis approach – SEM

The study aimed to understand the complex multivariate relationships between independent, dependent, mediator and moderator variables. Structural equation modelling (SEM) was employed to analyse the hypothesised relationship due to its superior capabilities over first-generation methods such as multiple regression (Hair et al., 2021). Though first-generation statistical methods such as multiple regression and analysis of variance are widely used in social science research, they have limitations to analyse multivariate complex models simultaneously whilst accounting for measurement error (Amani et al., 2024; Hair et al., 2021; Manley et al., 2021).

SEM is a second-generation multivariate statistical technique capable of analysing complex direct and indirect relationships with multiple dependent and independent variables, thus overcoming the limitations of regression analysis (Collier, 2020; Hair et al., 2021; Sardeshmukh & Vandenberg, 2017). Furthermore, it enables the researcher to account for observed measurement errors, making the models more accurate and aligned to reality where systematic or random error was present when dealing with perception-based constructs (Collier, 2020; Hair et al., 2021). Two methods are popular in SEM, and they include the largely used Covariance-based SEM (CB-SEM) and the Partial Least Squares SEM (PLS-SEM) also referred to as the variance-based SEM or path modelling (Hair et al., 2017b). Both SEM approaches are powerful methods that simultaneously combine exploratory and confirmatory techniques (Hair et al., 2019b).

The key distinction among the two methods relates to their statistical objectives. In this instance, CB-SEM aims to estimate parameters that will minimise the difference between the observed and the theoretical model covariances thus making it suitable for confirmatory (for instance, explanations) testing of established theories (Hair et al., 2017b; Hair et al., 2021). Whereas PLS-SEM aims to maximise the variance explained by the independent variables on the dependent variables, thus making it suitable for both predictive and confirmatory research while grounded in theory (Hair et al., 2017b; Hair et al., 2021). Given this study's moderated mediation model that aimed to assess the effects on entrepreneurial intentions, the study included both predictive and

confirmatory aspects, thus PLS-SEM was the most comprehensive method suitable for this study.

PLS-SEM was more flexible in its requirements in contrast to CB-SEM regarding model fit requirements. More so, multivariate normality was not a strict requirement as required in CB-SEM. Given the study's use of non-probability sampling, the data violated the normality assumptions which was a requirement for CB-SEM (Collier, 2020; Hair et al., 2019b). Furthermore, PLS-SEM's composite model approach handles complex relationships such as mediation and moderation more flexibly than CB-SEM, which is a common factor approach, thus overlooking other possible explanatory variances (such as specific and error) (Hair, et al., 2017b; Manley et al., 2021). Another highly cited reason for using PLS-SEM was its ability to deal with small sample sizes. However, Petter (2018) cautions against this practise, given that small sample sizes have issues with detecting relationships (Boubker et al., 2021; Gupta, 2024; Ivanov et al., 2024). Moreover, more recent studies within entrepreneurship were also using PLS-SEM, not only for the reasons cited above, but also for its out of sample predictive power through PLS-Predict, enabling relevant research for decision making (Amani et al., 2024; Manley et al., 2021; Munir et al., 2019; Saptono et al., 2020; Xie & Wang, 2025; Zulfiqar et al., 2025).

Following the guidance of how to use PLS-SEM provided in Manley et al. (2021) and Hair et al., (2019a), the data was analysed using SmartPLS 4.0. The initial step established the suitable measurement model to use, choosing between reflective and formative measurement items or both. Thereafter, after establishing reliability, validity, testing for common method variance, and multicollinearity; the structural model was assessed using bootstrap resampling to determine the path coefficients for the direct, indirect and moderated relationships. Moreover, the level of statistical significance for the study was set at 5%, based on a 95% confidence interval.

4.3.10.3 PLS-SEM measurement model

The measurement model in PLS-SEM assesses the congruency between the indicators and the constructs (latent variables) (Hair et al., 2017a; Manley et al., 2021). This phase of the model evaluates the internal consistency (reliability) and validity of the measures before moving onto the structural model phase (hypothesis testing). Depending on whether the model is a reflective (that is, latent variable or construct is reflected by the measurement items) or formative model (that is, measurement items determine the latent variable or construct) or both, determines which statistical tests could be

employed (Hair et al., 2020). To determine which items were used in the study, past theory and studies were assessed to determine the measurement model (Hair et al., 2019b). Furthermore, where the constructs indicated a high reliability and convergent liability this indicated the likelihood of reflective measures (Hair et al., 2017a). This study consisted mainly of reflective constructs (see Section 5.6.1.1).

In addition, to support the specification of the cause-effect relationship of the measurement model, a Confirmatory Tetrad Analysis (CTA) was used to empirically confirm the model perspective (Gudergan et al., 2008; Hair et al., 2017a). CTA assumed the constructs items were reflective measures unless this null hypothesis was rejected (Gudergan et al., 2008). The CTA included in Chapter Five indicated that the entrepreneurial intention could be formative as indicated by the four tetrads that deviated from 0, moving from + to + (Gudergan et al., 2008). However, upon closer assessment of the individual items and reflection of the theory, it was noted that the items are manifestations/effects of the construct (entrepreneurial intention) as can be noted in items such as “I will make every effort to start and run my own business”, “I am determined to create a business in the future”, “I have the firm intention to start a business someday”. Secondly, the items were interchangeable, where the removal of one item did not change the meaning of the construct (Hair et al., 2017a). Thirdly, the construct indicated high levels of multicollinearity as measured by the Variance Inflation Factor (VIF), which was expected for reflective constructs as they were expected to be highly correlated. Consequently, the entrepreneurial intention construct was thus treated as reflective.

1. Confirmatory composite analysis

The measurement model followed a systematic methodological approach referred to as Confirmatory Composite Analysis (CCA), a similar concept to CB-SEM's Confirmatory Factor Analysis (CFA) (Hair et al., 2020). Where CB-SEM's CFA aims to confirm the common factors by minimising the common variances among the measures; CCA aims to maximise the variance for combined measures to facilitate prediction and confirmation of dependent (endogenous) variables (Hair et al., 2020; Manley et al., 2021). As such, CCA retains a higher number of items than CFA, ultimately improving construct validity (Hair et al., 2020). Thus, the CCA analysis was applied in the current study through the assessment of reliability, convergent validity and discriminant validity discussed in the section below.

2. Measurement model reliability and validity

The reflective measurement model was tested for construct reliability and validity to establish the links between the measurement items and the latent constructs. Reflective indicators are predicted by the same constructs, as such, should be highly correlated and thus interchangeable to foster reliability and validity (Hair et al., 2017a). Firstly, the model assessed the factor loadings to examine the items' validity in reflecting the underlying construct (Misoska et al., 2016). High factor loadings above 0.78 across all the measured items indicated a higher correlation between items and latent variables and were likely to result in an indicator reliability that was ≥ 0.50 (Hair et al., 2020; Manley et al., 2021). However, according to Hair et al. (2017a), social science research is known to produce loadings below 0.70, and thus it is advised not to delete loadings below 0.70 before analysing their deletion impact on reliability and validity. Secondly, internal consistency or reliability of the constructs was assessed using Cronbach Alpha and composite reliability, where the values ≥ 0.70 indicated sufficient reliability (Hair et al., 2020; Maula & Stam, 2020). Given that measures were not all equally reliable, resulting in a conservative Cronbach Alpha, the composite reliability accounted for a weighting of measures providing a more accurate assessment of reliability (Hair et al., 2019b). Thus, reporting both measures resulted in a lower and upper bound assessment of reliability (Hair et al., 2017a).

Thirdly, the convergent validity was assessed by measuring the Average Variance Extracted (AVE), which was the average of the indicator reliabilities. Convergent validity assessed whether the varying measures positively correlated with the construct and thus theoretically related, and this was established when the AVE was above 0.50 (Amani et al., 2024; Ivanov et al., 2024). An AVE output > 0.50 shows that a change in the construct would result in a substantial change in the reflective indicators. Lastly, the discriminant validity was established to assess the uniqueness of the constructs from other constructs in the model. This was assessed by reviewing the cross-loadings of indicators (see Appendix B), where an indicators factor loading should be highest on its related construct relative to others, otherwise indicating discriminant validity issues (Hair et al., 2017a). However, cross-loading failed to identify discriminant validity when constructs were highly correlated as such, the Heterotrait-monotrait Ratio of Correlations (HTMT) was computed. HTMT assesses the true correlation (disattenuated correlation) between the constructs, where a disattenuated correlation close to 1 indicates discriminant validity issues; and a threshold of below 0.85 and 0.90 indicate

that constructs are distinct (Amani et al., 2024; Hair et al., 2020). The HTMT levels were below the thresholds indicating no issues with discriminant validity as shown in Table 12 in Section 5.6.1.5. Overall, this rigorous assessment of reliability and validity of all indicators ensured a solid foundation for hypothesis testing in the structural model discussed below (Duong & Vu, 2025).

4.3.10.4 PLS-SEM structural model

Following the confirmation of the measurement model above, the structural model was assessed to test the hypothesised relationships between the constructs (Hair et al., 2017a). Similar to the measurement model, this assessment followed a systematic approach. Firstly, multicollinearity was assessed among the sets of predictor constructs (entrepreneurship education, entrepreneurial self-efficacy, GenAI (ChatGPT) acceptance) as the underlying estimation procedure relied on multiple regression analysis concepts (Hair et al., 2017a). Multicollinearity assessed the extent to which the predictor items were correlated, as high correlations could lead to distortions of the regression weights (beta coefficients) and changing the signs of the coefficients in the structural model (Hair et al., 2020). To test for multicollinearity, the researcher assessed the variance inflation factor where a value below 3.3 was acceptable (Hair et al., 2020; Kock, 2015). Previous research accepted measures below 5.0; however further research indicated that this level was too high (Hair et al., 2021).

Secondly, when multicollinearity was established as not a concern (see Section 5.6.3), the hypothesised relationships among the constructs were tested. The size and direction of these relationships were assessed through path coefficients (β) which ranged from -1 to +1 (Hair et al., 2017a; Manley et al., 2021). The closer to 0 the path coefficient was, the weaker it was at predicting the dependent constructs, whereas the closer to ± 1 , the stronger it was at predicting the dependent construct (Hair et al., 2020). To assess the significance of the path coefficients, t-statistics were computed through 5000 bootstrapping resamples, where a t-value > 1.645 (one tailed) and a p-value < 0.05 indicated statistically significant coefficients (Hair et al., 2019b). Furthermore, the bootstrapping procedure performed in SmartPLS 4.0 reported the direct, indirect and total effects based on the hypothesised structural model which allowed for the complete assessment of the mediation and moderation hypotheses.

The hypothesised mediation role of entrepreneurial self-efficacy in the relationship between entrepreneurship education and entrepreneurial intention, was tested using the bootstrapping procedure on the specific indirect path of entrepreneurship education

to entrepreneurial self-efficacy to entrepreneurial intention (Hair et al., 2017a). The mediation is confirmed if the p -value was ≤ 0.05 (Hair et al., 2017a; Sardeshmukh & Vandenberg, 2017). Furthermore, the type of mediation (partial, full or no-effect) was assessed based on the path coefficients using the mediation analysis guidelines proposed by Hair et al. (2017a).

The moderation effect of GenAI (ChatGPT) acceptance in the mediated and direct relationships was assessed using the two-stage approach. In the first stage, the latent variable scores of the main effects of the independent construct (entrepreneurship education) and moderator construct (GenAI [ChatGPT] acceptance) were computed. The second stage created the interaction term (moderating effect) using the first stage latent variable score. The interaction term's path coefficient was then tested using bootstrapping procedure to determine its significance, where a p -value ≤ 0.05 confirmed significant moderation (Hair et al., 2017a). According to Hair et al. (2017a), the two-stage approach was suitable as it produced higher statistical power than both the product indicator and orthogonalising approaches. As such, the two-stage approach was suitable over the product indicator or orthogonalising approach (Hair et al., 2017a; Sardeshmukh & Vandenberg, 2017).

PLS-SEM not only performs confirmatory analysis but also predicts in and out of sample data. Similar to multiple regression, the coefficient determination (R^2) was used to assess in-sample model prediction and explanation of dependent variables (endogenous variables) (Hair et al., 2017a). This prediction, however, could not be postulated to the population and was limited to the sample data. According to Falk and Miller (1992) a value of ≥ 0.10 was adequate to explain variance in the endogenous variable. However, Cohen (1988) suggests R^2 values to be assessed as either weak (0.02), moderate (0.13) or substantial (0.26). Further, Hair et al. (2011, 2013) suggests that marketing research should consider R^2 values as weak (0.25), moderate (0.50) or substantial (0.75). This study followed the guidance by Cohen (1988).

The second measure of in-sample prediction was the assessment of effect size of the independent construct in the model using SmartPLS 4.0. The effect and size (f^2) of the independent construct was ranked either as small (0.02 to 0.15), medium (0.15 to 0.35) or large (> 0.35) (Hair et al., 2019b). Thirdly, the out-of-sample predictive indicator was also assessed using the PLSpredict method (Q^2) in SmartPLS 4.0. (Shmueli et al., 2019). When the Q^2 value is greater 0.00 it is indicative of predictive power, with > 0.50 representing large predictive power (Hair et al., 2020; Hair et al., 2019b).

Furthermore, the measurement item's predictive power for the endogenous variables is assessed by comparing the Root Mean-Square Error (RMSE) or the Mean Absolute Error (MAE) relative to their linear regression LM benchmarks. RMSE is used when the prediction error distribution of the endogenous variable is symmetric and MAE is used when its nonsymmetric (Shmueli et al., 2019). When the majority of the indicators of RMSE (or MAE) have smaller errors than the LM benchmark, the model indicates medium predictive power (Hair et al., 2019b; Shmueli et al., 2019).

4.3.11 Data distribution

Hair et al. (2017a) suggest that despite PLS-SEM being a nonparametric method, researchers could still test for normality, as extremely non-normal data could lead to misleading results even when using PLS-SEM. Moreover, the suitability of using either SEM methods would be reliant on the distribution of the data. As such, to measure normality, researchers recommend the measurement of skewness and kurtosis to assess the extent of dispersion from normality where a skewness and kurtosis outside z value of ± 2 is considered nonnormal (Hair, Hult, et al., 2017). Moreover, the Kolmogorov-Smirnov and Shapiro-Wilks test are also used to assess normality and determine whether the null hypothesis for normality should be accepted or rejected. However, these tests do not indicate the extent of the deviation from normality; that information is provided by the skewness and kurtosis (Hair et al., 2019a; Vaithilingam et al., 2024). This study employed both summary statistics for normality (skewness and kurtosis) and the Shapiro-Wilks test to assess the normality of the data, which both confirmed the data was nonnormal distributed. The skewness and kurtosis indicated z values greater than ± 2 and the Shapiro-Wilks test indicated a p -value of <0.05 indicative of a nonnormal distribution as reported in Section 5.2.5.

4.3.12 Common method bias

The limitation of the survey method could lead to common method bias which arises when the same participant responds to the independent and dependent variables in the same method (Ip, 2025; Udeozor et al., 2025). This could potentially inflate or deflate the relationships between the variables. This is a limitation of the survey method which could lead to incorrect conclusions (Amani et al., 2024; Ip, 2025). This study took several measures that were taken by similar studies to control for potential common method bias (CMB) (Amani et al., 2024; Xie & Wang, 2025). These measures included keeping the survey anonymous and confidential to minimise potential response bias

and fear of judgement and having clear and concise questions which were tested in the pilot phase.

Furthermore, multicollinearity was used to assess common method bias. Multicollinearity assessed the extent to which the independent variables of the study were correlated (Hair et al., 2017a, Kock, 2015). High correlations could lead to distortions of the regression weights (beta coefficients) and changing the signs of the coefficients in the structural model (Hair et al., 2020). To test for multicollinearity, the researcher assessed the variance inflation factor in PLS-SEM 4.0 where a value below 3.3 was acceptable (Hair et al., 2020; Kock, 2015). Previous research accepted measures below 5.0; however, further research indicated that this level was too high (Hair et al., 2019a). The inner model VIF was assessed at level below 3.0 indicating that data was free from multicollinearity concern (see Section 5.6.3).

4.4 Limitations

There were several limitations to the study that offer opportunities for future research. Firstly, the study employed non-probability sampling techniques which limits the generalisability of the findings; future studies could aim to use probabilistic sampling techniques and parametric statistical analysis. Secondly, data was collected from higher education institution students who were exposed to GenAI; for future research, this could be expanded to students in lower schooling levels who are equally exposed to the use of technology to test their entrepreneurial intentions. Thirdly, the study focussed on OpenAI's ChatGPT as the most ubiquitous GenAI tool available at the time; however, rapid developments in technology are introducing new GenAI tools that could be further studied in a direct or mediating construct capacity and not just in a moderation construct capacity.

