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JOHANNESBURG

**Perception of mobile phone learning to improve grade 12
students' performance in high schools in South Africa.**

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SHORT DISSERTATION

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Declaration

I, Solomon Mahlangu, hereby declare that this research report for the (MBA) titled “Perception of mobile phone learning to improve grade 12 students’ performance in high schools in South Africa” submitted to the Faculty of Commerce, Law and Management at the University of Witwatersrand has not been submitted previously for any degree at this or another university. The study is original to design and execution, and all reference material contained therein has been duly acknowledged.

Signature:



Date: 04 September 2025

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Abstract

The purpose of the study was to investigate the perception of mobile phone learning to improve mathematics performance in grade 12 for high schools located in the Secunda area of Mpumalanga, South Africa.

This study employed quantitative research methodology. Data was collected from 170 purposively sampled participants from high schools in Secunda using survey questionnaires. Participants were accessed through email and WhatsApp to ensure maximum reach. The collected data was analysed using statistical data analysis software's like SPSS and AMOS to test the hypotheses and structural equation model.

The study findings revealed a significant correlation between perceived mobile phone learning and improved mathematics performance. The hypotheses regarding mobile learning adoption, usage of mobile learning, and internet accessibility were supported and significant. However, the hypothesis concerning learners' and educators' resistance was not supported. This indicates that students who interact with educational materials via mobile devices have the potential to achieve positive results in mathematics and academic excellence. In addition, the study highlighted various challenges faced by students, such as internet connectivity issues, digital literacy, and distractions, which may be associated with mobile phone use when learning. The findings underscore the importance of stakeholder collaboration in improving learning through the implementation of mobile learning techniques and the creation of curricula to create an atmosphere favourable for performance in mathematics.

This study provides critical information on how mobile learning can be used to improve outcomes in mathematics and other science-based subjects in an ever-changing digital landscape. A longitudinal study was recommended by the study on mobile learning and the importance of training teachers on mobile learning platforms to be effective and on how they can build atmosphere conducive for learning to improve outcomes.

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Keywords

Mobile learning, Mobile phone, High school learner, Mathematics performance, science, technology, engineering, mathematics (STEM), Basic education

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List of acronyms

ML - Mobile learning

SA - South Africa

STEM - Science, Technology, Engineering, and Mathematics

DBE - Department of Basic Education

NSC - National Schools Certificate

CHAPTER 1: INTRODUCTION

1.1 Statement of Purpose

The purpose of this study was to investigate the perceived impact of mobile learning as strategy for improving the academic performance of Grade 12 learners in the Secunda area of Mpumalanga province, South Africa.

1.2 Background of the Study

The National Senior certificate (NSC) is a major yard stick with which the performance of the education system is measured in South Africa. In 2024, the national pass rate for NSC examinations jumped from 82.9% in 2023 to 87.3%, marking the most significant year-on-year improvement over the preceding five years. Almost half of the students who took the NSC examinations received a bachelor's pass, and the class of 2024 achieved 319,651 distinctions. Physical science and mathematics, subjects which provide foundation pursuing career in the Information and Communication Technology (ICT) industry, show signs of slow growth. According to Malinga (2025), grade 12 learners who passed mathematics successfully in 2024 marginally rose from 63.5% in 2023 to 69.1%, while learners who passed physical science marginally fell from 76.2% in 2023 to 75.6% (South African Government News Agency (2025).

Although the improved pass rate has been followed by a substantial improvement in the outcomes of subjects such as Mathematics and Physical Sciences, this improvement is not equally spread around the country. Provinces such as Mpumalanga are perennial underperformers when it comes to Mathematics (School Hive, 2024). The poor outcome in Mathematics could be linked to the teaching of the subject (Onaolapo and Oyewole, 2015). It is therefore important to continuously assess methods that could be used to help improve the outcomes for the subjects such as mathematics and physical science in rural provinces such as Mpumalanga. Several studies have been conducted on grade 12 learner performance in critical areas like mathematics. However, these studies did not examine the impact of mobile learning on the performance of grade 12 mathematics learners in South African context. The aim of this study is therefore to investigate the impact of mobile learning on the academic performance of Grade 12 learners in the Secunda area of Mpumalanga province, South Africa.

1.3 Research Problem and Gap

Every country's development is underpinned by proficiency in Science, Technology, Engineering, and Mathematics (STEM) subjects. STEM subjects groom learners for participation in the technology-based economy by equipping them with relevant skills, knowledge, and attitudes (Vijayatheepan, 2023). STEM subjects promote logical inquiry, independent thinking, and objective evaluation among learners. However, South Africa continues to underperform its peers in global STEM subjects' assessments, and this is negatively impacting the availability of critical skills in several sectors, that are STEM subjects dependent (redAcademy, 2023).

Currently, grade 12 learners pursuing mathematics in the country's high schools are perennially underperforming. This is even worst for students coming from disadvantage background as non-performance in STEM subjects could leads to non-admission to higher education and limited access to better job opportunities in the future (Vijayatheepan, 2023).

Turbill (2015) has observed the progressive adoption of mobile learning in schools worldwide. This study posits that the poor performance of the students in STEM subjects could be mitigated by the introduction of information technology as a teaching tool. To that end, mobile learning (m-learning) can be seen as a pedagogical strategy that has the potential to enhance learner performance in mathematics (Fazlina et al. 2013 and Onalapo and Oyewole, 2015). The primary objective of this study is to investigate the impact of mobile learning on mathematics performance of grade 12 learners in the Secunda area of Mpumalanga province, South Africa

1.4. Research Objectives & Hypotheses

1.4.1 Primary objectives

The primary objective of this study is to investigate the impact of mobile learning on mathematics performance of grade 12 learners in the Secunda area of Mpumalanga province, South Africa.

1.4.2 Secondary Objectives (Empirical Objectives)

Specifically, this study aims to achieve the following objectives:

- i. Investigate influence of the adoption of a mobile learning approach influences Grade 12 learners' performance in high school.
- ii. Evaluate how mobile phone learning influences high performance in mathematics among grade 12 learners?
- iii. Assess the impact of limited internet accessibility on the adoption of mobile learning.
- iv. Assess the impact of educators' resistance on the adoption of mobile learning.

1.4.3 Research Questions

This study investigated the impact of mobile learning on the academic performance of Grade 12 students in Secunda, Mpumalanga, South Africa. The research questions for this study are.

- i. To what extent does the adoption of a mobile learning approach influence Grade 12 learners' performance in high school?
- ii. How does mobile learning contribute towards high performances in mathematics among grade 12 learners?
- iii. Assess the impact of limited internet accessibility on the adoption of mobile learning.
- iv. How does educators' resistance affect the adoption of mobile learning?

1.5 Research Hypothesis

This study tested the following alternative hypotheses:

- **H1:** *The adoption of a mobile learning approach improves Grade 12 learners' engagement and motivation while learning mathematics.*
- **H2:** *The use of mobile learning tools leads to high mathematics performances among Grade 12 learners.*
- **H3:** *Limited internet accessibility and educators' resistance constrains mobile learning adoption.*
- **H4:** *learners 'and educators' resistance towards mobile learning constrains their adoption of mobile learning for grade 12 students.*

1.6 Rationale/Significance

The study findings led to insights that increased understanding on the effectiveness of mobile learning as a pedagogical innovation aligned with the context of the 21st century digital landscape. This understanding can better position policymakers, educators, learners, and other stakeholders to successfully adopt and use mobile learning as a viable strategy for improving performance in grade 12 mathematics within the Secunda area and beyond. Additionally, these insights enriched the body of knowledge on the key role of mobile learning for 21st century classrooms.

1.7 Delimitations of the Study

This study was limited to Grade 12 students and educators in selected high schools located around Secunda in the Mpumalanga province of South Africa. Furthermore, the research only investigated the utilisation of mobile devices for learning and excluded other forms of teaching and learning technologies. As such, the findings of this study may not be fully generalisable to other regions or grade levels within the South African education system.

1.8 Assumptions

This study assumed that Grade 12 students had access to mobile devices and the necessary infrastructure (e.g., internet connectivity) to engage in mobile learning activities. It was also assumed that students were willing to adopt and use mobile learning technologies to support their academic endeavours.

1.9 Definition of Terms

The following definitions of terms were used in this study:

- **Mobile Learning (m-learning)-** Learning facilitated through mobile devices such as smartphones and tablets, enabling learning in diverse environments at any time (Crompton, 2013).
- **Grade 12 Learners-** Students in their final year of high school (Davis, 2013).
- **Academic Performance-** Measurement of student learning outcomes and success (Hattie, 2009).
- **E-Learning-** Education conducted via electronic media, typically on the Internet (Moore, et al., 2011).
- **Student Achievement-** Results of educational processes and outcomes achieved by students (Kuh, et al., 2006).

- **Pedagogical Innovation-** Development and application of new teaching methods, including the use of technology (Sawyer, 2006).

1.10 Research design Matrix (RDM)

Choguill (2005:616) asserted that the Research Design Matrix (RDM) is an instrument for structuring and managing studies. The research design delineates the researcher's objectives in the study by elucidating the link between the primary and secondary research purposes and the nature of the data to be collected. This provides the researcher with a comprehensive summary of the research proposal, describing the study objectives and anticipated outcomes (see Table 1.1 below).

Table 1. 1: Research design matrix

RQ #	State Research Question or Objective	Prop/hyp #	State Proposition or Hypothesis	Data collection details	Data analysis method
1	To what extent does the adoption of a mobile learning approach influence Grade 12 learners' performance in high school?	1	The adoption of a mobile learning approach improves Grade 12 learners' engagement and motivation while learning mathematics	Survey: Likert scale	Quantitative-Linear regression analysis
2	How does mobile learning contribute towards high performances in mathematics among grade 12 learners?	2	The use of mobile learning tools led to high mathematics performance among Grade 12 learners.	Survey: Likert scale	Quantitative-Linear regression analysis
3	Assess the impact of limited internet accessibility on the adoption of mobile learning.	3	Limited internet accessibility and educators' resistance constrain the adoption of mobile learning.	Survey: Likert scale	Quantitative-Linear regression analysis
4	How does educators' resistance affect the adoption of mobile learning?	4	Learners and educator resistance constrains the adoption of mobile learning.	Survey: Likert scale	Quantitative-Linear regression analysis

Source: Author Derived (2024)

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter provides an in-depth review of the literature on the development of e-learning and mobile learning; integration of ICTs in education; key drivers of poor performance among learners; mobile learning landscape; application of mobile learning in diverse education contexts and theoretical and conceptual frameworks.

2.2 Development of e-learning and m-learning technologies

The dawning of the fourth industrial revolution (4IR) is characterised by various technological developments and advances that have drastically changed various aspects of life (Bouchrika, 2025). Despite primary use being for social interaction or communication purposes, additional functions such as learning have emerged from youths' increasing device usage habits (Baran, 2014). Importantly, the COVID-19 pandemic accelerated the uptake of latest technologies such as MS Teams and Zoom, for learning purposes across the globe (Clipper, 2020).

At the centre of the 21st-century pedagogical innovation are strategies for electronic learning (e-learning) and mobile learning (M-learning). Although often used interchangeably, the two terms have different meanings. E-learning refers to internet-driven teaching and learning activities, while m-learning involves teaching and learning by mobile devices (Mahamad & Taib, 2010). M-learning can provide learning experiences regardless of time or place to learners. According to (Priscilla., 2020), m-learning allows learners to access educational content through technological and digital platforms that can be accessed at one's convenience. In this case, m-learning frees learners from physical barriers such as time, geography, or immediate content (Mehdipour & Zerehkaf, 2013). This allows the learner to focus on different aspects of a given topic. Furthermore, (Mehdipour & Zerehkaf, 2013) emphasised that m-learning rather than just another combination of "learning" with "mobile device". (Pedro, et al., 2018) observed this natural progression upon which eLearning paved way for mobile computing in education, known today as M-Learning. Notably though Mehdi pour asserts earlier-defined E-Learning any form that disseminates academic materials via internet sources. Hence, at the core level arguing trees the same concept only separated into two categories "E&E." Whether using smartphones or other smart

devices, learners can access teaching content without necessarily being present in physical classrooms.

Electronic learning is limited to set times, delayed feedback, and formal and structured lessons. By contrast, mobile learning is characterised by marked flexibility, convenience, mobility, immediacy, and situativity. Most importantly, mobile learning underscores a unique and customised learning approach where learners acquire knowledge at their own pace regardless of location or physical presence of other learners. (Korucu & Alkan, 2011).

The proliferation of handheld and portable smart devices and phones coupled with increased access to the internet has made m-learning an attractive and innovative pedagogical approach that transcends physical barriers (Eom, 2022). For instance, the integration of mobile technology has a positive impact on the way schools deliver remote or virtual learning due to its flexibility. Specifically, this approach is relevant for a country like South Africa. Many high schools are leveraging digital technologies to address educational disparities and resource gaps prevalent in rural and underserved areas and enhance the overall academic experiences and performance of learners (Balula, et al., 2018).

