THE IMPACT OF ARTIFICIAL INTELLIGENCE ON SMALL-MEDIUM ENTERPRISES IN DEVELOPING COUNTRIES.

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"Vision without action is just a dream, action without vision just passes the time, and vision with action can change the world."
~ Nelson Mandela

Entrepreneurship has always been a part of my life from a young age, from receiving an allowance to water the plants to making Christmas bows and fixing radios. Thank you to my parents for always supporting my projects and encouraging me to be creative and make 'holiday money'. My heart has always been inspired to make an impact in some way, here at home in Africa. By creating empowering opportunities now, we not only help our communities and people to grow but also heal generations to come.

This research journey began at a very pivotal point in my life, in 2022, and over the past 3 years, it has grown and developed with me. This journey has been both challenging and rewarding; without faith and love, I would not have accomplished this. Thank you to my mom, Shena, for blessing me with this time and resources, and support to explore and do what's true to me in this life. Your "entrepreneurial spirit" continues to inspire me through every phase in our lives. Thank you to my brother Sudesh for always supporting me in whatever capacity you can, from asking me every day how the writing is going to brainstorming solutions with me when I went down confusing research spirals. Thank you to my sister Renita, you've been my cheerleader from day one through it all. Thank you to my friends Letlhogonolo, Michelle, and Sylvia for your ongoing support and assistance with the research participants. My best friend Simone, thank you for grounding me, listening to me, and being with me through every moment. And finally, thank you to my dream team – my friends and family, who continue to show up!

ABSTRACT

This research study investigates the impact of Artificial Intelligence (AI) on small and medium-sized enterprises (SMEs) in developing countries, with a specific focus on three critical dimensions: affordability, accessibility, and skills. Despite AI's potential to improve operational efficiency, decision-making, and innovation, SMEs in developing regions face significant barriers to adoption due to limited financial resources, infrastructural constraints, and human capital deficits. To address these challenges, the study develops and applies a hybrid analytical framework combining the Business Model Canvas (BMC) and PESTEL analysis, offering a multidimensional approach to evaluate both internal and external factors influencing AI integration.

The research is guided by three central questions: (1) What framework can SMEs use to assess the internal and external impact of AI, specifically regarding affordability, accessibility, and skills? (2) What support structures are required for successful AI adoption? (3) How can qualitative value creation through AI be identified in terms of operational growth? Using a qualitative methodology, the study presents ten single-case studies for the first question and employs a multiple-case and cross-case analysis for the second and third questions. Case data were collected from SMEs operating in diverse sectors, including renewable energy, hospitality, fitness, consulting, and telecommunications across countries such as Chile, Namibia, South Africa, India, Vietnam, Ghana, and Malawi.

Findings indicate that skills availability is the most influential factor in determining AI success, shaping the capacity to implement, scale, and sustain AI systems. Affordability and accessibility remain important but can be mitigated through ecosystem engagement and adaptive strategies. The study reveals that AI contributes primarily through qualitative value creation, such as improved service delivery, increased operational efficiency, and enhanced decision-making. It also shows that cultural beliefs, policy support, and regional infrastructure significantly shape AI outcomes.

This research contributes a practical framework for SMEs and policy makers in the Global South (developing countries) to evaluate AI readiness and impact. It offers theoretical insights into AI adoption under conditions of constraint and calls for further research that expands into inclusive, cross-sectoral, and longitudinal analyses. The study concludes that while AI holds transformative potential for SMEs in developing countries, its success depends on strategically aligned internal capacity and supportive external ecosystems.

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CHAPTER 1
INTRODUCTION

1. Introduction

Artificial Intelligence (AI) has triggered a production revolution and a radical transformation in business operations and practices. With the rise of the Fourth Industrial Revolution (4IR), the need for knowledge and resources has become increasingly prevalent for technological adoption across all industries. There is a vast interest in uncovering the influential factors to catalyse the understanding of AI potential and adoption for SMEs (Small- Medium Enterprises) in emerging economies, mainly, the global south.

AI has significantly disrupted and improved many industries on multiple levels of scale and scope. These industries include finance, manufacturing, healthcare, retail, agriculture, supply chains, and others. In current times, AI is mostly recognised as an umbrella term encompassing many subfields with multiple business applications under each one, including Machine Learning (ML) (i.e., the branch associated mostly with the resolution of classification problems), Natural Language Processing (NLP) (i.e., the branch directly involved in image-to-text recognition), robotics (i.e., the branch focusing on the design/creation of robots involved in the automation of production lines), among others (Atlam et al., 2018; Najdawi, 2020).

AI typically uses pattern recognition, reasoning, and decision-making under complex conditions, and often deals with noisy data, uncertainties, ill-defined problems, and the need for in-situ solutions (Venkatasubramanian, 2019). AI internally and externally by businesses and governments has provided the Global South with the possibility to address existing, new, and unforeseen opportunities and problems. Developing countries, characterised by diverse socioeconomic contexts, are at the crossroads of harnessing the potential benefits of AI to address existing challenges and propel economic development (Wakunuma et al., 2020; Guo and Li, 2018; Hendler, 2023). The middle-low-income countries in the Global South represent undeveloped and developing countries across South America, Africa, and Asia. The aspiration in many low-income countries is to leverage AI in order to achieve transformation by changing underlying systems of development and towards inclusion by addressing both the symptoms and causes of inequality (Wall et al., 2013).

AI has emerged as a powerful force shaping the global technological landscape, and its adoption trends in developing countries present a dynamic narrative influenced by a myriad of factors (Pan, 2016). Financial, Geographical, and Human Capital are integral factors to consider; the available research is mostly based on the adoption of AI in Developed countries, with reliable infrastructure and funding. While the transformative potential of AI is evident, its adoption and integration present a distinctive set of challenges and opportunities for developing countries (Sood, Sharma, and Bhardwaj, 2022; Biswas, 2020). The creation of jobs in AI development, maintenance, and oversight becomes essential, contributing to the growth of the skilled workforce and fostering entrepreneurship in emerging technological fields (Arntz et al., 2016).

Entrepreneurship has been identified as one of the key drivers of economic prosperity and is therefore considered a reasonable vehicle with which to help emerging economies grow (Christensen et al., 2010; Kimmitt, Muñoz, and Newbery, 2019). However, in many developing countries, entrepreneurs must navigate barriers and constraints, with limited access to support resources and institutional voids. Examples of these voids include the absence of financial service institutions (e.g., banks, capital providers, insurance agencies), quality certification firms (e.g., ISO equivalents in developed countries), institutional infrastructure enabling data processing (e.g., with fibre optic networks), public economic development agencies, employment agencies, and arbitration mechanisms (Khanna and Palepu, 2010).

Research focused on Western developed economies has revealed that an open exchange with an ecosystem, including the receipt and provision of support to private and professional network partners, can foster innovativeness and might stimulate prospective entrepreneurial behavior (Vrande et al., 2009; Huggins and Thompson, 2017; Elia, Margherita, and Passiante, 2020). However, a large gap is prevalent in research and resources that are impartial and widely conducted in underdeveloped and developing countries.

The analysis that will be conducted will do a deep dive to understand the implementation structures and dynamics in SMEs, it will also critically compare factors such as expertise, funding opportunities, and purpose, to get a clearer understanding of why seamless integration tactics and practises do not apply across many SMEs business models in developing countries. Once the key factors have been assessed, this will provide a clear indication of gaps and weaknesses that can be capitalised on as digital transformation opportunities. An integral part of the research is to understand all the factors that impact the business and an AI project from an internal and external vantage point, in regards to the potential adoption of an AI system within the business.

1.1. Research problem and questions

The promise of digital transformation brings many diverse factors into play, with everyone diving into it at a fast and sometimes risky pace. Industries consist of innovators, early adopters, early majority, late majority, and laggards, all building on their predecessors and disrupters. However, with limited available research, many development and implementation stages may overlook comprehensively analysing all external and internal issues that are specific to businesses in developing countries, and how they relate to each other. These issues revolve mostly around the needs of countries that have the economic affluence to undergo such technological investments (Heng et al., 2022).

Many stakeholders have fallen victim to strategising growth and innovation in developing countries from a Western lens. Proving that what works in developed countries cannot necessarily be applied verbatim to businesses in developing countries, especially in small-medium businesses that do not have access to a similar scale and standard of resources. Companies in developed countries usually take for granted the critical role that "soft" infrastructure plays in the execution of their business models in their home markets, but that infrastructure is often underdeveloped or absent in emerging markets (Khanna, Palepu, and Sinha, 2005).

In developing countries, where resources are already limited, applying multiple strategy-based business models and segmented models can become costly and inefficient. Stakeholders need to formulate strategies that are realistic and inclusive, taking into consideration the effects of region-specific factors.

Many Businesses' Theoretical Models and Conceptual Frameworks have become redundant and constricting, ideally, models should be adapted according to the needs of a business and its environment. Existing and emerging factors that economicly and operationally influence business, social, and environmental structures must be identified and recorded in a methodological order that can be referred to as needed by stakeholders. Rather than being confined to singular frameworks and conceptual models, it would be more efficient for the long term if small-medium businesses had access to a resource that can be used as a framework and guide, an integral aspect of developing this framework according to the business and regional needs is the inclusivity proponent, inclusivity in this regard iterates dissolving skill, business acumen, cultural, and language barriers. To identify and understand the impact of AI on Small and medium enterprises in developing countries, research specific to developing countries should be conducted.

Main research question: What is the impact of AI on SMEs in developing countries?

Sub-questions (Indicated as RQ):

Scope - Affordability, Accessibility, Skills

- RQ 1: What framework can SMEs utilise in their strategic planning to evaluate the impact of AI, internally and externally?
  Scope: Affordability
  Accessibility
  Skills
- RQ 2: What support structures are required to successfully adopt an AI system?
- RQ 3: How can the qualitative value-creation of AI concerning operational growth be identified?

1.2. Research objectives

The research objectives of this study are to identify influential factors that should be considered during the strategic planning stage of integrating AI systems in SMEs in developing countries, using Affordability, Accessibility, and Skills as a scope to analyse the internal and external impact. In relation to the broader overview of the research objectives and questions, the following sub-objectives will be addressed:

- To identify and recommend conceptual frameworks that SMEs can utilise/incorporate in their strategic planning to evaluate the internal and external impact of AI (RQ1)
- To assess the support structure and components that SMEs require to successfully adopt AI (RQ2)
  With a brief comparison to developed countries (Addressed in Chapter 2: Literature Review)
- To identify the qualitative value-creation of AI with relevance to the operational growth of SMEs (RQ3)

Many developing countries are faced with challenges that include limited resources that affect the impact of technological growth, this also includes limited business resources and skills that are fundamental in strategic planning. The implication of this study is to provide a clear understanding of how implementing AI systems is affected by affordability, accessibility, and skills, further providing stakeholders with a conceptual framework that highlights the interconnectedness of the Business Model Canvas and PESTEL.

1.3. Significance of the study

SMEs in developing countries require collective and institutional support to significantly grow and contribute to the economy through digital transformation. Theoretically, AI systems can bring a sense of evolution to business practices and operations; however, as more and more businesses in developing countries are trying to adopt AI for various reasons, they are commonly met with multiple challenges. These challenges and risks could've been mitigated during the strategic planning process by using a comprehensive conceptual framework that highlights internal and external influential factors and their shortcomings. Ideally, the impact of AI on SMEs in developing countries would be assumed to be positive and promising, however, research, case studies, and reports have shown that mimicking the same planning processes and assumptions used to implement AI systems in SMEs in developed countries has frequently resulted in delays or failure. This further emphasises the need for more research to be conducted in specific relation to developing countries, considering regional and social dynamics, as well as existing and realisable resources.

Overall, this research aims to contribute to the prevailing knowledge gap of AI concerning Developing countries, as well as creating a resource that can assist SMEs of various skill levels and expertise in all economies and regions. The conceptual framework that has been developed and adapted from pre-existing frameworks has been developed with the stakeholders in mind. Factors such as usability, relevance, and business training and knowledge have been taken into consideration, encouraging stakeholders of all skill levels to be able to effectively use this framework as part of their business planning process.

CHAPTER 2
LITERATURE REVIEW

2.1. Theoretical overview

Eisenhart(1991) defined a theoretical framework as "a structure that guides research by relying on a formal theory…constructed by using an established, coherent explanation of certain phenomena and relationships".

The theoretical overview of this research paper provides the foundational framework that guides the study, as previously discussed in Chapter 1. It outlines key theories, concepts, and models that inform the research design and analysis. This section positions the research within the broader scope of research that focuses on developing countries, highlighting existing theories that are relevant and identifying gaps that the study aims to address. By establishing a connection between the theoretical background and the research question and objectives, the theoretical overview helps justify the methodology and scope of the investigation. It also clarifies how the current research will contribute to or challenge established theoretical frameworks, ensuring coherence between the literature and the study's objectives. The following themes have been identified that support the scope and components of frameworks relevant to this study:

- Affordability –An influence on business decisions from a financial point of view
- Theoretical overview of the affordability of AI in developing countries
- Internal and external variables that impact affordability
- Affordability concerning the Business Model Canvas
- Analysis of Affordability Using the PESTEL Framework
- Accessibility – Identifying the level of accessibility of the resources that are required to plan, develop, integrate, and maintain an AI system in developing countries.
- Theoretical overview of the accessibility of resources in developing countries
- Impact of access to tangible resources from the global economy
- Impact of access to human resources from the global economy
- Accessibility concerning the Business Model Canvas
- Analysis of accessibility concerning the PESTEL framework
- Skills – The human capital (skills and training) required to plan, develop, integrate, and maintain an AI system in developing countries
- Theoretical overview of skills in developing countries

- Impact of importing skills and training
- Skills concerning the Business Model Canvas
- Analysis of the impact of Skills using the PESTEL Framework

The frameworks that will be utilised are mainly the Business Model Canvas and the PESTEL framework, each analysis will provide an overview of the direct relation of each component of these frameworks.

The Business Model Canvas components that will be analysed are as follows:

2. Key Partnerships
3. Cost Structure
4. Key Activities
5. Key Resources
6. Revenue Stream
7. Channels
8. Customer Relations (If applicable)
9. Customer Segment (If applicable)

The components of the PESTEL framework that will be analysed are as follows:

10. Political
11. Economic
12. Social
13. Technological
14. Environmental
15. Legal

The findings of the impact of how Affordability, Accessibility, and Skills are connected to each component of the Business Model Canvas and PESTEL framework will provide insight into the degree of influence and relevance that these factors have on the internal and external environment of SMEs in developing countries.

This section further establishes the theoretical underpinnings of the study, mapping each theory explicitly to the core framework components of affordability, accessibility, and skills, which are also directly aligned with the three research questions.

- Diffusion of Innovations Theory (Rogers, 2003) explains how new technologies spread and is applied to accessibility, particularly the barriers to AI adoption in developing countries due to infrastructure, connectivity, and knowledge limitations.

- The Technology Acceptance Model (TAM) (Davis, 1989) is used to understand skills by exploring how perceived ease of use and usefulness of AI systems affect user adoption and skill requirements.
- Digital Divide Theory (van Dijk, 2020) is linked to affordability, highlighting resource disparities and the socioeconomic divide in technology access and AI affordability among SMEs.

These theories inform the structure of the Business Model Canvas (BMC) and PESTEL analysis employed in this study. BMC explores internal strategic planning (key resources, cost structure, partnerships), while PESTEL analyses the external environment (economic and political constraints, social acceptance, and technological infrastructure). This theoretical integration supports the study's analytical framework, providing a basis for evaluating how SMEs in developing countries can strategically navigate AI adoption.

2.2. Theoretical overview of the affordability of AI in developing countries

The affordability of AI in developing countries is a critical area of research that intersects technology adoption, economic structures, and socio-political factors. Theoretical perspectives on affordability can be derived from the Diffusion of Innovation Theory, Technology Acceptance Models (TAM), and Digital Divide frameworks. These theories help explain how and why new technologies, such as AI, are adopted differently across regions with varying levels of development.

Diffusion of Innovations Theory

The Diffusion of Innovations theory (Rogers, 2003) posits that the spread of new technologies is affected by the socio-economic environment, including factors such as income levels, infrastructure, and education. Developing nations often face barriers to adopting AI due to limited resources and high costs associated with hardware, software, and skilled labour (OECD, 2020). The margin for successful adoption of AI by small businesses in developing countries is affected by factors such as limited access to financial resources and inadequate technological infrastructure. Thus, affordability becomes a crucial barrier to integration and innovation in these regions (Chui et al., 2018).

Technology Acceptance Model

The Technology Acceptance Model (TAM) is also applicable in understanding affordability, particularly in how perceived usefulness and ease of use of AI impact its uptake. According to the Technology Acceptance Model (Davis, 1989), perceived ease of use and perceived usefulness significantly influence individuals' and organisations' decisions to adopt new technologies. Higher costs may lead to lower perceived usefulness, as potential users may not see the immediate benefits or return on investment (Smit & De Vries, 2020).

Digital Divide Theory

The digital divide exacerbates inequalities in access to AI tools, as urban areas may have better connectivity and resources compared to rural regions, where infrastructure is underdeveloped (World Bank, 2019). However, it can also further be observed that even in areas that have the necessary infrastructure, in terms of internet fibre networks, the uptake in low-middle income areas remains low due to being unable to afford internet subscriptions. This is where public and private institutions need to enter markets at scale to provide low-cost internet services.

Therefore, a theoretical exploration of AI affordability in developing countries involves analysing the interplay between economic capabilities, technology diffusion processes, and structural barriers. By integrating these theories, the research aims to highlight the underlying challenges and propose solutions that could make AI technologies more affordable and beneficial to small businesses in developing countries.

2.3. Internal and external variables that impact affordability

The affordability of AI in businesses, especially in developing countries, is influenced by a range of internal and external variables. These variables determine how companies evaluate, acquire, and implement AI technologies, impacting their overall feasibility and cost-effectiveness. These variables influence how organisations in these regions can adopt, implement, and benefit from AI technologies.