Lastly, the study was cross-sectional with data collected at a point in time; therefore, students' perceptions, experiences and behaviours could have changed as they adopted and used ChatGPT and other similar GenAI tools. As such, longitudinal studies could provide more insights that could explain the impact of entrepreneurship education on entrepreneurial intention in the context of a more digital world.

4.5 Conclusion

This chapter discussed the research design and methodology approaches aligned with the literature and that were suitable for the research context. The suitability of the chosen methods was also discussed. The measurement instruments, data gathering

processes and statistical analysis methods were outlined. The quality controls to ensure reliability and validity were discussed including the limitations of the study. The next chapter focuses on presenting the results of the study that followed the procedures outlined in this chapter.

CHAPTER 5: RESULTS OF THE STUDY

5.1 Introduction

This chapter presents the results of the study that investigated the relationship between entrepreneurship education and entrepreneurial intention as mediated by entrepreneurial self-efficacy and moderated by GenAI (ChatGPT) acceptance. The chapter provides the results of the data collection and data integrity processes undertaken to ensure reliable and valid results. This is followed by the outcomes of the descriptive statistics assessment. Lastly, the results of the structural equation modelling performed in SmartPLS 4.0. are presented which include the reliability and validity tests from the measurement model assessment, and the findings of the hypotheses testing conducted in the structural model assessment.

5.2 Data Collection and Integrity

5.2.1 Data collection

Data was collected using an online survey method that was shared with potential participants over a four week period. The survey was shared through purposive and snowballing methods to widen the survey reach. The data was screened for missing data values, outliers and common method bias as presented in the sections below.

5.2.2 Missing data

According to Hair et al. (2021), missing data is required to remain within 5% missing per indicator, alternatively the researcher would need to delete the missing data. A total of 291 responses were collected; however, 80 respondents did not meet the minimum qualifying criteria (in other words, missing not at random), which required target respondents to be currently enrolled students who knew what generative artificial intelligence (GenAI) was. As such, these respondents did not complete more than 50% of the questionnaire. Consequently, these respondents were deleted, leaving a final sample of 211 respondents with no missing data.

5.2.3 Outliers

Though the study used non-parametric methods to collect data, outliers still needed to be assessed as extreme outliers could bias the results (Hair et al., 2017b). The outliers were assessed at a construct level using the z-score and box-plot method. A total of six outliers greater than ± 3.29 threshold were identified, with three for entrepreneurship education and three for GenAI (ChatGPT) acceptance constructs, their observation numbers together with the z-scores are presented in Table 1 (Tabachnick & Fidel, 2013).

Table 1: Outliers z-scores per construct

ID number	EE	ChatGPT accept
	Z-Score	Z-Score
6	-3.64	-3.89
15	-3.46	-4.07
94	-3.82	-2.51
117	-4.36	-3.55
163	-3.46	-2.16
201	-4.00	0.79

Source: Authors own (2025)

The outlier observations were assessed for errors, and they appeared to belong to the distribution; therefore, the researcher opted to retain the outliers given that they used non-parametric bootstrapping methods which were not sensitive to outliers, and as such, would not significantly impact the hypothesis testing results (Aguinis et al., 2013).

5.2.4 Common method bias

In this study VIF was used to assess collinearity and common method bias given that both the independent and dependent variables were tested using the same survey method to collect the data (Kock, 2015). Using the guidelines by Kock (2025) and Hair et al. (2017b), VIF was computed for each construct using Smart PLS 4.0. VIF values >3.30 are indicative of collinearity issues and thus common method bias. The VIF values for this study's inner model ranged between 1.000 and 1.723 as presented in Table 2. These VIF values were below the highlighted threshold of 3.30 (Hair et al., 2020; Kock, 2015).

Table 2: Collinearity results - Value inflation factor

Constructs	VIF
EE -> EI	1.723
EE -> ESE	1.000
ESE -> EI	1.404
ChatGPT acceptance -> EI	1.591
ChatGPT acceptance x ESE -> EI	1.203

Source: Authors own based on SmartPLS 4.0 results (2025)

5.2.5 Data distribution

PLS-SEM is a nonparametric method that makes no assumptions about data normality however, this should not be the only reason to use PLS-SEM (Vaithilingam et al., 2024). The data distribution was tested using both skewness and kurtosis to measure the extent of the dispersion from normality, as well as the Shapiro-Wilks test to assess for normality of the data. Skewness and kurtosis values above ± 2 , and Shapiro-Wilks test p -value < 0.05 would be indicative of a nonnormal distribution (Hair et al., 2019a). In cases where non-normality may affect PLS-SEM, Sarstedt and Cheah (2019) advocate to use Bias-Corrected and accelerated (BCa) bootstrapping to mitigate data bias. The Shapiro-Wilks test resulted in p -values less than 0.05, indicative of nonnormal data. Furthermore, the skewness and kurtosis were beyond the threshold ± 2 z -scores also validating the data was nonnormal as presented in Table 3. Given the non-normality of the distribution, this study employed the BCa bootstrapping method in SmartPLS 4.0 (Sarstedt & Cheah, 2019).

Table 3: Skewness, kurtosis & Shapiro Wilks Test

Construct	Mean	SD	Skewness	Kurtosis	Shapiro-Wilk		
					Statistic	df	p -value
EE	5.161	0.696	-1.658	4.437	0.875	211	0.000
ESE	4.471	1.312	-0.156	-0.465	0.986	211	0.040
EI	4.762	1.732	-0.499	-0.730	0.936	211	0.000
ChatGPT acceptance	5.790	1.151	-1.363	2.426	0.878	211	0.000

Source: Authors own based on SmartPLS 4.0 results (2025)

5.3 Demographics of respondents

The demographic profiles of the respondents presented in Table 4 and Figure 4 provide a contextual overview of the participants of the study. The sample of higher education institutions students comprised of 61.14% (N = 129) females, 37.44% (N = 79) male and 1.42% (N = 3) respondents selecting the other category. The majority of the respondents were enrolled in public higher education institutions (89.57%, N = 189) while 10.43% (N = 22) were from private institutions. Regarding entrepreneurial exposure, over half of the respondents reported having family who had prior experience in entrepreneurship. Whereas the majority of the individual students themselves had no prior entrepreneurial experience (51.18%, N = 108), highlighting the nascent nature of a large portion of the sample.

The highest level of education attained (NQF levels) in the sample showed the largest groups as NQF 4 (matric equivalent) with 29.28% (N = 62), and NQF 8 (Honours Degree) with 24.17% (N = 51), with the least represented being NQF 10 (Doctoral degree) at 1.9% (N = 4). Moreover, most of the participants were studying majors with entrepreneurship-related courses, which included studies in Business and Economics (55.92%, N = 118). A significant portion were majoring in science, technology, engineering and mathematics (STEM) courses (26.54%, N = 56) and the remaining 17.54% (N = 37) were majoring in social sciences.

Table 4: Sample demographics

Characteristic	Distribution	Frequency	Percentage
Gender	Male	79	37.44%
	Female	129	61.14%
	Other	3	1.42%
Highest level of education	NQF 4	62	29.38%
	NQF 5	5	2.37%
	NQF 6	14	6.64%
	NQF 7	37	17.54%
	NQF 8	51	24.17%
	NQF 9	38	18.01%
	NQF 10	4	1.90%
Higher education institution type	Public	189	89.57%
	Private	22	10.43%
Education major	Business & Economics	118	55.92%
	STEM	56	26.54%
	Social Science & Law	37	17.54%
Kin relationships with past entrepreneurship experience	Family	127	60.19%
	Friends	36	17.06%
	Colleague	3	1.42%
Respondents with past entrepreneurship	None	45	21.33%
	Yes	103	48.82%
	No	108	51.18%
Current entrepreneurship experience	Yes	48	22.75%
	No	163	77.25%

Source: Authors own based on SPSS 30 (2025)

The largest age group that participated in the survey was 20 to 24 years ($N = 75$, 35.55%), followed by 36 to 46 years ($N = 60$, 28.44%) and the smallest age group being 47 to 58 years ($N = 8$, 3.8%), Figure 4 shows the distribution of the age groups.

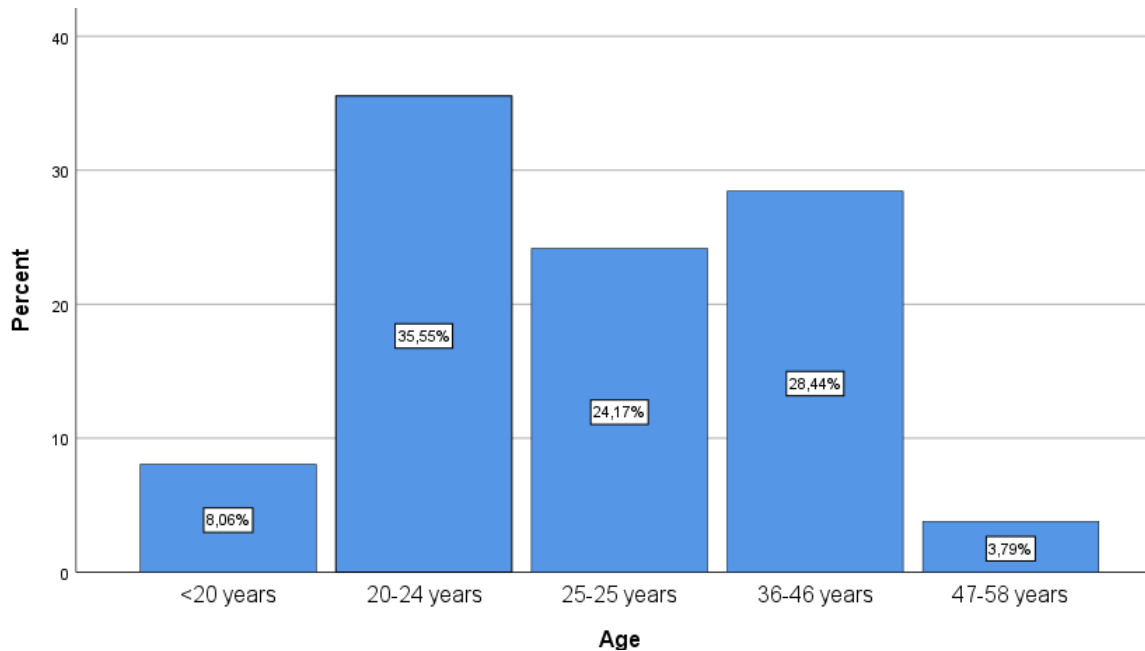


Figure 4: Age sample distribution

Source: Authors own based on SPSS 30 (2025)

5.4 Descriptive statistics

This section provides a summary of the data's central tendency measured through the construct and indicator means, and the data variability measured through the standard deviation. This is followed by a correlation analysis between the indicators and the constructs. The implication of these descriptive statistics is discussed in Chapter Six.

5.4.1 Entrepreneurship education

Using a 7-point Likert scale, the independent variable, Entrepreneurship Education (EE) showed an overall mean of $M = 5.16$ ($SD = 0.696$). This overall mean was computed using eight items as included in Table 5. The mean results showed that entrepreneurship education outcomes were highly perceived by the respondents. The understanding of the different types of entrepreneurship ventures (EE7) and the understanding that entrepreneurship involved risk taking (EE8), showed the highest means of 6.21 ($SD = 1.341$) and 6.12 ($SD = 1.340$) respectively. However, understanding the role that entrepreneurs played in our society was the only item with a mean score below 4.00 (Neutral) at 3.12 ($SD = 1.541$).

Table 5: Descriptive statistics entrepreneurship education

	Indicator	Minimum	Maximum	Mean	SD
EE1	I see entrepreneurial possibilities where others see problems	1	7	5.21	1.362
EE2	When I try, I generally succeed	1	7	5.40	1.278
EE3	I feel I can determine what happens in my life	1	7	5.07	1.532
EE4	In general, starting a business is disappointing	1	7	4.88	1.541
EE5	In general, starting a business is rewarding	1	7	5.27	1.430
EE6	I understand the role entrepreneurs play in our society	1	7	3.12	1.541
EE7	I understand that there are different reasons why people start business (e.g. social entrepreneurship, profit making, independency)	1	7	6.21	1.341
EE8	I understand that some business ideas work, and others don't	1	7	6.12	1.340
EE composite		2.13	6.25	5.16	0.696

Source: Authors own based on SPSS 30 (2025)

5.4.2 Entrepreneurial intention

The overall composite average results for the dependent variable, Entrepreneurial Intention (EI) of 4.76 (SD = 1.732) showed that students had an agreeable perception of entrepreneurial intentions as presented in Table 6. Students were determined to create businesses in the future (EI4) as shown by the high average mean of 5.14 (SD = 1.846). However, students were less ready to do anything to be entrepreneurs (EI1) as shown by the lowest mean of 4.31 (SD = 1.777). This proposed that students were open for entrepreneurship ventures in their futures; however, they were not necessarily committed to being the ones that drive new ventures in their immediate futures.

Table 6: Descriptive statistics entrepreneurial intention

	Indicator	Minimum	Maximum	Mean	SD
EI1	I am ready to do anything to be an entrepreneur	1	7	4.31	1.777
EI2	My professional goal is to become an entrepreneur	1	7	4.37	2.006
EI3	I will make every effort to start and run my own business	1	7	4.66	1.882
EI4	I am determined to create a business in the future	1	7	5.14	1.846
EI5	I have very seriously thought of starting a business	1	7	5.03	1.979
EI6	I have the firm intention to start a business some day	1	7	5.05	1.954
	EI composite	1	7	4.76	1.732

Source: Authors own based on SPSS 30 (2025)

5.4.3 Entrepreneurial self-efficacy

The intervening variable Entrepreneurial Self-Efficacy (ESE) with an overall mean of 4.47 (SD = 1.31) suggested that students had a positive perception of their confidence to pursue entrepreneurship as shown in Table 7. On average, to start a business and keep it working (ESE1) was not a task the students found they had high confidence in, as shown by the low mean of 4.18 (SD = 1.418); despite having the necessary practical details to start a business (ESE4, M= 4.64, SD = 1.711). Furthermore, the students had a belief that they would have a high probability of succeeding if they tried to start a business (ESE6, M = 4.17; SD = 1.396).

Table 7: Descriptive statistics entrepreneurial self-efficacy

	Indicator	Minimum	Maximum	Mean	SD
ESE1	To start a business and keep it working would be easy for me	1	7	4.18	1.418
ESE2	I am prepared to start a viable business	1	7	4.50	1.876
ESE3	I can control the creation process of a new business	1	7	4.48	1.596

	Indicator	Minimum	Maximum	Mean	SD
ESE4	I know the necessary practical details to start a business	1	7	4.64	1.711
ESE5	I know how to develop an entrepreneurial project	1	7	4.31	1.579
ESE6	If I tried to start a business, I would have a high probability of succeeding	1	7	4.71	1.396
ESE composite		1	7	4.47	1.312

Source: Authors own based on SPSS 30 (2025)

5.4.4 GenAI (ChatGPT) acceptance

As presented in Table 8, the overall mean of 5.79 (SD = 1.151) showed that the students positively perceived ChatGPT's (Chat acceptance) ease of use and usefulness. The ease of use of ChatGPT (EOU4) was the highest rated item with a mean of 6.17 and the lowest variability SD = 1.287. Having said that, though not as high as the useability result, students did find that using ChatGPT in their studies would increase their productivity (UCGT3, M= 5.45, SD = 1.625), and they were using it frequently (UCGT6, M= 5.48, SD = 1.666). The construct had the highest overall mean in the study, which suggested a potential significant impact of technology within the education environment, this could only be determined through hypothesis testing in section 5.6.4.

Table 8: Descriptive statistics GenAI (ChatGPT) acceptance

	Indicator	Minimum	Maximum	Mean	SD
EOU1	Learning to use ChatGPT would be easy for me	1	7	6.14	1.302
EOU2	My interaction with ChatGPT would be clear and understandable	1	7	5.99	1.347
EOU3	It would be easy for me to become skilful at using ChatGPT	1	7	6.01	1.345
EOU4	I would find ChatGPT easy to use	1	7	6.17	1.287
UCGT1	Using ChatGPT in my studies would enable me to accomplish tasks more quickly	1	7	5.83	1.449
UCGT2	I would find ChatGPT useful in my entrepreneurship education	1	7	5.78	1.345

	Indicator	Minimum	Maximum	Mean	SD
UCGT3	Using ChatGPT in my studies would increase my productivity	1	7	5.45	1.625
UCGT4	Using ChatGPT would enhance my effectiveness in entrepreneurship education	1	7	5.50	1.538
UCGT5	I would find ChatGPT useful for my entrepreneurship intentions	1	7	5.55	1.461
UCGT6	I use ChatGPT frequently	1	7	5.48	1.666
	Chat acceptance composite	1	7	5.79	1.151

Source: Authors own based on SPSS 30 (2025)

5.5 Correlation Matrix

A correlation analysis was performed to assess the strength and directions of associations between the demographic variables and the constructs of the study as presented in Table 9. Given the non-parametric nature of the study, the Spearman's rank correlation coefficient was employed (Liñán & Chen, 2009). The results showed a positive and significant correlation among the constructs of the study with all the p-values less than 0.01. The relationship between ESE and EI showed the strongest positive correlation with $r = 0.67$, followed by EE and ESE with a moderately positive correlation of $r = 0.53$. This potentially indicated an intervening role of ESE in the relationship between EE and EI. The acceptance of ChatGPT had a higher correlation with EE, with a $r = 0.428$ relative to the other constructs.