Literature suggests that mobile learning can provide students with personalised, on-demand access to learning materials, enable collaboration and communication with teachers and peers and offer opportunities for self-directed and contextual learning. (Fazlina, et al., 2013) (Balula, et al., 2018). This study focused on the effectiveness of mobile learning as a strategy for enhancing grade 12 learner performance in STEM subjects like mathematics.

2.3 Integration of ICTs in education

Davies and West (2014) discussed how the fourth industrial revolution has facilitated the widespread integration of information, technology, and communication (ICTs) into pedagogical approaches. The ongoing integration of ICT enables teachers to deliberately merge digital devices, resources and services into teaching and learning activities with the intention of maximising learner experiences and performance.

The effectiveness of such integration is influenced by the extent to which ICTs are aligned to learning outcomes as well as learners' contextual needs (Mdhlalose and

Mlambo, 2023). In this case, alignment can be achieved when the chosen ICTs comply with the principles outlined in Figure 2.1.



Figure 2. 1: Effective ICT integration. **Source:** Diyes International School (2023)

The integration of ICTs in education is associated with several benefits, such as increased and effective collaboration between teachers and learners, broadening of learners' knowledge and skills, and high levels of classroom engagement among learners. Nonetheless, the effectiveness of ICT-driven education can be constrained by factors such as inadequate internet access, systemic failures, and software incompatibility.

2.4 Key drivers of poor performance

South Africa is faced with the challenge of underperformance in STEM subjects like mathematics within its high schools. The key drivers of poor learner performance are discussed below.

2.4.1 Educational Disparities and Language Barriers

The legacy of apartheid in South Africa continues to affect the country's educational system, leading to inequalities and poor underperformance. This is due to historical disparities and ongoing governance challenges. Inadequate infrastructure and overcrowded classrooms contribute to poor educational outcomes (International, 2020). Poor students face challenges in accessing quality education (Daniels, 2007). Inadequate teacher training and outdated methods also contribute to poor student

performance. The shortage of qualified teachers, especially in mathematics and science, has worsened (Mokato, 2007).

2.4.2 Accessibility and affordability of mobile technology

Given the broad accessibility and increasing affordability of mobile technology, mobile learning represents a transformative approach to overcome educational barriers in diverse situations, including those affected by socioeconomic disadvantages and geographical isolation. This approach aligns with the need for innovative educational strategies that cater to the 21st-century learner and provide equitable access to quality education. Poor performance in South African schools is attributed to historical disparities, language barriers, outdated teaching methods and a lack of qualified teachers, which hinder critical subjects like mathematics and science.

2.5 Mobile Learning landscape

M-learning is a critical strategy because it transforms teaching and learning by facilitating accessibility and flexibility to impart personalised experiences (Greenhow & Lewin, 2016). Additionally, m-learning is suitable for learners with busy schedules or those residing in remote locations to progress at individual pace while focusing on learning content aligned to personal interests and learning styles (Selwyn, 2017). According to Kaisara et al. (2022), a mobile learning landscape comprises mobile classrooms, public and private sector collaborations, and e-learning platforms driven by various cutting-edge information and communication technologies (ICTs). Table 2.1 provides an overview of the typical 21st-century mobile learning landscape.

Table 2. 1: Mobile learning landscape

Components	Description
Interactive Whiteboards and Projectors	Digital tools that enable the presentation of multiple teaching and learning aids on smart boards in real time and thus increase learner engagement.
Mobile technologies	The use of mobile phones, tablets, laptops, and wearable devices to access various e-resources such as textbooks and educational apps

Virtual and Augmented Reality (VR and AR)	Use of innovative technologies to provide learners interactive and engaged learning experiences
Coding and robotics kit	Incorporation of coding and robotics in the teaching and learning of STEM subjects to foster logical thinking, problem-solving, and collaboration among learners
Learning Management Systems (LMS)	These systems use Google Classroom or Moodle for teaching and learning activities such as issuing, submission, and marking assignments, accessing e-resources, and communication

Source: Author Derived (2025)

2.6 Application of Mobile Learning in Diverse Educational Contexts

The use of mobile learning in various educational settings demonstrates its versatility and adaptability. For instance, in rural or poor regions, mobile learning provides a viable alternative to traditional classroom settings, offering students access to high-quality educational materials and interactive learning experiences. This adaptability is crucial in South Africa, where disparities in educational access and quality persist because of geographical and socioeconomic factors.

Mobile learning's potential to bridge these gaps is significant because it allows for a more equitable distribution of educational resources and opportunities. Studies have shown that mobile learning can enhance student engagement and motivation, leading to improved learning outcomes (Greenhow & Lewin, 2016). Additionally, the integration of mobile technology in education can facilitate a more collaborative and communicative learning environment, connecting students and teachers in innovative ways.

2.7 Developing a mobile learning application

The mobile device is the gateway for accessing the functioning and usage of a mobile application; therefore, it is not surprising that an app is a short name for a mobile application and more formally referred to as a mobile application (Inukollu, Keshamoni, Kang, & Inukollu, 2014). To define an app, one must consider a website as a platform or a means to access information or services; thus, an app is an alternative means to access the content of a website without using a web browser.

Software developers put together a sequence of commands and translate them into an app or algorithm. Some sequences can only be interpreted or understood if written in a certain way and that has to be in same language as the operating system of that specific device. This is how the descriptions according to (Inukollu, Keshamoni, Kang, & Inukollu, 2014) come to effect.

Figure 2.2 below, shows the activity process used during the conceptualisation step of app development and (Huynh & Ghimire, 2015) in detail.

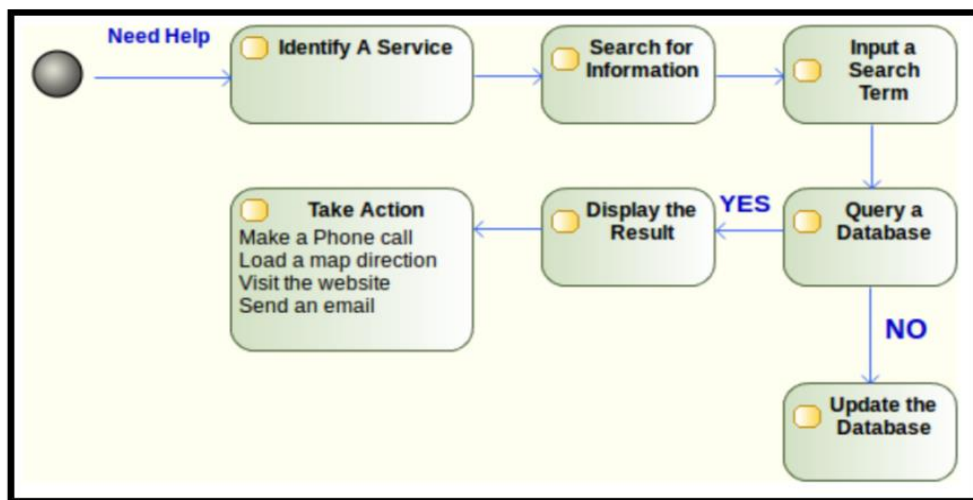


Figure 2. 2: conceptualisation step of app **Source:** Huynh & Ghimire, 2015)

According to (Nagesh & Caicedo, 2012), each operating system like iOS for iPhones, Android for Samsung, Hauwei, LG, Sony etc., and BB for BlackBerry, has its own software development kit. Thus, when an application is developed using SDK of Android and that application is run on Android, it becomes a native Mobile App. On the other hand, when an app is developed to be accessible through a web browser on a mobile device, it is classified as a mobile web app. Finally, there is a hybrid app which is realised by combining the (Inukollu, Keshamoni, Kang, & Inukollu, 2014).

Finally, (Huynh & Ghimire, 2015) argued that there is always a need for a new app because of rapid technological advances and (Inukollu, et al., 2014) proposed that designing an app is barely enough to keep the app relevant, there must be consistent maintenance and performance monitoring, as constant updates will advance the app into the latest technologies.

2.8 Background literature on independent variables

2.8.1 User adoption

The adoption of mobile learning can positively influence performance in STEM subjects like mathematics among high school learners. According to Greenhow and Lewin (2016); Pocon et al. (2022), the effectiveness of mobile learning lies its ability to integrate digital resources with existing pedagogical methodologies; promote learner engagement and motivation through various interactive tasks and facilitates tailored teaching and learning to meet unique learners' needs.

However, the adoption of mobile learning comes with its own challenges. For instance, the effectiveness of mobile learning depends on how stakeholders are able to leverage its upsides whilst mitigating various downsides (Krause et al. 2024). Examples of downsides linked to the adoption of mobile learning include excessive usage of mobile phones and other devices that can sidetrack students and challenges of equitable access to mobile devices and internet.

2.8.2 Mobile learning tools

Moreno (2025) and Halim and Phon (2020) argue that mobile learning tools are instrumental in enhancing learner performance in subjects which require mastery of cognitive skills. Excellence in STEM subjects is high dependent on students' capacity in terms of concentration, perceptive powers, memory, problem-solving and decision making. As such, mobile learning tools are known to increase learner motivation, facilitate customised teaching and learning and promote real time feedback.

2.8.3 Internet accessibility

Internet accessibility is one of the critical factors underpin mobile learning. As stated by Haleem (2022) and Ren and Zhu (2024), stable and dependable internet access is beneficial for educators and students because it facilitates regular access to a variety of learning content; promotes flexible learning that accommodates students' contextual situations; overcomes geographical limitations and intensifies students' engagement with content, peers and educators through collaborative and virtual reality experiences. Therefore, stakeholders should put in place measures that effectively mitigate against limited internet connectivity, especially, within marginalised communities.

2.8.4 Educator resistance

Educator resistance has been cited as one of the factors that can negatively impact the adoption and implementation of mobile learning (Mehrfar et al. 2024 and Titrocharjo, 2024). Educators resistance to innovative ideas like mobile learning is grounded in various reasons. Examples of these reasons are:

- Lack or absence of necessary skill sets for navigating the digital landscape
- Unfounded fears that mobile learning will lead to redundancy of educators

Hence, failure to address educator resistance can limit the usage of mobile learning and contribute towards to overlooked prospects and additional work burden for educators.

2.9 Theoretical Framework: Technology Acceptance Model (TAM)

The concept of Technology Adoption Theory provides valuable insights into how students interact with digital educational tools. According to the Technology Acceptance Model (TAM), the likelihood of students using e-mobile platforms increases when they view these tools as beneficial for their academic achievements and straightforward to use. For high school students, particularly those in Grade 12 facing significant academic stress, the perceived advantages may include enhanced preparation for exams, easy access to educational resources, and engaging revision aids.

A theoretical framework is a systematic structure of ideas about a phenomenon grounded in previously tested theories (Warmbrod, 1986). It helps situate and contextualise these theories, guides the research process, and links directly to the research problem (Creswell, 1994; Grant & Osanloo, 2014).

Mobile learning is a method for delivering education that emphasises the learning experience rather than technology (Ally & Prieto-Blazquez, 2014). It alters traditional teaching methods and interactions between learners and teachers (Matiwalla, 2007). The introduction of technology is associated with a "renewed epistemological approach". As noted by Pedro, Barbosa, and Santos (2018), this approach has led to changes in teaching methods. In addition, the approach's success is dependent on stakeholder collaboration (Prieto-Blazquez, 2014). This is substantiated by (Ozdamli

& Cavus, 2011), who identified the basic elements of m-learning, as depicted in Figure 2.3.

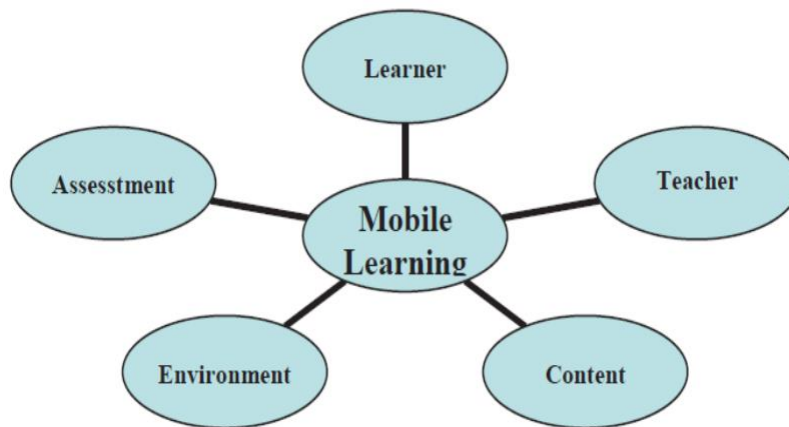


Figure 2. 3: Basic Elements of m-Learning (**Source:** Ozdamli & Cavus, 2011)

As a consequence, mobile learning has the potential to address historical inequalities and improve academic results for Grade 12 students.

2.10 Conceptual framework of the study

A conceptual framework shows the researcher's understanding of the possible relationships between the variables to be studied (Miles & Huberman, 1994). This supports the research plan by outlining key factors and presumed relationships among them (Grant & Osanloo, 2014), helping structure and focus on the investigation. Figure 2.4 highlights the conceptual framework developed for the study.