Internal Business Variables:

- Financial Resources: Financial capacity is a key internal variable that affects an organisation's ability to invest in AI technologies. Many developing country firms have limited budgets for large-scale AI projects, making cost a significant barrier (Wirtz et al., 2019). AI systems often require substantial initial investment in software, hardware, and specialised skills.

- Technological Infrastructure: An organisation's existing IT infrastructure directly impacts its ability to integrate AI solutions. Firms with outdated or insufficient technological frameworks may face higher costs in upgrading systems to support AI, which adds to affordability challenges (Khan & Alam, 2021).
- Human Capital: The availability of skilled workers that can be accessed by the organisation is crucial. Amongst others, AI requires expertise in data science, machine learning, and advanced computing. A lack of in-house expertise means that companies must either train existing staff or outsource, both of which are costly (Bessen, 2020).
- Leadership and Strategic Vision: Businesses whose leadership is committed to a strategic vision that comprises digital transformation and innovation are more likely to allocate resources toward AI implementation. Conversely, firms without a clear strategic direction toward AI are less likely to invest in these technologies (Makridakis, 2017).

External Business Variables:

- Market Demand: The level of AI demand in the market influences how much firms are willing to invest in such technologies. In developing countries, market readiness and customer demand for AI-driven solutions can be lower due to cost sensitivities and lower digital literacy, limiting AI adoption (Muller & Ngwenyama, 2021).
- Government Policies and Regulations: Supportive government policies such as subsidies, tax incentives, or AI-focused initiatives can lower the barriers to adoption (Yin, 2020). However, regulatory challenges around data privacy and security can increase the complexity and cost of AI integration.
- Technological Ecosystem: A reliable external technological ecosystem, including access to cloud computing, high-speed internet, and a reliable energy supply, is critical for AI deployment. In many developing countries, this ecosystem is underdeveloped, making AI technologies harder and more expensive to implement (OECD, 2021).
- Global AI Supply Chains: AI technologies and services are often produced in more advanced economies, which affects affordability through high import costs. Fluctuations in international trade policies, tariffs, and supply chain

disruptions can also increase the price of AI tools for businesses in developing countries (Wirtz et al., 2019).

The affordability of AI in businesses is determined by a complex mix of internal and external variables. Internal factors like financial resources, infrastructure, and human capital affect a business's willingness and approach to implement AI cost-effectively. Meanwhile, external variables such as market dynamics, technological trends, regulatory environments, and macroeconomic conditions influence the cost and availability of AI solutions. A holistic approach and comprehensive understanding of these variables are essential for businesses to make informed decisions about AI adoption, especially in developing countries where affordability remains a significant challenge.

2.4. Affordability concerning the Business Model Canvas

The Business Model Canvas (BMC) is a strategic tool that helps businesses visualise and design their business model by identifying key components such as value propositions, customer segments, revenue streams, and cost structures (Osterwalder & Pigneur, 2010). A detailed structure of the BMC includes the analysis of Key Partnerships, Cost Structure, Key Activities, Key Resources, Revenue Streams, Channels, Customer relationships, and Customer Segments. For small and medium-sized businesses (SMEs) in developing countries, this model can significantly influence the affordability of implementing an AI system. Key Elements of the Business Model Canvas and Their Impact on AI Affordability are as follows:

The Value Proposition outlines the unique value a business offers to its customers. When integrating AI, SMEs need to ensure that it enhances their value proposition, whether through better customer service, improved efficiency, or new product offerings (Osterwalder & Pigneur, 2010). If AI adds measurable value, such as increased productivity or cost reductions in operations, its high upfront cost can be justified. The BMC helps businesses clearly define this value and determine if AI is worth the investment based on customer needs and market demands (Cavalcante, Kesting, & Ulhøi, 2011).

2.4.1. Key Partnerships

The Key Partnerships highlights partnerships and potential collaborations that can help businesses access resources. For SMEs in developing countries, forming strategic partnerships with AI vendors, universities, or government bodies can help reduce the financial burden of implementing AI systems (Bailetti, 2012). Government support or collaboration with international tech companies could lead to discounts, grants, or shared AI infrastructure, making AI more affordable. Partnerships can provide access to affordable AI tools, consultancy services, or skilled personnel that SMEs may not have internally (Berman, 2012).

2.4.2. Cost Structure

The Cost Structure element in the BCM directly relates to the expenses incurred while operating the business, including AI implementation costs. AI involves various costs such as software, hardware, training, and maintenance. For SMEs in developing countries, the BCM helps to identify these costs, enabling effective budgeting. Understanding the cost structure allows businesses to explore cost-saving strategies, such as opting for modular AI solutions or using open-source AI platforms (Chalmers, Matthews, & Hyslop, 2021). A flexible cost structure, including the use of pay-per-use AI services (cloud-based AI platforms), can help reduce upfront costs (Kaplan, 2019).

2.4.3. Key Activities

Key activities in implementing AI systems include data collection, AI model development, testing, and deployment. These activities can prove to be resource-intensive for small businesses with limited technical capacity. Automating repetitive tasks through AI, however, could lead to long-term cost savings by streamlining operations (Jarrahi, 2018). Additionally, SMEs can reduce costs by outsourcing non-core AI development tasks, such as data labelling or model training, to specialised service providers, minimising the need for expensive in-house operations (Schwab, 2017).

2.4.4. Key Resources

The Key Resources of the BMC highlight the critical resources needed to run a business, including physical, intellectual, human, and financial resources (Osterwalder & Pigneur, 2010). For SME's in developing countries, AI systems require significant technical and financial resources, which can be challenging and costly. However, BMC allows SMEs to assess their existing resources and identify potential gaps, helping them explore affordable options such as cloud-based AI services or partnerships with local tech firms (Bailetti, 2012).

2.4.5. Revenue Streams

AI can also impact revenue generation by creating new channels, enhancing customer experiences, or improving operational efficiency. The revenue stream helps to evaluate whether the integration of an AI system would be cost-effective and profitable in the medium-long term of a business. For SMEs in developing countries, BMC encourages focusing on use cases where AI can directly contribute to increased revenues, such as through customer data analytics or automation of sales processes (Schneider & Spieth, 2013). By analysing the potential profitability, businesses can make decisions about AI affordability.

2.4.6. Channels

The distribution channels through which AI solutions are delivered also influence affordability. SMEs can utilise digital channels (e.g., cloud platforms) to access AI tools at a lower cost compared to traditional on-premise solutions. Cloud-based AI platforms provide scalable solutions that reduce the need for significant capital investments in hardware (Davenport & Ronanki, 2018). By leveraging digital channels, SMEs in developing countries have more accessibility and can adopt AI more affordably while staying competitive in their markets.

2.4.7. Customer relationships

AI can enhance customer relationships by providing personalised services, predictive analytics, and automated support (e.g., chatbots). These improvements can boost customer satisfaction and retention, providing intangible value. SMEs should evaluate the long-term value of improved customer relationships when assessing the affordability of AI systems (Kotler et al., 2020).

2.4.8. Customer Segments

Customer Segments emphasise the importance of understanding the target market and implementing AI that aligns with the customer expectations and preferences of the target market. BMC enables SMEs to assess if their customer base is willing to pay for AI-enhanced products or services, which can affect affordability. If AI helps serve more profitable customer segments or improves service to existing ones, it can justify the associated costs.

In conclusion, the Business Model Canvas plays a vital role in assessing the affordability of implementing AI in SMEs in developing countries. By helping businesses analyse their resources, cost structure, value propositions, revenue streams, partnerships, and customer segments, BMC provides a structured approach to evaluating whether AI is a feasible investment. This model encourages a more strategic and financially sound adoption of AI technologies, allowing SMEs to optimise costs and enhance their business value.

2.5. Analysis of Affordability Using the PESTEL Framework

The PESTEL framework analyses the Political, Economic, Social, Technological, Environmental, and Legal factors that provide a comprehensive overview to evaluate the affordability of AI in developing countries. Each element of the framework highlights unique challenges and opportunities that influence the cost and accessibility of AI in these regions. Below is an analysis using the PESTEL framework, with references to support the discussion.

2.5.1. Political Factors

Political stability and government policies play a crucial role in determining the affordability of AI. In developing countries where governments support technological innovation, AI can become more affordable through subsidies, tax incentives, and public-private partnerships (World Bank, 2021). Governments that prioritise AI adoption can help reduce implementation costs for businesses and public institutions. Conversely, political instability, bureaucracy, and corruption increase the risks and costs of adopting new technologies (Shah & Tripathi, 2020). For instance, AI projects can be delayed or face higher costs due to administrative inefficiencies or a lack of policy alignment.

2.5.2. Economic Factors

Economic conditions are a key determinant of AI affordability. Developing countries often experience lower income levels, limited access to capital, and currency instability, all of which affect the ability of businesses and governments to invest in AI (Miller & Atkinson, 2020). For instance, high upfront costs for AI systems, including infrastructure and skilled labour, can be a deterrent for small and medium-sized enterprises (SMEs). Additionally, fluctuating exchange rates and inflation in many developing countries further increase the cost of importing AI technologies and related infrastructure (Choi et al., 2021). Access to funding sources, such as venture capital or government-backed loans, is also limited, making it harder for businesses to afford AI investments. This financial barrier underscores the need for innovative financing models, such as microloans or development grants, to make AI more accessible in developing regions (UNESCO, 2021).

In addition to local economic conditions, global ecosystem factors significantly influence AI affordability. The cost of importing AI tools and services—including hardware, software licenses, and professional consultancy—is often elevated by trade tariffs, customs duties, and weak exchange rates (Wirtz et al., 2019). Developing countries often face high import taxes on technological equipment, making the initial cost of AI adoption prohibitive. Moreover, international trade agreements or restrictions can either enable or constrain access to affordable AI technologies (Banga & te Velde, 2018).

2.5.3. Social Factors

The social context, particularly education and skill levels, significantly influences the affordability of AI. A shortage of AI expertise in developing countries raises the cost of hiring skilled personnel, making it more expensive for businesses to adopt AI (Manda & Backhouse, 2020). In many regions, the local workforce lacks the necessary training in AI and data science, forcing companies to import talent or invest heavily in workforce development.

Moreover, societal perceptions of AI can impact its adoption and affordability. In some countries, there is scepticism about AI due to concerns about job displacement and privacy (Nishant, Kennedy, & Corbett, 2020). Businesses may need to invest in awareness and education campaigns to overcome these barriers, which increases the overall cost of implementation.

2.5.4. Technological Factors

Technological infrastructure in developing countries often lags behind that of more developed nations, further affecting the affordability of AI. Reliable internet access, electricity, and data storage systems are essential for AI deployment, yet many developing countries struggle with these foundational technologies (Banga & Velde, 2018). Without adequate infrastructure, the costs of implementing and maintaining AI systems rise significantly, as businesses must invest in upgrading existing systems or creating new ones.

On the positive side, the increasing availability of open-source AI tools and cloud-based services has the potential to lower costs. Cloud AI platforms, for example, reduce the need for expensive hardware and provide scalable solutions that can be more affordable for SMEs (Kaplan & Haenlein, 2020). Global tech collaborations, including international partnerships between governments and multinational AI firms, can lower these costs through negotiated access, training programs, and shared infrastructure (UNESCO, 2021). Encouraging South-South collaborations can also facilitate AI adoption through shared experiences and more accessible pricing models.

2.5.5. Environmental Factors

The environmental context also plays a role in AI affordability. AI systems, particularly those that involve large-scale data processing, can be energy-intensive, making them expensive to operate in countries with unreliable or expensive energy supplies (Malmodin & Lundén, 2018). Developing countries often face higher energy costs or unstable electricity grids, both of which add to the operational expenses of running AI systems.

However, AI has the potential to address environmental challenges in developing countries by optimising resource management and predicting climate-related events (Bene et al., 2020). In the long term, these applications could justify the investment in AI by offering significant cost savings in sectors such as agriculture, water management, and disaster preparedness.

Furthermore, environmental factors such as the reliability, affordability of energy sources play a major factor in the operational function of an AI project. In countries that have limited energy resources, access to a reliable source of electricity to power the technology poses many challenges, besides the direct cost of electricity, SMEs will have to determine and provision for backup sources of power at additional operational costs, to ensure that the system and its supporting technological components are operating as and when required.

2.5.6. Legal Factors

Legal frameworks governing AI in developing countries are often underdeveloped, which can either hinder or facilitate AI affordability. Countries with clear data protection laws and intellectual property (IP) rights create a more predictable environment for AI investment, reducing legal risks and associated costs (United Nations, 2020). However, strict data privacy regulations, like the General Data Protection Regulation (GDPR) in Europe, may require additional compliance measures, increasing the cost of AI deployment (Cohen, 2020).

In countries with weak IP enforcement, businesses may be reluctant to invest in AI technologies due to concerns about IP theft, counterfeiting, or a lack of protection for proprietary systems. These legal uncertainties can deter AI adoption, particularly in sectors where intellectual property is a key component of competitive advantage (Crawford et al., 2019).

The affordability of AI in developing countries is shaped by a complex interplay of political, economic, social, technological, environmental, and legal factors. Governments can play a pivotal role in lowering costs through supportive policies, while economic barriers and limited financial resource access remain significant challenges. Social factors, such as education and community culture, further impact AI adoption, while technological infrastructure and environmental factors influence the cost of implementation. Finally, a clear and supportive legal framework is necessary to reduce risks and make AI more accessible.

2.6. Theoretical overview of the accessibility of resources in developing countries

The accessibility of resources in developing countries is a critical issue that influences various factors such as economic development, social equality, and overall growth. A wide variety of concepts and theories from economics, development studies, and resource management offer frameworks for understanding the factors that shape access to essential resources such as education, healthcare, technology, and natural resources. These theories help to explain how the political, economic, and social structures in developing countries facilitate or hinder resource accessibility. Several theories can be utilised to further understand the implications of accessibility of resources in developing countries.

Resource Dependency Theory

Resource Dependency Theory (RDT) posits that organisations (or nations) are dependent on resources that are controlled by external entities, and this dependence shapes their behaviour (Pfeffer & Salancik, 1978). In the context of developing countries, access to key resources such as financial capital, technology, and raw materials may often be dependent on external factors like multinational corporations, foreign governments, and international organisations. This theory highlights the vulnerability of developing countries when they rely on external sources for essential resources, which can limit their accessibility due to geopolitical dynamics, trade imbalances, or unequal economic relationships (Mahoney, 2010). Commonly, access to advanced technologies such as artificial intelligence, renewable energy infrastructure, or healthcare innovations is often mediated by global power structures that favour developed economies.

Human Capital Theory

Human capital theory suggests that investment in education and skill development is essential for improving productivity and, by extension, increasing access to resources (Schultz, 1961; Becker, 1994). In developing countries, limited access to quality education and training systems creates a significant barrier to effectively utilise the available resources, further perpetuating cycles of poverty and inequality. This theory underscores the importance of building a skilled workforce to improve access to not only educational resources but also to higher-paying jobs and improved living conditions (Todaro & Smith, 2020). Education, therefore, becomes a critical resource that impacts accessibility to other resources, such as technology, healthcare, and capital.

Digital Divide Theory

Digital divide theory focuses on the gap between individuals, households, or countries regarding access to information and communication technologies (ICTs) (van Dijk, 2020). The theory highlights prevailing disparities between income, technology, and communities. Underlying social and technical barriers that small businesses and public institutions face. The digital divide in developing countries is particularly pronounced, with inadequate infrastructure, limited access to high-speed internet, and high costs for digital devices creating substantial barriers to accessing modern technological resources (Norris, 2001). This theory explains how technological inequality reinforces other forms of inequality, as access to digital resources directly impacts education, economic opportunities, and social mobility (Hilbert, 2016).

Institutional Theory

Institutional theory emphasises the role of formal and informal institutions in shaping access to resources (North, 1990). In developing countries, weak institutions such as ineffective governance, corruption, and a lack of transparency perpetuate the cycle of uneven distribution of resources. This lack of institutional capacity can further intensify social and economic inequalities, marginalising the majority of the population.

Sustainable Development Theory

Sustainable development theory provides a framework for understanding how developing countries can improve resource accessibility in a way that is socially, environmentally, and economicly sustainable. The theory, formalised by the United Nations Brundtland Report(1987), argues that development should meet the needs of the present without compromising the ability of future generations to meet their own needs. Enabling access to natural resources like water, energy, and land is essential for sustainable development, however, many developing countries face challenges in managing these resources due to overexploitation, environmental degradation, and climate change (World Bank, 2019).

Therefore, improving resource accessibility requires a focus not only on economic growth but also on environmental sustainability and equal distribution of natural resources.

Capability Approach

The capability approach, developed by economist Amartya Sen (1999), shifts the focus from economic resources to the individual's ability to convert resources into valuable opportunities and outcomes. According to this theory, improving access to resources in developing countries is not just about providing more goods and services but also ensuring that people have the freedom and capability to use them effectively. This approach emphasises the importance of removing barriers such as discrimination, lack of education, and poor health, which prevent individuals from fully utilising available resources.

Core-Periphery Theory

Core-Periphery Theory, often applied in world-systems analysis (Wallerstein, 1974), explains the uneven distribution of resources between developed (core) and developing (periphery) nations. Developing countries often find themselves in peripheral positions where they are reliant on core nations for access to critical resources such as technology, capital, and expertise. This disproportionate relationship limits the ability of developing nations to control their resources or benefit fully from global economic systems. The core-periphery framework highlights how global trade, investment patterns, and technology transfers often favour developed countries, making resource accessibility more challenging for developing economies (Chase-Dunn & Grimes, 1995).

The accessibility of resources in developing countries is influenced by a variety of theoretical frameworks, from economic and political dependencies to digital inequality and institutional weaknesses. Each of these theories, Resource Dependency Theory, Human Capital Theory, Digital Divide Theory, Institutional Theory, Sustainable Development Theory, the Capability Approach, and Core-Periphery Theory, provides an understanding of the complex and multifaceted barriers to accessing critical resources. By addressing these barriers through strategic policy-making and institutional reforms, developing countries can improve access to essential resources, fostering sustainable economic and social development.