There was positive significant correlation between EE and EI of $r = 0.43$, though not as strong as their relationships with ESE, respectively. Furthermore, the demographic variables that may influence EI are included in Table 9. These variables all have significant correlations with EI and may potentially need to be controlled for when testing the theoretical hypotheses of the study in Section 5.6.4 and Section 5.6.5.

Table 9: Correlation analysis

	EE	ESE	EI	Chat Accept	Gender	Kin exp	Previous exp	Current exp
EE	1							
ESE	.527**	1						
EI	.430**	.667**	1					

	EE	ESE	EI	Chat Accept	Gender	Kin exp	Previous exp	Current exp
Chat acceptance	.428**	.331**	.315**	1				
Gender	0.073	-.165*	.236**	-.174*	1			
Kin exp	0.087	-.136*	-.175*	-0.096	0.004	1		
Previous exp	.276**	-.346**	.309**	-.137*	0.083	.203**	1	
Current exp	.348**	-.394**	.348**	-.212**	0.079	.135*	.510**	1

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Source: Authors own based on SPSS 30 (2025)

5.6 Structural Equation Modelling Results

5.6.1 Measurement model results

The confirmatory composite analysis, similar to the confirmatory factor analysis phase deals with the measurement model assessment of the observed indicators and the constructs. The PLS-SEM outer model included in Figure 5 was derived based on the conceptual research model included in Chapter Three. The model assessment presented the results of the construct measurement, reliability and validity measurements. This was then followed by the assessment of the structural model analysis that presented the results of the inner model path analysis and hypothesis testing.

5.6.1.1 Construct measurement - Reflective determination

As mentioned in Section 4.3.10.3 the Confirmatory Tetrad Analysis (CTA) was used to determine the measurement model perspectives as either reflective or formative (Gudergan et al., 2008). Guided by the recommendations of Hair et al. (2019a), the theory, the internal consistency and AVE were taken into consideration to determine the model perspective.

The CTAs for all the constructs besides EI indicated that they were reflective measures as confirmed by previous studies and the CTA results in Table10. The composite reliabilities and AVE exceeded the minimum thresholds of 0.70 and 0.50 respectively, which indicated that the constructs could be reflective (Hair et al., 2020; Manley et al., 2021). The CTA's results showed that the tetrads retained a zero value, with the CI low and CI high moving from negative to positive.

Notwithstanding that four tetrads of EI (10, 16, 22 and 26) did not have a zero value between the CI and CI high, moving from positive to positive or negative to negative, implying that constructs could be formative; however, theory and previous research has treated EI as a reflective measure (Liñán & Chen, 2009; Nguyen & Nguyen, 2024). Moreover, the composite reliabilities (0.957) and AVE (0.824) of EI far exceeded the minimum thresholds as seen in Table 11, and implied that the construct was likely reflective. In addition, the variance inflation factors of EI measurement items indicated collinearity and a high likelihood of correlation, which was expected of constructs that were reflective, given that their measures are interchangeable. Consequently, EI was treated as a reflective measure as indicated in Figure 5.

Table 10: Confirmatory tetrad analysis for EE, EI and ESE

EE	CI low adj.	CI up adj.
1: EE_1,EE_2,EE_5,EE_6	-0.120	0.639
2: EE_1,EE_2,EE_6,EE_5	-0.083	0.742
4: EE_1,EE_2,EE_5,EE_7	-0.181	0.639
6: EE_1,EE_5,EE_7,EE_2	-0.273	0.330
7: EE_1,EE_2,EE_5,EE_8	-0.235	0.548
10: EE_1,EE_2,EE_6,EE_7	-0.066	0.892
16: EE_1,EE_2,EE_7,EE_8	-0.078	0.991
22: EE_1,EE_5,EE_6,EE_8	-0.326	0.440
26: EE_1,EE_5,EE_8,EE_7	-0.241	0.620
EI	CI low adj.	CI up adj.
1: EI1,EI2,EI3,EI4	-0.431	1.756
2: EI1,EI2,EI4,EI3	-0.314	1.923
4: EI1,EI2,EI3,EI5	-0.332	1.651
6: EI1,EI3,EI5,EI2	-0.955	0.816
7: EI1,EI2,EI3,EI6	-0.490	1.326
10: EI1,EI2,EI4,EI5	0.584	3.645
16: EI1,EI2,EI5,EI6	0.842	4.234
22: EI1,EI3,EI4,EI6	0.717	3.297
26: EI1,EI3,EI6,EI5	0.592	3.387
ESE	CI low adj.	CI up adj.
1: ESE_1,ESE_2,ESE_3,ESE_4	-0.860	0.469
2: ESE_1,ESE_2,ESE_4,ESE_3	-0.495	0.757
4: ESE_1,ESE_2,ESE_3,ESE_5	-0.738	0.522

6: ESE_1,ESE_3,ESE_5,ESE_2	-0.796	0.576
7: ESE_1,ESE_2,ESE_3,ESE_6	-0.816	0.391
10: ESE_1,ESE_2,ESE_4,ESE_5	0.246	2.111
16: ESE_1,ESE_2,ESE_5,ESE_6	-0.239	0.823
22: ESE_1,ESE_3,ESE_4,ESE_6	-0.054	1.002
26: ESE_1,ESE_3,ESE_6,ESE_5	-0.573	0.672

Source: Authors own based on Smart PLS 4.0 (2025)

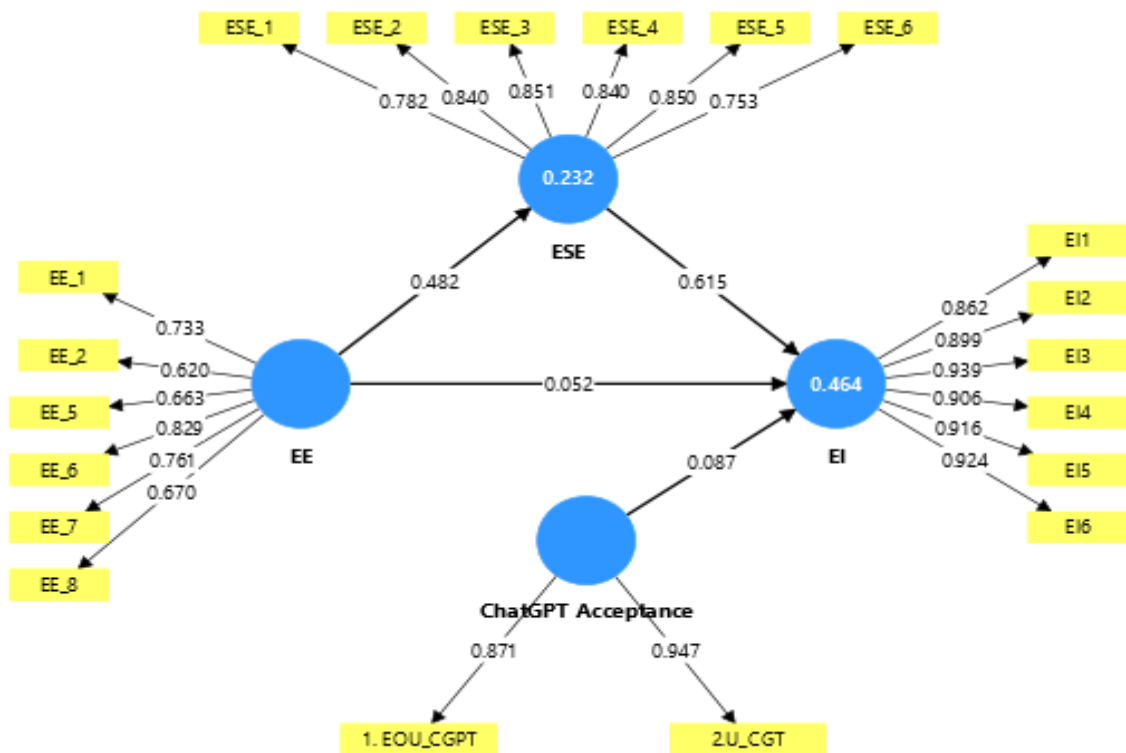


Figure 5: Outer measurement model

Source: Authors own based on SmartPLS 4.0 (2025)

5.6.1.2 Indicator loadings

All the factor loadings were above the threshold of >0.78 except for EE2, EE5 and EE8 which were above 0.60 but below 0.78. These items were retained because the AVE was ≥ 0.5 inclusive of these items therefore negating the need to remove them. However, EE3 (0.589 and EE4 (0.365) were deleted because their factor loadings were decreasing the AVE below 0.50 threshold (Manley et al., 2021). Social science research is known to report factor loadings below 0.70, and thus the reliability and validity of the model needed to be considered before items were deleted (Hair et al., 2017b). Post the

deletion of the low factor items, the reliability and validity improved above the minimum thresholds as indicated in Table 11. This implied that the retained items were more suitable measures for the constructs (Hair et al., 2017b).

Confirmatory Composite Analysis

5.6.1.3 Internal consistency

The Cronbach alpha and composite reliability were employed to evaluate internal consistency. Values of ≥ 0.70 indicated sufficient stability and consistency of the measurements over time (Maula & Stam, 2020). Both the reliability statistics results were above the minimum thresholds, with Cronbach alpha ranging from 0.817 to 0.957 and composite reliability ranging from 0.862 to 0.966 as shown in Table 11 indicating sufficient internal consistency.

5.6.1.4 Convergent validity

The convergent validity was assessed using AVE where a value of > 0.50 implied that the construct's items consistently correlated with the latent construct (Amani et al., 2024; Fornell & Larcker, 1981). Convergent validity was supported as all loadings were above 0.50 as presented in Table 11.

Table 11: Factor loading, reliability and convergent validity

Constructs	Items	Factor loading	Cronbach Alpha	Composite reliability	AVE
EE	EE1	0.733	0.817	0.862	0.513
	EE2	0.620			
	EE5	0.663			
	EE6	0.829			
	EE7	0.761			
	EE8	0.670			
	EI1	0.862			
	EI2	0.899			
EI	EI3	0.939	0.957	0.966	0.824
	EI4	0.906			
	EI5	0.916			
	EI6	0.924			
	ESE1	0.782			
	ESE2	0.840			
ESE	ESE3	0.851	0.902	0.925	0.673
	ESE4	0.840			
	ESE5	0.850			
	ESE6	0.753			
	UCGT1	0.823			
			0.801	0.906	0.828

Constructs	Items	Factor loading	Cronbach Alpha	Composite reliability	AVE
ChatGPT acceptance	UCGT2	0.866			
	UCGT3	0.899			
	UCGT4	0.929			
	UCGT5	0.913			
	UCGT6	0.655			
	EOU1	0.908			
	EOU2	0.931			
	EOU3	0.912			
	EOU4	0.856			

Source: Authors own based on Smart PLS 4.0 (2025)

5.6.1.5 Discriminant validity

Discriminant validity was evaluated to determine the extent to which constructs were distinct from one another in the model. The Heterotrait-Monotrait Ratio (HTMT) was used to assess the correlation between the constructs with a recommended threshold below 0.90 for related constructs, and below 0.85 for unique constructs (Amani et al., 2024; Hair et al., 2020). Moreover, the cross loadings of indicators were also assessed, where the highest loadings were required on the related construct (Hair et.al., 2017). Both the HTMT and cross loadings indicated no issues with discriminant validity, as no HTMT coefficients exceed 0.90 and 0.85 as shown in Table 12, and no cross-loading issues were noted as indicated in Appendix B.

Table 12: Discriminant validity - Heterotrait-monotrait ratio

	EE	EI	ESE	EOU	UCGT
EE					
EI	0.392				
ESE	0.488	0.714			
EOU	0.683	0.239	0.309		
UCGT	0.515	0.355	0.366	0.730	

Source: Authors own based on Smart PLS 4.0 (2025)

5.6.2 Structural model results (hypotheses testing)

Following the confirmation of the robustness of the measurement model, the structural model was evaluated. The model firstly assessed the collinearity of the inner model then moved to examine the path coefficients (β) for hypotheses testing with control variables, followed by the explanatory factors (R^2), and the predictive relevance assessment f^2 and Q^2 . Lastly, the mediation and moderation analysis was assessed.

5.6.3 Collinearity of the inner model

Multicollinearity was assessed using VIF where a value below 3.3 was acceptable (Hair et al., 2020; Kock, 2015). The VIF values in Table 13 were all below 3.3 establishing that multicollinearity and common method bias were not concerns for the inner model analysis (Hair et al., 2017b, Kock, 2015).

Table 13: Variance inflation factor

	VIF
ChatGPT acceptance -> EI	1.743
EE -> EI	1.870
EE -> ESE	1.000
ESE -> EI	1.378

Source: Authors own based on Smart PLS 4.0 (2025)

5.6.4 Hypotheses testing

The structural model was developed to evaluate the significance of the predictor variables on the outcome variable. The individual standardised path coefficients for hypotheses testing are reported below. These were computed using BCa bootstrapping in SmartPLS 4.0, running 5000 resamples from the dataset, with one tail selected given that the directions of the relationships were known (Hair et al., 2021). T-statistics greater than 1.645 and p -values < 0.05 indicated significant results, thus leading the researcher to reject the null hypothesis (Hair et al, 2019).

5.6.4.1 Hypothesis one

H₁: Evaluated whether entrepreneurship education positively and significantly influenced entrepreneurial intention

Figure 6 illustrates that the direct relationship results revealed that EE has a statistically significant and positive influence on EI ($\beta = 0.404$, $t = 7.710$ $p < 0.000$).

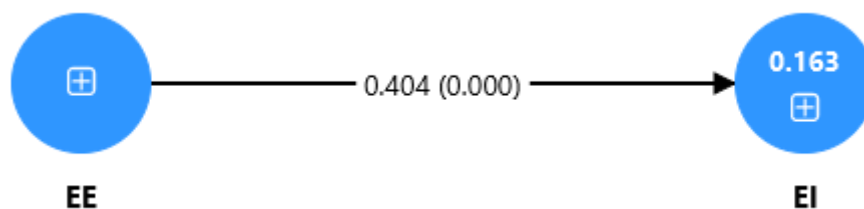


Figure 6: Model of entrepreneurship education on entrepreneurial intention

Source: Authors own based on SmartPLS 4.0 (2025)

5.6.4.2 Hypothesis two

H₂: Evaluated whether entrepreneurship education positively and significantly influenced entrepreneurial self-efficacy

Figure 7 shows strong support that EE has a significant and positive influence on ESE ($\beta = 0.488$, $t = 10.227$, $p < 0.000$).

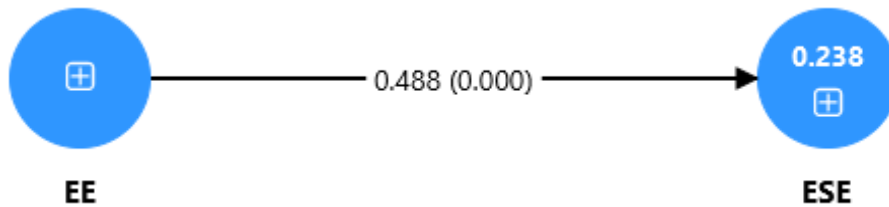


Figure 7: Model of entrepreneurship education on entrepreneurial self-efficacy

Source: Authors own based on SmartPLS 4.0 (2025)

5.6.4.3 Hypothesis three

H₃: Evaluated whether entrepreneurial self-efficacy positively and significantly influenced entrepreneurial intention

The results illustrated in Figure 8, revealed very strong evidence that ESE has a significant positive influence on EI ($\beta = 0.676$, $t = 14.721$, $p < 0.000$). The standardised beta coefficient (β) for ESE was notably high, indicating it was the most influential direct path in the model. The results of the direct paths are summarised in Table 14.