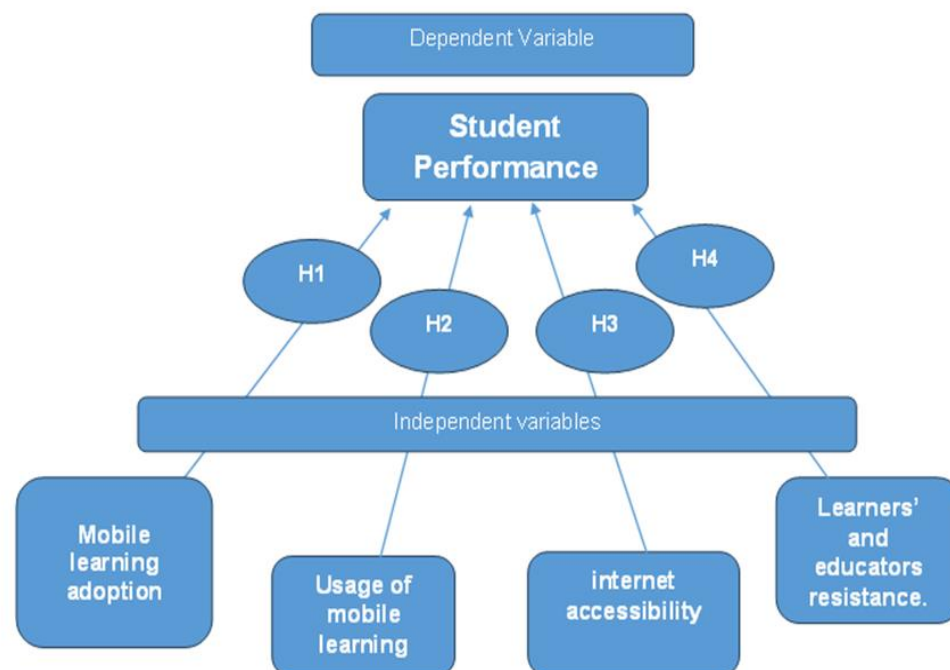


Figure 2. 4: Conceptual Framework

Source: Authors' derived (2025)

The conceptual model above was proposed as a contribution to mobile learning knowledge and will assist in creating an understanding of the relationships that are hypothesised and highlighted in the framework above.

2.11 Conclusion

Chapter 2 reviews the available literature on mobile learning pertaining to developments surrounding e-learning and mobile learning; application of mobile learning; educational technology acceptance; key drivers of poor performance in mathematics; mobile learning landscape; mobile app development; and theoretical and conceptual frameworks.

CHAPTER 3: Research Methodology and Design

3.1 Introduction

This chapter describes the methodology adopted to address research questions and test various hypotheses.

3.2 Research Design

A research design comprising interlinked tasks acts as a blueprint for sampling, data collection, and analysis (Kothari, 2019 & Lewis, Thornhill, and Saunders, 2019). The study adopted a cross sectional design to address various research questions and test hypotheses.

3.3 Research Methodology

According to Kumar (2015), a research methodology refers to the systematic selection and justification of an appropriate approach, design and method that can be utilised to achieve research objectives; answer research questions, test hypotheses, sample participants, gather and analyse data. This study adopted a quantitative methodology grounded within a positivist philosophical worldview. The methodology is relevant because it relies on empirical observations, data, and statistical analysis to answer research questions and test hypotheses.

3.4 Population and Sampling

Chigwende (2021) delineates two primary categories of sampling approaches in research: non-probability and probability methods. Probability sampling encompasses systematic sampling, stratified random sampling, basic random sampling, and multi-stage and cluster sampling techniques. Non-probability sampling methods include judgmental sampling, convenience sampling, quota sampling, and snowball approaches. (Saunders et al., 2019).

The study population comprised all grade 12 teachers and learners who use mobile devices for teaching and learning activities. After considering factors that affect sample representativeness, the study sample was delimited to four (4) high schools within the Secunda area of Mpumalanga province. A convenience sampling technique was employed to select twenty (20) mathematics teachers and 150 Grade 12 students who completed their grade 12 exams within the last five years. In addition to being old enough to make independent decisions, the participants were deemed to possess sufficient information on the study topic.

3.5 Data collection method and tool

A survey questionnaire tool was used to collect quantitative data required for hypothesis testing. This tool was justified due to its cost-effectiveness and ease of access to study participants. In the survey, questionnaires were sent to participant using e-mails and WhatsApp social media platform. Before the actual data collection, tools were test-piloted to evaluate their clarity and validity.

3.6 Data analysis and Interpretation

According to Saunders (2019), the analysis of quantitative data entails the use of statistical techniques to interpret numerical information and establish relationships and trends thereof. Once the data were collected, the data were cleaned to verify completeness, and an analysis was conducted by means of the Statistical Package for Social Sciences (SPSS) and AMOS software. The software evaluated the measurement dependability and tested responses using Cronbach's alpha.

3. Limitations of the Study

Potential limitations included response biases, variability in mobile learning implementation, and technological disparities among participants. As such, limitations affected the quality and generalizability of the study findings. The key limitations associated with this study include a narrow study focus area (Secunda) and the selection of participants from urban schools while excluding those in rural areas.

3.8 Quality Assurance

To ensure quality, the study will strive for transferability through detailed documentation, credibility through method triangulation, and dependability through an audit trail. The strategies used to implement quality assurance throughout the study. will include participant validation of findings and peer debriefing.

3.8.1 External Validity

Chigwende (2021) argued that external validity guarantees the extent to which quantitative study findings are generalisable to broader contexts. External validity is influenced by factors like sample size, sample diversity, and the context in which the research is conducted. As a means of increasing the generalizability of the study findings, the researcher used a well-defined population and context for sample selection.

3.8.2 Internal Validity

Internal validity is the process of evaluating the design, execution, and analysis of a study to provide reliable responses to the research questions (Andrade, 2018). As a result, internal validity is critical for determining causal relationships between variables while mitigating biases from confounders. Hence, the survey questionnaire was designed in accordance with the theoretical framework to determine the correlation between mathematics performance among grade 12 learners and the usage of mobile learning.

3.8.3 Reliability

According to Taherdoost (2021), reliability refers to the accuracy and consistency of results measured during quantitative research. Reliability focuses on the extent to which a measuring tool or tools consistently produces stable results during data collection. This study applied Cronbach's alpha test was used to evaluate the reliability of the questionnaire tool used in the survey. For instance, a high Cronbach's alpha value implies a measuring tool with high reliability.

3.9 Ethical considerations

The role of ethical consideration in research studies is to maintain the propriety of the research process and the validity of findings (Creswell, 2009; Resnik, 2021; Zimmer, 2010). Ethics not only safeguards the rights and wellbeing of study participants but also promotes trust, transparency, and accountability during the research process. Therefore, the researcher adopted several strategies to comply with prescribed research ethics. Approval was obtained from the Ethics Committee of the University of Witwatersrand before commencement of the study. Furthermore, a cover letter was sent to all participants, offering clarity on study aims; lack of compensation; guarantees of confidentiality and anonymity in line with the principle of informed consent, voluntary participation, and freedom to withdraw from the study at any point.

As a guarantee of the privacy of personal information, data collection from study participants has been stored on a password-secured computer. These data will be kept for a period of five years and will only be used for research-related purposes. Participants will be invited via an invitation letter and consent form.

3.10 Conclusion

This chapter unpacked the research methodology by discussing the research design, study time, population and sampling techniques, data collection and analysis

strategies, study limitations, and ethical considerations. The next chapter analyses, discusses, and interprets the study findings.

CHAPTER 4: ANALYSIS AND INTERPRETATION OF THE FINDINGS

4.1 Introduction

The purpose of chapter 4 was to analyse, discuss, and interpret the findings gathered through a survey questionnaire.

4.2 Data Analytical Procedures

Data analysis involves various statistical techniques to interpret the results and draw meaningful conclusions from the collected data (Taherdoost, 2021). The analytical procedures adopted to ensure a thorough interpretation of the findings are as follows: descriptive analysis, and inferential statistics.

4.2.1 Descriptive Statistics

Descriptive statistics provide a summary of the main features and characteristics of the data collected (Bhandari, 2020). Measures such as mean, median, mode, standard deviation, and variance were used to describe the basic features of the data in the study (Appendix 1).

4.2.2 Inferential Statistics

According to Bhandari (2020), inferential statistics are used to make inferences from the data to more general conditions. The purpose of inferential statistics is to confirm or reject study hypotheses and determine the generalizability of findings to a broader context. Examples of the techniques used include regression analysis, ANOVA, and chi-square tests.

Data analysed using specialised statistical software such as SPSS and AMOS. This decision was warranted due to the efficiency of these software programs in managing large datasets and offering diverse functions for comprehensive data analysis. Prior to the analysis, the data was meticulously inspected for errors and inconsistencies to guarantee accuracy and quality. The results of data analysis were presented in the form of tables, graphs, and charts. The visual representations improved the understanding and interpretation of the findings. The results are discussed in detail, linking them to the research objectives and questions. These software tools were chosen for their efficiency in handling large datasets and their comprehensive data analysis functions. Before analysis, data was checked for errors and inconsistencies to ensure accuracy and quality.

The study used SPSS V24 and AMOS as a tool for the statistical analysis of empirical data and to test, validate, and assess items and instrument reliability. Microsoft excel was used for the analysis of descriptive statistics; SPSS for measurement of instrument reliability and validity; AMOS version 29 to determine model fit, path modelling analysis, and hypotheses testing; Cronbach's Alpha, to measure reliability, validity, and Goodness of Fit Index; and RMSEA to assess model fit.

4.3 Data Screening and Cleaning

Data screening and cleaning are integral steps for a meaningful analysis of data. The process involved identifying and handling missing or erroneous data, which could lead to inaccurate results. The initial step involves a thorough inspection of the dataset to detect any anomalies, such as missing values, outliers, and inconsistencies. These issues are addressed using various techniques, such as imputation for missing values and transformation or removal of outliers. The cleaned data are then prepared for subsequent analysis.

Next, the data was categorised based on the variables of interest to ensure that the dataset was structured in a way that facilitates efficient analysis. This categorisation helped in organising the data and revealed patterns that might not be evident in raw, unstructured data. The cleaned and organised dataset was then subjected to the selected analytical procedures to extract meaningful insights.

Blumberg, Cooper, and Schindler (2014) emphasises the importance of data screening before statistical analysis, suggesting that questionnaires should be reviewed, edited, coded, and incomplete entries discarded. This ensures the reliability and validity of the data used in the analysis. In this study, 170 of 200 questionnaires were completed by respondents. This represents a response rate of 85%.

4.4 Analysis of themes: labelling, elaboration, grouping, and coding

Coding facilitates the structuring of raw data while analysis uses questionnaires, hypotheses, research questions, and research problem to create key themes and organise unstructured information into meaningful patterns and concepts (Samuels, 2020). Table 4.1 provides an overview of the labels, codes, and theme sequences.

Table 4. 1: Coding and Labelling of selected themes

Students- theme label	Theme code	Selected Questions, Statements, and Items (Direct Questionnaire Statements)
Theme A: Student Attitudes towards Mobile learning	SA1-3	Question(s) 1, 2, and 3 (consult questionnaire in Appendix A)
Theme B: Student Interest in Learning with Mobile Learning	SB4	Question(s) 4 (consult questionnaire in Appendix A)
Theme C: Mobile device availability	SC5-8	Question(s) 5,6,7 and 8(consult questionnaire in Appendix A)
Teachers' theme label	Theme code	Selected Questions, Statements, and Items (Direct Questionnaire Statements)
Theme A: Student Attitudes towards Mobile learning	TA1-3	Question(s) 1, 2, and 3 (consult questionnaire in Appendix A)
Theme B: Student Interest in Learning with Mobile Learning	TB4	Question(s) 4 (consult questionnaire in Appendix A)
Theme C: Mobile device availability	TC5-8	Question(s) 5,6,7 and 8(consult questionnaire in Appendix A)

Source: Author compilation (2024)

4.5 Descriptive statistics

4.5.1 Demographic Statistics

Table 4.2 summarises respondents' demographic profiles based on gender, age, and work experience.

Table 4. 2:Demographic analysis

Students gender	Frequency	Percentage(%)
Male	50	33%
Female	100	67%
I prefer not to say the following:	0	0%
Total	150	100%
Student age distribution		
18 Years	26	17%
19 Years	25	16%
20 Years	30	20%
21 Years	31	21%
22 Years	30	20%
23 years +	8	5%
Total	150	100%
Teachers gender		
Male	8	40%
Female	11	55%
I prefer not to say the following:	1	5%
Total	20	100%
Teachers' years of experience		
0-5	6	30%
6-10	3	15%
11-15	1	5%
16-20	9	45%
20 Above	1	5%
Total	20	100%

Source: Autor Derived (2025)

According to Figure 4.1, female learners comprised most respondents (66.7%), with male learners making up only 33.3% of the total. Female learners were more enthusiastic about mobile learning.