2.7. Impact of access to tangible resources from the global economy

Access to tangible resources from the global economy plays an important role in enabling SMEs in developing countries to leverage AI technologies. Tangible resources, which include financial capital, technological infrastructure, and skilled human capital, are vital components for the successful implementation and adoption of AI technologies. The interplay between these resources and SMEs' ability to participate in the global market has significant implications for their growth and sustainability.

Financial capital is one of the most critical tangible resources for adopting AI. Access to funding from global investors or development banks can facilitate investments in AI technologies, infrastructure, and training (Mazzucato, 2018). Without sufficient financial resources, SMEs may struggle to invest in the necessary technologies or develop AI capabilities, ultimately limiting their competitiveness in both local and global markets (Zhu et al., 2021).

Technological infrastructure is another essential resource to consider. Developing countries often face challenges related to inadequate digital infrastructure, which can hinder the deployment of AI applications (Bharadwaj et al., 2013). Access to global networks and resources can help improve technological infrastructure, enabling SMEs to adopt AI solutions that can optimise operations, enhance productivity, and support decision-making processes (Mishra et al., 2021).

Additionally, the accessibility and availability of skilled labour are vital for SMEs to harness AI effectively. Global economic access can facilitate knowledge transfer and training opportunities, allowing SMEs to build a workforce capable of developing and implementing AI solutions (Khan et al., 2020). Collaboration with international organisations and participation in global supply chains can provide SMEs with the necessary skills and expertise to innovate and thrive in the global economy.

In summary, access to tangible resources from the global economy significantly impacts SMEs in developing countries by enabling them to adopt AI technologies that enhance their operational efficiency and competitive advantage. By securing financial capital, improving technological infrastructure, and fostering skill development, these enterprises can better navigate the challenges of the global market.

2.8. Impact of access to human resources from the global economy

Access to human resources from the global economy is a critical factor that influences the adoption and effective utilisation of Artificial Intelligence (AI) by Small and Medium-sized Enterprises (SMEs) in developing countries. Human resources identifies the availability of skilled labour, together with the potential for knowledge transfer, collaboration, and innovation that are essential for leveraging AI technologies.

The interplay between global human resources and the capabilities of SMEs can significantly enhance their competitive edge and operational efficiency. With the rise of connectivity and remote working opportunities, SMEs have a wider opportunity to utilise the talent pool within the global economy. One of the most significant impacts of access to global human resources is the ability of SMEs to recruit talent with specialised skills in AI and data science. Developing countries often face shortages of skilled professionals in these fields, which can impede AI adoption (Zhang et al., 2020). By tapping into global talent pools, SMEs can access expertise that is otherwise unavailable or unaffordable locally. This access allows SMEs to implement AI solutions that can optimise processes, improve decision-making, and enhance customer engagement (Saldanha et al., 2018).

Moreover, international collaboration and partnerships can facilitate knowledge transfer and capacity building for current and future team members. When SMEs engage with global networks, they gain exposure to best practices, innovative approaches, and cutting-edge technologies (Liu et al., 2021). This exchange of knowledge not only enhances the capabilities of the workforce but also fosters a culture of innovation and diversification within the organisation, enabling SMEs to adapt and thrive in rapidly changing technological and social landscapes.

Furthermore, access to global human resources can support SMEs in navigating the complexities of AI implementation and its global exposure, and participation in the global economy in real time. Experienced professionals from abroad can provide guidance on the integration of AI into existing business processes, risk management, and ethical considerations (Bharadwaj et al., 2013). This support is particularly important for SMEs that may lack the resources or experience to manage such transitions independently.

In conclusion, access to human resources from the global economy provides a variety of internal and external opportunities and business exposure for SMEs in developing countries seeking to adopt AI technologies. By leveraging global talent and expertise, SMEs can enhance and improve their innovative capacities, transferable skills, workplace diversification, and operational efficiencies, and better compete in the global market.

2.9. Accessibility concerning the Business Model Canvas

The Business Model Canvas is a strategic tool that provides a framework for understanding how businesses create, deliver, and capture value. Applying this model to the accessibility of artificial intelligence (AI) in developing countries provides a structured analysis of how AI can be implemented and scaled within small and medium-sized enterprises (SMEs) and other business sectors. Each component of the BMC plays a role in shaping how AI technologies can be accessible and sustainable in these regions.

Value Propositions

The value proposition of AI for businesses in developing countries lies in its potential to optimise operations, improve decision-making, and enhance customer experiences through automation, predictive analytics, and process efficiencies (Bughin et al., 2018). AI can address specific challenges like resource management, supply chain optimisation, and customer engagement, further offering businesses a competitive advantage.

2.9.1. Key Partnerships

Partnerships are essential for accessing the necessary resources and expertise for AI adoption. Collaborations with technology firms, governments, international organisations, and academic institutions can provide SMEs in developing countries with the infrastructure, training, and AI tools they need (Ransbotham et al., 2017). Global partnerships help to bridge the gap in technological knowledge and resource shortages, fostering innovation.

2.9.2. Cost Structure

The cost structure for AI adoption in developing countries includes the upfront investment in technology infrastructure, software development, and training, as well as ongoing maintenance and support costs (Manyika et al., 2017). Due to the limitations of accessibility of resources, skills, and infrastructure, the financial costs of acquiring the necessary resources tend to increase. As a result, due to limited financial resources, high initial costs often hinder the adoption of AI. A direct correlation exists between accessibility and influences the overall cost structure of an AI project. However, cost-sharing models, government subsidies, and access to global markets may alleviate some of these financial burdens.

2.9.3. Key Activities

The key activities for making AI accessible involve data collection and analysis, machine learning model development, integration of AI systems into business operations, and continuous monitoring and improvement of AI technologies (Dwivedi et al., 2021). In developing countries, businesses must also focus on capacity building and ensuring alignment with local market needs and conditions.

2.9.4. Key Resources

Critical resources include access to skilled labour, data infrastructure, and AI technologies. Human capital, such as data scientists and engineers, is particularly scarce in developing countries (Zhang et al., 2020). Investing in training and educational programs is essential to build local talent and ensure long-term sustainability.

2.9.5. Revenue Streams

AI technologies can create new revenue streams for businesses by enabling the development of innovative products and services, improving efficiency, and reducing costs (Bessen et al., 2020). For example, AI can enhance customer segmentation, enabling more personalised marketing and increasing sales. It also opens opportunities for data monetisation and AI-as-a-service models in underserved markets.

2.9.6. Channels

AI technologies are typically accessed via digital platforms, cloud computing services, and online tools. In developing countries, limited internet penetration and digital infrastructure can pose significant challenges (Mishra et al., 2021). To overcome these barriers, businesses need to explore alternative delivery mechanisms, such as mobile-first strategies and partnerships with telecom providers.

2.9.7. Customer Relationships

AI-driven automation and analytics can help businesses in developing countries improve customer relationships by delivering personalised experiences, enhancing customer service, and predicting customer needs (Ostrom et al., 2019). Trust-building and customer education about AI technologies are also critical to overcoming potential resistance to AI solutions.

2.9.8. Customer Segments

AI technologies can benefit a wide range of customer segments in developing countries, including SMEs, large enterprises, governments, and consumers (Dwivedi et al., 2021). Tailoring AI applications to meet the unique needs of these segments, such as offering affordable solutions. Addressing specific public sector challenges can enhance the relevance and impact of AI technologies.

2.10. Analysis of accessibility concerning the PESTEL framework

The PESTEL framework, which considers Political, Economic, Social, Technological, Environmental, and Legal factors, provides a comprehensive tool to analyse how external forces impact the accessibility and adoption of AI for SMEs in developing countries. Each element of the framework plays a role in shaping both the opportunities and barriers to AI adoption.

2.10.1. Political Factors

Political stability, government support, and policy frameworks significantly influence the accessibility of AI for SMEs. In developing countries, governments that implement AI-friendly policies, provide tax incentives, and offer financial support can accelerate AI adoption (Mazzucato, 2018). Conversely, political instability and lack of regulatory clarity can act as barriers. Governments play a crucial role in fostering international partnerships and collaborations with technology firms to ensure that SMEs can access AI technologies.

For example, countries with digital agendas or national AI strategies are more likely to facilitate AI adoption through public-private partnerships, educational programs, and AI research funding (Reddy et al., 2020).

2.10.2. Economic Factors

Economic factors, such as GDP, access to financial resources, and the cost of technology, greatly influence the ability of SMEs in developing countries to adopt AI. The cost of AI infrastructure, such as computing power and data storage, is often high, making it difficult for resource-constrained SMEs to invest in AI solutions (Bughin et al., 2018). Additionally, limited access to capital markets and financial resources can restrict the ability of SMEs to acquire advanced AI tools, hire skilled professionals, or develop AI-driven products.

However, global economic initiatives, international funding, and micro-financing can help mitigate some of these challenges, allowing SMEs to access the financial resources needed to integrate AI technologies into their operations (Zhu et al., 2021). The global supply chain for AI technologies is concentrated in developed economies, leading to supply bottlenecks and limited availability in developing markets (Manyika et al., 2017). These constraints are exacerbated by geopolitical tensions, export restrictions, and global semiconductor shortages, limiting access to critical components such as GPUs and cloud infrastructure (Chui et al., 2018). Additionally, cross-border collaborations with universities, NGOs, and technology firms can facilitate knowledge transfer and improve accessibility. Global initiatives such as the AI for Good Global Summit promote inclusive access to AI by offering training and subsidised technology access (ITU, 2023). Participation in such global networks is essential for SMEs to reduce isolation and benefit from shared innovations.

2.10.3. Social Factors

Cultural and social acceptance of AI, as well as the availability of skilled labour, impact the accessibility of AI technologies for SMEs in developing countries. Social attitudes toward AI, such as trust in technology and fears of job displacement, can influence adoption rates (Dwivedi et al., 2021). Moreover, the lack of widespread digital literacy and limited AI-specific skills among the workforce can hinder the ability of SMEs to effectively implement AI solutions.

SMEs that prioritise workforce development, invest in training, and build digital literacy programs can overcome these social barriers. Additionally, international partnerships can play a role in bringing skilled talent and training opportunities to local workers, enhancing AI readiness (Khan et al., 2020).

2.10.4. Technological Factors

Technological infrastructure, such as internet connectivity, cloud computing, and access to data, is critical for AI adoption. In developing countries, many SMEs face significant challenges related to inadequate digital infrastructure and limited access to affordable AI technologies (Manyika et al., 2017). Poor internet connectivity, in particular, can hinder cloud-based AI applications, which are often essential for SMEs that cannot afford in-house infrastructure.

Technological accessibility can be improved through investments in digital infrastructure, mobile-first AI solutions, and collaborations with global tech firms offering affordable AI-as-a-service models (Mishra et al., 2021).

2.10.5. Environmental Factors

While environmental factors may seem less directly connected to AI adoption, they can have an impact, especially in terms of the sustainable use of AI technologies. AI has the potential to help SMEs in developing countries optimise resource use, reduce waste, and improve environmental sustainability (Tambe et al., 2019). For example, AI-driven solutions can help SMEs in the agriculture and energy sectors manage resources more efficiently and mitigate the environmental impacts of their operations.

However, the environmental cost of implementing AI technologies, including energy consumption for AI training and cloud computing, can pose challenges, particularly in regions with fragile ecosystems or unreliable energy sources.

2.10.6. Legal Factors

The legal framework governing data privacy, intellectual property rights, and AI ethics plays a significant role in determining the accessibility of AI technologies for SMEs. In many developing countries, the legal infrastructure around AI is still underdeveloped, creating uncertainty for businesses looking to adopt these technologies (Ransbotham et al., 2017). Weak data protection laws can deter both local SMEs and international partners from implementing AI solutions that rely heavily on data-driven insights.

Governments need to develop robust legal frameworks that provide clear guidelines for AI use, data protection, and intellectual property to create an enabling environment for AI adoption (Mazzucato, 2018). Global cooperation on legal standards for AI can also help SMEs in developing countries navigate the regulatory landscape more effectively.

Using the PESTEL framework, it is evident that accessibility to AI for SMEs in developing countries is shaped by a complex interplay of political, economic, social, technological, environmental, and legal factors. Political support, economic resources, social readiness, technological infrastructure, environmental sustainability, and a clear legal framework are essential for improving AI accessibility. Addressing these external factors through targeted policies, partnerships, and investments can significantly enhance the ability of SMEs in developing countries to adopt and benefit from AI technologies.

2.11. Theoretical overview of skills in developing countries

The successful adoption of artificial intelligence (AI) by small and medium-sized enterprises (SMEs) in developing countries heavily depends on the availability and development of appropriate skills. AI is a complex technology requiring expertise in areas such as data science, machine learning, and computational engineering, along with domain-specific knowledge. In developing countries, the lack of necessary technical and managerial skills creates a significant barrier to AI adoption, affecting both the implementation and the utilisation of AI-driven solutions. The skills gap within SMEs impacts their ability to innovate, compete in the global market, and enhance operational efficiency using AI.

Technical Skills

Technical skills are crucial for developing, implementing, and maintaining AI systems. AI relies on advanced programming languages (such as Python and R), machine learning algorithms, and data processing capabilities, which require trained professionals (Mishra et al., 2021). The shortage of technical expertise in areas like data analytics, AI model development, and cloud computing is a primary barrier for SMEs in developing countries (Zhang et al., 2020). Without skilled personnel, SMEs struggle to deploy AI tools, manage data pipelines, and integrate AI solutions into business processes.

Training and educational programs are essential to fill this technical skills gap. By investing in human capital through vocational training, partnerships with educational institutions, and government initiatives, SMEs can build a workforce that is better equipped to handle AI technologies (Liu et al., 2021). Moreover, international collaborations and partnerships with global technology firms can facilitate knowledge transfer and capacity building in developing regions.

Managerial Skills

AI adoption is not only about technical knowledge; managerial skills play a critical role in the strategic implementation of AI solutions. Managers need to understand AI's potential for business transformation and possess the ability to align AI-driven strategies with broader organisational goals (Dwivedi et al., 2021). The ability to make data-driven decisions, manage AI projects, and oversee the integration of AI into existing systems is essential for realising the full value of AI in SMEs.

In developing countries, many SME managers lack the awareness and strategic insight needed to prioritise AI investments or integrate AI into business processes effectively. This knowledge gap often results in a reluctance to adopt new technologies, further widening the digital divide (Ransbotham et al., 2017). Managerial training programs focused on AI literacy, change management, and innovation strategy are crucial for overcoming these challenges.

Soft Skills

In addition to technical and managerial expertise, soft skills such as critical thinking, problem-solving, and adaptability are vital for AI adoption in SMEs. AI technologies often require human workers to collaborate with automated systems, adjust to new workflows, and reorient their roles around AI tools (Bessen et al., 2020). The ability of employees to adapt to the evolving workplace environment, embrace continuous learning, and collaborate across interdisciplinary teams significantly enhances the success of AI initiatives.

SMEs in developing countries need to foster a culture of learning and innovation, where employees are encouraged to upskill and reskill to remain competitive in an AI-driven economy (Manyika et al., 2017). Organisations that prioritise building a versatile and agile workforce are more likely to succeed in leveraging AI technologies.

Collaborative Networks and Ecosystems

To overcome the skill shortage, SMEs in developing countries can benefit from collaborative networks and ecosystems that support skill development. Engaging with global AI ecosystems, participating in AI research and innovation clusters, and forming partnerships with universities and technical institutions can provide SMEs with access to a broader pool of talent and knowledge (Khan et al., 2020). These collaborations allow SMEs to tap into external expertise and resources, enabling them to bridge the skills gap and accelerate AI adoption.

Challenges and Opportunities

The skills gap in AI adoption presents both challenges and opportunities for SMEs in developing countries. On the one hand, the shortage of technical expertise and the lack of training infrastructure hinder the ability of SMEs to leverage AI. On the other hand, targeted investments in skill development through education, government initiatives, and partnerships with global organisations can help SMEs overcome these barriers and unlock the full potential of AI for growth and innovation (Bessen et al., 2020).

In Conclusion, skills play a fundamental role in determining the accessibility and effectiveness of AI adoption for SMEs in developing countries. The lack of technical, managerial, and soft skills limits the ability of SMEs to implement and utilise AI technologies effectively. Addressing this skills gap through training programs, collaborative partnerships, and investments in human capital is crucial for enabling SMEs to harness AI's potential and enhance their competitiveness in the global economy.

2.12. Impact of importing skills and training

The impact of importing skills and training for artificial intelligence (AI) in small and medium-sized enterprises (SMEs) in developing countries is multifaceted. The importation of skills and training for AI adoption in SMEs in developing countries plays a crucial role in overcoming the skills gap and enhancing competitiveness. As developing economies often face a shortage of local talent proficient in AI, importing expertise can help bridge this gap, providing SMEs with the knowledge and capacity required to leverage AI technologies.

The impact of this approach can be analysed in terms of immediate benefits, long-term sustainability, and challenges. These impacts can be further understood in terms of economic growth, competitiveness, and innovation. Below are the key areas where importing AI skills and training can influence SMEs in developing countries:

Immediate Benefits of Importing Skills and Training

Importing AI skills and training offers several immediate advantages to SMEs in developing countries. Given the scarcity of local AI talent, SMEs can rely on external experts to kickstart AI projects, implement advanced technologies, and provide essential training to local workers. These imported skills can enable SMEs to overcome the initial barriers to AI adoption by giving them access to knowledge they would otherwise lack (Dwivedi et al., 2021).

Experts from developed countries or global tech hubs bring with them cutting-edge knowledge of AI algorithms, data science techniques, and best practices for integrating AI into business operations (Tambe et al., 2019). This immediate transfer of skills allows SMEs to quickly adopt AI solutions, optimising processes like supply chain management, customer service automation, and predictive analytics. Furthermore, imported AI training can enhance local workforce capabilities, accelerating the diffusion of AI expertise throughout the organisation.

Building Local Capacity and Sustainable AI Adoption

While importing skills provides a short-term solution, the long-term impact lies in the development of local capacity. Training programs facilitated by imported AI experts can upskill local workers, gradually reducing the dependency on external resources (Zhang et al., 2020). Through knowledge transfer and capacity building, SMEs can develop an internal pool of AI talent capable of managing and maintaining AI systems in the long run.