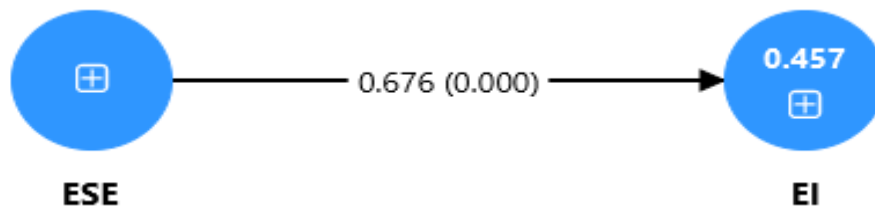


Figure 8 : Model of entrepreneurial self-efficacy on entrepreneurial intention

Source: Authors own based on SmartPLS 4.0 (2025)

Table 14 : Path coefficients of the direct relationships

Hypotheses	Beta Coefficient (β)	<i>t</i> -statistic	<i>P</i> -values	Results
H₁: EE → EI	0.404	7.710	0.000	Supported

Hypotheses	Beta Coefficient (β)	<i>t</i> -statistic	<i>P</i> -values	Results
H₂ : EE → ESE	0.488	10.227	0.000	Supported
H₃ : ESE → EI	0.676	14.721	0.000	Supported

Source: Authors own based on Smart PLS 4.0 (2025)

5.6.4.4 Mediation analysis – Hypothesis four

H₄: Evaluated whether entrepreneurial self-efficacy significantly mediated the relationship between entrepreneurship education and entrepreneurial intention.

Mediation analysis was conducted to evaluate the mediating role of ESE in the relationship between EE and EI. The total effect (the results without the effects of the mediator) of EE on EI was statistically significant ($\beta = 0.374$, $t = 5.450$, $p < 0.000$). Moreover, the results showed a statistically significant indirect effect of EE on EI via ESE ($\beta = 0.292$, $t = 7.084$, $p < 0.000$). The inclusion of the mediating variable (ESE); however, significantly reduced the magnitude of the direct effect of EE, which became insignificant with a $\beta = 0.082$ ($t = 1.196$, $p < 0.116$).

Since the direct path between EE and EI was insignificant, and the indirect path was highly significant, this demonstrated that ESE fully mediated the relationship between EE and EI. Thus, H₄ was supported (see Table 15). Moreover, the BCa bias confidence interval for the indirect effect confirmed the significance of the mediating effect by excluding the value of zero (Hair et al., 2019a). The results showed that EE primarily influenced EI indirectly, by first increasing the student's ESE.

Table 15: Mediation analysis

H4	Beta Coefficient (β)	<i>P</i> - values	BI [5%, 95%]	Conclusion
Total effect path: EE → EI	0.374	0.000	0.240 - 0.027	Direct effect insignificant, full mediation H4 supported, full medication
Direct effect path: EE → EI	0.082	0.116	-0.031– 0.192	
Indirect effect path: EE → ESE → EI	0.292	0.000	0.198 - 0.328	

Source: Authors own based on Smart PLS 4.0 (2025)

5.6.4.5 Moderation analysis– Hypothesis five

H₅: Evaluated whether GenAI (ChatGPT) acceptance positively moderated the relationship between entrepreneurship education and entrepreneurial intention

Moderation analysis was conducted to evaluate the influence of the GenAI (ChatGPT) acceptance on the relationship between EE and EI. Without the inclusion of the moderating effect (EE * GenAI (ChatGPT) acceptance), the structural model R² value for EI was 0.459. With the inclusion of the moderating term, the R² value slightly increased to 0.476 indicating an increase of 1.7% in variance explained in EI. Furthermore, the significance of the interaction effect was analysed, and this showed a statistically significant moderating impact of GenAI (ChatGPT) acceptance on the relationship between EE and EI ($\beta = 0.071$, $t = 2.076$ $p < 0.019$), thus H₅ was supported (see Table 16).

A slope analysis is presented in Figure 9 to understand the nature of the moderating effects. The lines are not parallel which signifies a moderation effect (an interaction). The figure confirms the positive relationship visually. The solid red line (low ChatGPT acceptance) slopes upward but is less steep than the blue line for high GenAI (ChatGPT) acceptance. This implies that when ChatGPT acceptance is low, although the impact of EE on EI is still positive, the gain in EI is relatively small. Conversely the blue line is slightly steeper, indicating that the positive effects of EE are stronger on EI when GenAI (ChatGPT) acceptance is high. The f^2 effect size was 0.017 which indicated that while the moderation was statically significant, its contribution to explaining the variance in the dependent variable (EI) was low (Cohen, 1988; Hair et al., 2019a).

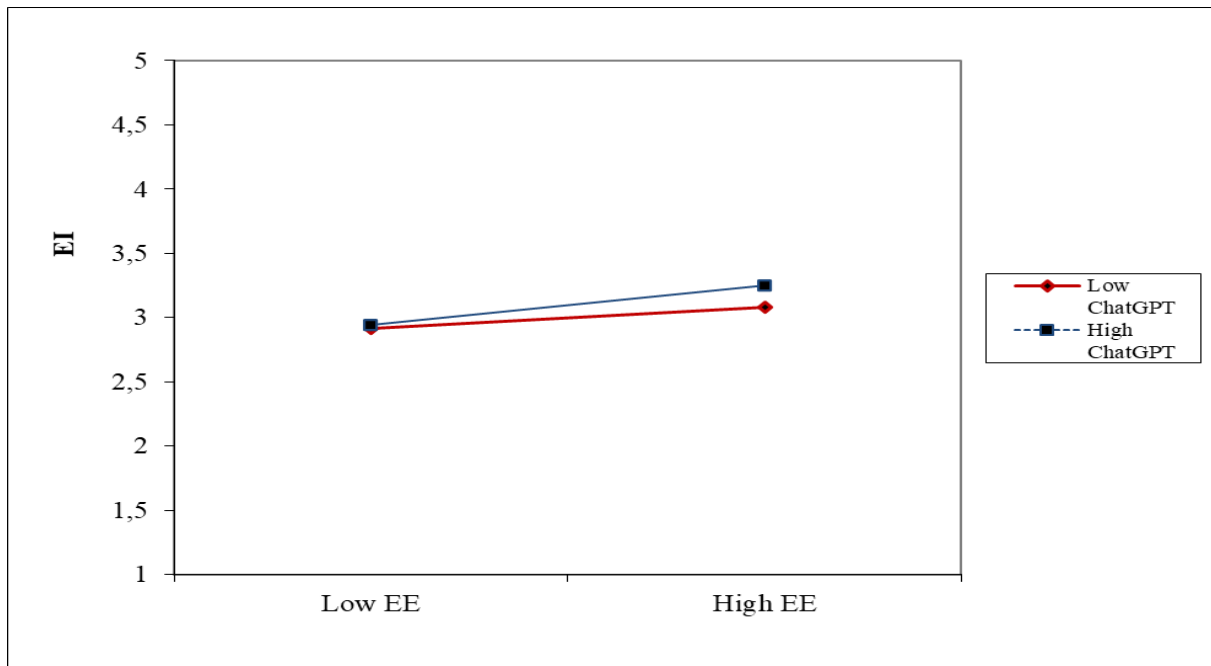


Figure 9: Moderating effect of GenAI (ChatGPT) acceptance on relationship of EE and EI

Source: Authors own based on Smart PLS 4.0 (2025)

Table 16: Moderation analysis results

Hypothesis	β	SD	<i>t</i> -value	<i>p</i> -value	BI [5%, 95%]	Conclusion
H5: Moderating effect: (GenAI (ChatGPT) acceptance* EE) → EI	0.071	0.034	2.076	0.019	0.015 – 0.128	Supported
H6: Moderating effect: (GenAI (ChatGPT) acceptance* ESE) → EI	-0.132	0.065	2.028	0.021	- 0.235 – (-0.021)	Not Supported

Source: Authors own based on Smart PLS 4.0 (2025)

5.6.4.6 Moderation - Hypothesis six

H₆: Evaluated whether GenAI (ChatGPT) acceptance positively moderated the relationship between entrepreneurial self-efficacy and entrepreneurial intention

The results revealed that the interaction term (ESE * GenAI [ChatGPT] acceptance) showed a statistically significant moderating impact on the relationship between ESE and EI ($\beta = -0.132$, $t = 2.028$ $p < 0.021$). However, the moderation demonstrated a negative effect ($\beta = -0.132$), which was contrary to the hypothesised positive direction in H₆. Therefore, H₆ was not supported. This implied that an increase in GenAI (ChatGPT) acceptance weakened the relationship between ESE and EI, as summarised in Table 16.

Moreover, a slope analysis is presented in Figure 10 to better understand the nature of the moderating effects. The figure confirms the inverse relationship visually. The line is steeper for low GenAI (ChatGPT) acceptance (solid red line), showing that when acceptance is low, the positive impact of ESE on EI is much stronger. Conversely, at higher GenAI (ChatGPT) acceptance (blue line), the line is less steep, indicating that the benefits of increased ESE are slightly dampened by a high acceptance of GenAI (ChatGPT). The f^2 effect size was 0.020 which indicated that while the moderation was statically significant, its practical contribution to explaining the variance in the dependent variable (EI) was low (Cohen, 1988; Hair et al., 2019a).

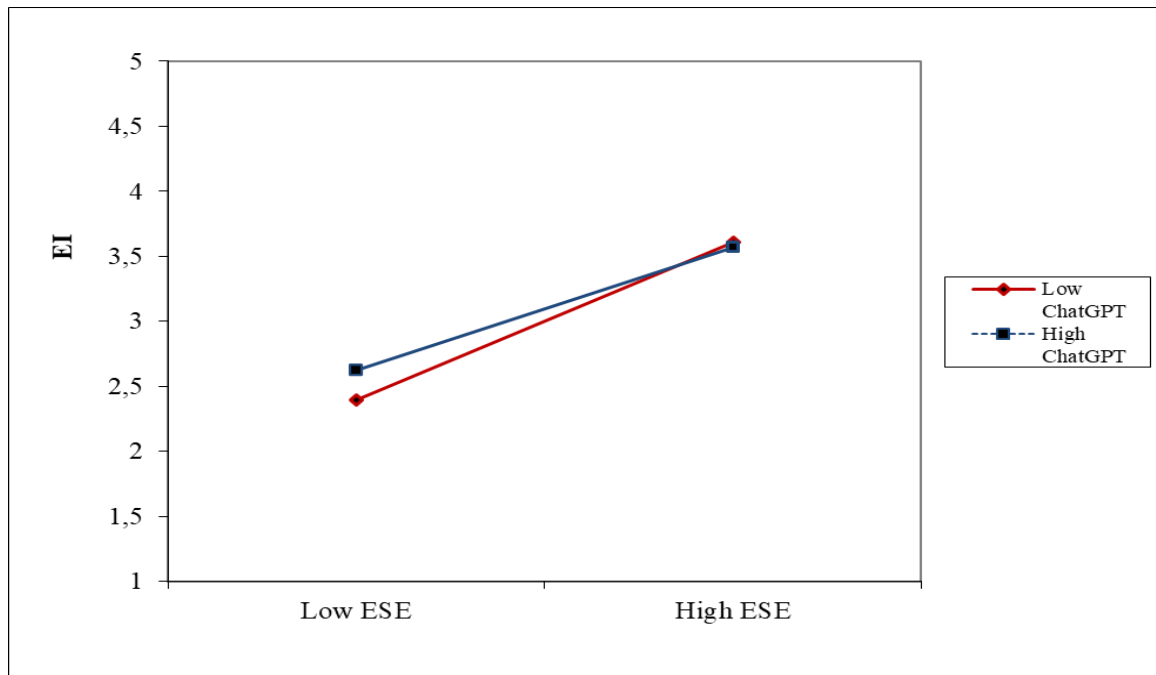


Figure 10: Moderating effect of GenAI (ChatGPT) acceptance on relationship of ESE and EI

Source: Authors own based on Smart PLS 4.0 (2025)

5.6.5 Control variables

The gender, current and previous entrepreneurship experience of respondents and their kin relationships were included as control variables to account for potential confounding factors, given their correlation with the endogenous (dependent) variables of the study (see Table 9). The results revealed that the two control variables had a statistically significant impact on EI, which were gender ($\beta = -0.122$, $t = 2.520$, $p < 0.006$) and family entrepreneurship history ($\beta = 0.27$, $t = 1.999$, $p < 0.023$). The remaining control variables (current and previous personal entrepreneurship experience) had no statistical impact, as shown in Table 17.

Gender demonstrated a negative effect ($\beta = -0.122$), suggesting that, gender differences may decrease the development of EI. Furthermore, a family history of entrepreneurship demonstrated a positive effect ($\beta = 0.27$), indicating that a kin relationship to entrepreneurship increased the development of EI.

These findings suggested that, while most demographic characteristics were non-significant, the model's primary relationships must be interpreted with caution regarding the confounding influence of gender and family history on EI. The inclusion of these two

significant control variables increased the R^2 of EI from 0.476 to 0.495 thus accounting for their influence strengthens the validity of the reported main effects.

Table 17: Control variable results

	Beta Coefficient (β)	<i>t</i> -statistic	<i>P</i> -values
Gender → EI	-0.122	2.520	0.006
Current → EI	-0.135	1.012	0.156
Previous → EI	-0.061	0.485	0.314
Family → EI	0.270	1.999	0.023
Friend → EI	0.263	1.597	0.055

Source: Authors own based on Smart PLS 4.0 (2025)

5.6.6 Predictiveness of the structural model

The predictive analysis was conducted to assess how well the structural model could explain and predict the dependent variables. This was done by computing the R^2 , f^2 and Q^2 values presented in Table 18. The R^2 explained how much change in the dependent variable was attributed to the independent variable(s), thus it was considered a measure of a model's explanatory power. The R^2 of EI was 0.476, as guided by Cohen (1988) and this explanatory power was considered substantial. The R^2 of ESE of 0.232 showed that the model's explanatory power was also substantial (Cohen, 1998).

The effect size (f^2) was determined to evaluate the effect of removing an independent variable(s) from the model and its impact on the dependent's variable R^2 . The effect was determined as either small (0.02 to 0.15), medium (0.15 to 0.35) or large (> 0.35) (Hair et al., 2019a). As such, the removal of EE would have a medium influence on ESE and a small effect on EI, while the removal of ESE would have a large effect on the R^2 of EI.

To assess the model's predicate power, the Q^2 metric was determined using PLSpredict, where a value >0 was indicative of predictive power (Hair et al., 2019a; 2020). The Q^2 for the dependent latent variables were greater than 0, hence predictive power was established (see table 18). Furthermore, the measurement variables RMSE were assessed relative to the LM_RMSE (see Table 19). Though all items had a $Q^2 > 0$, the majority of the items had greater RMSE errors than their respective LM benchmarks, which indicated that the model may have low predictive power (Hair et al., 2019a; Shmueli et al., 2019).

Table 18: Explanatory power

Predictor	Outcome	R ²	f ²	Q ² predict
EE	EI	0.476	0.007	0.152
ESE	EI		0.509	
EE	ESE	0.232	0.302	0.213

Table 19: Endogenous measurement variable predictive power

Measurement Variable	Q ² predict	PLS-SEM_RMSE	LM_RMSE
EI1	0.094	1.696	1.599
EI2	0.076	1.933	1.822
EI3	0.129	1.760	1.732
EI4	0.135	1.721	1.725
EI5	0.170	1.809	1.791
EI6	0.152	1.805	1.801
ESE_1	0.076	1.368	1.362
ESE_2	0.131	1.753	1.601
ESE_3	0.139	1.484	1.429
ESE_4	0.209	1.526	1.458
ESE_5	0.159	1.452	1.382
ESE_6	0.141	1.297	1.307

Source: Authors own based on Smart PLS 4.0 (2025)

5.7 Summary of findings

A summary of the study's results is presented in Table 20, including an illustration of the final structural model in Figure 11.