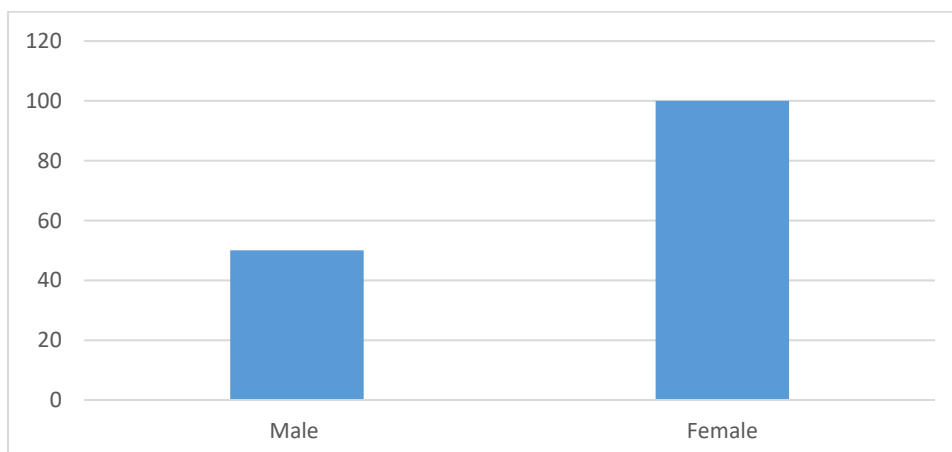


Figure 4. 1: Gender of the student participants. Source: Authors derived (2025)

According to Figure 4.2 below, the average age of participants (20.7%) was 21 years, with just 5% being above the age of 22 years, representing the lowest participation. The youngest participant was 18 years (17%).

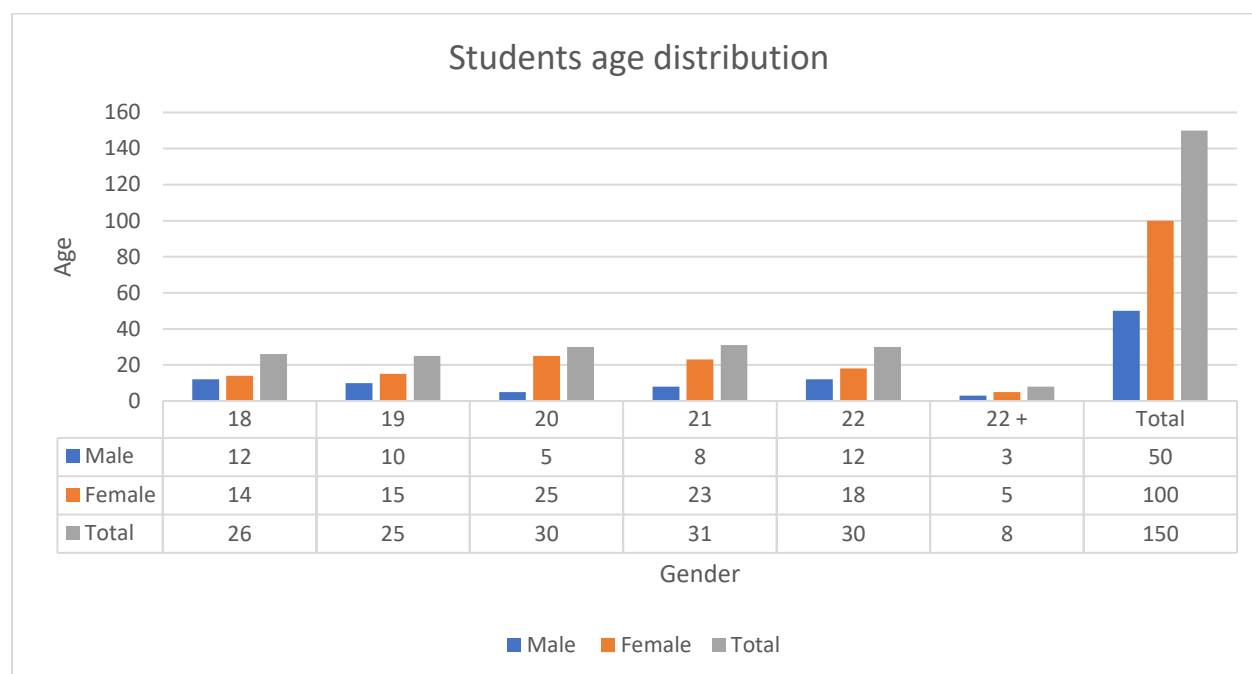


Figure 4. 2: Student age distribution

Source: Authors' derived (2025)

Figure 4.3 indicates that most respondents (60%) were female teachers; male teachers comprising only 40%.

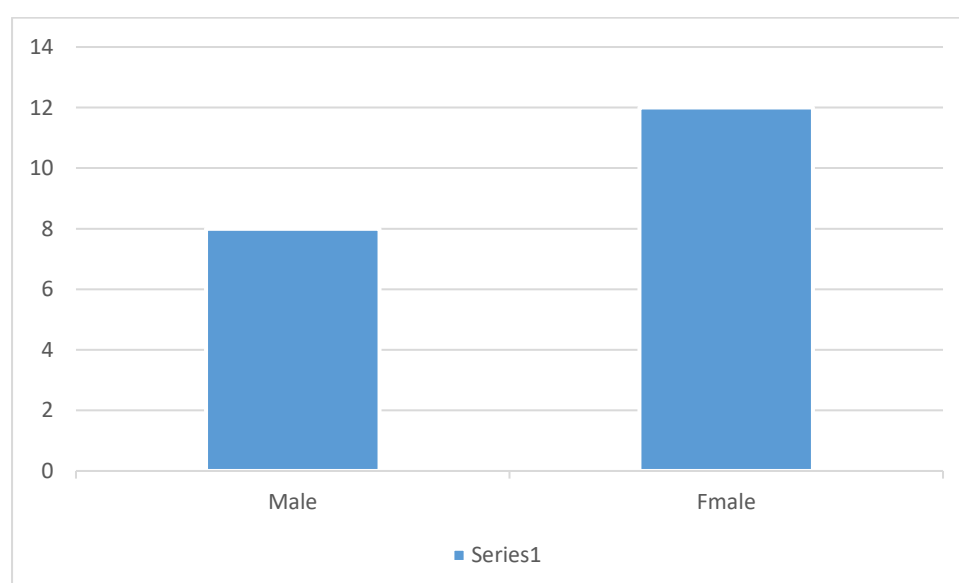


Figure 4. 3: Teacher's gender

Source: Authors' derived (2025)

Figure 4.3 shows that the majority of teachers (40%) have 16-20 years of teaching experience, 5% have 11-15 years, and 10% have more than 20 years of experience.

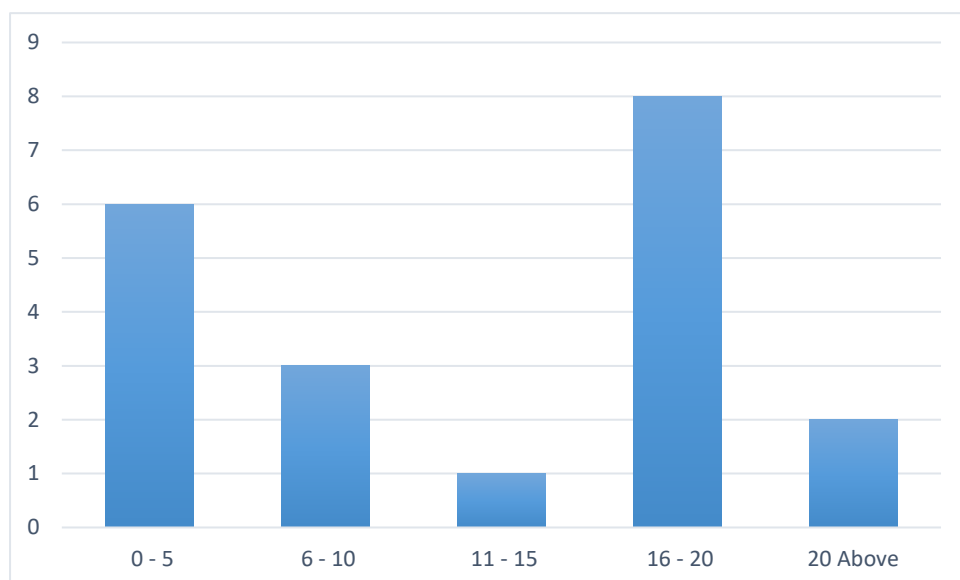


Figure 4. 4: Teachers' years of experience **Source:** Authors' derived (2025)

4.5.2 Likert Scale results

This section summarises findings derived from a Likert scale questionnaire with five points: SD = Strongly Agree (1); D = Disagree (2); N = Neutral (3); A = Agree (4); SA = Strongly Agree (5). These questions assessed and measured the use of mobile learning as a strategy for enhancing Grade 12 mathematics learners' performance. According to Hair et al. (2009), a modest estimated standard deviation (SD) indicates that the participants' responses are consistent and that the response distributions are close to the mean.

The mean values ranged from 1.90 to 2.25 for teachers and 1.41 to 2.03 for students, with standard deviations ranging from 0.447 to 0.910 for teachers and .506 to .779 for students. Higher mean indicates that respondents regard mobile learning as an important driver of mathematics performance by teachers. By contrast, the lower mean among students demonstrates their reluctance in the assertion that mobile learning fosters mathematics performance (see appendices 1 and 2).

4.6 Inferential statistics and data analysis procedures

4.6.1 Reliability Testing

The study evaluated the survey questionnaire's reliability using Cronbach's Alpha (α). Cronbach's alpha values ranging from 0.813 to 0.833 (see Tables 4.4 and 4.5) indicated that the reliability test results were satisfactory, acceptable, and supported the consistency of overlapping replies.

Reliability testing is conducted to assess the scale's internal consistency, which indicates how well the items measure a common underlying construct. The item reliability was measured using Cronbach's Alpha, where a value above 0.7 is generally considered acceptable.

4.6.1.1 Cronbach's Alpha: Teachers and students

The reliability analysis for teachers revealed a Cronbach's Alpha of 0.813, indicating good internal consistency among the 8 items. Most items had acceptable corrected item-total correlation values above 0.5, suggesting a strong relationship with the overall scale (see table 4.3 below).

Table 4. 3: Cronbach's alpha teachers

Item-Total Statistics

	Scale mean if item is deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's alpha if item is deleted
Students are willing to attempt m-learning	14.60	12.779	.226	.845
Mobile learning can help improve students' mathematics performance	14.60	11.200	.620	.777
Students like to participate in online discussions	14.95	10.892	.775	.755
Students will be willing to perform online exercises	14.80	12.274	.420	.807
My students have a mobile device.	14.75	13.145	.536	.798
The area in which the school is located experiences network problems.	14.80	12.379	.549	.791
Learning through virtual classrooms is a waste of time.	14.85	11.082	.828	.752
I see a need for m-learning to enhance the performance of learners.	14.60	11.095	.521	.796

Reliability Statistics

Cronbach's Alpha	N of Items
.813	8

Source: Author derived (2025)

4.6.1.2 Cronbach's Alpha: students

For students, the reliability analysis revealed a Cronbach's Alpha of 0.833, also indicating strong internal consistency across the 8 items. Most items exhibited satisfactory corrected item-total correlation values above 0.6 (see table 4.4 below).

Table 4. 4: Cronbach's Alpha: Students

Item-Total Statistics: Students

	Scale mean if item is deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's alpha if item is deleted
I am willing to attempt m-learning.	11.93	10.605	.645	.807
Mobile learning will help improve my mathematics performance	11.85	10.493	.630	.807
I like to participate in online discussions	11.90	10.695	.540	.817
I think online exercises will benefit me as a student.	11.75	9.935	.646	.802
I owned a mobile device while studying for Grade 12	11.53	9.231	.671	.797
The area where I am located experiences network problems	11.69	10.056	.601	.808
Learning through virtual classrooms is a waste of time.	11.31	10.375	.402	.838
I see a need for m-learning to enhance my performance as a learner.	11.39	10.066	.468	.829

Reliability Statistics

Cronbach's Alpha	N of Items
.833	8

Source: Author derived (2025)

4.6.2 Validity testing

Validity testing is used to evaluate whether the set of items measures the underlying construct is intended to measure—in this case, perceptions and readiness towards mobile learning (m-learning). The Kaiser-Meyer-Olkin (KMO) sampling adequacy measure assesses the suitability of the data.

The KMO (Kaiser-Meyer-Olkin) test and Bartlett's Test of Sphericity assess validity. The tests evaluate the appropriateness of a dataset for factor analysis, with the KMO assessing sampling adequacy and Bartlett's test determines correlation matrix if it deviates significantly from an identity matrix, thereby indicating adequate correlation among variables to advance with factor analysis.

4.6.2.1 Validity testing: teachers and research

The results of the validity testing for teachers indicate that the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy is 0.697, which falls within the acceptable range, suggesting that the data is suitable for factor analysis. This value reflects a middling level of adequacy, implying that the items have sufficient shared variance. Additionally, Bartlett's test of sphericity was significant, with a chi-square value of 77.197, degrees of freedom (df) = 28, and a p-value less than 0.001. This significance indicates that the correlation matrix is not an identity matrix, confirming the presence of significant correlations among the items (see table 4.5 below).