In addition to formal training, exposure to international AI experts allows local professionals to develop informal networks, learn about emerging trends, and engage in collaborative innovation. This interaction can enhance local innovation ecosystems, supporting the growth of AI startups and technology clusters in developing regions (Bessen et al., 2020). Over time, these networks can help SMEs and the broader business environment integrate AI into various industries, contributing to sustainable economic development.

Fostering Innovation and Competitiveness

The importation of AI skills can foster innovation within SMEs in developing countries. Access to global AI expertise provides SMEs with the opportunity to adopt best practices and customise AI technologies to fit local market needs (Khan et al., 2020). As a result, SMEs can develop innovative products and services that cater to local consumers, driving market differentiation and competitiveness.

In developing countries, where economic challenges and resource limitations often hinder innovation, importing AI skills can act as a catalyst. For example, AI technologies can enable SMEs in agriculture, healthcare, and retail to automate processes, improve resource management, and make data-driven decisions (Manyika et al., 2017). By applying AI to local challenges, SMEs can not only enhance their operational efficiency but also create new market opportunities that drive regional economic growth.

Challenges of Importing Skills and Training

Despite the advantages, importing AI skills and training also presents challenges. One major issue is the high cost of hiring international experts and conducting training programs, which can be a financial burden for resource-constrained SMEs (Mishra et al., 2021). Furthermore, reliance on imported expertise may create dependency, where local workers are not fully empowered to take ownership of AI projects.

Another challenge is the potential mismatch between imported solutions and local contexts. AI technologies developed in advanced economies may not always be directly applicable to the unique market conditions, infrastructure limitations, and regulatory environments of developing countries. Without proper customisation and local adaptation, AI solutions may not yield the expected results, leading to failed implementations or underutilised technology (Zhu et al., 2021).

Additionally, there may be cultural and language barriers between foreign experts and local staff, hindering effective communication and knowledge transfer. Overcoming these challenges requires a well-designed approach that combines external expertise with localised training programs and capacity-building efforts.

The Role of Government and International Partnerships

Governments in developing countries play a critical role in facilitating the importation of AI skills and training. By creating favourable policies, offering tax incentives, and fostering partnerships between local businesses and international AI firms, governments can support SMEs in accessing the expertise they need to adopt AI (Mazzucato, 2018). International development organisations and global technology companies also play a role by providing funding, mentorship, and resources to promote Capacity Building and long-term

Development

Collaborative efforts between governments, educational institutions, and the private sector can further enhance the impact of imported skills. In the long term, importing AI skills and training fosters capacity building within the country. As local employees receive training and exposure to AI technologies, they can develop new skills that may eventually lead to local innovations and knowledge transfer. Establishing AI training hubs, promoting university-industry partnerships, and sponsoring exchange programs can help integrate AI into local business practices and educational curricula. This also reduces the dependency on external expertise over time, creating a sustainable AI ecosystem within the country (Chui et al., 2018).

Enhanced Competitiveness and Innovation

Importing AI skills and training allows SMEs in developing countries to compete more effectively in global markets. AI technologies enable firms to automate processes, enhance decision-making, and personalise customer experiences. SMEs that adopt AI can streamline operations, reduce costs, and improve product or service quality. This competitive edge can be crucial in markets where cost efficiency and customer satisfaction are key factors (Gupta et al., 2020).

Addressing the Skills Gap

Many developing countries face a shortage of AI expertise. Importing AI skills helps bridge this gap, enabling SMEs to adopt advanced technologies without needing to wait for domestic talent development. This can accelerate the adoption of AI technologies and the integration of AI into business processes, giving SMEs access to tools and techniques that would otherwise be out of reach (De Cremer & Kasparov, 2021).

Fostering Economic Growth

By adopting AI through imported skills, SMEs in developing countries can enhance productivity, which contributes to economic growth. AI can help optimise supply chains, reduce waste, and create new business models. SMEs that are equipped with AI tools are better positioned to innovate, scale, and contribute to their respective economies (Bughin et al., 2019).

Challenges in Adaptation and Implementation

Importing AI skills requires adapting them to local contexts, which may differ significantly from where the skills originated. Moreover, without a strong digital infrastructure, SMEs in developing countries may struggle to fully leverage AI, even with imported skills. Ensuring that AI training aligns with the specific needs and capacities of SMEs is essential for effective technology transfer (World Bank, 2020).

Digital Divide and Equity Issues

On the downside, the rapid adoption of AI by SMEs with access to imported skills could widen the digital divide between urban and rural businesses or between different socioeconomic groups within the country. Policymakers need to ensure that the benefits of AI adoption are equitably distributed to avoid exacerbating existing inequalities (Mills, 2021).

Importing skills and training for AI offers significant opportunities for SMEs in developing countries by providing access to the expertise needed to adopt and implement AI technologies. This approach addresses the immediate skills gap, fosters innovation, and contributes to the development of local talent. However, long-term success depends on building local capacity, ensuring that AI technologies are adapted to local contexts, and overcoming challenges such as cost and dependency. Through strategic government support and international collaboration, SMEs can leverage imported skills to drive sustainable AI adoption and regional economic growth.

2.13. Skills in relation to the Business Model Canvas

The adoption of artificial intelligence (AI) by small and medium-sized enterprises (SMEs) in developing countries is strongly influenced by the availability and development of relevant skills. The Business Model Canvas provides a useful framework to analyse the critical role that skills play in different aspects of AI adoption within SMEs, including Value Propositions, Key Partnerships, Key Resources, Key Activities, Cost Structure, Revenue Streams, Channels, Customer Relationships, and Customer Segments.

Value Proposition

AI offers value propositions such as improved operational efficiency, automation of routine tasks, enhanced customer experiences, and data-driven decision-making (Dwivedi et al., 2021). AI enables SMEs to offer data-driven insights, predictive analytics, and enhanced service offerings, which differentiate them in the market (De Cremer & Kasparov, 2021). However, realising these benefits depends on the availability of employees with the skills to develop and implement AI solutions. SMEs with skilled AI professionals can provide more customised and innovative services, such as predictive analytics, chatbot-based customer support, and optimised supply chain management (Manyika et al., 2017). Without these skills, SMEs may struggle to deliver competitive and differentiated value propositions.

2.13.1. Key Partnerships

For the successful adoption of an AI Project, skills-related key partnerships are crucial. SMEs in developing countries often face skills gaps in AI-related fields such as data science, machine learning, and cloud computing (Mishra et al., 2021). To address these gaps, SMEs must partner with external entities such as educational institutions, AI service providers, or international technology firms to gain access to skilled personnel or training programs. Partnerships with global or regional AI firms allow SMEs to access cutting-edge AI technologies and expertise that they may not be able to develop internally (Gupta et al., 2020).

2.13.2. Cost Structure

Implementing AI requires a significant investment in skills, technology infrastructure, and training. The cost structure of SMEs implementing AI includes expenses related to hiring skilled personnel, training existing staff, and collaborating with external AI experts (Mishra et al., 2021). Despite these upfront costs, AI can lead to long-term cost savings by automating repetitive tasks, optimising resource use, and reducing operational inefficiencies (Chui et al., 2018). However, given the scarcity of AI skills in developing countries, the cost of acquiring or importing talent may be significantly high. Additionally, training programs aimed at upskilling the workforce add to the cost structure. It is essential to invest in the development of skills and training to optimise the long-term gains of AI adoption and directly contribute to operational efficiency and innovation.

2.13.3. Key Activities

The implementation of AI in SMEs requires several key activities such as data collection, algorithm development, and AI model training (Khan et al., 2020). With AI adoption, key activities shift towards automation, data analysis, and innovation. SMEs in developing countries may focus on leveraging AI for customer service automation (e.g., chatbots), supply chain optimisation, and predictive maintenance (Bughin et al., 2019).

These activities depend on the availability of skilled personnel who can manage large datasets, optimise AI models, and ensure seamless integration into business processes. Lack of adequate skills in these key activities often hinders SMEs in developing countries from adopting AI solutions effectively.

2.13.4. Key Resources

Human capital with AI-specific expertise is one of the most critical resources for SMEs aiming to adopt AI technologies (Bessen et al., 2020). Skilled employees who can design, develop, and maintain AI systems are necessary for the successful integration of AI tools into business processes. In developing countries, where AI expertise is limited, investing in training and importing skills becomes a key resource strategy (Zhu et al., 2021). Additionally, the combination of human skills and technological resources, such as data infrastructure, forms the foundation for AI deployment.

Furthermore, Access to quality data is also a critical resource for training AI systems and ensuring their effectiveness (World Bank, 2020). Therefore, an essential skill that is required is the ability to clearly and constructively organise the data into a sensical structure that can be interpreted logically, as a system is only as effective and reliable as the quality and accuracy of that data.

2.13.5. Revenue Stream

AI can help SMEs diversify their revenue streams by creating new products, services, and business models. AI can also open opportunities for subscription-based or platform-driven revenue models (Mills, 2021). Additionally, AI can create new revenue streams for

SMEs by enabling them to offer AI-driven services such as predictive maintenance, personalised marketing, and AI-based product recommendations (Dwivedi et al., 2021). However, the ability to capitalise on these new revenue streams is contingent upon having a skilled workforce capable of developing and deploying these AI solutions. Without the necessary skills, SMEs may not be able to fully yield the revenue potential that AI offers.

2.13.6. Channels

The use of AI enables SMEs to enhance their customer engagement channels, such as chatbots, virtual assistants, and personalised digital marketing campaigns (Manyika et al., 2017). However, developing and managing AI-driven channels requires skilled professionals who understand AI systems and customer behaviour. SMEs lacking in-house AI expertise may need to rely on third-party providers, increasing costs and reducing control over the customer experience.

2.13.7. Customer Relations

AI allows SMEs to build stronger, more personalised customer relationships through tools like chatbots, AI-powered recommendation engines, and tailored marketing strategies. AI has the potential to transform customer relationships by enabling personalised services, automated responses, and predictive insights. AI enables real-time customer feedback, enhances customer service, and provides insights into customer preferences, fostering loyalty and engagement (De Cremer & Kasparov, 2021. To implement and maintain these systems, SMEs need employees with the right technical and analytical skills (Khan et al., 2020). Without these skills, SMEs risk falling behind in customer service innovations.

2.13.8. Customer Segment

AI tools can segment customers based on behaviour, preferences, and buying patterns, allowing SMEs to tailor their offerings to specific demographics or market niches (Bughin et al., 2019). This precise targeting helps SMEs in developing countries focus their limited resources more effectively. AI allows SMEs to better understand and segment their customer base through data analysis, predictive modelling, and personalized marketing (Bessen et al., 2020), AI can process and analyse vast amounts of data at a much faster pace to optimize the rate at which decisions and actions are taken, further enabling better turnaround times and competitive advantages. However, achieving these outcomes depends on having skilled personnel who can leverage AI tools to analyse customer data and deliver tailored solutions. SMEs in developing countries that lack AI expertise may struggle to compete with more technologically advanced firms in this regard.

The successful adoption of AI in SMEs in developing countries is deeply intertwined with the availability and development of relevant skills. The Business Model Canvas framework highlights how skills impact various aspects of the business model, from value propositions to revenue streams. By investing in skills development, whether through training, partnerships, or importing expertise, SMEs can enhance their ability to leverage AI technologies, improve customer relations, and create new market opportunities.

2.14. Analysis of the Impact of Skills using the PESTEL Framework

The PESTEL framework (Political, Economic, Social, Technological, Environmental, Legal) provides a structured approach to understanding the external factors influencing the adoption of AI in small and medium-sized enterprises (SMEs) in developing countries. The availability and development of AI-related skills significantly influence how SMEs in these regions adopt and leverage AI technologies across all PESTEL dimensions.

2.14.1. Political

The political environment in developing countries plays a pivotal role in influencing the availability of AI-related skills. Countries that invest in AI education and training programs provide SMEs with a skilled workforce capable of leveraging AI technologies (Dwivedi et al., 2021). Conversely, a lack of political will to support such initiatives may result in a significant skills gap, limiting SMEs' ability to implement AI-driven solutions (Manyika et al., 2017). Government policies that promote education, technology transfer, and investment in AI-related training programs either facilitate or hinder AI adoption by SMEs.

2.14.2. Economic

The economic conditions in developing countries have a profound impact on AI adoption. The cost of hiring skilled AI professionals or investing in training can be prohibitive for SMEs, especially in countries with lower per capita income (Mishra et al., 2021). Access to financial resources, market conditions, and overall economic stability affect the availability of training programs and opportunities to import skilled labour. In economically constrained environments, SMEs often lack the financial resources to invest in

AI training or hire skilled personnel, as a result, many SMEs struggle to acquire or develop the necessary AI skills internally. However, external funding from international organisations and foreign investment in skills development programs can help bridge the skills gap. Imbalances in educational infrastructure and access to advanced training shape the global AI skills ecosystem. Importing AI expertise from global labour markets is often necessary for SMEs in developing countries, but this comes at a high cost and increases dependency (Zhu et al., 2021). Visa regulations, international wage disparities, and brain drain further complicate skill accessibility.

2.14.3. Social

Social factors such as education levels, cultural attitudes towards technology, and demographic trends can influence the development of AI skills in developing countries. These factors determine whether the local population is receptive to acquiring new skills and technologies. In regions with a low level of digital literacy or where technology adoption is slow, it is challenging for SMEs to find workers with the necessary AI skills. Educational institutions in developing countries may not yet be fully equipped to provide training in advanced technologies like AI (Zhang et al., 2020). International educational partnerships, such as joint degree programs and online learning platforms (e.g., Coursera, edX), can help democratize access to AI knowledge. Multinational tech firms are increasingly offering open training programs, bootcamps, and AI literacy initiatives to upskill emerging markets (Bessen et al., 2020). Global AI research initiatives, such as those by UNESCO and OECD, emphasise equitable skills development as critical to closing the gap between developed and developing economies. Furthermore, societal attitudes towards technology, such as scepticism or fear of job displacement due to automation, can also limit the willingness of individuals to engage in AI-related skill development. However, a younger, tech-savvy population with access to online learning platforms may positively influence skill development in AI.

2.14.4. Technological

The technological infrastructure and innovation ecosystem of a country significantly impact the development of AI skills and the capacity of SMEs to implement AI solutions. Access to high-speed internet, computing resources, and data infrastructure is critical for AI training and development. In developing countries, limited access to technological infrastructure, such as reliable internet or high-performance computing systems, can inhibit AI skill development (Manyika et al., 2017). Without a strong technological foundation, SMEs cannot efficiently train AI models or deploy AI systems. Moreover, the lack of access to advanced tools like cloud computing and AI software can hinder the practical learning and application of AI skills. However, technological partnerships and collaboration with international firms can mitigate these challenges by providing SMEs with access to necessary technological resources and skill-building programs (Tambe et al., 2019).

2.14.5. Environmental

Environmental factors, including a country's commitment to sustainable development and addressing local environmental challenges, can influence how AI is used by SMEs across many sectors, like agriculture, energy, and manufacturing. SMEs in developing countries that operate in sectors heavily impacted by environmental concerns (e.g., agriculture, water management) can benefit significantly from AI solutions. However, implementing AI-driven environmental solutions requires specific skills, such as knowledge of AI algorithms related to climate data modelling or resource optimisation. A lack of skills in these areas may prevent SMEs from harnessing AI to address local environmental challenges. Conversely, training programs focused on the intersection of AI and environmental sustainability can provide SMEs with the expertise needed to innovate in this space (Zhu et al., 2021).

2.14.6. Legal

The legal and regulatory framework of a country can either facilitate or hinder the development of AI skills and the adoption of AI by SMEs. Issues such as intellectual property rights, data privacy laws, and labour regulations impact how AI technologies are developed and used. Legal frameworks that support AI research and innovation, including protections for intellectual property and investments in AI education, are essential for creating an environment conducive to skill development (Dwivedi et al., 2021). Conversely, restrictive data privacy regulations may complicate the use of AI, especially for SMEs lacking legal expertise. Legal barriers may limit access to data, stifling the growth of AI skills in key sectors like finance, healthcare, and e-commerce. Governments that create AI-friendly policies can promote skill development by incentivising education, research, and entrepreneurship in AI.

The development of AI-related skills in SMEs in developing countries is influenced by multiple factors under the PESTEL framework. Political support for education and innovation, economic conditions, societal attitudes towards technology, technological infrastructure, environmental priorities, and legal frameworks all play a role in determining whether SMEs can acquire the skills needed to adopt AI effectively. Without sufficient AI skills, SMEs may struggle to compete in a rapidly evolving global economy. However, targeted interventions in education, policy, and infrastructure can help bridge the skills gap and unlock the potential of AI for SMEs in developing countries.