Table 20: Summary of study results

Hypotheses		Beta Coefficient	t-statistic	P-values	Hypothesis results
H ₁	EE → EI	0.404	7.710	0.000	Supported
H ₂	EE → ESE	0.488	10.227	0.000	Supported
H ₃	ESE → EI	0.676	14.721	0.000	Supported
H ₄	EE → ESE → EI	0.292	7.084	0.000	Supported

Hypotheses		Beta Coefficient	t-statistic	P-values	Hypothesis results
H₅	GenAI (ChatGPT) acceptance x EE → EI	0.071	2.076	0.019	Supported
H₆	GenAI (ChatGPT) acceptance x ESE → EI	-0.132	2.028	0.021	Positive relationship not Supported

Source: Authors own based on Smart PLS 4.0 (2025)

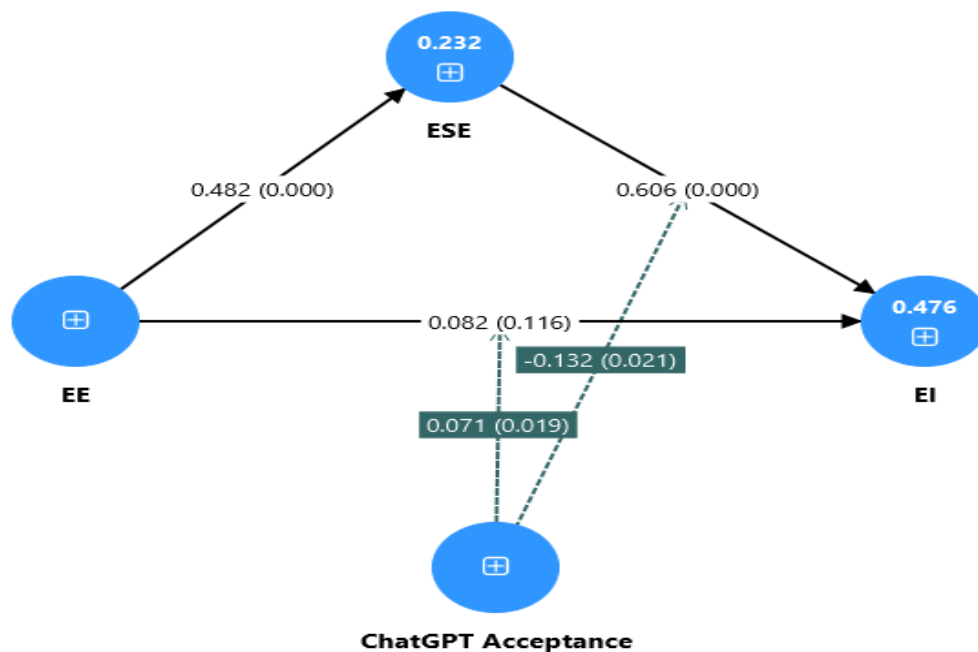


Figure 11: Partial least square - structural equation model

Source: Authors own based on Smart PLS 4.0 (2025)

5.8 Conclusion

This chapter provided an overview of the results of the study using the PLS-SEM model. The theoretical relationships established from the literature in Chapters Two and Three were tested using rigorous statistical methods resulting in three of the six hypotheses being significantly supported. The results are further discussed in Chapter Six and their implications considered in the closing chapter of the study (Chapter Seven).

CHAPTER 6: DISCUSSION

6.1 Introduction

In an effort to increase entrepreneurial intentions which are established precursors for entrepreneurial behaviour (Ahmed et al., 2020; Ajzen, 2020; Batista-Canino et al., 2024), this research aimed to provide empirical insights for education institutions and policymakers to enhance entrepreneurship education efficacy, through the strategic integration of modern technology such as GenAI, specifically ChatGPT. To this end, the research study examined the key entrepreneurship constructs (entrepreneurship education, entrepreneurial self-efficacy, entrepreneurial intentions and technology acceptance) that were identified in literature as crucial factors that were influencing the students' intentions to engage in entrepreneurial behaviour thereby contributing to the reduction of the high youth unemployment which South Africa is grappling with (Meyer et al., 2022; Munyati, 2024; Statistics South Africa, 2025).

Integrating the core principles of the theory of planned behaviour and the technology acceptance model to understand the hypothesised relationships, this study tested six hypotheses aligned with the research objectives in Chapter One, using the PLS-SEM in SmartPLS 4.0. The combined results for hypotheses H_1 , H_2 , H_3 and H_4 provided strong validation for the fundamental psychological principles of the theory of planned behaviour in the context of entrepreneurship. The findings of H_3 that entrepreneurial self-efficacy, the occupational manifestation of perceived behavioural control, was the most powerful predictor of entrepreneurial intention validated the foundation of the theory of planned behaviour (Bayona-Oré, 2023).

Interestingly, the results relating to technology integration, however, revealed an unexpected tension. Though the moderation results of H_5 and H_6 validated the principles of the technology acceptance model, wherein the intention to use a particular technology (GenAI, ChatGPT) is based on the perceived ease of use and usefulness, due to the combination of the theories, the results revealed a secondary psychological consequence of a high usage of GenAI (ChatGPT) (Zhai et al., 2024). A cautioning note that the model results, need to be accepted within the limitations of the low prediction power revealed in Section 5.6.6 and the non-probabilistic nature of the study.

This chapter will now focus on the in-depth discussion of these results, firstly unpacking the demographics of the study, followed by a discussion of the descriptive statistics and then a deeper discussion of the results for the hypothesised direct, mediating and

moderating relationships, then lastly the final research model is presented before concluding the chapter.

6.2 Demographics of the study

Similar to other related studies, the sample population consisted of a final sample of 211 students from public and private higher education institutions. This was similar to Soomro and Shah (2022) who studied public higher education student's need for achievement and entrepreneurial intention in Pakistan using a final sample of 184 students. Similarly, Xie and Wang (2025) in their study examining how GenAI integrated education enhanced entrepreneurial intention through self-efficacy, included 346 university students from China. Other similar studies that included university students, had sample sizes that ranged from 234 (Zulfiqar et al., 2025) to 804 (L. Wu et al., 2022). This study's sample exceeded its intended target of 150 to 200 respondents.

The gender demographic showed that the study consisted of a higher number of female respondents (62.14%) which was similar to L. Wu et al. (2022), whose study had 70.64% female respondents. This study found gender disparity to be a significant control variable that influenced entrepreneurial intentions (see Section 6.4), however L. Wu et al. (2022) found that gender had no significant moderating effect on entrepreneurial intentions. This demographic distribution suggests that the population engaging in entrepreneurship education research may be skewed towards female students, reflecting possible trends in academic enrolment or interest in the research topic. The groups with the largest respondents were 20-24 years and 36-46 years. This aligned with the academic achievement demographics which showed a higher number of undergraduate students whose highest education level was NQF4 (29.38%) (matric/national senior certificate) and postgraduate students with NQF 8 (24.17%) (Honours/postgraduate diplomas).

Most students were enrolled in business and economic related courses (55.92%) which may have influenced the resultant significant findings relating to entrepreneurial self-efficacy and entrepreneurial intention. Soomro and Shah (2022), whose study focused on commerce students, found a significant positive effect between entrepreneurship education, entrepreneurial self-efficacy, and entrepreneurial intentions. The remaining demographics relating to the entrepreneurship history of kin relationships were also included as control variables; however, only family entrepreneurship history showed a statistically significant influence on entrepreneurial intention as discussed in Section 6.4.

6.3 Descriptive Statistics

6.3.1 Entrepreneurship education

The overall composite mean for entrepreneurship education was $M = 5.16$ ($SD = 0.696$) on a 7-point Likert scale. This implied that on average the students positively perceived their exposure to entrepreneurship education. The highest means were observed for items related to technical knowledge EE7 “I understand that there are different reasons why people start business” ($M = 6.21$ [$SD = 1.341$]) and risk awareness EE8 “I understand that some business ideas work, and others don't” ($M = 6.12$ [$SD = 1.340$]), indicating that education intervention was most successful at promoting foundational knowledge on entrepreneurship. The students acquired human capital assets concerning the mechanics of entrepreneurship including different motivations for entrepreneurship (for profit, social impact, independence etc.) and the inherent risks involved. This aligned with the intended goals of entrepreneurship which is to impart knowledge and skills (Alakaleek et al., 2023; Iwu et al., 2021; Martínez-Gregorio et al., 2021).

However, a below neutral mean was noted regarding the awareness about the societal role entrepreneurs played EE6 “I understand the role entrepreneurs play in our society” ($M = 3.12$ [$SD = 1.541$]). This implied that students did not comprehend the broader social and economic significant role of entrepreneurs. This may be indicative of a technical and theoretical appreciation for entrepreneurship rather than a practical and community centric understanding of entrepreneurship as required by Lyu et al. (2024) as well as Piperopoulos and Dimov (2015).

6.3.2 Entrepreneurial intention

The composite mean score for entrepreneurial intention (dependent variable) was $M = 4.76$ ($SD = 1.732$) which was above the neutral point indicating that students had a moderate perception of entrepreneurial intention. The highest item means were noted for future aspirational behaviour regarding entrepreneurship, EI4 “I am determined to create a business in the future” ($M = 5.14$ [$SD = 1.846$]), EI6 “I have the firm intention to start a business someday” ($M = 5.05$ [$SD = 1.954$]) and EI5 “I have very seriously thought of starting a business” ($M = 5.03$ [$SD = 1.979$]) which confirmed positive perceptions toward future entrepreneurial behaviour.

The results further revealed, however, that students had a lower commitment to immediate entrepreneurial behaviour given the lower mean scores for items related to immediate willingness to sacrifice what is required for entrepreneurship EI1 “I am ready

to do anything to be an entrepreneur” ($M = 4.31$ [$SD = 1.777$]) (Taneja et al., 2024). Given that the largest number of respondents were between 20-24yrs, and pursuing undergraduate studies, they were still being exposed to alternative career paths which may explain the reluctance to commit to entrepreneurship outright (Davidsson & Honig, 2003; Martin et al., 2013). Moreover, the lower urgent commitment to behaviour scores highlighted the importance of interventions such as entrepreneurial self-efficacy and education to channel nascent cognitive processes towards committed action (Ahmed et al., 2020).

6.3.3 Entrepreneurial self-efficacy

The descriptive statistics for the overall composite mean of 4.47 ($SD = 1.312$) which lies above the neutral midpoint on the Likert scale implied that students had a positive perception of their confidence in their abilities to pursue and succeed in entrepreneurship. The highest means were observed for indicators related to the perception of control and belief in potential success, particularly ESE6 “If I tried to start a business, I would have a high probability of succeeding” ($M = 4.71$ [$SD = 1.396$]), ESE4 “I know the necessary practical details to start a business” ($M = 4.64$ [$SD = 1.711$]) and ESE3 “I can control the creation process of a new business” ($M = 4.48$ [$SD = 1.596$]). These high mean averages showed that students were adequately equipped with the internal resources required to manage the entrepreneurial process. This further suggested that entrepreneurship education is successfully providing sufficient mastery experiences and social persuasion opportunities (which are two of four pathways of entrepreneurial self-efficacy) (Chen et al., 1998; Nowiński et al., 2019).

Although students feel confident in the initial stages and final outcome, the lower mean averages for ESE1 “To start a business and keep it working would be easy for me” ($M = 4.18$ [$SD = 1.418$]), implied that students may perceive significant challenges in managing demands of a long-term venture. This may be addressed through pedagogical interventions that expose students to business challenges through experiential learning opportunities to develop that longer term psychosocial capital (Lyu et al., 2024).

6.3.4 GenAI (ChatGPT) acceptance

The overall composite mean for GenAI (ChatGPT) acceptance was a combination of items measuring the perceived ease of use and usefulness of ChatGPT. The mean score of $M = 5.79$ ($SD = 1.151$) revealed a significantly positive perception of ChatGPT’s usability and usefulness within their academic environment. These results indicated the

manifestation of successful acceptance as predicted by the technology acceptance model (Zaineldeen et al., 2020). The indicators with the highest means related to perceived accessibility confirming ChatGPT's usability EOU4 "I would find ChatGPT easy to use", (M = 6.17 [SD = 1.287]) and EOU1 "Learning to use ChatGPT would be easy for me", (M = 6.14 [SD = 1.302]). These results implied that students anticipated minimal cognitive effort to engage with the technology platform which aligned to the historical precedents of ChatGPT's rapid adoption (Kumar et al., 2025). Furthermore, UCT1 "Using ChatGPT in my studies would enable me to" (M = 5.83 [SD = 1.449]) and UCGT4 "Using ChatGPT would enhance my effectiveness in entrepreneurship education" (M = 5.50 [SD = 1.538]) mean scores showed that ChatGPT was perceived as an efficient tool that assisted students in their academic endeavours (Jo, 2023; Niloy et al., 2024).

The consistently high scores showed that convenience and the perceived efficiency may lead to frequent usage that could expose students to dependency issues (Zhang & Xu, 2025). The data showed that students had embraced GenAI (ChatGPT) as a source of efficient problem-solving driven by the technology acceptance model measures; however, its very strength potentially initiates a psychological shift towards an external locus of control as discussed in Section 6.5.6 below (Tarisayi, 2024; Zhang & Shaw, 2012).

6.4 Control Variables

The inclusion of demographics such as gender, family history and prior entrepreneurship experience in the model as control variables was important to account for potential confounding factors given the correlations of these variables as shown in Table 9. Most of the control variables were found to be insignificant except for gender ($\beta = -0.122$, $t = 2.520$, $p\text{-value} < 0.006$) and family entrepreneurship history ($\beta = 0.270$, $t = 1.999$, $p\text{-value} < 0.023$) which had a statistically significant impact on entrepreneurial intentions. These results contrasted the findings of L. Wu et al. (2002) who found that gender, grade level and family background had no significant moderating influence on entrepreneurial intentions. The negative effect of gender implied that female respondents showed lower intentions when controlling other factors. This may be linked to the socioeconomic and cultural context of South Africa, where normative gender roles and social expectations influence the expected behavioural control that lower entrepreneurial intention among females (Meyer et al., 2022). However, while gender and family history should be considered as significant background factors influencing

entrepreneurial intention, most of the control variables were insignificant which supported the conceptual strength of the primary structural model. It suggested that the variance explained in entrepreneurial intention is mainly attributed to the hypothesised educational and psychological pathways (discussed below), rather than the influence of demographic variables.

6.5 Hypotheses testing results

The next sections discuss the results of the study focussing on the significance of the hypotheses testing outcomes, and how these findings compared with the existing literature. Each section aligns with a specific research objective together with the particular hypothesis.

6.5.1 *Direct relationship between entrepreneurship education and entrepreneurial intention*

Aligned with research objective one, the study aimed to examine and understand how the relationship between entrepreneurship education and entrepreneurial intentions could be leveraged to ultimately increase entrepreneurial behaviour in South Africa. As such, the direct relationship between entrepreneurship education and entrepreneurial intentions was crucial to understand, given education's ability to form students' career ambitions (Bae et al., 2014). To assess this relationship the study aimed to test the following hypothesis:

H₁: Entrepreneurship education positively and significantly influences entrepreneurial intention.

The results of this study revealed that the direct path from entrepreneurship education to entrepreneurial intention was statistically significant ($\beta = 0.404$, $t = 7.710$, p -value < 0.000), thus supporting H₁. This result aligned with the findings from Martínez-Gregorio et al. (2021), Nabi et al. (2018) and Ramadani et al. (2022) who found a positive association between entrepreneurship education and entrepreneurial intention. Ramadani (2022) found that entrepreneurship education had a significant positive effect on entrepreneurial intentions for both male and female Bangladeshi graduates, despite the low female business ownership in Bangladesh. This implied that the students who received entrepreneurship education, could use their knowledge, skills and attitudes to pursue entrepreneurship. This was supported by Martínez-Gregorio (2021) who also found in their meta-analysis of 35 studies that entrepreneurship education positively affected entrepreneurial intention. Nevertheless, they observed the average effect size

of entrepreneurship education on entrepreneurial intention to be small (adjusted effect size = 0.207). The small effect size was supported by Nabi et al. (2018), who found that entrepreneurship education could have mixed effects on first year higher education students in Britain. They posited that entrepreneurship education was multidimensional consisting of theoretical and practical components which led to fluctuating entrepreneurial intentions. Furthermore, the authors argued that student's entrepreneurial intentions could be influenced by a combination of positive theoretical and practical learning experiences, and positive social influences from peers, tutors, educators and hands-on experiences (Nabi et al., 2018). The current study's findings were, however, contrary to the findings of X. Wang et al. (2023), who found that entrepreneurship education did not directly influence entrepreneurial intention, but indirectly influenced entrepreneurial intention through entrepreneurial self-efficacy.

The inconsistent effects implied that the relationship between entrepreneurship education and entrepreneurial intentions was indeed complex with other factors interfering in the relationship. This was supported by Oosterbeek et al. (2010) who found that while entrepreneurship education increased knowledge, it could result in negative effects, implying there's more factors that interact in this relationship. The examination of entrepreneurship education's efficacy on forming entrepreneurial intentions has been a subject of continuous debate, given the wide range of entrepreneurship education sources and pedagogies which yield varying outcomes on entrepreneurial intentions (Debarliev et al., 2022; Lyu et al., 2024; Nabi et al., 2017). This study's current findings further contribute to this debate, revealing a nuanced understanding of how entrepreneurship education effects entrepreneurial intentions. The positive relationship infers that entrepreneurship education serves both an enlightening and transformative purpose, whereby it informs students of the realities of entrepreneurship through theoretical and practical exposure to entrepreneurship theories. Similarly, it transforms the acquired knowledge, skills, attitudes and mindsets into internal attributes that foster students' entrepreneurial self-efficacy, which in turn drive entrepreneurial intentions (Iwu et al., 2021).