Table 4. 5: KMO and Bartlett's Test: Teachers

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.			.697
Bartlett's test of sphericity	Approx. Chi-Square		77.197
	df		28
	Sig.		.000

4.6.2.2 Validity testing: students

The Kaiser-Meyer-Olkin (KMO) value of 0.838 is considered meritorious and suggests excellent sampling adequacy for factor analysis. This high value indicates that the items included in the scale share a strong common variance and are appropriate for uncovering the underlying factor structures. Furthermore, Bartlett's Test of Sphericity yields a chi-square value of 455.132 with 28 degrees of freedom and a highly significant p-value ($p < 0.001$), confirming that the correlation matrix significantly differs from an identity matrix. These results demonstrate that the scale items for students possess strong construct validity (see table 4.6 below).

Table 4. 6: KMO and Bartlett's Test-Students

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.			.838
Approx. Chi-Square			455.132
Bartlett's	test	of	df
sphericity			28
Sig.			.000

4.6.3 Assessment of normality

The Kolmogorov-Smirnov and Shapiro-Wilk tests demonstrate that none of the variables adhere to normal distribution. Although both tests are sensitive to high sample sizes, the persistent rejection of the null hypothesis suggests a non-normal distribution. This may require non-parametric statistical tests or data transformations if the assumptions of normalcy are essential for further analysis.

4.6.3.1 Assessment of normality: Teachers

The assessment of normality for the teacher responses using both the Kolmogorov-Smirnov and Shapiro-Wilk tests indicates that all items significantly deviate from a normal distribution. The significance values (p-values) for both tests are below 0.05 for each item, suggesting that the assumption of normality is violated across the dataset. The Shapiro-Wilk test, which is more reliable for small sample sizes like this one (N=20), also confirms non-normality for all items, with the lowest p-value being .000 and the highest at .016. These results imply that the data distribution is not normal and thus non-parametric statistical techniques may be more appropriate for analysing these responses (See appendix 3: Normality Tests – Teachers)

4.6.3.2 Assessment of normality – students

For the student data, the results of the Kolmogorov-Smirnov and Shapiro-Wilk tests also indicate a statistically significant departure from normality for all items. With a sample size of 150, both tests consistently showed p-values less than 0.001 across all variables, confirming that the responses were not normally distributed. The Shapiro-Wilk test statistics range from 0.645 to 0.818, further reinforcing the non-normal nature of the data (See appendix 4: Normality Tests – students).

For the student data, the results of the Kolmogorov-Smirnov and Shapiro-Wilk tests also indicate a statistically significant departure from normality for all items. With a sample size of 150, both tests consistently showed p-values less than 0.001 across

all variables, confirming that the responses were not normally distributed. The Shapiro-Wilk test statistics ranged from 0.645 to 0.818, further reinforcing the non-normal nature of the data.

4.6.4 Structural equation modelling (SEM)

4.6.4.1 Model Fit testing

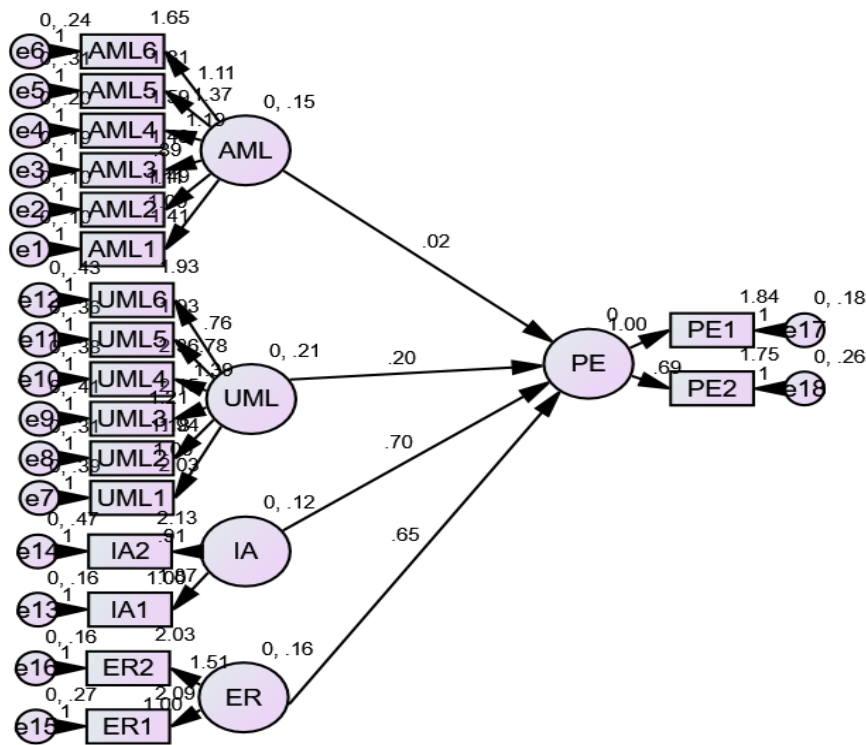
A conceptual framework for assessing the contributions of mobile learning to the field of education was provided in Section 2.9. The proposed conceptual framework was intended to facilitate the development and comprehension of the connections posited and illustrated in the framework. To assess the model's fit for purpose, AMOS assessments were conducted.

4.6.4.2 Structural Model (Conceptual Model)

This section evaluates the model fit of the study using Regression Weights and Variances. Nusair et al. (2010) suggested that structural model testing evaluates the causal relationships among variables using metrics such as CMIN, RMR, GFI, Parsimony-Adjusted Measures, Baseline Comparisons, NCP, FMIN, and Root Mean Square Error of Approximation (RMSEA).

An RMSEA value below 0.05 or 0.08 indicates a favourable model fit (Hooper, Coughlan, and Mullen, 2008). Table 4.17 indicates that the RMSEA value of 0.108 reflects a moderate model that marginally exceeds the established threshold. Figure 4.5 illustrates the model test and its conclusions.

Figure 4. 5: Structural model (Structural equation modelling (SEM))



Source: Author Derived (2025)

4.6.4.3 Regression weights

Regression weights indicate the strength and significance of relationships between latent variables and their respective indicators, as well as between constructs. The **PE (Psychological Empowerment)** variable is influenced by several other constructs, and the estimates, standard errors, critical ratios (C.R.), and significance levels (P) help interpret the results.

- **AML to PE:** The regression weight from AML to PE was .018, with a p-value of .849, indicating a non-significant relationship between AML and PE.
- **UML to PE:** The regression weight from UML to PE is .201, with a p-value of .027, which is significant and suggests a moderate positive relationship between UML and PE.
- **IA to PE:** The regression weight from IA to PE was .698, with a p-value of .005, indicating a strong and significant positive relationship between IA and PE.
- **ER to PE:** The regression weight from ER to PE was 0.647, with a p-value of less than 0.001, indicating a strong and significant relationship between ER and PE.

For the measurement model, each indicator's regression weight is reported, where all the items for AML, UML, IA, and ER exhibit strong and significant relationships with their respective latent variables. The standardised regression weights represent the strength of relationships in standardised units, which makes it easier to compare the relative importance of each relationship.

- **AML to PE:** The standardised weight is 0.020, indicating a very weak and almost negligible effect of AML on PE.
- **UML to PE:** The standardised weight is .252, indicating a moderate effect of UML on PE.
- **IA to PE:** The standardised weight is .661, indicating a strong effect of IA on PE.
- **ER vs. PE:** The standardised weight is .707, showing the strongest effect of ER on PE.

The items in the measurement model for AML, UML, IA, and ER show varying strengths, with AML having weaker relationships (ranging from .589 to .778) compared with ER and IA (See appendix 6: Intercepts: Group number 1 - Default model)).

The intercepts indicate the starting value for each indicator, irrespective of the predictor's effect; this is essentially the baseline level of each item. All intercepts were highly significant, with p-values below .001 for each item. This means that the values for each item (AML, UML, IA, ER, PE) are significantly different from zero; thus, these initial values are crucial to interpreting the model (See appendix 6: Intercepts: Group number 1 - Default model)).

4.6.5 Variances

Appendices 5 and 6 show the dispersion of data points for each variable in the model. The elevated critical ratios (C.R.) and diminished p-values (***) reflect the importance of these variations. The variances indicate the amount of unexplained variation for each construct and indicator. A higher variance suggests more unexplained variability in the respective indicators or construct.

- AML, UML, IA, and ER show significant variances with p-values below .05, indicating substantial unexplained variability in these constructs. Specifically, the IA and ER constructs have variances of .118 and .158, respectively, suggesting moderate variability in these factors.

- The individual error variances (e1 to e18) also show significant values, with most having insignificant p-values, indicating that the residual errors are significant and need to be accounted for.

The factor score weights represent the relative contributions of the indicators to their respective latent factors. The weights indicate how much each indicator contributes to the construct. For instance:

- IA has factor score weights ranging from .000 to .324, with the highest weight for IA1 (.324), suggesting that IA1 has the strongest relationship with the IA construct.
- ER has the strongest weight for ER2 (.829), indicating that ER2 is the most influential indicator of the ER construct.
- The other factor score weights were relatively weaker, indicating the relative importance of each item for the constructs.

4.6.6 Model Fit indicators

This section summarises numerous measures employed to assess the model's fit. Comprehending these discrepancies and factor score weights enhances the interpretation of the overall model fit and the dependability of the assessed constructs. To further test the model fit, various critical indicators are examined, including the Chi-square value (CMIN), which evaluates the extent of deviation between the observed and anticipated covariance matrices. This helps assess whether the model is appropriately suited for the given data.

4.6.6.1 Chi-square value (CMIN)

CMIN determines whether the observed variables and the expected findings are sufficiently statistically significant to provide an adequate fit for analysis (see table 4.7 below).

Table 4. 7: CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	57	372.511	132	.000	2.822
Saturated model	189	.000	0		
Independence model	36	1086.728	153	.000	7.103

4.6.6.2 HOELTER

In SEM, Hoelter's critical N is a technique for figuring out the smallest sample size required for a specific degree of statistical power. According to Gew (2023), the crucial N number is the smallest sample size at which the chi-square statistic of the model achieves statistical significance at the required power level(see table 4.8 below).

Table 4. 8: HOELTER

Model	HOELTER .05	HOELTER .01
Default model	64	70
Independence model	26	27

4.6.6.3 Baseline Comparisons

Baseline Comparisons shown in Table 4.9 are initial measurements of a condition that is taken early point and used for comparison over time to look for changes.

Table 4. 9: Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.957	.603	.748	.801	.942
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

4.6.6.4 Parsimony-Adjusted Measures

Parsimony-adjusted measures are a goodness-of-fit index commonly used in structural equation modelling. According to Gew (2023), the improvement in model fit is measured when adding a path or a set of paths to the null model (see Table 4.10)

Table 4. 10: Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.863	.567	.641
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

4.6.6.5 Non-Centrality Parameter (NCP)

The NCP (λ) indicates the extent to which a null hypothesis is false (Kirk, 2012). In other words, it reveals the statistical strength of a test (Gew,2023) (see table 4.11 below).

Table 4. 11: NCP

Model	NCP	LO 90	HI 90
Default model	240.511	186.696	301.973
Saturated model	.000	.000	.000
Independence model	933.728	832.864	1042.059

4.6.6 Akaike Information Criterion (AIC)

The AIC is a metric used to assess the fit of a statistical model to a data sample. The AIC scores are meaningful only when compared with the other AIC scores from the same data collection. The lower the AIC number, the better (see table 4.12 below).

Table 4. 12: AIC

Model	AIC	BCC	BIC	CAIC
Default model	486.511	503.173		
Saturated model	378.000	433.246		
Independence model	1158.728	1169.251		

4.6.6.7 Function Minimum Fit Function (FMIN)

FMIN is a model fit measure used in structural equation modelling (SEM) to indicate the difference between the observed and predicted covariance matrix (Gew, 2024). The smaller the value of FMIN, the better the model fit (see Table 4.13).

Table 4. 13: FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	2.500	1.614	1.253	2.027
Saturated model	.000	.000	.000	.000
Independence model	7.293	6.267	5.590	6.994

4.6.6.8 Root mean square error of approximation (RMSEA)

According to Gew (2024), the RMSEA (see Section 4.14) is an absolute fit index that measures how far a hypothesised model differs from a perfect model.

Table 4. 14: RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.085	.097	.124	.000
Independence model	.202	.191	.214	.000

4.6.6.9 Expected Cross-Validation Index (ECVI)

The ECVI is a metric for model fit utilised in Structural Equation Modelling (SEM) that assesses the anticipated prediction error of the model. The ECVI formula is contingent on the number of parameters in the model, the sample size, and the estimated

parameters. A lower ECVI score indicates superior model fit. Nevertheless, globally recognised reference values for ECVI are absent because ECVI is frequently employed with other fit indices to evaluate model fit (Gew, 2024) (see table 4.15 below).

Table 4. 15: ECVI.