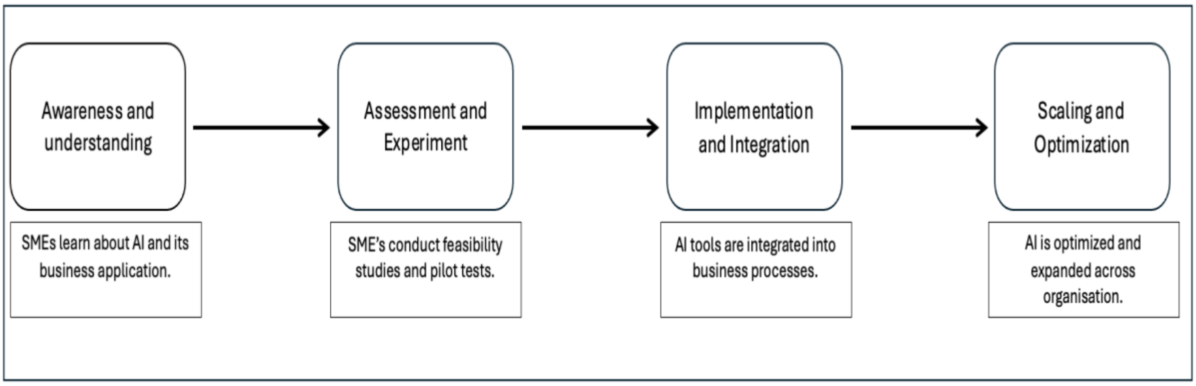
2.15. AI Adoption Processes and Support Structures

Adopting artificial intelligence in small and medium-sized enterprises (SMEs) in developing countries follows a structured process influenced by various support mechanisms. The adoption journey typically includes awareness, experimentation, implementation, and scaling, while support structures involve financial aid, technical expertise, policy frameworks, and collaborative ecosystems. The adoption process can be structured according to the following steps:

1. Awareness and Understanding - The first step in AI adoption involves SMEs becoming aware of AI's potential benefits and understanding how it applies to their business processes. This stage is critical because many SMEs in developing countries have limited exposure to AI technologies (Dwivedi et al., 2021).
2. Assessment and Experimentation- After gaining awareness, SMEs conduct an initial assessment to determine feasibility. This involves evaluating their technical capabilities, financial resources, and readiness to implement AI solutions (Goyal et al., 2023). Pilot projects and proof-of-concept implementations help SMEs test AI applications before full-scale deployment.
3. Implementation and Integration- In this phase, SMEs integrate AI into their business processes, often starting with automation and data analytics. The implementation requires investment in software, cloud computing, and skilled personnel (Tambe et al., 2019). Successful integration depends on the availability of AI talent and infrastructure, which are often scarce in developing countries.
4. Scaling and Optimisation- Once AI proves beneficial, SMEs scale up its use across different business functions, such as customer service, marketing, and supply chain

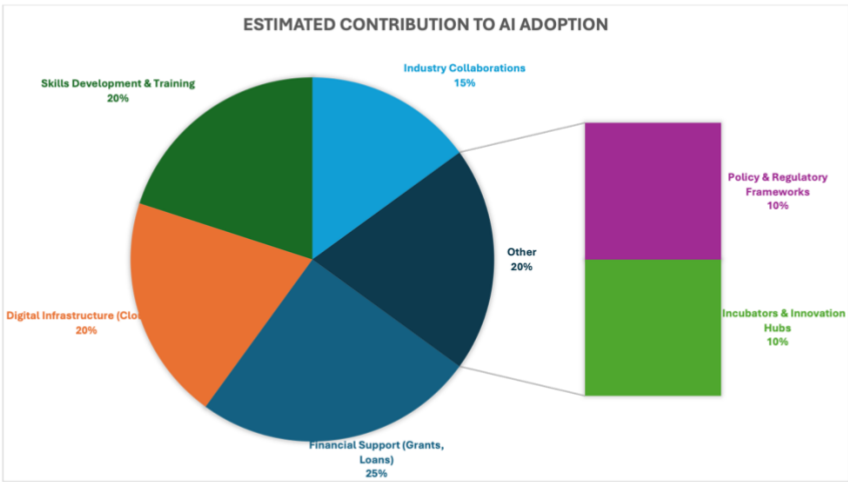
management. Continuous monitoring and optimisation ensure AI aligns with business goals and adapts to market changes (Mishra et al., 2021).

Figure 1: AI Adoption Process, adapted from Dwivedi et al. (2021)



To best efficiently implement a seamless adoption process, the following support structures can be obtained:

Figure 2: Key enablers of AI adoption, adapted from World Economic Forum (2021)



- Financial and Government Support- Many SMEs struggle with the high costs of AI adoption. Government grants, subsidies, and tax incentives help lower barriers to entry. For instance, countries like India and South Africa offer funding programs to support digital transformation in SMEs (OECD, 2022).
- Digital Infrastructure and Cloud Computing- Developing countries often lack the necessary infrastructure for AI deployment. Cloud-based AI services help SMEs overcome hardware limitations by providing scalable computing power and pre-trained AI models (World Bank, 2021).

- Skills Development and Capacity Building- A shortage of AI-skilled professionals is a major challenge. Training programs, online courses, and partnerships with universities play a key role in bridging the skills gap (Manyika et al., 2017). Governments and private sector initiatives provide AI literacy programs to enhance SME capabilities.
- Industry Collaborations and Innovation Hubs- Collaborating with larger corporations, AI startups, and research institutions allows SMEs to access expertise and funding. Innovation hubs and tech incubators support SMEs by offering mentorship, AI tools, and networking opportunities (Zhang et al., 2020).
- Policy and Regulatory Frameworks- Supportive AI policies and data governance frameworks ensure SMEs can adopt AI without excessive legal and ethical risks. Countries like Kenya and Nigeria are developing national AI strategies to guide SMEs in their AI transformation (ITU, 2023).

AI adoption in SMEs in developing countries follows a structured process, from awareness to scaling. However, financial constraints, skills shortages, and infrastructure limitations pose significant challenges. Support structures such as government funding, cloud computing, skills training, and industry collaborations play a vital role in enabling SMEs to integrate AI into their operations. Policymakers must ensure that AI ecosystems are inclusive, providing SMEs with the necessary resources to leverage AI for business growth.

2.16. Measuring the value-creation of AI

Integrating AI in SMEs in developing countries offers significant opportunities for value creation. Measuring this value, both quantitatively and qualitatively, remains a challenge. Value creation in the context of AI refers to the process through which organisations leverage AI technologies to enhance their products, services, and operational efficiencies, ultimately leading to increased profitability, improved customer satisfaction, and competitive advantage. AI-driven value creation can manifest in various forms, including cost reduction, revenue growth, innovation, and enhanced decision-making capabilities (Choudhury et al., 2021).

Many stakeholders would expect to see mostly the financial gains of a project; however, for SMEs that are in environments that are socially influenced, value creation poses a multilayer dynamic of how and what should be measured and deemed valuable, going beyond the basic financial gains factors. Measuring the value creation of AI projects in SMEs in developing countries requires a balanced approach that incorporates both quantitative and qualitative metrics. By employing financial metrics like ROI and cost savings alongside qualitative assessments such as stakeholder feedback and organisational impact, SMEs can gain a comprehensive understanding of the value generated by their AI initiatives. This multifaceted evaluation approach can help SMEs make informed decisions about future AI investments and strategies:

1. Quantitative Measurement of Value Creation- Quantitative metrics provide concrete data that can be analysed statistically to assess the value of AI projects. The following are key quantitative measures SMEs can adopt:

1.1 Return on Investment (ROI)

ROI is a fundamental financial metric used to evaluate the profitability of an investment. It can be calculated using the formula: ROI $= \frac{\text{NET PROFIT}}{\text{COST OF INVESTMENT}} \times 100$

This metric helps SMEs determine the financial returns generated by AI projects relative to their costs (Huang & Rust, 2021).

1.2 Cost Savings

AI can lead to significant operational efficiencies and cost reductions. SMEs can track reductions in labour costs, error rates, and time savings as a result of AI implementation. For example, automating routine tasks can free up resources for more strategic initiatives, leading to cost savings that can be quantified (Davenport & Ronanki, 2018).

1.3 Revenue Growth

AI applications can enhance customer experiences and enable better decision-making, contributing to increased sales and revenue. Tracking changes in sales figures before and after AI implementation provides SMEs with a quantitative measure of revenue growth attributable to AI (Chatterjee et al., 2020).

1.4 Key Performance Indicators (KPIs)

Developing specific KPIs aligned with business objectives helps SMEs measure the success of AI projects. These KPIs could include customer acquisition rates, customer retention rates, operational efficiency metrics, and product/service quality indicators (Pérez & Cebrián, 2021).

2. Qualitative Measurement of Value Creation - Qualitative assessment focuses on the non-numeric aspects of value creation, providing insights into the broader impact of AI projects.

2.1 Stakeholder Feedback

Gathering feedback from employees, customers, and other stakeholders can provide valuable insights into the perceived value of AI initiatives. Surveys, interviews, and focus groups can be used to assess satisfaction levels, user experience, and perceived benefits (González et al., 2022).

2.2 Case Studies and Success Stories

Documenting case studies and success stories related to AI projects can highlight qualitative benefits such as improved decision-making, innovation, and competitive advantage. These narratives can be powerful tools for communicating the value of AI to stakeholders and investors (Seddigh et al., 2022).

2.3 Organisational Culture and Capability Development

Assessing changes in organisational culture and employee skill sets due to AI implementation can provide qualitative insights into the value created. For instance, AI projects may foster a culture of innovation, collaboration, and continuous learning within SMEs (González et al., 2022).

2.4 Alignment with Strategic Goals

Evaluating how well AI projects align with the organisation's strategic goals can help measure their qualitative value. This alignment ensures that AI initiatives contribute to broader business objectives and enhance overall organisational performance (Chatterjee et al., 2020).

For many stakeholders, particularly in developing countries, it is crucial to consider the long-term value that an AI project can bring to the organisation, encompassing skill development, operational efficiency, competitive market advantage, and the ability to expand and adapt to further digital transformation. By automating tasks, analysing large datasets, and providing actionable insights, AI enables businesses to optimise processes and respond more effectively to market demands (Bharadwaj et al., 2013). This enables organisations to harness the power of intelligent systems to drive organisational success and foster sustainable growth.

2.17. Identifying Operational Growth

Operational growth can result from various factors, including scaling operations, adopting new technologies, optimising supply chains, and improving workforce capabilities (Rajan & Zingales, 2001). Operational growth can be identified as the increase in a company's efficiency, effectiveness, and overall capacity to produce goods or deliver services. It encompasses enhancements in processes, technologies, and resource management that lead to increased output, improved quality, and reduced costs.

Furthermore, the variability of operational growth may also differ across regions. It may differ across regions due to various factors such as economic conditions, regulatory environments, access to technology, and cultural attitudes toward innovation. For example: Developed Regions: In developed economies, operational growth may be driven by advanced technologies, high levels of investment in research and development, and a skilled workforce. Companies in these regions often have better access to capital and resources, enabling them to implement sophisticated operational strategies (Mazzucato, 2013).

Developing Regions: In contrast, SMEs in developing regions may face challenges such as limited access to funding, inadequate infrastructure, and regulatory hurdles. Operational growth in these areas may be slower and more dependent on incremental improvements rather than disruptive innovations. However, the adoption of mobile technology and AI can accelerate operational growth by improving efficiency and reaching new markets (Kraemer-Mbula & Wamae, 2010).

Thus, operational growth can be identified as a variable that is widely subjective and relative to internal and external factors that can be examined as both qualitative and quantitative constructs, depending on the aim of the observation.

2.18. Summary and Gaps from the Literature Review

Based on the review of current and previously existing research, it is evident that the available literature that pertains to the impact of AI on SMEs in developing countries is limited and overshadowed by research focused on developed countries. Much of the research on the impact of AI has taken place in countries that have the resources to develop and adopt AI systems. These governments, institutions, and businesses have access to and financial opportunities to support technological development.

Many frameworks and conceptual models thoroughly provide in-depth analysis and high-level overviews that support strategic planning; however, that’s frameworks reveal and segment internal and external factors that affect SMEs. Common theories exhibit exclusive examinations and considerations without further elaborating on the relational interconnectedness of all internal and external business components; an example of this is the stark individualisation of the Business Model Canvas and PESTEL Framework.

In Developing Countries, where resources are limited and constrained by time, finances, and skills, management within SMEs may not have the capacity to utilise multiple models and frameworks for strategic planning. Furthermore, the working knowledge of how to implement existing models and frameworks in the planning stage of an AI project may also be limited. Overlooking internal and external factors that are country-specific has, countless times, proven to be detrimental to AI projects, especially in the cases of international collaborations. There have been many occurrences in which an organisation from a developed country has attempted to copy and paste their strategies and project plans with the expectation that it being able to work in developing countries, not taking country-specific challenges into account. When SMEs in developing countries attempt to follow similar project plans and frameworks, without extensive knowledge and skills, it can result in a misuse of resources (I.E., Time and Finances) and a strategic plan that has not accounted for all the potential risk factors that will affect the project.

While the existing frameworks and theories provide a solid foundation to develop strategic project plans for the implementation and adoption of AI systems, the output of internal and external factors is oversimplified through the lens of 'what works' in developed countries. This study aims to provide an effective model that SMEs, without any specialised and expert knowledge, can use to identify all internal and external factors and their relation to the affordability, skills, and accessibility of resources required to develop and sustain a valuable AI system. Further assisting stakeholders in an SME to understand the impact that an AI project will have on their specific business and location. By offering a model that is accessible, understandable, and relevant to all SMEs, risks can be mitigated, and time and costs can be optimised.

Chapter 3 will examine the proposed qualitative methodologies that can be applied to address the research questions that have been presented, supporting the overall aim of this research and presenting a practical method to identify and understand the impact of Artificial Intelligence on small - medium enterprises in Developing Countries.

CHAPTER 3
METHODOLOGY

3.1. Overview of Research Problem

As globalisation and connectivity capabilities rapidly increase, ambitious and hardworking developing countries look to developed countries to strive towards their level of technological and economic advancement, while developed countries look towards developing countries to help improve and render investment and development opportunities as a way of assisting developing countries. Many SMEs in developing countries also look to these examples of technological growth as a representation of hope and success, and a prosperous future.

Being influenced and inspired by technological advancements has encouraged SMEs in developing countries to delve into the possibilities and opportunities of digital transformation. Promising financial growth and competitive advantage, these SMEs are springing into the wide possibilities of AI. However, this is resulting in SMEs trying to use preconstructed project plans and strategies, without any prior experience or guidance. In the context of internal and external business factors in developed countries and developing countries, the information that is provided in the plans and strategies can be misjudged, irrelevant, and misplaced. These consequences can prove to be major challenges when SMEs do not adapt and critically evaluate the relevance of all the information that has been presented in the project plans. Mimicking strategies is not a viable option, and often creating personalised strategies is not feasible or accessible.

This study provides an opportune layout of how to develop a model that is based upon the successes of the frameworks that are utilized within the Research and Development phase of AI projects in developed countries and the immediate identifiable micro and macro gaps that are evident in the implementation of AI projects in developing countries by international stakeholders. By combining a framework that clearly structures the nuanced challenges that are geographically and demographically prevalent and outlining overlapping factors that are likely to influence an SME in a developing country, risks can be accounted for and mitigated at the planning stage of an AI project. Stakeholders at multiple levels will be able to engage and provide a diverse perspective and input that can be advantageous at some point. For this study, a pilot model consisting of multiple frameworks that have been appropriately adapted will be utilised as the qualitative research method. At this point in the research, a qualitative research method has been selected as the most viable and reliable method that can best elaborate and accommodate business factors that are influenced by social, environmental, and cultural factors that are country-specific.

The pilot model that has been developed will be applied to form case studies of a sample of existing SMEs in developing countries that are, from an operational standpoint, ready to include an AI system in their daily business operations. Within the process of creating these individual case studies, the researcher has the opportunity to delve into an in-depth analysis of the intricate issues and situations that are country-specific, further providing a preview of the overarching challenges that SMEs face at a managerial level.

Using the scope of affordability, accessibility, and skills required enables us to understand the unique and complex business relationships, showing how access to multifaceted support structures that are available in and for the region can have a ripple effect impact across communities. For SMEs with limited resources, who do not have the expertise or budget to outsource strategic planning and research, this pilot model aims to create a tool that business owners and managers from any academic background and professional experience can use in a simple and comprehensible way that is not time-consuming or requires additional costs.

3.2. Research Purpose and Questions

The main purpose of this research is to identify and analyse how an SME is impacted by AI, both internally and externally, to understand the specific opportunities and challenges within each region. This research integrates the components of the Business Model Canvas and the PESTEL framework through the scope of Affordability, Accessibility, and Skills and draws upon each individual component's degree of relativity and relation to one another. The research purpose is refined, and the research questions are as follows:

Main research purpose: What is the impact of AI on SMEs in developing countries?

- RQ 1: What framework can SMEs utilise/incorporate in their strategic planning to evaluate the impact of AI, internally and externally?

Measurement Scope: Affordability
Accessibility
Skills

- RQ 2: What support structures are required to successfully adopt an AI system?

- RQ 3: How can the qualitative value-creation of AI concerning operational growth be identified?

3.3. Definition and Operationalisation of Theoretical Constructs

The study focuses on three core constructs—affordability, accessibility, and skills—that influence AI adoption in SMEs. These constructs were guided by relevant theoretical frameworks (Digital Divide Theory, Diffusion of Innovations, and Technology Acceptance Model) and were operationalised using specific, measurable indicators to ensure consistency in data collection and analysis (Creswell & Poth, 2018; Patton, 2015). A qualitative approach was chosen because the research questions required an in-depth understanding of contextually specific phenomena that are not easily quantified, such as perceptions of AI value, sector-specific barriers, and nuanced human behaviours around skills and technology. A qualitative design was particularly suitable for capturing rich, narrative data on how SMEs navigate AI adoption in environments with high variability in infrastructure, policy, and culture (Yin, 2018; Miles, Huberman, & Saldaña, 2014). This methodology enabled a grounded exploration of both commonalities and unique deviations across cases.

3.3.1. Operationalisation of Theoretical Constructs

To address the research questions, the following theoretical constructs were explored in the case studies. Strategic planners in SMEs need to identify the impact, defined as theoretical constructs, of the potential adoption of AI within their business operations:

- Affordability (RQ1)

Affordability, as a theoretical construct, refers to the capacity of an individual or organisation to acquire or sustain a product, service, or technology without experiencing significant financial hardship or compromising other essential needs. It encompasses the absolute cost of an offering and the perceived value or return on investment (ROI) in relation to the available financial resources of the entity (Rangan et al., 2011; Prahalad, 2010). In the context of SMEs in developing countries, affordability includes the initial cost of adoption, recurring costs, and the financial mechanisms available to support such investments (Ansari et al., 2012).

For a case study on SMEs in developing countries, affordability can be operationalised through the following measurable dimensions:

1. Direct Costs

- Upfront Costs:
  The initial financial outlay required for acquiring AI technology, including hardware, software, installation, and training (World Bank, 2016).
- Recurring Costs:
  Ongoing expenses such as maintenance, subscriptions, updates, and operational overhead (OECD, 2019).