Having said that, the current study did not provide a pedagogical distinction in its measurement of entrepreneurship education but, rather examined entrepreneurship education as a composite construct that combines both theoretical and practical orientated programmes (Moberg et al., 2014). Previous studies by Piperopoulos and Dimov (2015) have found that theoretically and practically orientated entrepreneurial

courses do not have a homogenous impact on students' intentions, with the latter having a higher effect on developing entrepreneurial skills and attitudes through self-efficacy development. Nevertheless, the results of the current study support the findings of Chaker and Jarraya (2021) who advocate for a combined pedagogical approach. The value of teaching about and teaching through entrepreneurship develops both cognitive and non-cognitive skills, ensuring students capabilities are broadly developed to pursue entrepreneurship. Chaker and Dellagi (2023) found that theoretical-based education developed the cognitive skills of Tunisian students through financial literacy, entrepreneurial knowledge, and entrepreneurial thinking skills. The practical-based education that is action and simulation orientated, developed the students' non-cognitive entrepreneurial skills such as, entrepreneurial attitudes, mindset and self-confidence to manage ambiguity (Chaker & Dellagi, 2023; Lyu et al., 2024). Therefore, a combination of the varying pedagogical tools developed a large set of entrepreneurial skills that interact to foster entrepreneurial intentions. This interaction is what results in the positive association between the constructs, further supporting a combination of pedagogies. Furthermore, Onjewu et al. (2021) captured varying entrepreneurship education influences finding that computer simulation, workshop-based training and course-related entrepreneurship education significantly influenced entrepreneurial intentions, even when self-efficacy was mediating the relationship.

Because of the wide definition of entrepreneurship education (Hägg & Gabrielsson, 2020; Martin et al., 2013; Lackéus, 2020; Unger et al., 2011), and the lack of pedagogical alignment, scholars may continue to find contrasting findings regarding the relationship between entrepreneurship education and entrepreneurial intentions (Debarliev et al., 2022; Lyu et al., 2024; Piperopoulos & Dimov, 2015). Thus, to contribute theoretically to this discourse, and examine the mechanisms by which entrepreneurship education influences entrepreneurial intention; it was vital to assess its effects on other factors which have been noted to influence entrepreneurial intentions as postulated by the theory of planned behaviour (Kufaine, 2024). Though entrepreneurship education imparts human capital assets such as knowledge, skills and mindsets, that alone is insufficient to translate into entrepreneurial intention, without first building the individual's confidence in their own abilities to translate the acquired human capital assets into entrepreneurial intentions and actions (Iwu et al., 2021; Nowiński et al., 2019). Consequently, to have a nuanced understanding of the effects of

entrepreneurship education, its relationship to entrepreneurial self-efficacy was also assessed in H₂.

6.5.2 Direct relationship between entrepreneurship education and entrepreneurial self-efficacy

Entrepreneurship education is acknowledged for its major influence in building entrepreneurial self-confidence through its varied methods of imparting entrepreneurial skills and knowledge. This interaction of human capital transformation and psychological development made it a crucial relationship to examine for raising entrepreneurial intentions and examining research objective two. Therefore, to further understand the dynamics this study aimed to test the following hypothesis:

H₂: Entrepreneurship education positively and significantly influences entrepreneurial self-efficacy.

The results provided robust support for H₂ ($\beta = 0.488$, $t = 10.227$, $p\text{-value} < 0.000$), confirming that entrepreneurship education does have a significant positive effect on entrepreneurial self-efficacy. The high beta coefficient indicated that this was one of the strongest relationships of the conceptual model. This finding aligned with results from previous studies, which posited entrepreneurship education as a key conduit for developing entrepreneurial self-confidence, making entrepreneurial self-efficacy a critical outcome for entrepreneurship education (Amani et al., 2024; Chen et al., 1998; Jiatong et al., 2021; Newman et al., 2019).

The findings align with the principles of the social cognitive theory which suggests that self-efficacy is developed through learning and experiences (Chen et al., 1998; Zhao et al., 2005). As previously mentioned, entrepreneurial self-efficacy is an entrepreneurship occupation specific self-efficacy, thus it is not surprising that entrepreneurship education would positively affect entrepreneurial self-efficacy development, given the structured learning environment and opportunities for skills development that education offers (X. Wang et al., 2023). Moreover, the varying education methods help to cement knowledge and skills in the different aspects of entrepreneurship (for instance, opportunity identification, market development, funding evaluation etc.), enabling individuals to develop wider confidence and perceived ability, which are core attributes of entrepreneurial self-efficacy (Chaker & Dellagi, 2023; Chaker & Jarraya, 2021).

In addition, the strength of the relationship in the South African context shows the effectiveness of entrepreneurship educational interventions in creating entrepreneurial

self-confidence among a population often characterised by high economic uncertainty, and necessity driven entrepreneurship (Neneh, 2022). The ability for entrepreneurship education to create environments for mastery experiences which can be provided through practical activities, simulations, reflections and structured theoretical learning opportunities develops a strong attribute of self-efficacy (Chaker & Jarraya, 2021; Onjewu et al., 2021). Furthermore, opportunities for vicarious learning from guest speakers, experienced lecturers, case studies and mentorship opportunities is another self-efficacy development pathway that is offered by structured entrepreneurship education, which supports the findings of this study (Newman et al., 2019; X. Wang et al., 2023).

Moreover, the social persuasion that is facilitated by positive feedback and encouragement from educators and peers helps to develop entrepreneurial confidence, which is another attribute of self-efficacy (Zhao et al., 2005; X. Wang et al., 2023). Likewise, negative feedback from the education environment, however, could also reduce the self-confidence ultimately resulting in lower entrepreneurial intentions (Howell, 2021; Nabi et al., 2018). Nevertheless, the structured education environment enables students to develop all the attributes of entrepreneurial self-efficacy development including affective awareness to deal with real-world entrepreneurial pressures.

The significant relationship between entrepreneurship education and entrepreneurial self-efficacy provides justification for structuring pedagogical approaches towards high impact methods that combine the best of practical and theoretical orientated learning programmes. The results of H₂ confirmed the necessity of entrepreneurship education as an efficacy building platform that provides the perceived control essential for students to transition into entrepreneurial intention and action (Ajzen 1991, 2020). As such, the strength of H₂ and H₃ (discussed in section below) highlights the need to focus on teaching methods that instil high self-confidence necessary to behave entrepreneurially.

6.5.3 *Direct relationship between entrepreneurial self-efficacy and entrepreneurial intention*

Aligned with research objective three, the study examined the relationship between entrepreneurial self-efficacy and entrepreneurial intention to understand the psychological linkage within the theoretical model, representing the manifestation of perceived behavioural control on the intention to engage in entrepreneurial action (Ajzen, 2020; Hagger et al., 2022).

H₃ Entrepreneurial self-efficacy positively and significantly influences entrepreneurial intention

The results revealed very strong evidence supporting H₃ ($\beta = 0.676$, $t = 14.721$, p -value < 0.000), with this relationship showing the highest beta coefficient and the highest f^2 effect size (0.509) in the entire structural model. This suggested that the removal of entrepreneurial self-efficacy would have a significant impact on entrepreneurial intention. These results were consistent with prior research from Amani et al (2024), Taneja et al (2024), Newman et al (2019) and X. Wang et al (2023); which repeatedly identified self-efficacy as an important predictor of intention. Amani et al (2024) in their study revealed that the entrepreneurial environment moderated the positive relationship between entrepreneurial self-efficacy and entrepreneurial intention. This confirmed entrepreneurial self-efficacy's role as the operational component of perceived behavioural control, and a key construct of three antecedents that form intentions (Krueger & Carsrud, 1993). It is the perceived control that enables the formation of intentions because students with high entrepreneurial self-efficacy perceive entrepreneurial tasks as attainable and more feasible leading to greater commitment to act entrepreneurially (X. Wang et al., 2023).

Despite this study's lack of focus on the other two antecedents of intention, being social norms and attitudes towards behaviour, Hagger and Hamilton (2024) found perceived behavioural control to be most stable and influential over longer periods of time. The high beta coefficient in the current study, supports the influential significance of perceived behavioural control in intention formation. As such, the relationship between entrepreneurial self-efficacy and intention is expected to remain the most consistent, thus resources channelled towards developing self-efficacy are likely to yield greater results in entrepreneurial intention (Chen et al., 1998; Newman et al., 2019; X. Wang et al., 2023). With the challenging economic environment in the South African context that is characterised by high unemployment, the resolve to persist through inevitable challenges may largely be dependent on the individual's belief in their own abilities to successfully navigate the entrepreneurial environment (Neneh, 2022).

Though other barriers to entrepreneurial intention formation exist, such as social support, personal fit and gender inequalities (Hsu et al., 2019; Neneh, 2022; Vu et al., 2025), the strength of this relationship based on the current study's results, posits that internal self-belief is powerful enough to overcome perceived external constraints for this student sample. If the student's entrepreneurial self-efficacy is high enough, their

intentions may be strong enough, and they could withstand the negative societal factors or low social support mentioned by Neneh (2022). If the entrepreneurship education programmes are structured to develop entrepreneurial self-efficacy by exposing students to various entrepreneurial challenges that build not only their human capital assets, but also their self-beliefs, they would be contributing to bridge the intention to behaviour gap that leads to business creation (Roos & Botha, 2022).

6.5.4 Mediating role of entrepreneurial self-efficacy on entrepreneurship education and entrepreneurial intention

As suggested above, the link between entrepreneurship education and entrepreneurial intention is critical to strengthen, and this can be achieved through the mediating role of entrepreneurial self-efficacy (Nowiński et al., 2019). Despite the strong correlation results (0.43) between entrepreneurship education and entrepreneurial intention as shown in Table 9 and the strong direct relationship in H_1 , this relationship has been shown to falter when entrepreneurial self-efficacy is included, which aligned with research objective four, necessitated a closer examination of this phenomenon leading to the following hypothesis:

H₄ Entrepreneurial self-efficacy significantly mediates the relationship between entrepreneurship education and intention

The results showed support for H_4 ($\beta = 0.292$, $t = 7.084$, $p\text{-value} < 0.000$) revealing a significant indirect effect of entrepreneurship education on entrepreneurial intention via entrepreneurial self-efficacy. The total effect results ($\beta = 0.374$, $t = 5.450$, $p < 0.000$), which exclude the effects of mediating variables of the study, did show a statistically significant relationship between entrepreneurship education and entrepreneurial intention aligned with H_1 . However, following the inclusion of the mediator, the direct results of the relationship between entrepreneurship education and entrepreneurial intention became statistically insignificant, implying the benefits of entrepreneurship education were completely transposed through entrepreneurial self-efficacy (X. Wang et al., 2023). The findings aligned with X. Wang et al. (2023), who also found full mediation by entrepreneurial self-efficacy in the relationship between entrepreneurship education and entrepreneurial intention. This implied that the higher the entrepreneurial self-efficacy in students, the higher their confidence to start entrepreneurial ventures. The full structural model was able to convey the true interactions of the hypothesised exogenous and endogenous relationships, thus enlightening scholars of the mechanisms through which the constructs interacted.

Studies have shown that entrepreneurial self-efficacy plays a mediating role in the relationship between entrepreneurship education and entrepreneurial self-efficacy; however, the extent of the mediation has ranged between partial and full mediation (Jiatong et al., 2021; Onjewu et al., 2021; X. Wang et al., 2023; Zhang & Chen, 2024). Similar to this study's results, X. Wang et al. (2023), L. Wu et al. (2022) and Zhao et al. (2025) also found that entrepreneurial self-efficacy fully mediated between entrepreneurship education and entrepreneurial self-efficacy. Aligned with these previous studies, the current results provide a potential explanation for the contradictory findings in prior studies regarding the direct relationship between entrepreneurship education and entrepreneurial intention (Oosterbeek et al., 2010). The human capital acquired through education (knowledge, skills, theory etc.) requires a psychological process to convert it into entrepreneurial commitment, intention and ultimately behaviour. By excluding mediating effects, previous studies (Oosterbeek et al., 2010) may have negated the opportunity of understanding how the relationship between entrepreneurship education and entrepreneurial intention manifested. Notably, this study's inclusion of a mediating variable provided a nuanced understanding of how entrepreneurship education impacts entrepreneurial intention, which according to the results is mainly indirect.

Entrepreneurial self-efficacy plays a crucial role transposing entrepreneurship education effect to entrepreneurial intention, thereby enhancing the impact of entrepreneurship education (Nowiński et al., 2019). This highlights the need to include perceived behavioural control (entrepreneurial self-efficacy) in behavioural intention models, as entrepreneurship education is most effective when enhancing students' internal locus of control rather than directly influencing intention itself (Ajzen, 2020; Hagger et al., 2022).

Studies that have found partial mediation such as Onjewu et al. (2021) as well as Zhang and Chen (2024), have used different scales to measure entrepreneurship education relative to this study. Furthermore, the study by Onjewu et al. (2021) delineated the different pedagogies of entrepreneurship education (simulation, workshops, courses and guest speakers) which may have led to different outcomes. Cui and Bell (2022), Debarliev et al. (2022) as well as Hägg and Gabrielsson (2020) suggest that different pedagogical approaches lead to different outcomes which made the standard objective measurement of entrepreneurship education challenging. Though the entrepreneurship education items for this study were found to be reliable (see Table 11), the differences

in study contexts, model complexity and different variables considered invariably results in different outcomes which will likely continue to be subject for future research.

6.5.5 Moderating role of GenAI (ChatGPT) on entrepreneurship education and entrepreneurial intention

The prominence of GenAI and its emerging use cases in the entrepreneurship and education landscapes has created a lot of research interest in how this technology is shaping our world (Chalmers et al., 2021; Obschonka & Audretsch, 2020; Sardi et al., 2025). In education, the technology has provided opportunities for personalised learning, boosting perceived confidence in complex problem solving and empowering students to control their self-learning (Ivanov et al., 2024; Sardi et al., 2025; Taneja et al., 2024). These progressive qualities of the technology have led researchers to explore the impact it has on established relationships, including entrepreneurship education and intentions (Bell & Bell, 2023; Vecchiarini & Somià, 2023). Given the ubiquitousness of technology and the interest in research objective five and six, this study focussed on assessing the following hypotheses:

H₅: GenAI (ChatGPT) acceptance positively moderates the relationships between entrepreneurship education and entrepreneurial intention

The results did support H₅ as the interaction term was statistically significant ($\beta = 0.071$, $t = 2.076$ p -value < 0.019), though the effect size f^2 (0.017) was small. This finding indicated that a student's acceptance of GenAI significantly influenced the direct impact of entrepreneurship education on their intention to pursue entrepreneurship. The finding aligned to Vecchiarini and Somi (2023), Xie and Wang (2025) and Zulfiqar et al.'s (2025) optimistic views of GenAI's potential to infuse experiential learning and creativity into traditional entrepreneurship education. Vecchiarini and Somi (2023) reveal that ChatGPT has the potential to improve student efficiency, streamline processes and supporting creativity. ChatGPT provides students with useful insights on market research and competitor analysis, helping students develop their business model canvas. Figure 9 supports this finding, showing that the high use of ChatGPT in education, resulted in higher entrepreneurial intentions. Furthermore, Xie and Wang (2025) reveal that in a technology supportive University environment, GenAI integrated entrepreneurship education significantly improved the students' entrepreneurial self-efficacy and increased entrepreneurial intentions. As such, this study's findings support the transformative nature of GenAI (ChatGPT) to amplify entrepreneurship education's efficacy (Zulfiqar et al., 2025).

Furthermore, a high acceptance of a GenAI tool that is perceived as easy to use and useful, creates a more conducive environment for learning, therefore strengthening the relationship between entrepreneurship education input and behavioural output (Zaineldeen et al., 2020). This implies that the acceptance of GenAI (ChatGPT) within structured and deliberate integration into pedagogy is useful for entrepreneurial intentions (Kumar et al., 2025). Despite its significant influence on entrepreneurship education, the acceptance of the technology does not address the pedagogical challenges identified by Piperopoulos and Dimov (2015). If GenAI is used only for research or clarification of theoretical concepts in theory-based learning, it may not generate or help facilitate the psychological depth required to move from theoretical knowledge to intentional commitment (Bell & Bell, 2023; Yu & Guo, 2023). Instead, it should be leveraged to increase practical learning opportunities within traditional education (Bell & Bell, 2023).

In particular, the technology acceptance model posits that perceived usefulness (for instance, easier complex data analysis, faster business plan modelling etc.) should increase the intention to use the technology (Strzelecki, 2023). Though the use of GenAI (ChatGPT) can enhance the effects of entrepreneurship education, the most effective pathway to entrepreneurial intentions remains psychological through entrepreneurial self-efficacy (X. Wang et al., 2023; L. Wu et al., 2022; Zhao et al., 2025). In short, developing nations such as South Africa, while grappling with the imperative to adopt GenAI due to its low costs and high benefits (Dept Com & Digital Tech, 2024), should not only focus on wide acceptance, but also focus on structured and intentional integration to strengthen the link of entrepreneurship education, entrepreneurial self-efficacy and entrepreneurial intention (Redondo-Rodríguez et al., 2024; Vecchiarini & Somià, 2023).