Model	ECVI	LO 90	HI 90	MECVI
Default model	3.265	2.904	3.678	3.377
Saturated model	2.537	2.537	2.537	2.908
Independence model	7.777	7.100	8.504	7.847

The model fit indicates an overall acceptable-to-good fit. The chi-square/degrees of freedom ratio (CMIN/DF) for the default model was 2.822, which falls within the acceptable range (less than 3), suggesting a reasonable fit between the hypothesised model and the data. The RMSEA value of 0.085 is slightly above the ideal cutoff of 0.08, but remains within a tolerable limit, and the associated PCLOSE value of 0.000 suggests marginal support. The Comparative Fit Index (CFI) of 0.942 and the Normed Fit Index (NFI) of 0.957 both exceed the recommended threshold of 0.90, indicating good incremental fit.

The parsimony indices (PCFI = 0.641 and PNFI = 0.567) further support model adequacy by balancing fit and model complexity. The ECVI value of 3.265, which was slightly higher than that of the saturated model, still indicates reasonable predictive relevance. Lastly, Hoelter's Critical N values of 64 (at .05) and 70 (at .01) suggest that the sample size is adequate to support the fit model. Overall, these indices collectively support the conclusion that the model demonstrates a good and acceptable fit to the observed data.

4.7 Hypotheses testing

This section describes how the hypotheses were supported or rejected based on the tests and correlation path coefficients, as presented in the following tables.

4.7.1 Test of hypothesis 1- Adoption of mobile learning approach

H1-The adoption of mobile learning approach improves Grade 12 learners' engagement and motivation while learning mathematics

The model summary reveals that the regression model explains approximately 26.5% of the variance in learners' perceived improvement in mathematics performance ($R^2 = 0.265$), indicating a moderate relationship between mobile device ownership and perceived benefits of mobile learning. Table 4.16 shows the regression analysis findings obtained during hypothesis (H1) testing.

Table 4. 16: Hypothesis 1: Model Summary

Model	R	R Square	Adjusted R-squared value	Std. Error in Estimate
1	.515 ^a	.265	.260	.465

a. Predictors: (Constant): I owned a mobile device while studying grade 12

- R (Correlation Coefficient): An R value of 0.515 indicates a strong positive correlation between learners' performance and mobile use.
- R Square (Coefficient of Determination): An R Square value of .583 means that approximately 26% of the variance in grade 12 learners can be explained by the perceived benefits of mobile learning.
- Adjusted R Square: The adjusted R Square value of .260 is close to the R Square value, indicating a good fit for the model.
- Std. Error of the Estimate: The standard error of .465 gives us an idea of how much the observed values deviate from the regression line.

Table 4. 17: H1 - ANOVA^a

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	11.536	1	11.536	53.460	.000 ^b
	Residual	31.937	148	.216		
	Total	43.473	149			

a. Dependent Variable: Mobile learning will improve my mathematics performance.

b. Predictors: (Constant): I owned a mobile device while studying grade 12

The ANOVA table 4.17 above shows that the regression model is statistically significant ($F(1, 148) = 53.460, p < .001$), meaning that the model significantly predicts

the dependent variable and that the predictor variable contributes meaningfully to the explanation of variance.

- Regression Sum of Squares: The regression sum of squares (11.536) represents the variation explained by the model.
- Residual Sum of Squares: The residual sum of squares (31.937) represents the variation not explained by the model.
- F-Statistic: An F value of 53.460 is very high, and a significance value (Sig.) of .000 indicates that the model is statistically significant.

The Coefficients table indicates that the predictor variable ("I owned a mobile device while studying Grade 12") has a positive and statistically significant impact on the dependent variable ($B = 0.359$, $p < .001$). The standardised beta value ($\beta = 0.515$) suggests a moderate to strong positive effect, implying that students who own a mobile device are more likely to believe that mobile learning enhances their mathematics performance (see table 4.18 below).

. Table 4. 18: H1 - Coefficients^a

Coefficients ^a						
Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.838	.097		8.678	.000
	I owned a mobile device while studying for Grade 12	.359	.049	.515	7.312	.000

a. Dependent Variable: Mobile learning will improve my mathematics performance.

- Constant (Intercept): The constant value of .838 represents the expected value of how mobile learning can help improve mathematics performance.
- Coefficient: The unstandardised coefficient of .359 indicates that performance is expected to increase by .359 units.
- Standardised Coefficient (Beta): The standardised coefficient of .515 signifies the strength of the relationship.
- t-Statistic and Significance: A t value of 7.312 and a significance level of .000 indicate that the mobile learning coefficient is statistically significant.

4.7.2 hypothesis 2 test: Use of mobile learning tools

H2 The use of mobile learning tools lead to high mathematics performances among Grade 12 learners.

The model summary explains 33.8% of the variance in teachers' perceptions of mobile learning's role in enhancing performance ($R^2 = 0.338$). The adjusted R^2 is 0.302, indicating a moderate level of explanatory power after adjusting for the number of predictors. This suggests that a fair amount of variation in perceived academic benefit can be accounted for by student device ownership. Table 4.19 provides regression analysis findings for hypothesis (H2) testing.

Table 4. 19: Hypothesis 2-Model Summary

Model	R	R Square	Adjusted R-squared value	Std. Error in Estimate
1	.582 ^a	.338	.302	.761

a. Predictors: (Constant): My students own a mobile device.

- R (Correlation Coefficient): An R value of .582 indicates a strong positive correlation between mobile learning and performance.
- R Square (Coefficient of Determination): An R Square value of .338 means that approximately 33.8% of the variance in mathematics performance can be explained by learning tools.
- Adjusted R Square: The adjusted R Square value of .302 is close to the R Square value, indicating a good fit for the model.
- Std. Error of the Estimate: The standard error of .761 gives us an idea of how much the observed values deviate from the regression line.

The ANOVA table confirms that the model is statistically significant ($F(1, 18) = 9.205$, $p = .007$), indicating that the relationship between student mobile device ownership and the perceived need for mobile learning is not due to chance(see table 4.20 below).

Table 4. 20: H2 - ANOVA^a

Model	Sum of Squares	df	Mean Square	F	Sig.
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1	Regression	5.329	1	5.329	9.205	.007 ^b
	Residual	10.421	18	.579		
	Total	15.750	19			

a. Dependent Variable: I see a need for m-learning to enhance learners' performance.

b. Predictors: (Constant): My students own a mobile device.

- Regression Sum of Squares: The regression sum of squares (5.329) represents the variation explained by the model.
- Residual Sum of Squares: The residual sum of squares (10.421) represents the variation not explained by the model.
- F-Statistic: The F value of 9.205 is very high, and the significance value (Sig.) of .007 indicates that the model is statistically significant.

In the Coefficients table, the unstandardised coefficient for the predictor is $B = 1.184$, with a p-value of .007, which is statistically significant. The standardised beta ($\beta = 0.582$) indicates a moderate to strong positive relationship. This implies that as more students own mobile devices, teachers are more likely to recognise and support the use of mobile learning tools as beneficial for improving mathematics performance (see table 4.21 below).

Table 4. 21: H2 - Coefficients^a

Coefficients^a

Model	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	-.237	.837		-.283	.780
1 My students have a mobile device.	1.184	.390	.582	3.034	.007

a. Dependent Variable: I see a need for m-learning to enhance learners' performance.

- Constant (Intercept): The constant value of -.237 represents the expected value of m learning when the mobile device is.007.
- Mobile device coefficient: The unstandardised coefficient of 1.184 indicates that performance is expected to increase by 1.184 units.

- Standardised Coefficient (Beta): The standardised coefficient of .582 signifies the strength of the relationship.
- t-Statistic and Significance: A t value of 3.034 and a significance level of .007 indicate that the mobile device coefficient is statistically significant.

4.7.3 Test hypothesis 3 (Internet Accessibility)

H3 The adoption of mobile learning is constrained by limited internet accessibility and educators' resistance.

The model Summary indicates that the model explains 45% of the variance in teachers' perceptions of virtual classroom learning ($R^2 = 0.450$), with an adjusted R^2 of 0.419, suggesting that a significant portion of the perception variation is explained by the predictor. The model's standard error of 0.495 reflects the average distance between the observed and predicted values. Tables 4.22; 4.23 and 4.24 illustrate the regression analysis findings from hypothesis (H3) testing.

Table 4. 22: H3-Model Summary

Model	R	R Square	Adjusted R-squared value	Std. Error in Estimate
1	.671 ^a	.450	.419	.495

a. Predictors: (Constant) The area in which the school is located experiences network problems.

- R (Correlation Coefficient): An R value of .671 indicates a strong positive correlation between internet accessibility and performance.
- R Square (Coefficient of Determination): An R Square value of .450 means 45% of the variance in mobile learning can be explained to include internet accessibility and educators' resistance.
- Adjusted R Square: The adjusted R Square value of .419 is close to the R Square value, indicating a good fit for the model.
- Std. Error of the Estimate: The standard error of .495 gives us an idea of how much the observed values deviate from the regression line.

The ANOVA table reveals that the model is statistically significant ($F(1, 18) = 14.706$, $p = .001$), confirming that the relationship between network problems and the perception of virtual classrooms as a waste of time is unlikely to be due to chance (see table 4.7 below).

Table 4. 23: H3 - ANOVA^a**ANOVA^a**

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	3.597	1	3.597	14.706	.001 ^b
Residual	4.403	18	.245		
Total	8.000	19			

a. Dependent Variable: Learning through virtual classrooms is a waste of time.

b. Predictors: (Constant): The area in which the school is located experiences network problems.

- Regression Sum of Squares: The regression sum of squares (3.597) represents the variation explained by the model.
- Residual Sum of Squares: The residual sum of squares (4.4.3) represents the variation not explained by the model.
- F-Statistic: The F value of 14.706 is very high, and the significance value (Sig.) of .001 indicates that the model is statistically significant.

In the Coefficients table, the unstandardised coefficient for the predictor is $B = 0.719$, and the standardised beta ($\beta = 0.671$) indicates a strong positive relationship. The p-value of the predictor was .001, which is highly significant. Therefore, as network problems in the school area increase, teachers are more likely to view virtual classrooms negatively, which agrees with the hypothesis (see table 4.7 below).

Table 4. 24: H3 - Coefficients^a**Coefficients^a**

Model	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
1 (Constant)	.525	.400		1.312	.206
The area in which the school is located experiences network problems.	.719	.188	.671	3.835	.001

a. Dependent Variable: Learning through virtual classrooms is a waste of time.

- (Intercept): The constant value of .525 represents the expected value of learning virtually when the network problem is .001.

- Promotion Coefficient: The unstandardised coefficient of .719 indicates an increase in network access that is expected to increase by .719 units.
- Standardised Coefficient (Beta): The standardised coefficient of .671 signifies the strength of the relationship.
- t-Statistic and Significance: A t value of 3.835 and a significance level of .000 indicate that the coefficient for network access is statistically significant.

4.7.4 hypothesis 4 test: learners and educators' resistance

H4 The adoption of mobile learning is constrained by learners and educators' resistance.

The Model Summary shows that the model explains only 12.7% of the variance in the willingness of students to try mobile learning ($R^2 = 0.127$), with an adjusted R^2 of 0.078, indicating that the predictor variable does not explain much of the variation. The standard error of the estimate was 0.874, indicating moderate prediction accuracy. Hypothesis (H4) was tested using regression analysis, and the findings are highlighted in table 4.25.

Table 4. 25: H4-Model Summary

Model	R	R Square	Adjusted R-Squared	Std. Error in Estimate
1	.356 ^a	.127	.078	.874

a. Predictors: (Constant): Learning through virtual classrooms is a waste of time.

- R (Correlation Coefficient): An R value of .356 indicates a strong positive correlation between virtual classrooms and educators' resistance.
- R Square (Coefficient of Determination): An R Square value of .356 means that approximately 35.6% of the variance in the virtual classroom can be explained by educators' resistance.
- Adjusted R Square: The adjusted R Square value of 0.078% is not close to the R Square value, indicating a moderate fit for the model.
- Std. Error of the Estimate: The standard error of .874 gives us an idea of how much the observed values deviate from the regression line.

The ANOVA table reveals that the model is not statistically significant ($F(1, 18) = 2.618$, $p = 0.123$), meaning there is no strong evidence that educators' resistance, as

measured by their perception of virtual classrooms being a waste of time, has a significant effect on students' willingness to adopt mobile learning (see table 4.26 below).

Table 4. 26: H4 - ANOVA^a

ANOVA ^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.000	1	2.000	2.618	.123 ^b
	Residual	13.750	18	.764		
	Total	15.750	19			

a. Dependent variable: Students who are willing to attempt m-learning

b. Predictors: (Constant): Learning through virtual classrooms is a waste of time.

- Regression Sum of Squares: The regression sum of squares (2.000) represents the variation explained by the model.
- Residual Sum of Squares: The residual sum of squares (13.750) represents the variation not explained by the model.
- F-Statistic: The F value of 2.618 is very high, and the significance value (Sig.) of .123 indicates that the model is statistically significant.

In the Coefficients table, the unstandardised coefficient for the predictor is $B = 0.500$, with a standardised beta ($\beta = 0.356$). However, the p-value for the predictor was 0.123, which is above the commonly accepted threshold of 0.05 for statistical significance, indicating that the relationship was not statistically significant (see table 4.27 below).