2. Financial Capacity
   - Revenue Allocation:
     The proportion of SME revenue allocated to technology investments and its impact on cash flow and profitability (Ansari et al., 2012).
   - Access to Credit and Financing:
     The availability of affordable loans, grants, or subsidies for AI adoption, reflecting the financial ecosystem's role in affordability (Sharma et al., 2020).
3. Economic Context
   - Macroeconomic Conditions:
     Influence of inflation, exchange rates, and economic stability on the cost of acquiring and maintaining AI systems (Prahalad, 2010).
   - Market Price Variability:
     Comparison of AI technology prices within the local and international markets, including availability of low-cost alternatives (OECD, 2019).
4. Perceived Value
   - Cost-Benefit Analysis:
     SMEs' perception of the benefits of AI adoption compared to its cost, including improvements in efficiency, revenue generation, or competitive advantage (Rogers, 2003).
   - Time to ROI (Return on Investment):
     The expected time required for the financial gains from AI adoption to offset its cost (Brynjolfsson & McAfee, 2014).
5. Payment Flexibility
   - Financing Models:
     Availability of flexible payment plans, such as instalment-based financing, leasing options, or pay-as-you-use pricing (World Economic Forum, 2018).

- Subsidy and Support Programs:
  Government or institutional subsidies to offset the cost of AI adoption (Rangan et al., 2011).

6. Opportunity Cost

- Competing Financial Priorities:
  Trade-offs SMEs must make to allocate resources toward AI adoption versus other operational or growth investments (Ansari et al., 2012).

By operationalising affordability in this way, the case study can explore how SMEs in developing countries assess and navigate financial constraints when considering AI adoption.

- Accessibility (RQ1)

Accessibility, as a theoretical construct, refers to the ease with which individuals or organisations can obtain, utilise, and benefit from a product, service, or technology. It encompasses both physical and non-physical dimensions, including availability, usability, affordability, and awareness. Accessibility in the context of SMEs in developing countries involves the ability to access the necessary infrastructure, knowledge, and support systems for adopting technologies such as AI, while navigating barriers like infrastructure deficits, technical expertise gaps, and economic constraints (Penchansky & Thomas, 1981; Van Dijk, 2005).

For a case study on SMEs in developing countries, accessibility can be operationalised through the following measurable dimensions:

1. Infrastructure Access

- Physical Infrastructure:
  Availability and reliability of electricity, internet, and hardware needed for AI systems (World Bank, 2016).
- Digital Infrastructure:
  Access to software, cloud services, and AI platforms in the local market (OECD, 2019).

2. Technical Access

- Technology Availability:
  Presence of AI technologies in the region, including access to vendors and service providers (Sharma et al., 2020).

- System Compatibility:
  Compatibility of AI solutions with existing systems and workflows used by SMEs (OECD, 2019).

3. Knowledge and Skill Access
   - Training and Education:
     Availability of training programs or educational resources to build AI-related skills among SME employees (World Economic Forum, 2018).
   - Awareness:
     SMEs' awareness of AI tools, benefits, and implementation processes (Rogers, 2003).
4. Financial Access
   - Cost-Related Barriers:
     Financial affordability of AI systems, including costs of acquisition, maintenance, and upgrades (Prahalad, 2010).
   - Subsidies and Financing Options:
     Access to loans, grants, or subsidies specifically designed for technology adoption (Ansari et al., 2012).
5. Institutional Support
   - Policy Environment:
     Government and institutional support, including tax incentives, regulatory frameworks, and public-private partnerships for promoting technology adoption (Van Dijk, 2005).
   - Legal and Compliance Accessibility:
     Ease of understanding and meeting legal and compliance requirements related to AI systems (OECD, 2019).
6. Social and Cultural Access
   - Cultural Acceptance:
     Social attitudes toward AI and technology adoption within the SME ecosystem (Sharma et al., 2020).
   - Networking Opportunities:
     Access to partnerships, collaborations, and industry networks that facilitate AI adoption (Brynjolfsson & McAfee, 2014).

By operationalising accessibility, the case study can systematically evaluate the ease with which SMEs in developing countries can engage with AI systems and the specific challenges they encounter.

- Skills (RQ1)

Skills, as a theoretical construct, refer to the abilities, expertise, and competencies that individuals or organisations possess to perform specific tasks effectively. In the context of SMEs in developing countries, skills pertain to the technical, managerial, and operational knowledge required to adopt, implement, and utilise technologies such as AI systems. Skills encompass both individual-level capabilities (e.g., employee expertise) and organisational-level capacities (e.g., training systems and knowledge-sharing processes) (Becker, 1964; OECD, 2019).

For a case study on SMEs in developing countries, skills can be operationalised through the following dimensions:

1. Technical Skills:
    - Programming and Development: Ability to develop or customise AI tools (OECD, 2019).
    - Data Analysis: Competency in processing and interpreting data for AI models (Brynjolfsson & McAfee, 2014).
    - System Maintenance: Capability to maintain and troubleshoot AI technologies (World Economic Forum, 2018).
2. Managerial Skills:
    - Strategic Thinking: Understanding of how AI can align with business goals and strategies (Davenport & Kirby, 2016).
    - Project Management: Ability to oversee AI adoption projects, including budgeting, timelines, and stakeholder coordination (Bresnahan et al., 2002).
    - Change Management: Skills to manage organisational change and resistance during AI implementation (Kotter, 1996).
3. Digital Literacy:
    - Basic IT Skills: Proficiency in using computers, internet tools, and basic software applications (Van Dijk, 2005).
    - AI Awareness: Knowledge of AI capabilities, limitations, and applications relevant to the business (World Bank, 2016).

4. Soft Skills:
    - Collaboration and Communication: Ability to work in cross-functional teams and communicate AI-related insights effectively (OECD, 2019).
    - Problem-Solving and Critical Thinking: Skills to identify challenges and opportunities related to AI use (World Economic Forum, 2018).
5. Organisational Skills Infrastructure:
    - Training Programs: Availability and effectiveness of in-house or external training to upskill employees (Sharma et al., 2020).
    - Knowledge Management Systems: Mechanisms for sharing AI-related knowledge within the organisation (Nonaka & Takeuchi, 1995).

To ensure consistency, transparency, and analytical rigour in data collection and interpretation, the key constructs of affordability**,** accessibility, and skills were operationalised using specific, measurable indicators as mentioned above. Additionally, Affordability was defined as the financial feasibility of AI adoption and measured using three core indicators: the proportion of AI-related investment relative to annual revenue, access to external financing options (e.g., grants, loans, subsidies), and total cost of ownership, which includes hardware, software, training, and ongoing maintenance expenses. These indicators provided a multidimensional view of financial capacity and constraints (Patton, 2015; Miles, Huberman, & Saldaña, 2014). Accessibility**,** referring to the ability of SMEs to engage with AI-enabling infrastructure and tools, was assessed through indicators such as internet penetration and speed, access to cloud computing and software-as-a-service (SaaS) platforms, and geographic or virtual proximity to AI or technology hubs. These factors were chosen based on their practical influence on SMEs' ability to trial, implement, and maintain AI systems, particularly in under-resourced settings (Guest, Bunce, & Johnson, 2006; Yin, 2018). For instance, the presence of regional tech accelerators or innovation centres was used as a proxy for ecosystem accessibility and knowledge spillover potential. Skills**,** the third construct, were defined as the availability and quality of human capital capable of working with AI technologies. It was measured through the number of staff with AI-related competencies (e.g., data analytics, programming, machine learning), the number of training hours per employee devoted to AI or digital literacy, and the SME’s access to external expertise, including consultants, training providers, or academic partnerships. These indicators reflect both internal workforce capacity and the ability to bridge skill gaps through external engagement (Creswell & Poth, 2018; Braun & Clarke, 2006; Eisenhardt, 1989).

By incorporating these clearly defined and validated indicators into both the interview and survey instruments, the study enhanced the reliability of intra-case and cross-case comparisons, allowing for meaningful analysis of how SMEs in different sectors and regions navigate the challenges of AI adoption.

Successful Adoption of an AI project (RQ2)

Successfully adopting an AI project in an SME in developing countries entails the effective integration, implementation, and utilisation of AI technologies to achieve defined organisational objectives, such as improving efficiency, enhancing decision-making, increasing revenue, or gaining a competitive advantage. This includes not only the technical deployment of AI but also the development of supporting infrastructure, workforce alignment, and measurable outcomes (Brynjolfsson & McAfee, 2014; Sharma et al., 2020).

This construct can be operationalised through measurable dimensions and criteria that reflect the different stages and outcomes of the adoption process:

1. Project Planning and Preparation
   - Defined Objectives: Clear identification of goals and key performance indicators (KPIs) for the AI project (Rogers, 2003).
   - Feasibility Assessment: Conducting technical and financial assessments to ensure readiness for AI implementation (Davenport & Kirby, 2016).
2. Infrastructure Development
   - Technical Readiness: Adequacy of IT infrastructure, including hardware, software, and internet connectivity, to support AI deployment (World Bank, 2016).
   - Data Availability: Access to relevant, high-quality, and structured data for training and using AI models (OECD, 2019).
3. Workforce Engagement
   - Skill Development: Training employees to operate, maintain, and leverage AI systems effectively (World Economic Forum, 2018).
   - Change Management: Managing resistance and aligning organisational culture to support AI integration (Kotter, 1996).
4. Implementation Process
   - Technical Deployment: Successful installation, customisation, and integration of AI systems into existing workflows (Sharma et al., 2020).

- Process Integration: Seamless incorporation of AI into business operations, ensuring minimal disruption (Brynjolfsson & McAfee, 2014).

5. Measurable Outcomes
   - Operational Efficiency: Improvements in productivity, cost savings, or process automation due to AI adoption (Ansari et al., 2012).
   - Decision-Making Enhancement: Use of AI to improve accuracy, speed, or quality of decision-making (Rangan et al., 2011).
   - Financial Returns: Positive financial outcomes, such as increased revenue or ROI, within a defined time frame (Prahalad, 2010).
6. Sustainability
   - Scalability: Ability to expand AI use cases or scale up the project without significant barriers (OECD, 2019).
   - Maintenance and Support: Establishing mechanisms to ensure ongoing support, upgrades, and troubleshooting for AI systems (Sharma et al., 2020).
7. Ecosystem Engagement
   - Partnerships: Collaboration with AI providers, industry networks, or government initiatives to ensure project success (World Bank, 2016).
   - Regulatory Compliance: Adherence to local laws, data privacy regulations, and ethical guidelines related to AI use (OECD, 2019).

Qualitative Value-Creation of AI (RQ3)

The qualitative value creation of an AI project refers to the non-financial or non-quantitative benefits an SME derives from implementing AI technologies. These benefits are often more subjective but no less significant and can include improvements in operational efficiency, customer satisfaction, employee engagement, innovation capacity, and strategic positioning in the market. Qualitative value creation focuses on enhancing processes, relationships, and capabilities that may not immediately translate into financial metrics but contribute to the long-term sustainability and competitiveness of the SME (Brynjolfsson & McAfee, 2014; Sharma et al., 2020).

In SMEs in developing countries, qualitative value-creation often includes overcoming technological barriers, improving business processes, and fostering a culture of innovation. These outcomes help SMEs adapt to changing market conditions, increase their resilience, and gain a competitive edge, which are crucial for survival and growth in resource-constrained environments (OECD, 2019; Prahalad, 2010).

For a case study on SMEs in developing countries, the qualitative value-creation of an AI project can be operationalised through the following measurable dimensions:

1. Operational Efficiency
   - Process Automation: Improvement in business processes such as customer service, inventory management, and production scheduling through AI-driven automation (Brynjolfsson & McAfee, 2014).
   - Time Savings: Reduction in time spent on repetitive tasks or decision-making, allowing employees to focus on higher-value activities (Sharma et al., 2020).
   - Resource Optimisation: Better allocation and use of resources (human, financial, and physical) resulting from AI insights (OECD, 2019).
2. Customer Experience
   - Personalisation: Enhanced customer experience through AI systems that deliver personalised products or services (e.g., tailored recommendations) (Van Dijk, 2005).
   - Customer Engagement: Improved communication channels, such as chatbots or AI-driven customer support systems, which lead to increased customer satisfaction and loyalty (Brynjolfsson & McAfee, 2014).
   - Customer Trust: Strengthening customer relationships and trust by providing more accurate and timely service, fostering long-term engagement (OECD, 2019).
3. Employee Engagement and Empowerment
   - Skills Development: Employees are gaining new skills through AI training programs and working with advanced technologies (Sharma et al., 2020).
   - Decision Support: AI acting as a decision-support tool, improving the quality of decisions made by employees or managers (Prahalad, 2010).
   - Job Satisfaction: Increased employee satisfaction due to reduced manual tasks and more fulfilling, strategic roles (World Economic Forum, 2018).
4. Innovation and Competitive Advantage
   - Innovation Capacity: Enhanced ability to innovate and create new products, services, or business models based on AI-driven insights (OECD, 2019).
   - Market Differentiation: Ability to offer unique value propositions or enhance existing offerings through AI, creating a competitive edge (Sharma et al., 2020).

- Agility and Adaptability: The SME's ability to adapt to market changes quickly and effectively through AI-enhanced decision-making (Brynjolfsson & McAfee, 2014).

5. Organisational Culture and Strategic Alignment

- Culture of Innovation: The fostering of an organisational culture that values technological adoption, continuous learning, and process improvement (OECD, 2019).
- Strategic Alignment: The alignment of AI projects with the overall strategic goals of the organisation, enhancing long-term sustainability (Prahalad, 2010).
- Leadership Development: AI projects contribute to the development of leadership capabilities within the SME, fostering visionary thinking and long-term strategic planning (Sharma et al., 2020).

Operational Growth (RQ3)

Operational growth refers to the expansion and improvement of a firm's internal processes, efficiency, and overall capacity to deliver goods and services. It is a key performance indicator that reflects an enterprise's ability to scale its operations, optimise resource utilisation, and improve productivity over time (Rajan & Zingales, 2001). Within the context of AI adoption in SMEs in developing countries, operational growth involves leveraging AI-driven solutions to enhance automation, decision-making, and workflow optimisation, leading to improved efficiency, reduced operational costs, and increased output (Choudhury et al., 2021).

As a theoretical construct, operational growth can be measured through both qualitative and quantitative indicators. The following dimensions can be used to operationalise this concept:

- Process Efficiency – Measured by reductions in production time, improved task automation, and streamlined workflows due to AI integration (Davenport & Ronanki, 2018).
- Cost Optimisation – Assessed through financial indicators such as reduced operational expenses, improved resource allocation, and enhanced supply chain efficiency (Huang & Rust, 2021).
- Productivity Enhancement – Evaluated based on increases in output per employee, faster service delivery, and improvements in quality control (Mazzucato, 2013).

- Scalability and Expansion – Reflected in the ability of SMEs to scale operations, enter new markets, and sustain business growth through AI-driven insights and automation (Chatterjee et al., 2020).
- Technological Adoption – Measured by the extent of AI implementation, integration with existing systems, and the development of AI-related competencies within the workforce (Pérez & Cebrián, 2021).

For the case studies, four theoretical constructs were operationalised by applying the definition of each construct as a guideline to interpret and examine the relativity of the scope and factors to consider when analysing the impact of Affordability, Accessibility, and Skills in relation to an SME in a developing country, adopting an AI project.

Three theoretical constructs, relating to RQ2 and RQ3, were operationalised by utilising the definitions as a guideline and boundary to ensure that concepts such as the 'successful adoption of AI', 'Qualitative Value-Creation', and 'Operational Growth' were subjectively understood and interpreted uniformly amongst all case study participants.

Each theoretical construct was further operationalised by identifying measurable dimensions to examine the relevance and qualifying criteria of all the information that was gathered during the development of the case studies.

The constructs of affordability, accessibility, and skills were operationalised through the lens of the Business Model Canvas (internal business dimensions) and PESTEL analysis (external environmental conditions). Affordability is defined in terms of financial barriers; accessibility refers to digital and infrastructural access; and skills encompass technical, managerial, and digital competencies. Successful adoption is measured by AI integration into workflows; value creation by improved client offerings and internal efficiency; and operational growth by enhanced decision-making, scalability, and service innovation.

3.3.2. Framework Operationalisation and Replication Protocol

To enable replication and practical application of this study's framework, a replication protocol was developed based on the combined Business Model Canvas (BMC) and PESTEL analytical approach. This protocol outlines a structured checklist that SMEs and other stakeholders can use to assess readiness for AI adoption. It ensures methodological transparency and provides a guide for future studies or organisational assessments using the same framework. The full checklist is provided in Appendix C.

The protocol allows for cross-sectional and longitudinal replication across various sectors and countries, accommodating both qualitative and quantitative extensions.

3.4. Research Design

Based on the extensiveness and subjectivity of the research questions, particularly related to regional and business-social-culture factors, A qualitative multiple-case study methodology was selected as the primary research design. According to Yin (2018), case studies are especially suitable for exploratory research in real-world settings where contextual variables are complex and interrelated.

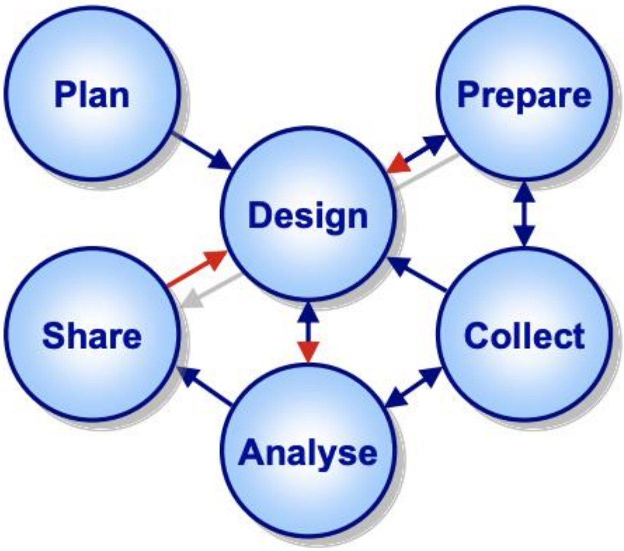
To understand the impact of AI, within the scope of affordability, accessibility, and skills, a broad range of internal and external business factors was identified that would provide a comprehensive analysis of each scope. These factors were further filtered and included based on their relevance. Internal factors that were identified as relevant are components of the Business Model Canvas, and external factors that were identified as relevant are components of the PESTEL framework. In light of the demands of this study and to further bridge the gap between strategic planning and stakeholders, a comprehensive analysis model has been developed and adapted with the research scope to produce an output of relevant information that is understandable and widely accessible to all stakeholders. This Model solves for RQ1 Part 1(The Framework), and consequently provides a conclusive overview that shows the Impact of AI in relation to Accessibility, Affordability, and Skills (RQ1 Part 2). This also creates the platform to explore and answer RQ2 and RQ3.
RQ1 was further dissected into two parts, the first part that posed the question of "What framework…" was presented as a model and the second part that aimed to understand the impact was researched using a more descriptive approach.