6.5.6 Moderating role of GenAI (ChatGPT) on entrepreneurial self-efficacy and entrepreneurial intention

H₆: GenAI (ChatGPT) acceptance positively moderates the relationships between entrepreneurial self-efficacy and entrepreneurial intention

The results showed a statistically significant moderating effect ($\beta = -0.132$, $t = 2.028$, p -value < 0.021) with a small effect size f^2 of 0.020, however, the beta coefficient was negative, directly contrasting the hypothesised positive effect. Therefore, the significant negative moderation led to a rejection of H₆. Moreover, the BCa bias confidence interval of these results confirmed the significance of the negative moderating effect (see Table

16) (Hair et al., 2019a). Given the strong and significant direct and indirect relationship between entrepreneurial self-efficacy and entrepreneurial intention, the results opposed existing findings by Duong et al. (2024), who found that ChatGPT adoption significantly increased perceived AI capabilities and digital entrepreneurial self-efficacy, which in turn had a positive influence on entrepreneurial intentions. Moreover, Zulfiqar et al. (2025) also confirm that AI tools serve as effective and dynamic educational tools that shape students' entrepreneurial attitudes and intentions.

The findings of this study, however, presented a theoretically challenging outcome which implied that the wide acceptance of GenAI (ChatGPT) tools may erode the psychological determination of capable students. As depicted in Figure 10, the negative moderation implied that a high acceptance of GenAI (ChatGPT) dampened the significant effect of entrepreneurial self-efficacy on entrepreneurial intention. Nevertheless, these unexpected results may be argued through the lenses of the dependency and the paradoxical effect of GenAI posited by Zhai et al. (2024), and Zhang and Xu (2025) respectively. These studies proposed that the frequent use of GenAI enhanced student's perceived self-confidence and efficiency, which in turn led to more trust in the AI, simultaneously increasing their dependence on the technology (known as the dependency effect) (Zhai et al., 2024). The short-term benefits of the learning efficiency may carry long-term consequences of potentially undermining the students own cognitive abilities, weakening their internal locus of control and reducing their agency (known as the paradoxical effect) (Zhang & Xu, 2025). The process of acquiring knowledge and skills requires students to actively engage in inquiry and cognitive struggle as they build their internal locus of control (Bell & Bell, 2023). Engaging GenAI can short circuit this fundamental learning process by making solutions easily accessible with minimal effort from the student, thus reducing the impact of education and stalling the development of self-efficacy (Zhai et al., 2024). This diminished confidence in one's independent skills and abilities (entrepreneurial self-efficacy) counters the self-confidence that may have been developed by entrepreneurial education or other experiences, thus, reducing intentions and behaviours. With the continual reduction of self-efficacy, this may lead students to rely even more on the technological tools eroding their initiative to think critically, creatively and independently (Al-kfairy et al., 2024; Zhai et al., 2024).

Moreover, the above average use of GenAI (ChatGPT) in the student sample ($M = 5.48$, $SD = 1.666$), may be indicative of potential dependency issues which resulted in the

negative moderation effect. The findings of this study suggested that the integration of transformative tools such as GenAI within the entrepreneurial education, need to be balanced with the requirements of developing critical and analytical skills in students which are crucial for entrepreneurial decision-making. Entrepreneurship is inherently filled with uncertainty; thus, students need to have confidence in their own skills to assess and comprehend vast information in a critical manner that enables them to make reasonable decisions. While GenAI can be useful to assist students with entrepreneurial tasks, the technology integration should be structured to amplify students' cognitive capabilities and to regulate patterns that may lead to dependency and overreliance (Zhang & Xu, 2025; Zhong et al., 2024). To achieve this, GenAI integration may need to be structured for specific tasks (for example, business plan writing, market research and data analysis) where students can still demonstrate how they've applied their critical judgment to outputs from the tool, thus balancing the need for efficiency and attributing success to student's judgment and decision making (Sardi et al., 2025).

6.6 Final research model

The final research model presented in Figure 12 shows the empirical conclusions of the study. The model validates the psychological framework of the theory of planned behaviour and demonstrates the utility of the technology adoption model in explaining entrepreneurial intentions and ChatGPT acceptance (Hagger & Hamilton, 2024; Zulfiqar et al., 2025). The model highlights the contextual (entrepreneurship education), and psychological nature (entrepreneurial self-efficacy) of entrepreneurial intention. The findings indicated that the direct relationship between entrepreneurship education and entrepreneurial intention was fully mediated by entrepreneurial self-efficacy (L. Wu et al., 2022). Furthermore, the relationship between entrepreneurial self-efficacy and entrepreneurial intention relationship may be vulnerable to the moderating influence of technology dependence (Zhang & Xu, 2025).

The final research model (Figure 12) has four constructs indicating the significant direct relationships (solid green line), a weak direct relationship between the independent and dependent variable (red solid line), the mediating effect in the dashed blue curve line, and the moderating influence for ChatGPT (dark blue dashed line).

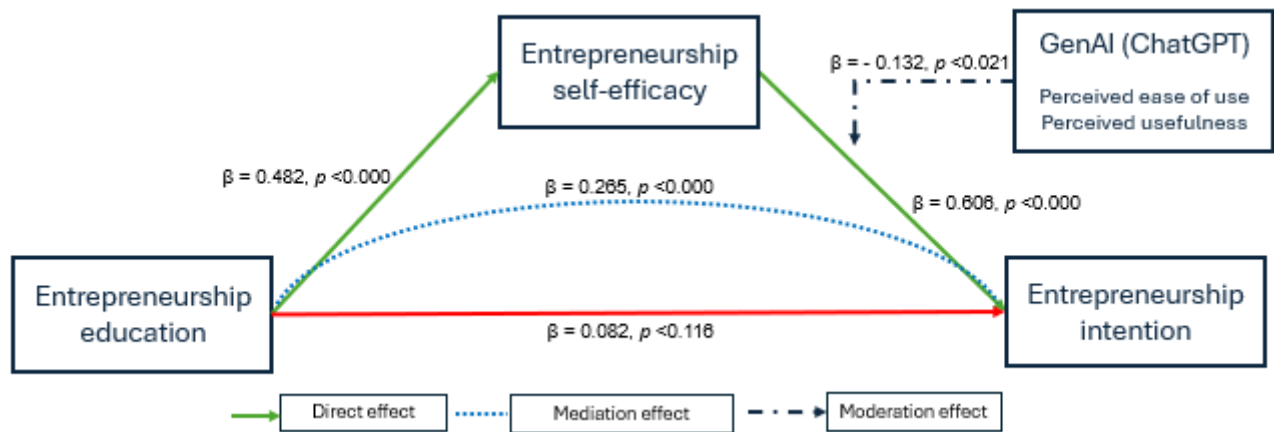


Figure 12: Final research model

Source: Authors own (2025)

The final model confirms the contextual nature of self-efficacy, whereby it is influenced by among other factors, entrepreneurship education. Entrepreneurship education equips students with skills, knowledge and mindsets that help students to form internal beliefs and confidence their entrepreneurial capabilities (Duong & Vu, 2025). The education environment also provides access to lecturers or educators who can foster self-efficacy development through role modelling. The model supports that entrepreneurial education should be tailored not only to impart theoretical entrepreneurial knowledge but also to develop student's self-efficacy through practical exposure (Lyu et al., 2024; Taneja et al., 2024). Furthermore, the significant positive influence of entrepreneurial self-efficacy on entrepreneurial intention, supports that entrepreneurial self-efficacy, as a manifestation of perceived behavioural control, has a significant effect on entrepreneurial intentions, which validates the theory of planned behaviour. Thus, it becomes imperative to manage negative influences that can dampen entrepreneurial self-efficacy. It thus follows that the paradoxical effect from the rampant use of GenAI needs to be controlled and the technology must be ethically integrated into entrepreneurship education to ensure GenAI enables students and does not detract from self-belief.

Given the prominence of GenAI and its rising utility, the students cannot avoid being exposed to transformative technology given that people live in an increasingly digital world with human-AI collaboration (Kumar et al., 2025). However, students need to be guided on the ethical concerns of GenAI (for instance, AI hallucinations, algorithmic biases, plagiarism and privacy concerns) and educated on the risks of abdicating their critical thinking to GenAI, which though may provide short-term benefits of efficiency,

may result in long-term consequences of dependence (Al-kfairy et al., 2024; Zhai et al., 2024). Moreover, the underrepresentation of developing nations contextual data in the AI large language model training dataset, implies that the outputs of the GenAI tools can be biased against developing nations issues (Kajiita & Kang'ethe, 2025; Zhai et al., 2024). As potential entrepreneurs, students need to be able to develop contextually relevant ventures if they want to be impactful, thus healthy scepticism of GenAI outputs is more required for developing contexts such as South Africa (Unesco, 2025). Thus, education institutions have a vital role in integrating GenAI and providing AI literacy in an ethical and responsible manner that empowers students to retain their contextual relevance and internal locus of control (Zhai et al., 2024).

6.7 Conclusion

This chapter focused on the discussion of the study's empirical results, which supported the fundamental psychological principles of the theory of planned behaviour and confirmed the relevance of the technology acceptance model as posited in the literature. Furthermore, the discussion detailed the linkages between human capital transformation (entrepreneurship education) and psychological development (entrepreneurial self-efficacy) which highly influence the development of entrepreneurial intentions. Despite the high acceptance of GenAI (ChatGPT), the simple use of the tool could not amplify insignificant relationships. In fact, it's over reliance could result in unintended consequences of paradoxical dependence. This highlighted the need for careful integration of the powerful technology, ensuring it is used to boost psychological capital, and not to erode it.

The next chapter focuses on summarising the theoretical and practical implications of this study's findings, concluding on how educational institutions and policymakers can use the outcomes of this study to improve the efficacy of education to indirectly influence entrepreneurial intentions in the South African context.

CHAPTER 7: CONCLUSION

7.1 Introduction

Confounded by the high levels of unemployment, in particular youth unemployment in South Africa, the current research sought to aid in the resolution of this challenge by contributing to research that could increase the level of entrepreneurial activity in the country (Meyer et al., 2022). Despite being one of the most advanced countries on the African continent, South Africa is punching below its weight, with a minimal GDP growth rate and an increasing unemployment crisis (Munyati, 2024; Statistics South Africa, 2025). The level of entrepreneurial intentions which is a precursor to entrepreneurial behaviour, remains below continental averages despite having some of the most advanced entrepreneurship environments on the continent (GEM, 2023). The advent of artificial intelligence provides the opportunity to leapfrog the economic development of the country and the continent (Unesco, 2025). As such, the research aimed to interrogate the relationship between entrepreneurship education and entrepreneurial intention as mediated by entrepreneurial self-efficacy and moderated by GenAI (ChatGPT).

The study employed a quantitative, cross-sectional design using PLS-SEM. The current study reviewed the scholarly discourse regarding the key constructs to identify six hypotheses in Chapter Three that were tested to interrogate the research objectives outlined in Chapter One. The study used an integration of the theory of planned behaviour and the technology acceptance model to interpret the findings of the study which were presented in Chapter Five and discussed in detail in Chapter Six. This chapter provides a synthesis of the outcomes of this research study, outlining a summary of the key findings and the theoretical and practical implications for stakeholders. Furthermore, it highlights the limitations of the current study and identifies opportunities for future research, ending this chapter with closing remarks.

7.2 Major Findings

The study drew on the work of Moberg et al. (2014), Liñán and Chen (2009) as well as Zaineldeen et al. (2020) to empirically measure and assess the relationships between entrepreneurship education, entrepreneurial intention, entrepreneurial self-efficacy and GenAI (ChatGPT) acceptance. AI, and in particular GenAI, is impacting all industries including, education and is offering new opportunities to enhance learning and democratise access to education (Bell & Bell, 2023). It is offering opportunities to address the education access gap by increasing access to remote areas and improving

the efficacy of entrepreneurship education (PWC Education, 2023). This vital intersection of powerful technology and education was at the centre of the current research. The key findings of this research are summarised in sections below:

7.2.1 *Entrepreneurship education and entrepreneurial intention (H₁)*

Education has been acknowledged for its pertinent role in developing human capital that provides students with the requisite skills, knowledge and capabilities to participate meaningfully in society (Amani et al., 2024; Debarliev et al., 2022). Equally, entrepreneurship education is recognised for its contribution in developing entrepreneurial mindsets and attitudes in students to view entrepreneurship as a viable career option (Cui & Bell, 2022; Taneja et al., 2024). This current study aimed to evaluate the relationship between entrepreneurship education and entrepreneurial intention. Within the current study, the researcher found a significant direct relationship between the constructs. The findings implied that entrepreneurship education imparted entrepreneurial skills, knowledge, and attitudes that developed cognitive and psychological capital that fostered intentions for entrepreneurship and ultimately commitment to entrepreneurial behaviour (Bae et al., 2014). Furthermore, the outcomes of entrepreneurship education were subject to nuanced interaction of inputs such as contexts, pedagogies, educational environmental factors and educator skills (Lyu et al., 2024; Martínez-Gregorio et al., 2021; Nabi et al., 2017; Shirokova et al., 2016). Thus, to achieve positive effects on entrepreneurial intention, educational outcomes must be directed to develop psychological capital, such as self-efficacy, expanding education's value beyond knowledge transfer, but also to entrepreneurial self-efficacy and entrepreneurial intention intervention (Nowiński et al., 2019; X. Wang et al., 2023).

7.2.2 *Entrepreneurship education and entrepreneurial self-efficacy (H₂)*

The outcome of the interrogations in the current study supported the relationship between entrepreneurship education and entrepreneurial self-efficacy, implying that education does indeed develop the psychological capital for entrepreneurship (Amani et al., 2024; Chen et al., 1998; Jiatong et al., 2021). The educational environment, although not the only source for entrepreneurial self-efficacy development, can accelerate its development by creating learning opportunities that simultaneously ignite the four pathways of self-efficacy development (mastery, vicarious learning, social persuasion, and emotional regulation) (X. Wang et al., 2023; Zhao et al., 2005). Leveraging technology, entrepreneurship educational courses can be specifically designed and tailored to shorten the time and amplify the development of

entrepreneurial self-efficacy to maximise its effects on entrepreneurial intention and behaviours (Duong et al., 2024; Duong & Vu, 2025).

7.2.3 Entrepreneurship education and entrepreneurial intention (H_3)

The most significant relationship in the model with the highest effect size was established between entrepreneurial self-efficacy and entrepreneurial intention. This relationship provided theoretical evidence for the key role of entrepreneurial self-efficacy (manifested as perceived behavioural control) as an antecedent for entrepreneurial intentions (Ajzen, 1991b; Kufaine, 2024). The robust strength of the relationship showed that if the student's entrepreneurial self-efficacy is high enough, they can develop strong enough intentions that sustain long-term commitments to behaviour (Hagger & Hamilton, 2024). Thus, focussing on the antecedents of entrepreneurial self-efficacy and exposing students to varying opportunities to enhance their internal locus of control and agency is vital to amplify entrepreneurial intentions (Chen et al., 1998; Newman et al., 2019).

7.2.4 Mediating effect (H_4)

The mediating effect of entrepreneurial self-efficacy on the relationship between entrepreneurship education and entrepreneurial intention was supported, showing that entrepreneurial self-efficacy fully mediated the effect of entrepreneurship education on entrepreneurial intentions (X. Wang et al., 2023; Zhao et al., 2005). Entrepreneurship education's knowledge transfer of the skills required for new venture creation (for instance, opportunity recognition, business plan development, business evaluation, reflection, marketing and idea pitching to funders) enables students to develop self-belief and confidence in their abilities to behave entrepreneurially (Nowiński et al., 2019; Onjewu et al., 2021). This psychological development of self-belief is the very mechanism that drives entrepreneurial intentions. Thus, the full mediation relationship emphasises that educational programmes that are structured to develop entrepreneurial self-efficacy, through sharpening students' awareness about the pros and cons of entrepreneurship, may amplify entrepreneurial outcomes (Roos & Botha, 2022).

7.2.5 Moderating effect (H_5 and H_6)

The impact of GenAI (ChatGPT) in entrepreneurship education was examined through a moderation analysis. It was included to test if the acceptance of technology that was perceived as easy to use and useful would interfere with the strength or the direction of existing mediation and direct relationship between entrepreneurship education and

entrepreneurial intentions. The results showed that ChatGPT negatively interferes with the relationship between entrepreneurial self-efficacy and entrepreneurial intentions. Although the effect size of the interference was low, its statistical significance indicates the existence of a secondary psychological consequence of rampant GenAI (ChatGPT) acceptance and adoption, indicative of a dependency effect (Zhai et al., 2024). The current findings demonstrate that, while powerful technology such as ChatGPT can boost student efficiency and comprehension of complex entrepreneurial tasks, it must be delicately balanced with the need to develop students' internal confidence (hang & Xu, 2025). Students externalising their agency to technology, risked eroding psychological capital and, ultimately, entrepreneurial intentions. The findings emphasised that GenAI integration within education must be designed to facilitate maximum ownership of students' cognitive capabilities, positioning ChatGPT as an enabler and not a substitute for self-belief.