Table 4. 27: H4 - Coefficients^a

Coefficients ^a						
Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.250	.648		1.928	.070
	Learning through virtual classrooms is a waste of time.	.500	.309	.356	1.618	.123

a. Dependent variable: Students who are willing to attempt m-learning

- Constant (Intercept): The constant value of 1.250 represents the expected value of m-learning when educator resistance is .070.

- Coefficient: The unstandardised coefficient of .500 indicates that an increase in educator resistance is expected to increase by .500 units.
- Standardised Coefficient (Beta): The standardised coefficient of .356 signifies the strength of the relationship.
- t-Statistic and Significance: A t value of 1.618 and a significance level of .123 indicate that the coefficient for virtual learning is statistically significant.

4.8 Hypotheses results

H1-The adoption of mobile learning approach improves Grade 12 learners' engagement and motivation while learning mathematics

A variance of 26.6% (see Table 4.16) demonstrates that mobile learning is critical in increasing levels of performance. The regression analysis findings confirm the hypothesis that there is a strong and significant positive relationship between mobile learning and mathematics performance for Grade 12 learners. The regression model is statistically significant, and the independent variable has a meaningful positive impact, hypothesis H1 is accepted.

H2-The use of mobile learning tools lead to high mathematics performance among Grade 12 learners.

In table 4.19 a 33.8% variance indicates that the use of mobile learning tools is critical for learners' performance. The significance levels in hypothesis (H2) regarding mathematics performance are associated with increased use of mobile learning tools. Given that the model is statistically significant and the predictor variable has a meaningful positive effect, hypothesis H2 is accepted.

H3: The adoption of mobile learning is constrained by limited internet accessibility.

An estimated 45% variance (Table 4.22) in mobile learning is constrained by internet accessibility. The predictor variable "network problems" has a significant and positive effect on the dependent variable; thus, hypothesis H3 is supported.

H4: The adoption of mobile learning is constrained by learners and educators' resistance.

Based on a variance of 12.7% from the regression analysis, the implication is that the relationship between educator resistance and learners' performance is not significantly strong (Table 4.25). Given the insignificance levels of the predictor variable "Learning through virtual classrooms is a waste of time" does not have a statistically significant effect on students' willingness to try mobile learning ($p > 0.05$); therefore, hypothesis H4 is rejected.

4.9 Chapter summary

This chapter provides respondents' demographic profiles; descriptive statistics of the individual variables on respective mean and standard deviation values; Cronbach's alpha reliability assessment findings; structural model fit and hypothesis tests.

Chapter 5 uses insights from the analysis of the findings to draw conclusions and make recommendations regarding the research topic.

CHAPTER 5: DISCUSSION, CONCLUSION AND RECOMMENDATION

5.1 Introduction

This chapter provides a conclusion on the findings of the study, limitations, and recommendations for future studies.

5.2 Discussion on Findings

Outlined below is discussion on the relationships between grade 12 learner performance in mathematics and the four independent variables, adoption of mobile learning; usage of mobile learning; internet accessibility, and educators' resistance.

Hypothesis 1: "The adoption of mobile learning approach improves Grade 12 learners' engagement and motivation whilst learning mathematics"

Hypothesis 1 suggested that adoption of a mobile learning approach enhances Grade 12 students' engagement and motivation in mathematics. Findings from the regression tests support this assertion. The results indicate a strong significant positive relationship between mobile learning and mathematics performance. In essence, the adoption of mobile learning better positions grade 12 learners to perform better in mathematics

Mobile learning enables educators to innovatively provide learners with a variety of learning content and resources, thus leading to increased levels of engagement during mathematics lessons. Studies have indicated that mobile learning can increase learners' motivation. according to Bamidele (2021), mobile learning devices' high levels of immediacy and interactivity can improve learners' concentration effort. Typically, mathematics learners with abstract concepts, mobile learning, and applications can improve interactive simulations through visual aids.

This aligns with the findings of the regression analysis, which suggests that when mobile learning tools are used, students demonstrate higher levels of engagement and improved academic performance in mathematics.

The positive relationship between mobile learning and academic performance can also be attributed to the collaborative features of many mobile applications. Wang et al. (2013) stated that mobile learning creates a collaborative learning atmosphere that encourages interaction and support among peers. Collaborative learning can enhance

retention of mathematical concepts, which can be enhanced with mobile learning platforms through group work and discussion. Such platforms can also facilitate further motivating among learners to engage on the subject matter.

The use of mobile learning in mathematics education aligns perfectly well with the principles of constructivist learning theories, which advocate active learning experiences. Piaget (1973) posited that learners construct knowledge through experiences, and mobile learning can provide a good platform for learners to engage actively in problem-solving activities and in the real-world applications of mathematical concepts and principles. This kind of experiential learning approach does not only enhance interaction amongst students but also reinforces fosters deeper understanding and retention of mathematical knowledge.

The findings in Hypothesis 1 are supported. The adoption of a mobile learning approach can significantly improve Grade 12 learners' engagement and motivation in mathematics lessons. The significant positive relationship in hypothesis 1 underscores the potential of mobile learning to improve mathematics performance. South Africa should incorporate technological methods in education; mobile learning can be a viable strategy capable of enhancing performance in mathematics through learners' engagement.

Hypothesis 2: “The use of mobile learning tools leads to high performances in mathematics amongst Grade 12 learners”

The study hypothesis posits that the utilisation of mobile learning tools is positively correlated with enhanced mathematics performance among grade 12 learners. Based on a 33.8% variance, it can be implied that the use of mobile devices for learning purposes is positively correlated to grade 12 learners' mathematics performance.

The findings in hypothesis 2 agrees with several research studies that demonstrated the positive impact of mobile learning on learner performance. Mobile learning facilitates personalised learning experiences for learners and accommodates different learning styles and needs for learners (Cheung and Slavin, 2013 and Kukulska-Hulme, 2012).

According to Wu et al. (2012) and Sharples et al. (2015), improved performance among learners who regularly use mobile devices for learning can be attributed to a

number of factors. First, access to mobile devices allows learners to engage with mathematical concepts outside the traditional classroom environment, promoting continuous learning and practice. This flexibility is most advantageous for Grade 12 learners considering the mounting academic pressure experienced during preparations for final examinations. Second, learners benefit from interactive features such as quizzes, simulations, and visual aids found on mobile devices. These interactive features can enhance learner engagement and motivation as well as lead to improvements in the retention of complex mathematical concepts common in Grade 12 curricula. Lastly, mobile learning tools enable the sharing of learning experiences among grade 12 learners. For instance, most learning apps allow learners to participate in peer-to-peer interactions that create high levels of belonging and support.

On the whole, a large body of evidence supports the hypothesis about how the use of mobile learning tools result in high mathematics performance among Grade 12 learners. Therefore, it is imperative for educational institutions to incorporate mobile learning into teaching and learning strategies to ensure learners' better mathematics performance.

Hypothesis 3: “The adoption of mobile learning is constrained by limited internet accessibility”

An estimated 45% variance led to the acceptance of hypothesis 3. This outcome suggests that a significant number of teachers and learners are unable to adopt mobile learning due several constraints linked to internet accessibility and network problems. there are several critical factors that constrain its uptake.

There are several ways in which these constraints limit the adoption and usage of mobile learning. First, residents of rural and underserved areas lack reliable internet access. In this case, internet connectivity can be erratic most of the time. As such, unreliable internet access prevents teachers and learners from engaging in mobile learning on a regular basis, thus compounding inequalities. It not only affects students' ability to engage with mobile learning platforms but also exacerbates existing educational inequalities (Akmand and Abatayo, 2024). The argument is that unreliable internet access not only prevents or interrupts engagement between teachers and learners but also delays learners from getting learning e-resources and submitting

assessments. As consequence, there is a need for responsible stakeholders to upgrade digital infrastructure. Lastly, some educators show resistance to the adoption of mobile learning strategy due to several reasons (Fernando and Sanjiv, 2022). For instance, some educators lack the necessary digital literacy to navigate mobile devices and lack faith in the efficacy of mobile learning as a teaching strategy. Consequently, such educators still prefer traditional teaching strategies. In some cases, educators who are digitally challenged often have problems choosing relevant content for teaching and learning.

The challenge of educators' resistance can be addressed through a multipronged approach. The aims of such an approach should be to equip educators with appropriate digital skills, knowledge and attitudes. Furthermore, stakeholders should foster a spirit of innovativeness and experimentation among educators of critical subjects like mathematics.

Hypothesis 4: “The adoption of mobile learning is constrained by learners’ and educators’ resistance.”

Hypothesis 4 is grounded in the premise that educators, as key facilitators of learning, play an important role to play in ensuring that mobile learning is successfully implemented. However, a variance of 12.7% in the regression analysis indicates a weak relationship between educator resistance and the adoption of mobile learning; hence, Hypothesis 4 was rejected.

Findings presented in Table 4.25 indicate that the impact of educator resistance on the adoption of mobile learning is minimal. Although some educators might be reluctant to adopt mobile learning, available evidence suggests that this has not prevented schools from adopting such a strategy. Rather, the factors that influence the adoption and use of mobile learning can be explained in the context of the technology acceptance model (TAM). According to Schorr (2024), TAM provides insights into how people's perceptions about convenience and usefulness are key factors that underpin the adoption of any technology. For instance, resistance may dissipate once educators see the upside of mobile learning as an integral part of teaching and learning. Therefore, prioritising professional development of educators is an effective strategy for eliminating such resistance. In addition, stakeholders must

create conducive environments that can moderate educators' resistance and facilitate the adoption of mobile learning in the teaching of mathematics.

Considering the results, it is evident that the impact of educator resistance is not prominent as posited in H4. Instead, the statistical insignificance of the results calls for a review of other factors that constrain the widespread adoption of mobile learning for teaching grade 12 mathematics in South African high schools. For this reason, future studies should investigate how key factors like learner engagement, curriculum alignment and the role of peer collaboration among educators drive effective implementation of mobile learning.

5.3 Conclusion

The adoption of mobile learning in South African high schools has the potential to enhance Grade 12 learners' performance in critical STEM subjects like mathematics. This study investigated the relationship between mobile learning and mathematics performance among Grade 12 learners in South Africa. To achieve this goal and address literature gaps, the researcher reviewed various secondary publications. Additionally, the researcher used a survey tool to collect quantitative primary data from learners and teachers in the Secunda area of Mpumalanga province. Thereafter, data was analysed using software apps such as SPSS version 24 and AMOS version 29 to test the four alternative hypotheses. Three of the hypotheses (H1, H2, and H3) were supported by study findings and duly accepted. On the contrary, results failed to support H4, leading to its rejection.

The study findings suggest that performance in mathematics among grade 12 learners is related to variables such as the adoption and usage of mobile learning by teachers and learners and internet accessibility and reliability. For instance, learner mathematics performance is positively correlated with the level of adoption and use of mobile learning in high schools. However, the independent variable of internet accessibility negatively impacts learner mathematics performance. By contrast, the study failed to demonstrate any relationship between the adoption of mobile learning and educators' resistance after hypothesis H4 was not supported by findings.

It is therefore imperative for the Department of Basic Education (DBE) stakeholders to prioritise and leverage the strategic innovativeness of mobile learning as a tool for improving mathematics performance among grade 12 learners.

5.4 Limitations of the Study

The study has certain limitations that will probably impact the reliability, representativeness, generalisability, and dependability of the findings. The study sample was purposively drawn from Secunda while excluding other areas in the Mpumalanga province. As such, this sample of 150 learners and 20 teachers is not representative of populations outside the Secunda area. Additionally, the use of a quantitative approach to gather data denied the researcher an opportunity to explore participants' subjective but enriching views on the study topic.

Therefore, it should be noted that the study findings are difficult to reproduce in different contexts by other researchers. Moreover, the use of a purposive sample from a small study area raises challenges of generalising findings to broader contexts within and beyond the country.

5.5 Recommendations

The study findings suggest several courses of action that can enable stakeholders to leverage mobile learning as a pedagogical strategy for improving grade 12 learners' performance in mathematics. The following recommendations should be considered by the stakeholders:

- i. Investments in educator training and professional development: There is a need to equip educators with the necessary skill sets, knowledge, and attitudes for the effective implementation of mobile phone learning.
- ii. Development of mobile learning policies: Schools must put in place policies to provide clarity on the appropriate and responsible usage of mobile learning devices and the safety and privacy of users.
- iii. Community engagement: Engaging communities facilitate the creation of an environment that accelerates acceptance levels of mobile learning and promotes collaborative problem solving.

- iv. Integrating mobile learning into school curricula -Integration can expedite the normalisation of mobile learning as a mainstream pedagogical strategy rather than a supplementary one.
- v. Continuous monitoring of mobile learning programmes -The practice is aimed at soliciting feedback and insights from users of mobile learning in order to deal with implementation challenges.
- vi. Promotion of collaborative learning -Schools should explore ways in which mobile learning can be leveraged to promote collaboration and peer-to-peer learning activities among the community of grade 12 mathematics learners across regions and provinces.

5.6 Further studies

Considering existing literature gaps. Academics and other stakeholders should conduct contextual as well studies with wider scopes on mobile learning. For example, there is a need for mixed methodology studies. Such studies can result in increased insights into and understanding the impact of mobile learning in enhancing mathematics performance among grade 12 learners. On the other hand, studies with wider scopes can facilitate sample representativeness and generalisability of findings to broader populations and contexts.