For RQ1(Part 2), RQ2, and RQ3, in order to accurately represent the nature of the study and the participants, the Case Study method has been adopted. The case study method is a qualitative research approach that provides in-depth insights into complex phenomena within their real-world contexts (Yin, 2018). It provides a contextual understanding that allows the researchers to explore the unique challenges and opportunities SMEs face in specific economic, social, and technological contexts. Given that AI adoption in SMEs intersects with socio-economic, infrastructural, and cultural dimensions, the case study approach offers a robust method to understand these dynamics in depth. It enables a holistic investigation of phenomena where the boundaries between context and subject are not clearly defined.

Within the scope of this, and to maintain a rigorous and efficient flow of communication, the research design was thoroughly developed to meet the needs of the researchers and participants. The design stage focuses on defining the unit of analysis and the likely cases to be studied, developing theory/propositions and identifying issues underlying the anticipated study, identifying the case study design (single, multiple, holistic, embedded), and developing procedures to maintain case study quality (Yin, 2009).

The Case Study Process, adapted by Yin(2009), was implemented to guide researchers and assist the flow of information within the various amongst the various stages of the case development.

Figure 3: Case Study Process, Adapted by Yin(2009) & Baskarada (2014)



Furthermore, it provides relevance based on the observation that SMEs in developing countries often operate in environments characterised by limited infrastructure, financial constraints, and skill shortages (Dwivedi et al., 2021). A case study can capture these contextual details and highlight how SMEs navigate such conditions to adopt and leverage AI technologies. A prime example of this is the study on how an SME in Kenya uses AI for agricultural optimisation could reveal localised strategies that are not generalisable from studies conducted in developed countries (Reuters, 2019).

A total of 10 case studies were developed using SMEs from a range of industries in several developing countries. The total number of ten case studies was justified by two key principles. First, this selection allows for theoretical saturation, where recurring patterns and themes across diverse cases become apparent, offering reliable analytical generalisations (Guest et al., 2006). Second, the cases were chosen to maximise diversity in SME characteristics, including variations in sector (e.g., renewable energy, consulting, tourism, retail), geographic location (e.g., Africa, Asia, Latin America), size, and level of digital maturity. This heterogeneity enhances the richness of the data and allows for meaningful cross-case comparisons to identify context-specific as well as common enablers and constraints in AI adoption (Eisenhardt, 1989). This identified multiple complex variables, and the case study method was well-suited to analysing complex interactions between variables, such as the interplay between AI adoption, organisational culture, and market dynamics. AI adoption in SMEs involves multiple factors, including technology availability, workforce skills, and customer demand. A case study can provide a detailed account of how these factors influence each other, offering insights that quantitative methods might overlook (Yin, 2018).

Within the scope of the Case Study Methods that can be employed, sub-methods can be further explored for deeper insights. According to Yin (2018) and Stake (1995), qualitative case studies can be categorised based on their purpose and design: exploratory, descriptive, and explanatory. Additionally, multiple-case and embedded case study designs can offer deeper insights into the phenomenon. Relevant sub-methods were chosen that would be able to provide a viable answer to each research question. The sub-method that was utilised for each research question is as follows:

- RQ1 – An instrumental case study enables researchers to explore a larger subject through different, separate studies and use the findings to understand its relationship to another subject. This type of design also provides insight into an issue or helps refine a theory (Dovetail,2023). For this part of the research question, for part 1 of the question, to provide a solution for 'What' framework could be utilised, the instrumental case study method was used to develop a model that integrated business frameworks and models in a generalised format.

For Part 2, to gain a more in-depth understanding of the measurement scope of impact, a multiple case study method was utilised.

- RQ2 – To understand what support structures are required, a multiple case study method was selected. The researcher selects multiple cases to illustrate the one issue or concern (Creswell & Poth, 2018). To measure the success component of the research question, a longitudinal case study method would be ideal.

However, to accommodate real-time and actionable results for stakeholders in the research and development phase, the support structures that are considered to enable "successful" adoption will be factors that mitigate risk and support efficiency during development and implementation. This will be deduced from multiple case studies.

- RQ3 - Using a multiple case study method and cross-referencing predetermined considerations of "value creation" helped to identify common factors that can lead to growth within the defined parameters of "growth".

As mentioned, the model that was used to conduct this research was developed with the stakeholders as front-end users. It aimed to consolidate data in an efficient way that can be understood. While the model's main objective was to assist the researcher in organising vast qualitative information, it further aimed to provide a high-level overview of factors behind the research questions presented while simultaneously determining concise answers to the pertinent questions within the confines of this research. The researcher used a pilot model to input data, which was then presented in the model's format to understand the usability while concurrently answering the research questions. The data collected from the participants was to create a profile of the business, a profile containing industry and location information was used to input information into each component of the model, once the models were completed, the researcher went through it with the business representatives to further explore the accuracy and relevance of the information, the model was further revised to accommodate any changes and then consolidated into a final iteration. The initial personal interaction with the participants helped the researcher to observe and enquire about cultural and social factors that influence SMEs in that area.

3.5. Sampling Technique and Participant Selection

Before a sample is taken, we must first define the population to which we want to generalise our results (Lammers & Badia, 2013). For this study, the primary sample comprises two necessary elements: the subject is required to be classified as an SME and should conduct business operations in developing countries. To further create a base standard for the selection criteria, exclusive parameters were introduced when identifying said *SMEs* and *Developing Countries*, this was implemented to ensure that the subjects were all more or less relatable and in the case of comparisons within the study, there would be a level of objectivity and equality for the researcher to comply with.

The classification of a developing country was determined primarily on socioeconomic factors. Simply put, these are most often countries with a lower income, an underdeveloped industrial base, a lower standard of living, and a lack of access to modern technology (Investopedia, 2024).

The sample selection was based on the following five key criteria:

1. Gross National Income (GNI) per Capita
   The World Bank categorises countries based on their GNI per capita, adjusted for purchasing power parity (PPP). Developing countries generally fall into the "low-income" or "lower-middle-income" categories (World Bank, 2021).
2. Human Development Index (HDI)
   The HDI, developed by the United Nations Development Programme (UNDP), measures a country's social and economic development based on life expectancy, education, and income per capita. Developing countries often have low to medium HDI scores (UNDP, 2021).
3. Economic Structure and Dependency
   Developing countries typically rely heavily on agriculture, natural resources, or primary goods exports rather than diversified industrial or service-based economies (Todaro & Smith, 2020).
4. Infrastructure Development
   Limited access to basic infrastructure, including healthcare, education, transportation, and clean water, is a hallmark of developing countries (Chenery & Srinivasan, 1988).
5. Poverty and Inequality
   High levels of poverty and income inequality are prevalent in developing nations. These issues are often compounded by weak social safety nets and limited public resources (Sachs, 2005).

According to the UN, there were 125 developing economies in 2024. These “economies” spread throughout Africa, Asia, Latin America and the Caribbean. It was pertinent that the sample that was selected was recognised and classified as *Developing;* the UN’s 2024 list was utilised as a point of reference.

The classification of an SME was interpreted and defined according to the most common and regional-specific, as follows:

The World Bank defines SMEs broadly but notes that these thresholds may differ depending on the income level of a country. For instance, lower thresholds may apply in low-income countries where businesses operate on a smaller scale (International Finance Corporation [IFC], 2020). The classification of SMEs in developing countries is generally based on quantitative and qualitative parameters. These parameters can vary by country and are often defined by national governments, international organisations, and development institutions like the World Bank and the International Finance Corporation (IFC). The classification of SMEs varies across countries and organisations, typically based on the following parameters:
Key Parameters

1. Number of Employees - This is the most commonly used parameter. SMEs are often categorised based on the size of their workforce:
    - Micro enterprises: Typically fewer than 10 employees.
    - Small enterprises: 10–49 employees.
    - Medium enterprises: 50–249 employees.

Example: In India, SMEs are classified based on their workforce size and other factors under the Micro, Small, and Medium Enterprises Development (MSMED) Act, 2006.

2. Annual Revenue/Turnover - SMEs are often classified based on their annual revenue. For example:
    - Micro enterprises: Revenue less than $50,000.
    - Small enterprises: Revenue between $50,000 and $3 million.
    - Medium enterprises: Revenue between $3 million and $15 million (IFC, 2020).
3. Total Assets - Total investment in physical assets (excluding real estate) is another criterion used to define SMEs. For instance:
    - Micro enterprises: Total assets below $100,000.
    - Small enterprises: Total assets between $100,000 and $3 million.
    - Medium enterprises: Total assets between $3 million and $15 million.
4. Industry-Specific Parameter - In some developing countries, SME classifications differ by industry to account for sector-specific variations in capital intensity, such as manufacturing, services, or agriculture.
5. Ownership and Independence - SMEs are often defined as businesses that are independently owned and operated, with no dominant ownership by larger corporations (World Bank, 2020).

These criteria differ across countries and regions, reflecting the economic structure and regulatory frameworks of each location. Below is an overview of SME classification criteria for key developing countries in South America, Africa, and Asia.

Table 1: Examples of SME Classifications in Developing Countries

Region	Country	Number of Employees	Annual Turnover	Total Assets	Source
South America	Brazil	Micro: ≤ 9, Small: 10–49, Medium: 50–99	Micro: ≤ BRL 360,000, Small: BRL 360,001–4.8M, Medium: BRL 4.8M–300M	Not specified	SEBRAE (Brazilian Micro and Small Business Support Service)
Africa	South Africa	Micro: ≤ 10, Small: 11–50, Medium: 51–200	Varies by sector, e.g., ZAR 13M (agriculture) to ZAR 220M (manufacturing)	Varies by sector, e.g., ZAR 5M (agriculture) to ZAR 55M (manufacturing)	South African Department of Trade, Industry and Competition (2021)
Africa	Kenya	Micro: ≤ 10, Small: 11–50, Medium: 51–100	Micro: ≤ KES 500,000, Small: KES 500,001–5M, Medium: KES 5M–800M	Not specified	Kenya National Bureau of Statistics (KNBS, 2016)
Africa	Nigeria	Micro: ≤ 10, Small: 11–49, Medium: 50–199	Micro: ≤ NGN 5M, Small: NGN 5M–100M, Medium: NGN 100M–500M	Micro: ≤ NGN 5M, Small: NGN 5M–100M, Medium: NGN 100M–500M	Small and Medium Enterprises Development Agency of Nigeria (SMEDAN, 2020)
Asia	India	Micro: ≤ 10, Small: 11–50, Medium: 51–200	Micro: ≤ INR 5 crore, Small: INR 5–50 crore, Medium: INR 50–250 crore	Micro: ≤ INR 1 crore, Small: INR 1–10 crore, Medium: INR 10–50 crore	Indian Ministry of Micro, Small, and Medium Enterprises (MSME Act, 2020)
Asia	Indonesia	Micro: ≤ 4, Small: 5–19, Medium: 20–99	Micro: ≤ IDR 300M, Small: IDR 300M–2.5B, Medium: IDR 2.5B–50B	Micro: ≤ IDR 50M, Small: IDR 50M–500M, Medium: IDR 500M–10B	Indonesian Ministry of Cooperatives and SMEs (Law No. 20/2008)

Based on the above table, and further research from the IFC and the World Bank, some key insights were also taken into consideration during the sample selection process, such as:

1. Employee Numbers:
    - In most countries, SMEs are classified as businesses with fewer than 200 employees.
    - The thresholds for micro, small, and medium enterprises vary across nations but generally align with local economic structures.
2. Turnover and Assets:
    - Turnover thresholds are influenced by the currency value and purchasing power parity (PPP) of each country.

- Some nations, such as South Africa and Indonesia, also consider total assets as a classification parameter.

3. Sector-Specific Variations:
    - Certain countries, like South Africa, define SME criteria differently for various sectors due to differences in capital intensity and revenue generation capacity.
4. Government Policies:
    - SME classification criteria are often linked to government policies, including access to financial incentives, grants, and tax relief programs.

For the 10 Samples that were selected, the non-probability sampling technique was used. Within this technique, sub-set non-probability techniques are used for RQ1-RQ3. Convenience Sampling is used in conjunction with Purposive Sampling. Convenience sampling is when participants are selected based on their accessibility and willingness to participate rather than their suitability for the research question (SAGO, 2024). In this case, it is applicable due to researchers selecting SMEs that aren't necessarily using digital transformation as a growth strategy. In purposive sampling, researchers intentionally select participants with specific characteristics or unique experiences related to the research question (SAGO, 2024).

A purposive sampling strategy was employed to identify SMEs that represented a diverse range of industries, geographic regions, organisational sizes, and AI maturity levels. SMEs were selected using the following criteria:

- Geographic diversity: Cases were drawn from Africa (Namibia, South Africa, Malawi, Ghana), Asia (India, Vietnam), and Latin America (Chile) to capture cross-regional perspectives.
- Sectoral diversity: Selected SMEs operated in renewable energy, fitness, construction, telecommunications, consulting, hospitality, retail, tourism, and food services.
- Organisational size: Participants ranged from micro-enterprises to medium-sized businesses based on employee count and revenue.
- AI maturity: The sample included both AI adopters and non-adopters to ensure a balanced view of perceived benefits, challenges, and readiness barriers.

SMEs were identified through regional business networks, digital innovation hubs, LinkedIn professional groups, and SME directories. Initial contact was made via digital channels and professional referrals. Participants were selected if they had strategic or operational oversight of AI-related decisions. This approach ensured the inclusion of firms at different stages of digital transformation and allowed for diverse perspectives.

To address potential selection bias, special effort was made to avoid overrepresentation of successful adopters. The inclusion of non-adopters provided contrasting views that enriched analysis and ensured more representative conclusions. This strategy aligns with recommendations for mitigating bias in qualitative research by enhancing representativeness and reducing overreliance on extreme or outlier cases (Patton, 2015).

3.6. Data Collection and Instrumentation

The data collection for RQ1 – RQ3 will be gathered and interpreted as qualitative data, which will aid the study in exploring the malleability of the data that is collected directly from the participants, as the direct data received would be filtered through social constructs and subject to the location of the business. It will further provide insight into the complexities that may arise from the research questions and results.

Both nominal and descriptive non-numerical data, which cannot be shown as numbers, are known as qualitative data in words or sentences (Taherdoost, 2022). Data were collected using a multi-source strategy to ensure depth and reliability. All data that is required for this research will be qualitatively collected. The first technique of the data collection is Primary data collection, which involves the collection of original data directly from the source or through direct interaction with the respondents (Jain, 2024). The primary data collection for the study is conducted through interviews with the participants, which is then followed by a questionnaire that is used to compile a profile of the business. The researcher followed the three steps of the interview process, as depicted in Table 2, which was adapted by Kasunic (2010):

Table 2: Interview Process, adapted from (Kasunic, 2010; Baskarada, 2014)

Orientation	Introductions and exchange of contact details. Description of the study and the interview process. Clarification of any expectations regarding non-attribution, sharing of data, and any other issues.
Information Gathering	The interviewer uses a questionnaire to guide the interview and to record responses.
Closing	The interviewer reviews the key points, any issues, and/or action items, and confirms accuracy with the respondent. The interviewee is invited to provide feedback on the

	interview process. The interviewer thanks the interviewee and seeks permission for any future contact.

Additionally, interviews were guided by a protocol aligned with the conceptual framework and included open-ended questions designed to elicit detailed narratives about AI adoption experiences, cost implications, infrastructure access, and staff capabilities.

To address response bias, which is common in self-reported data (Podsakoff et al., 2003), the study implemented triangulation by incorporating objective secondary sources. These included publicly available infrastructure data (e.g., internet penetration statistics from national regulators), and industry reports on AI adoption in SMEs. Where direct triangulation was not feasible, member checking was used to validate participant responses by sharing interview summaries for confirmation (Lincoln & Guba, 1985). In addition, probing techniques were employed during interviews to clarify vague or potentially overstated responses, particularly concerning AI cost-effectiveness, training investment, or infrastructure challenges. This triangulated and reflexive approach strengthens the credibility and confirmability of findings by reducing reliance on a single data source and by checking for consistency across multiple forms of evidence (Miles, Huberman, & Saldaña, 2014; Yin, 2018).

For RQ1 Part 1, to present a conceptual framework that can be used to assist SMEs in identifying the impact that AI has on their business, both internally and externally, a model has been presented. The Model uses a tabular format to organise and present the data, data that is collected will be gathered according to the components of the BMC and PESTEL frameworks. This will form the reference point for RQ1 Part 2, in which the data will be organised and grouped following the scope of the research, I.E., Affordability, Accessibility and Skills. For RQ2, to identify what support structures are required to successfully adopt an AI system, Secondary Data Collection will provide relevant historical data that can be used concurrently with the data presented from RQ1. Due to the subjective nature of RQ3, to understand how the qualitative value creation of AI concerning operational growth can be identified, primary data will be collected from the first questionnaire and cross-referenced with findings from secondary data sources, the RQ1 model, and regional-specific social factors. The timeline in which research was conducted between 2022 – 2025 was mainly to develop the research instrument - RQ1 Model, and the data collected from the pilot model was compiled in 2025 to develop the individual case studies.