7.3 Theoretical implications

This study significantly contributes to the calls for more research on the impact of GenAI engagement in entrepreneurship education, particularly in developing countries' contexts (Duong & Vu, 2025; Nguyen & Nguyen, 2024; Shepherd et al., 2025; Uriarte et al., 2025; Zulfiqar et al., 2025). The study contributes to entrepreneurial research, especially regarding the role of entrepreneurial self-efficacy as a significant mediating factor between entrepreneurship education and entrepreneurial intention (X. Wang et al., 2023; L. Wu et al., 2022; Zhao et al., 2025). The finding of full mediation provides empirical evidence that corroborates the debate regarding the direct link between entrepreneurship education and entrepreneurial intentions (Debarliev et al., 2022; Oosterbeek et al., 2010; Piperopoulos & Dimov, 2015). This study showed that entrepreneurship education's value is non-linear; it must successfully convert human capital assets into psychological capital (entrepreneurial self-efficacy) before any measurable impact on intention can occur (Nowiński et al., 2019). This validated the theory of planned behaviour's emphasis on perceived behavioural control as the necessary and stable psychological precursor for entrepreneurial intentions (Hagger & Hamilton, 2024). This established entrepreneurial self-efficacy as the non-negotiable step in the formation of entrepreneurial intention.

Furthermore, the study contributes to the value of integrating the theory of planned behaviour with the technology acceptance model to evaluate the behavioural and psychological interactions of GenAI acceptance and adoption (Zulfiqar et al., 2025). The

finding of the significant negative moderation is a significant theoretical contribution of this study. It empirically highlights that while the technology acceptance model accurately predicted GenAI (ChatGPT) acceptance due to perceived usefulness and ease of use, this market success generates a secondary psychological consequence (Davis, 1989; Zhang & Xu, 2025).

The high use of GenAI may lead to dependence and an unintended subsequent erosion of the internal attribution of competence (Zhang & Xu, 2025). Moreover, GenAI's inclusion in entrepreneurship education, may reduce education's effects on entrepreneurial intention if the moderation effects are not taken into account in the pedagogical design of entrepreneurship education programmes. Furthermore, the moderation results contribute to the emerging AI dependency literature, demonstrating that overreliance on GenAI tools may undermine the individual's sense of locus of control, weakening their determination to act independently, thus weakening entrepreneurial intentions and ultimately entrepreneurial behaviours (Al-kfairy et al., 2024; Sardi et al., 2025; Zhai et al., 2024; Zhang & Xu, 2025)

7.4 Practical Implications

7.4.1 Educational institutions

The study revealed several practical implications for education institutions and educators. Firstly, the findings provided empirical evidence of the important role education institutions play in not only knowledge and skills development, but also in the development of student's self-confidence in their abilities to act on their acquired knowledge. The findings can empower institutions to design educational programmes that enable both knowledge acquisition and practical application to develop the psychological capital that students require enact behaviour. Secondly, AI and GenAI are tools that can be leveraged by educational institutions to provide a holistic learning experience that achieves both human and psychological capital development (Dwivedi, 2025; Zulfiqar et al., 2025). The literature showed that integrating GenAI tools can assist to educators to foster entrepreneurial mindsets by providing real-world settings whereby students can have hands-on learning opportunities to generate business ideas, business plan writing, market research, product development, marketing strategies, risk assessments and scenario planning (Ahmed et al., 2020). As such, educational institutions should aim to provide GenAI tailored learning programmes that emphasise the practical competencies of entrepreneurial tasks, coupled with critical-based AI literacy training to educate students on how to ethically use GenAI tools for their

personalised learning and development (Zhang et al., 2025). Providing awareness about the powerful potential and shortcomings of GenAI tools will enable students to be aware of the risks of dependency and overreliance on the technology.

Thirdly, based on the negative moderation that was noted, education institutions can structure critical thinking-based GenAI integrated learning opportunities that aim to maximise students' exposure to both the advantages and disadvantages of entrepreneurship in a risk-free environment that encourages students to develop themselves according to their specific gaps (Zulfiqar et al., 2025). Educational institutions can design guidelines that guide students on how to interact with GenAI technology in a manner that enhances decision making, analysis and critical thinking (Zhai et al., 2024). Moreover, the educational institutions can also develop deliberate and structured pedagogical approaches for integrating GenAI in a manner that reduces the dependency risks and enhances self-efficacy, for instance using micro-credentials. Using micro-learning, enables students to develop critical skills on a cumulative basis which enables personal mastery at each phase even if GenAI is used. Such education pedagogies could ensure that students use GenAI to augment and not replace their own critical thinking. This implies that students could have stronger attribution for their internal competence, growing in confidence as an ongoing process and not only at the end of the education programme. These approaches may better align with a tailored development of self-efficacy, giving students ample opportunities for mastery, vicarious learning and emotional regulation development in simulated environments. The adoption of such strategies would enable educators to not only modernise education using the best technology but, also preserve some of the vital requirements for entrepreneurial intention formation, which is self-efficacy.

7.4.2 Government

The study's findings have important implications for government entities and policymakers regarding the implementation of AI. As South Africa develops its National AI policy, the current AI framework outlines the intentions of using AI and digital technology to promote economic growth and enhance societal goals, while positioning South Africa as a leader in AI innovation (Dept Com & Digital Tech, 2024). To achieve these objectives, government and policymakers should consider the results of this study by focusing on AI integration into entrepreneurship education that demonstrates effectiveness in raising entrepreneurial self-efficacy rather than just knowledge transfer. Channelling AI resources into high impact experiential learning models that foster

entrepreneurial skills, mindsets and entrepreneurial self-confidence will lead to higher entrepreneurial intentions which may contribute to the economic growth and higher societal impacts (Duong et al., 2024).

While internet penetration is high in South Africa (78.9%), only 15% of the population have basic ICT skills and 5% have advanced skills; thus, policy interventions need to be instituted that require education institutions to provide AI literacy for all students from primary to higher education (McInnes, 2025; Unesco, 2025). Furthermore, an increase in ICT skills will aid in achievement of the 2004 White paper on e-Education and the 2020 National Digital and Future Skills Strategy objectives of a wide adoption of digital literacy and fluency. Furthermore, government will need to invest in digital network infrastructure to reduce the structural inequalities that marginalise rural populations from digital benefits (Kajiita & Kang'ethe, 2025). Specifically, a focus on improving digital infrastructures of schools will help drive the objective of positioning South Africa as an AI leader.

7.4.3 Education students

The findings of the study had interesting implications for students who have embraced the use of GenAI tools. Students can use the findings of negative moderation to caution the risks of an overreliance on technology. Technology is a tool meant to serve humanity, and not where humanity gives up its ingenuity to serve technology. Students need to recognise the value of technology for what it truly is, which is just an enabler that can make them more efficient and effective (Zhang & Xu, 2025). Students are ultimately responsible for their own self-development and growth; thus, they should use the technology to amplify their strengths and improve their weaknesses. Using the technology to improve their quality of writing, their data processing skills and synthesis of wide information sources can sharpen critical skills and increase confidence (Zhai et al., 2024). This self-confidence and belief are what will enable them to preserve and achieve what their intentions steer them towards.

7.5 Limitations of the research

Further to the limitations included in Chapter Four, the study poses certain limitations which may be addressed in future research. The research was focused on the South African context which may limit its applicability to other developing nations with different social and cultural contexts. Further, in assessing the dependent variable, this study measured entrepreneurship education as a homogenous composite construct without

distinguishing between different pedagogies (theoretical and practical) which may have yielded different effects in the model.

Another limitation was the study's focus on assessing only perceived behavioural control (entrepreneurial self-efficacy) as an antecedent of entrepreneurial intentions, without considering social norms and attitude towards behaviour as the other influencing factors of entrepreneurial intentions as postulated by the theory of planned behaviour. Extending this study's SEM model to include the other intention antecedent may yield different effects.

Lastly, the study only focussed on three variables that may affect entrepreneurial intentions; however, other entrepreneurial environmental factors such as funding, economic growth, and policy environment may influence entrepreneurial intentions despite entrepreneurship education, entrepreneurial self-efficacy and regulated GenAI use being in place. Thus, expanding the model by considering other moderating or mediating factors may yield different results.

7.6 Future research directions

Given the dynamic nature of GenAI technology development and a dearth of research on the impact of other prominent GenAI tools such as Gemini, Co-pilot etc., this study can be replicated in a comparative study which assesses how different GenAI tools moderate the relationship between this study's key constructs. Furthermore, the paradoxical outcome of this study challenges researchers to move beyond GenAI technology adoption and toward examining the psychological costs of technology integration. Future research can focus on interrogating the types of secondary impacts that emanate from the long-term use or multiple use of GenAI tools on student's or individual's internal locus of control. This research would enable scholars to understand the safe and ethical use of the technology given its growing importance and use in developing nations.

Future studies may also benefit from longitudinal studies, to test the if moderation and mediation effects hold over longer periods of time. This would enable scholars to capture the long-term psychological effects of entrepreneurship education on entrepreneurial intention as mediated by entrepreneurial self-efficacy and provide a more definitive perspective on the interaction of behaviour and psychology. Lastly, with the continuous integration of AI in entrepreneurship, future research could examine the

potential moderating or mediating role of GenAI engagement beyond entrepreneurial intention and expand it to entrepreneurial behaviour.

7.7 Conclusions

In closing, this study provides crucial insights into the role which entrepreneurship education fulfils in fostering entrepreneurial intentions through entrepreneurial self-efficacy, with the cautionary moderating effects of GenAI (ChatGPT) acceptance. The findings of the study provide the empirical evidence for educational institutions, governments and policymakers to prioritise resources in the development of entrepreneurship education programmes that emphasise skills, mindsets and self-efficacy development ensuring students are well equipped to form strong entrepreneurial intentions.

As South Africa aims to achieve wider adoption of AI technology to foster economic and social development, this study offers valuable insights into the psychological balance that needs to be considered as AI is broadly integrated into learning institutions. The study advocates for the adoption of transformative technology as an enabler that amplifies students' innate abilities and not dampen them through overreliance, by encouraging students to use GenAI tools critically and ethically. Lastly, the integration of the theory of planned behaviour and the technology adoption model contributed to a balanced interrogation of the behavioural and psychological factors that needed to be bolstered to promote higher entrepreneurial intentions that ultimately inspire entrepreneurial behaviours that contribute to the reduction in unemployment.

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APPENDICES

APPENDIX A: ONLINE SURVEY QUESTIONNAIRE

Section A: Demographics									
1	Are you currently a student enrolled in a public or private higher education institution in South Africa	Yes	No						
2	Do you know what is ChatGPT (Gen AI)?	No, I don't know ChatGPT or other generative AI platforms	Yes, I do know ChatGPT but have not used it	Yes, I do know ChatGPT, but have used similar generative AI platforms	Yes, I have used ChatGPT or similar generative AI platforms				
3	Age	<20 years	20-24 years	25 - 35 years	36 -46 years	47 -58 years	58 years <		
4	Gender	Male	Female	Prefer not to say					
5	What is the name of your higher learning institution (HEI)?	Drop downlist with 26 preloaded public university's and other category for private HEI							
6	What type of educational programme are you enrolled in today?	Drop downlist with prepopulated main faculties (Natural sciences, Law, Accounting, Humanities, Engineering, Health etc)							
7	What is your highest level of education	< NQF4	NQF4	NQF5	NQF6	NQF7	NQF8	NQF9	NQF10
8	Is there anyone close to you who is an entrepreneur or self-employed?	Parent	Sibling	Spouse/partner	Other relatives	Friends	Colleagues		
9	Are you currently an entrepreneur or self-employed?	Yes	No	Other (specify)					
10	Are you participating in or did you previously participate in entrepreneurship, business management/ business management studies and/or entrepreneurship course	Yes	No						
11	Do you have any entrepreneurship experience from current or previous business attempts?	Yes	No						

Section B: Entrepreneurship Education (EE)								
	Very Strongly Disagree	Strongly Disagree	Disagree	Neither Disagree	Agree	Strongly Agree	Very Strongly Agree	
	1	2	3	4	5	6	7	
12	I see possibilities where others see problems							
13	When I try, I generally succeed							
14	I feel I can determine what happens in my life							
15	In general, starting a business is Disappointing							
16	In general, starting a business is Rewarding							
17	I understand the role entrepreneurs play in our society							
18	I understand That there are different reasons why people start business (e.g. social							
19	I understand that some business ideas work and others don't							

Section C: Entrepreneurship Self- Efficacy (ESE)								
	Very Strongly Disagree	Strongly Disagree	Disagree	Neither Disagree	Agree	Strongly Agree	Very Strongly Agree	
	1	2	3	4	5	6	7	
Section C-1: Perceived Behavioural control								
20	To start a business and keep it working would be easy for me							
21	I am prepared to start a viable business							
22	I can control the creation process of a new business							
23	I know the necessary practical details to start a business							
24	I know how to develop an entrepreneurial project							
25	If I tried to start a business, I would have a high probability of succeeding							

Section D: Entrepreneurship Intention (EI)								
		VeryStronglyDisagree	StronglyDisagree	Disagree	Neither Disagree	Agree	Strongly Agre	VeryStrongly Agree
		1	2	3	4	5	6	7
26	I am ready to do anything to be an entrepreneur ???????							
27	My professional goal is to become an entrepreneur ???????							
28	I will make every effort to start and run my own business ???????							
29	I am determined to create a business in the future ???????							
30	I have very seriously thought of starting a business ???????							
31	I have the firm intention to start a business some day							
Section E: Gen AI (Chat GPT) Engagement								
		VeryStronglyDisagree	StronglyDisagree	Disagree	Neither Disagree	Agree	Strongly Agre	VeryStrongly Agree
		1	2	3	4	5	6	7
Section E-1: Ease of use of ChatGPT (EOU)								
32	Learning to operate ChatGPT would be easy for me							
33	My interaction with ChatGPT would be clear and understandable							
34	It would be easy for me to become skilful at using ChatGPT							
35	I would find ChatGPT easy to use							
Section E-2: Usefulness of ChatGPT (UCGT)								
36	Using ChatGPT in my studies would enable me to accomplish tasks more quickly							
37	Using ChatGPT in my studies would increase my productivity							
38	Using ChatGPT would enhance my effectiveness in entrepreneurship education							
39	I would find ChatGPT useful in my entrepreneurship education							
		Never	Once a month	Several times a month	Once a week	Several times a week	Once a day	Several times a day
		1	2	3	4	5	6	7
40	I use ChatGPT frequently							

APPENDIX B: CROSS LOADINGS

Items	EE	EI	ESE	EOU	UCGT
EE1	0.733	0.370	0.488	0.450	0.410
EE2	0.620	0.130	0.276	0.325	0.211
EE5	0.663	0.348	0.317	0.228	0.233
EE6	0.829	0.332	0.412	0.533	0.409
EE7	0.761	0.176	0.194	0.548	0.370
EE8	0.669	0.140	0.138	0.451	0.297
EI1	0.314	0.862	0.679	0.181	0.316
EI2	0.294	0.900	0.605	0.122	0.327
EI3	0.362	0.939	0.611	0.236	0.370
EI4	0.375	0.906	0.547	0.247	0.320
EI5	0.421	0.915	0.606	0.275	0.345
EI6	0.394	0.923	0.597	0.248	0.327
ESE1	0.306	0.485	0.782	0.159	0.223
ESE2	0.382	0.689	0.840	0.231	0.392
ESE3	0.391	0.568	0.851	0.272	0.313
ESE4	0.475	0.544	0.840	0.314	0.350
ESE5	0.415	0.516	0.850	0.257	0.298
ESE6	0.391	0.474	0.753	0.221	0.230
EOU1	0.551	0.155	0.222	0.908	0.549
EOU2	0.545	0.254	0.317	0.931	0.622
EOU3	0.479	0.258	0.294	0.912	0.621
EOU4	0.549	0.143	0.199	0.856	0.610
UCGT1	0.453	0.208	0.223	0.699	0.823
UCGT2	0.466	0.288	0.335	0.652	0.866
UCGT3	0.367	0.335	0.324	0.577	0.899
UCGT4	0.402	0.385	0.392	0.564	0.929
UCGT5	0.418	0.399	0.385	0.554	0.913
UCGT6	0.270	0.100	0.078	0.429	0.655