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Annexures

Annexure 1: Letter to the research participants

Consent Form

Study Title: Perception of mobile phone learning to improve grade 12 students' performance in high schools in South Africa.

Introduction:

You are invited to participate in a research study conducted by Solomon Mahlangu, an MBA candidate at Wits Business School. This study aims to investigate how mobile learning can be utilized to improve the mathematics academic performance of Grade 12 students in South African high schools.

Purpose of the Study:

The purpose of this study is to explore the effectiveness of mobile learning technologies in enhancing the learning experiences and outcomes of Grade 12 students. The study will examine the perspectives of both teachers and students who wrote mathematics grade 12 exam regarding the use of mobile devices for educational purposes.

I,, agree to participate in the research project.

I agree to the following:

(Please circle the relevant options below)

1. The research study was explained to me. I understand what this study is about.	YES	NO
2. I understand that I can volunteer to take part in the study	YES	NO
3. I agree that the interview/focus group/ other activity may be audio recorded	YES	NO
4. I agree that direct quotations from my interview/focus group/other activity may be used by the researcher in their research report/manuscript/book chapter	YES	NO
5. I agree that my participation will remain anonymous (my name or other identifying data will not be used by the researcher in their research report/manuscript/book chapter	YES	NO

Name of participant:	
Signature:	
Date:	

Name of the researcher/person seeking consent:	
Signature:	
Date:	

Annexure 2: Research Instruments A and B

Annexure A: Teacher's questionnaire							
Gender	Male		Female				
Experience	0 – 5 yrs	5 – 10 yrs	10 – 15 yrs	15 – 20 yrs	20 – 25 yrs	25 – 30 yrs	
Qualifications	Matric		Diploma	Degree			
Race	African		White	Coloured	Indians		
	Statement						
		SA*	A*	N*	DA*	SDA*	
A. Student Attitudes towards Mobile learning							
Item							
1	The students are willing to try m-learning						
2	Mobile learning will assist in improving students' mathematics performance						
3	The students like to participate in online discussions						
B. Student Interest in learning with Mobile Learning							
4	Students will be willing to work on exercises online						
C. Availability of Mobile devices							
5	My students own a mobile device						
6	The area where the school is located experiences network problems						
7	Learning through virtual classrooms is a waste of time						
8	I see a need for m-learning to enhance performance of the learners						

*Legend: SA, Strongly Agree; A, Agree; N, Neutral; DA, Disagree; and SDA, Strongly Disagree

Annexure B: Student questionnaire						
Gender	Male		Female			
Race	African	White	Coloured	Indian		
Age greater than 18 yrs:	Yes	No				
	Statement	SA*	A*	N*	DA*	SDA*
A. Student Attitudes towards Mobile learning						
Item						
1	I be willing to try m-learning					
2	Mobile learning will assist in improving my' mathematics performance					
3	I like to participate in online discussions					
B. Student Interest in learning with Mobile Learning						
4	I think online exercises will benefit me as a students					
C. Availability of Mobile devices						
5	I owned a mobile device while studying grade 12					
6	The area where I am located experiences network problems					
7	Learning through virtual classrooms is a waste of time					
8	I see a need for m-learning to enhance my performance as a learner					

*Legend: SA, Strongly Agree; A, Agree; N, Neutral; DA, Disagree; and SDA, Strongly Disagree

Appendices

Appendix 11: Descriptive Statistics - Teachers

Descriptive Statistics: Teachers

		N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Code	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Students are willing to attempt m-learning	A1	20	1	4	2.25	.910	.378	.512	-.371	.992
Mobile learning can help improve students' mathematics performance	A2	20	1	4	2.25	.786	.225	.512	-.018	.992
Students like to participate in online discussions	A3	20	1	3	1.90	.718	.152	.512	-.880	.992
Students will be willing to perform online exercises	B4	20	1	4	2.05	.759	.716	.512	1.195	.992
My students have a mobile device.	C5	20	1	3	2.10	.447	.549	.512	2.663	.992
The area in which the school is located experiences network problems.	C6	20	1	3	2.05	.605	-.012	.512	.189	.992
Learning through virtual classrooms is a waste of time.	C7	20	1	3	2.00	.649	.000	.512	-.279	.992
I see a need for m-learning to enhance the performance of learners.	C8	20	1	4	2.25	.910	-.087	.512	-1.001	.992
Valid N (listwise)		20								

Appendix 2: Descriptive Statistics of Students

Descriptive Statistics: Students

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
I am willing to attempt m-learning.	150	1	3	1.41	.506	.541	.198	-1.337	.394
Mobile learning will help improve my mathematics performance	150	1	3	1.49	.540	.442	.198	-1.020	.394
I like to participate in online discussions	150	1	3	1.43	.561	.846	.198	-.306	.394
I think online exercises will benefit me as a student.	150	1	4	1.59	.647	.802	.198	.307	.394
I owned a mobile device while studying for Grade 12	150	1	4	1.81	.775	.702	.198	.041	.394
The area where I am located experiences network problems	150	1	4	1.65	.657	.810	.198	.852	.394
Learning through virtual classrooms is a waste of time.	150	1	4	2.03	.777	.650	.198	.410	.394
I see a need for m-learning to enhance my performance as a learner.	150	1	4	1.94	.779	.882	.198	.953	.394
Valid N (listwise)	150								

Appendix 3: Normality Tests - Teachers

Tests of Normality: Teachers and

	Kolmogorov-Smirnov ^a			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Students are willing to attempt m-learning	.258	20	.001	.877	20	.016
Mobile learning can help improve students' mathematics performance	.275	20	.000	.864	20	.009
Students like to participate in online discussions	.255	20	.001	.812	20	.001
Students will be willing to perform online exercises	.326	20	.000	.817	20	.002
My students have a mobile device.	.438	20	.000	.611	20	.000
The area in which the school is located experiences network problems.	.333	20	.000	.768	20	.000
Learning through virtual classrooms is a waste of time.	.300	20	.000	.793	20	.001
I see a need for m-learning to enhance the performance of learners.	.245	20	.003	.859	20	.007

a. Lilliefors Significance Correction

Appendix 4: Normality Tests - students

Tests of Normality

	Kolmogorov-Smirnov ^a			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
I am willing to attempt m-learning.	.389	150	.000	.645	150	.000
Mobile learning will help improve my mathematics performance	.350	150	.000	.687	150	.000
I like to participate in online discussions	.380	150	.000	.680	150	.000
I think online exercises will benefit me as a student.	.311	150	.000	.746	150	.000
I owned a mobile device while studying for Grade 12	.238	150	.000	.809	150	.000
The area where I am located experiences network problems	.278	150	.000	.753	150	.000
Learning through virtual classrooms is a waste of time.	.307	150	.000	.818	150	.000
I see a need for m-learning to enhance my performance as a learner.	.316	150	.000	.786	150	.000

a. Lilliefors Significance Correction

Appendix 55: Regression weights (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
PE	<---	AML	.018	.096	.190	.849	par_14
PE	<---	UML	.201	.091	2.208	.027	par_15
PE	<---	IA	.698	.247	2.820	.005	par_16
PE	<---	ER	.647	.137	4.713	***	par_17
AML1	<---	AML	1.000				
AML2	<---	AML	1.105	.112	9.848	***	par_1
AML3	<---	AML	.886	.119	7.449	***	par_2
AML4	<---	AML	1.187	.135	8.773	***	par_3
AML5	<---	AML	1.370	.163	8.423	***	par_4
AML6	<---	AML	1.105	.139	7.974	***	par_5
UML1	<---	UML	1.000				
UML2	<---	UML	1.184	.197	6.015	***	par_6

			Estimate	S.E.	C.R.	P	Label
UML3	<---	UML	1.212	.209	5.797	***	par_7
UML4	<---	UML	1.387	.227	6.114	***	par_8
UML5	<---	UML	.776	.160	4.849	***	par_9
UML6	<---	UML	.757	.166	4.547	***	par_10
IA1	<---	IA	1.000				
IA2	<---	IA	.908	.344	2.638	.008	par_11
ER1	<---	ER	1.000				
ER2	<---	ER	1.514	.338	4.474	***	par_12
PE1	<---	PE	1.000				
PE2	<---	PE	.687	.164	4.193	***	par_13

Appendix 6: Standardised Regression Weights: (Group number 1 - Default model)

			Estimate
PE	<---	AML	.020
PE	<---	UML	.252
PE	<---	IA	.661
PE	<---	ER	.707
AML1	<---	AML	.778
AML2	<---	AML	.806
AML3	<---	AML	.623
AML4	<---	AML	.723
AML5	<---	AML	.696
AML6	<---	AML	.663
UML1	<---	UML	.589
UML2	<---	UML	.695
UML3	<---	UML	.653
UML4	<---	UML	.717
UML5	<---	UML	.506
UML6	<---	UML	.466
IA1	<---	IA	.656
IA2	<---	IA	.414
ER1	<---	ER	.608
ER2	<---	ER	.829
PE1	<---	PE	.648
PE2	<---	PE	.443

Appendix 77: Intercepts: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P	Label
AML1	1.407	.041	34.028	***	par_18
AML2	1.487	.044	33.709	***	par_19
AML3	1.433	.046	31.312	***	par_20
AML4	1.587	.053	30.035	***	par_21
AML5	1.807	.063	28.567	***	par_22
AML6	1.647	.054	30.706	***	par_23
UML1	2.027	.063	31.956	***	par_24
UML2	1.940	.064	30.494	***	par_25
UML3	2.153	.069	31.053	***	par_26
UML4	2.360	.072	32.680	***	par_27
UML5	1.933	.057	33.752	***	par_28
UML6	1.927	.061	31.771	***	par_29
IA1	1.867	.043	43.407	***	par_30
IA2	2.133	.062	34.525	***	par_31
ER1	2.087	.053	39.033	***	par_32
ER2	2.033	.059	34.237	***	par_33
PE1	1.840	.046	40.027	***	par_34
PE2	1.753	.046	37.968	***	par_35

Appendix 88: Variances: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P	Label
AML	.154	.029	5.354	***	par_36
UML	.208	.059	3.528	***	par_37
IA	.118	.050	2.373	.018	par_38
ER	.158	.050	3.156	.002	par_39
e1	.101	.015	6.641	***	par_40
e2	.102	.016	6.224	***	par_41
e3	.191	.024	7.822	***	par_42
e4	.199	.028	7.220	***	par_43
e5	.307	.041	7.419	***	par_44
e6	.240	.032	7.627	***	par_45
e7	.391	.053	7.443	***	par_46
e8	.312	.048	6.515	***	par_47
e9	.411	.059	6.960	***	par_48
e10	.377	.061	6.234	***	par_49
e11	.364	.046	7.867	***	par_50
e12	.429	.054	8.017	***	par_51

	Estimate	S.E.	C.R.	P	Label
e13	.157	.046	3.399	***	par_52
e14	.471	.067	7.069	***	par_53
e15	.268	.045	6.010	***	par_54
e16	.164	.075	2.203	.028	par_55
e17	.183	.031	5.816	***	par_56
e18	.255	.033	7.804	***	par_57

Appendix 99: Variances: Factor Score Weights (Group number 1 - Default model)

	P E 2	P E 1	E R 2	E R 1	I A 2	I A 1	U M L 6	U M L 5	U M L 4	U M L 3	U M L 2	U M L 1	A M L 6	A M L 5	A M L 4	A M L 3	A M L 2	A M L 1
I A	. 0 8 4	. 1 7 0	- . 0 6	- . 0 3	. 0 9 8	. 3 2 4	- .0 0 3	- .0 0 4	- .0 0 7	- .0 0 6	- .0 0 7	- .0 0 5	.0 0 0	.0 0 0	.0 0 0	.0 0 0	- .0 0 1	- .0 0 1
U M L	. 0 1 7	. 0 3 5	- . 0 1	- . 0 5	- . 0 4	- . 0 2	.0 7 4	.0 9 0	.1 5 5	.1 2 4	.1 6 0	.1 0 8	.0 0 0	.0 0 0	.0 0 0	.0 0 0	.0 0 0	.0 0 0
A M L	. 0 0 1	. 0 0 1	. 0 0 0	. 0 0 0	. 0 0 0	. 0 0 1	.0 0 0	.0 0 0	.0 0 0	.0 0 0	.0 0 0	.0 0 0	.0 9 0	.0 8 8	.1 1 7	.0 9 1	.2 1 4	.1 9 5
E R	. 0 5 3	. 1 0 9	. 3 4 7	. 1 4 1	. 0 1 2	. 0 3 9	- .0 0 2	- .0 0 3	- .0 0 5	- .0 0 4	- .0 0 5	- .0 0 3	.0 0 0	.0 0 0	.0 0 0	.0 0 0	- .0 0 1	- .0 0 1
P E	. 0 9 6	. 1 9 6	. 1 8 3	. 0 7 4	. 0 6 0	. 1 9 8	.0 1 1	.0 1 3	.0 2 3	.0 1 9	.0 2 4	.0 1 6	.0 0 1	.0 0 1	.0 0 2	.0 0 1	.0 0 3	.0 0 3