Furthermore, to account for cultural, economic, and technological differences across regions and sectors, the interview and survey instruments were adapted to local contexts. This included adjusting terminology, phrasing, and examples to reflect sector-specific applications of AI (e.g., predictive maintenance in energy vs. chatbot usage in hospitality) and cultural perceptions of automation or job displacement. Instruments were pilot tested in three SMEs, one each from Africa, Asia, and Latin America, to evaluate clarity, relevance, and contextual fit. Feedback from these pilots informed revisions, such as simplifying technical jargon and including culturally relevant probes (e.g., on trust in technology or decision-making autonomy). Additionally, language support was provided where necessary, and interviewers were briefed on local communication norms and sensitivities to improve engagement and reduce misinterpretation (Patton, 2015). A selection of sample interview and survey questions used across sectors and countries is included in Appendix A to illustrate the adaptability of the instruments. These context-aware modifications enhanced the validity and reliability of cross-case comparisons, ensuring that key constructs were interpreted consistently while remaining sensitive to local realities (Creswell & Poth, 2018; Miles, Huberman, & Saldaña, 2014).

3.7. Data Analysis

Eisenhardt (1988) notes that analysis is the backbone of case study research. The depth of analysis is one of the primary virtues of the case study method (Gerring, 2004). A qualitative multiple-case study methodology was selected as the primary research design. Qualitative analysis has been described as both the most difficult and the least codified part of the case study process (Eisenhardt, 1989). Qualitative research focuses on analytical generalisation rather than statistical generalisation. Analytical generalisation involves the extraction of abstract concepts from each unit of analysis (Yin, 2013). While case studies do not aim to generalise to populations (statistical generalisation), similar to experiments, they aim to generalise to theories (analytical generalisation; Yin, 2009). As such, analytical generalisation is made to theory and not to population; the theory can be further strengthened by performing cross-case comparisons (Yin, 1981, 2009). Thus, according to Yin, replication may be claimed "if two or more cases are shown to support the same theory". Stake (1978), on the other hand, argues that case studies are particularly well-suited for naturalistic generalisations that are based on experiential transformation of tacit knowledge into explicit knowledge.

To accommodate the vast complexities of the data collected and the existing body of knowledge, multiple types of case analysis were employed to directly analyse the research questions, while sub-types of case studies were further used to explore supporting analysis. To encompass the entire research study, the iterative analysis process was incorporated. The iterative analysis process allows the emergence of themes that closely fit the data, leading to construct identification along with their relationships - This allows the researchers to start refining the constructs and build evidence within the data that measures the constructs, the constant comparison that happens between the tentative construct and the evidences from the data finally results into well-defined constructs for theory building. Thematic analysis was employed to identify key patterns and insights within and across the cases (Braun & Clarke, 2006). Coding was guided by the BMC and PESTEL frameworks, and cross-case synthesis was used to compare findings systematically. Analytical generalisation, rather than statistical generalisation, was the goal, following the logic of replication across multiple cases (Yin, 2018).

For RQ1, a single-case analysis with embedded units was selected as RQ1 was dissected into two components. As previously mentioned, RQ1 Part 1 used a framework model to collect and illustrate the data in a dynamic manner in which each participant enabled individual cases, and RQ1 Part 2 drew upon the model to examine the relevant data that explored the scope of affordability, accessibility, and skills an SME required to implement an AI system.

An Induction approach was utilised to find patterns, themes, or categories in the data to create theoretical frameworks that RQ1 Part 1 presented to RQ1 Part 2, which was then analysed using Within-case analysis. Within-case analysis, these write-ups are often simply pure descriptions, but they are central to the generation of insight (Gersick, 1988; Pettigrew, 1988) because they help researchers to cope early in the analysis process with the often enormous volume of data.

Case studies that use both within and cross-case analysis are more effective at generating theoretical frameworks and formal propositions than studies only employing within-case or only cross-case analysis (Barratt et al., 2011). RQ2 used a cross-case analysis with a multiple case study approach to understand what support structures are required to successfully adopt an AI system. Cases were grouped and analysed according to regions to create an overview of conditions such as infrastructure, skills, energy and other micro and macro environment factors that SMEs faced. Thus, cross-case analysis increases the reliability of the emerging theory as it is corroborated by multiple structured analyses and increases the likelihood of finding novel patterns that could have gone unnoticed (Mishra, 2021).

For RQ3, cross-case analysis with individual cases was used. The data was organised into two main groups: location and industry. Locational factors were used to understand what the concept of tangible versus intangible and short-term versus long-term Value Creation meant in specific areas, subject to socioeconomic dependencies. This was based on the belief that value creation differed across cultural beliefs and social structures. Given that qualitative researchers generally assume that social reality is a human creation, they interpret and contextualise meanings from people's beliefs and practices (Denzin & Lincoln, 2011).

The second unit that facilitated this qualitative measure of operational growth, Industry, used multiple case analyses to determine what factors determine the degree of operational growth per industry. This analysis was further applied and cross-referenced with the completed RQ1 Model, specifically the Value Proposition component within the model's framework.

For RQ2 and RQ3, an abduction approach in the analysis was used. With the abduction approach, researchers start with something noticeable in the data, like a pattern or observation, and then use reasoning to understand the phenomenon behind it, I.E. the cause and how it works. Pattern matching is one of the most desirable techniques as it involves the comparison of predicted patterns and/or effects with the ones that have been empirically observed, and the identification of any variances or gaps (GAO, 1990). This analytical approach uses two types of thinking, deductive and inductive reasoning, to come up with new insights and ideas. Explanation building is a special type of pattern matching which aims to analyse the case study data by building an explanation about the case (Yin, 2009). In this context, explaining refers to the process of building a set of causal links about how or why something happened (Miles & Huberman, 1994).

Data analysis followed a multi-step qualitative process, incorporating thematic coding, within-case analysis, and cross-case synthesis. The goal was to identify patterns across the ten case studies that explain how affordability, accessibility, and skills shape AI adoption and outcomes. First, all interview transcripts and survey responses were analysed using thematic analysis, following the six-phase approach outlined by Braun and Clarke (2006): (1) familiarization with the data, (2) generation of initial codes, (3) searching for themes, (4) reviewing themes, (5) defining and naming themes, and (6) producing the report. Coding was both inductive and deductive. Inductive to allow emergent insights and deductive based on predefined categories derived from the BMC (e.g., Key Resources, Cost Structure) and PESTEL (e.g., Economic, Technological, Social) frameworks. Second, a within-case analysis was conducted for each SME, mapping coded themes onto the integrated BMC-PESTEL framework. This allowed for structured case descriptions, highlighting how each factor (e.g., skills availability or AI investment cost) manifested within its context. Third, the study employed cross-case pattern matching and synthesis, comparing themes across all ten cases. Patterns were identified based on frequency, recurrence, and theoretical significance (Yin, 2018). For example, skills emerged as a high-frequency, high-impact enabler across most sectors and regions. These patterns were not only counted but also contextualised, the weight of each pattern was determined by how consistently it influenced AI adoption outcomes across cases (Miles, Huberman, & Saldaña, 2014).

Discrepancies or outliers, such as cases where affordability was not a barrier due to funding, were examined in detail to explain divergence rather than exclude them. This reflexive approach allowed for theoretical replication, strengthening internal validity. This analytical process ensured that conclusions were grounded in systematic, transparent comparisons, supported by both empirical evidence and conceptual frameworks.

3.8. Research Design Rigour

The complex nature and subjectivity of this study examine the multitude of constructs that must be considered and applied to answer the research questions. The study uses qualitative case study methods and approaches to systematically interpret research findings from various sources. Although researchers can employ great flexibility in the selection of study methods, the inclusion of best practice methods for assuring the rigour and trustworthiness of results is critical to study design (Johnson et al., 2020). Numerous frameworks have been developed to evaluate the rigour or assess the trustworthiness of qualitative data (e.g., Guba, 1981; Lincoln & Guba, 1985). To accommodate the qualitative nature of this study, four criteria have been applied. Lincoln & Guba (1994) outline four criteria for establishing the overall trustworthiness of qualitative research results:

1. Credibility, the researcher ensures and imparts to the reader supporting evidence that the results accurately represent what was studied. Triangulation of sources and member checking ensured accuracy.

2. Transferability, the researcher provides detailed contextual information such that readers can determine whether the results apply to their situation or other situations. Thick descriptions allow other researchers to assess relevance in similar contexts.
3. Dependability, the researcher describes the study process in sufficient detail that the work could be repeated. A clear audit trail documented data collection and analysis steps.
4. Confirmability, the researcher ensures and communicates to the reader that the results are based on and reflective of the information gathered from the participants and not the interpretations or bias of the researcher. Researcher reflexivity and transparent coding minimized bias.

The credibility rigour within the research was met by providing a thorough review of the concepts pertinent to this study in the literature review; the existing knowledge formed the foundation of the research questions. The literature review provided an understanding of the broader scope of research that focuses on developing countries and their multiple internal and external business influential factors, further forming qualitative benchmarks of the degree of resources that are available to them, specifically in terms of Accessibility, Affordability, and skills within the domain of AI. Exploring the dynamics of existing theories and frameworks inspired the development of the model that was adapted to solve RQ1. Explicit verified sources were provided to demonstrate the development of the theoretical constructs and selection criteria. The interview process provided direct sources of information about each case study, and input from the interviewee who was directly involved in the SMEs ensured the credibility and reliability of the data that was gathered to compile the business profiles for each case.

The transferability criteria for rigour in qualitative research are met, as one of the design purposes for the RQ1 Model is to provide a platform that is understandable and functional to a diverse group of people, further catering to users without any business or academic backgrounds. The model aims to illustrate findings in a manner that can be easily transferred between people and regions. Furthermore, the descriptive and interpretive analysis was used and supported by detailed explanations of how RQ2 and RQ3 were resolved. Furthermore, each component of the RQ1 Model was concisely explained to enable the reader to understand the relevance of each component within the domain of AI in developing countries, and detailed research demonstrated the interpretive nature of constructs such as operational growth, success factors and value creation. Despite the dynamic language structures that were presented by participants from diverse regions, the constructs were filtered through globally accepted standards and definitions. Regional-specific data informed the potential for relatability amongst readers and participants, allowing readers to assess if and how the research findings are transferable to other organisations and other countries.

The dependability criteria for rigour in qualitative research are met by using cross-case and multiple-case analysis to identify patterns, trends, and similarities amongst the case studies. The uniformity of the type of data that was collected was enforced by the RQ1 Model; this ensured that all the data that was gathered addressed the same themes throughout the study without conforming to any case-specific data challenges. Therefore, questions could not be adapted to counter socioeconomic challenges that may have developed throughout the research study. Although this was a medium-term study, 2022-2025, profiles and results were presented within the same time frames to eliminate the influences of socioeconomic phases that countries experienced throughout the years and to ensure that all the data that was presented was within reasonably current global experiences.

The confirmability criteria are met based on the input received from the participant (business representative) during the business profile development phase, as information is gathered directly from the source. Furthermore, content used within the model is verified by both international and national regulated and reliable sources.

CHAPTER 4
RESULTS

4.1. Data Collection

The aim of this is to understand the impact that AI has on SMEs in developing countries, specifically looking at the affordability, accessibility, and skills required to successfully adopt AI systems. The challenge that was presented in this study was to gain microeconomic and macroeconomic insight into all the factors that are brought into play and that should be considered in the strategising and planning stage of the AI project. This will mitigate risks and failures that occur when organisations in developing countries directly apply the same development and deployment strategies that they used in organisations that operate in developing countries. Time and research continuously highlight the oversight of regional-specific conditions that are often lacking in adequate research and understanding of "what's happening on the ground". To identify the impact of AI within a wide variety of industries and countries, the universal frameworks were utilised, specifically, the PESTEL model and the Business Model Canvas. To present the data in a manageable way, a model was adapted and formulated to provide a concise data format that is understandable by all stakeholders and other readers; this provided a bridge between skills/academic or professional background and the ability to efficiently use business frameworks without requiring "business" experience. The model presented an opportunity to provide a platform that could easily be transferred across regions, industries, and skill levels.

This enables systematic exploration of the degree of impact and the specific factors that cause the impact. Understanding how and why an SME is impacted by AI in terms of affordability, accessibility, and skills and what drives these factors is an important step in the strategic planning stage. Stakeholders should know how Political, Environmental, Social, Technological, Economic, and Legal conditions affect the Key Partnerships, Cost Structure, Key Activities, Key Resources, Revenue Stream, Channels, Customer Relations, and Customer Segments, consequently affecting the affordability, accessibility of resources, and skills required to use an AI system in a business's operations. By looking at relevant economic factors and assessing if they impact the cost structure, the business can determine if it can afford the project, and possibly explore options to mitigate any risks of shortfalls or find opportunities that could assist them.

The model shows the correlation between all these influential factors and further acts as the primary source of data for all of the research questions. To study RQ2 and RQ3, both the primary and secondary data sources are used. The secondary data are sourced from government institutions, national organisations, international organisations and research institutes. Data was obtained from diverse sources, mainly official documents, reviewed published articles, published journals and academic resources, as well as reports published by international organisations. Each research question presented a variety of analysis techniques to properly organise and interpret the findings, further encouraging the researcher to explore patterns and the emergence of trends, and encouraging the creation of malleable theories. An important facet in RQ2 and RQ3 involved considering social and cultural dynamics within countries and understanding how success, growth, and value creation are represented in different cultures. Factors such as Profit, Workforce Expansion, Diversification, Business Transformation, and Community Development/Involvement weigh differently in terms of *Operational Growth* across regions. Hence, it was integral to maintain a standardised format to organise the data and collate individual case studies, while still upholding the relevance and integrity of using single-case analysis for RQ1 and multiple-case analysis for RQ 2 and RQ3. 10 Case studies were developed, the secondary research and data was collected between 2022-2025, and the primary data collection and profiling was conducted in 2025.

To collect data that was relevant to the study, the research questions were supported by the following propositions to encourage a level of uniformity of the content.
RQ 1: What framework can SMEs utilise in their strategic planning to evaluate the impact of AI, internally and externally?
Within the following scope: Affordability
Accessibility
Skills
This research question formed the basis of the study. To provide a comprehensive analysis for this question, the research question was dissected into two parts. As follows:
RQ Part 1: What framework can SMEs utilise in their strategic planning to evaluate the impact of AI, internally and externally?
Part 1 presented a model that comprised a combination of frameworks and models that can be used for both internal and external evaluations. The layout of this model forms the components that should be analysed to answer the second part of this question. The

components to be analysed were selected from the Business Model Canvas for an internal evaluation and combined with the PESTEL framework for an external evaluation.

Part 2, which uses the model presented in Part 1, illustrates the relationship between the internal factors that were mentioned and the scope of the question. It further presents and categorises each component according to the scope, with a concise flow of overlapping relationships.

The following figure shows the format of the RQ1 model, which will be customised per case study.

Figure 4: RQ1 Model format

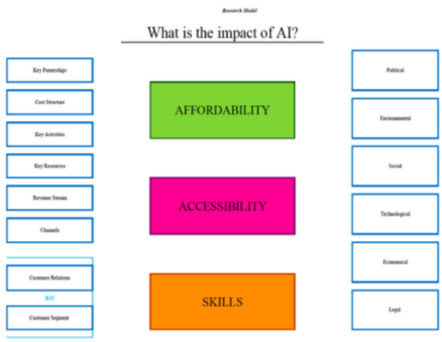


Figure 5: Relational format of Affordability

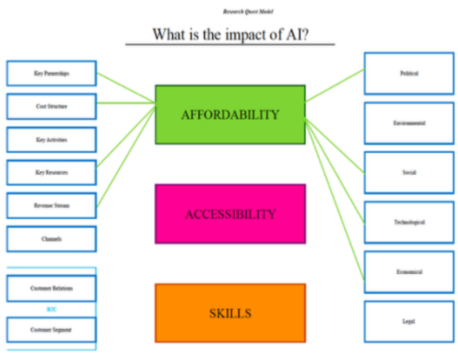


Figure 6: Relational format of Accessibility

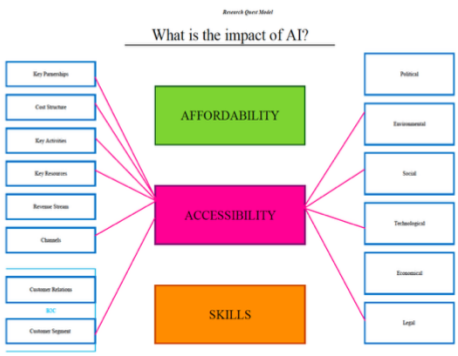
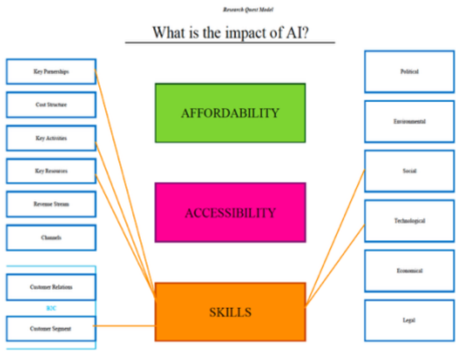


Figure 7: Relational format of Skills



As mentioned, the models presented in Figures 4 – 7 were reconstructed according to the findings in the single case studies. The relationships showed the impact of AI within each scope.

For RQ2, to identify what support structures are required to successfully adopt an AI system, the support structures were propositioned from various secondary sources and cross-referenced with the data collected from RQ1 to establish emerging trends and patterns in resources that were found to be necessary to plan and develop an AI system to efficiently operate in an SME with resources that can be accessed from developing countries.

Adopting an AI system in an SME in a developing country requires multiple support structures to overcome financial, technical, and infrastructural barriers. These structures ensure that SMEs can implement, maintain, and maximise the benefits of AI while mitigating potential challenges. The following six structures and their sources were identified as guidelines to support the exploration of findings from the primary research. These structures can be applied across developing countries.

1. Digital and Physical Infrastructure

AI adoption depends on access to reliable digital and physical infrastructure.

- Stable Internet Connectivity – High-speed and affordable internet is essential for cloud-based AI applications. (World Bank, 2016)
- Computing Power and Hardware – SMEs need AI-compatible hardware such as servers, GPUs, and edge computing devices. (OECD, 2019)
- Energy Supply – Reliable electricity is crucial for AI operations, especially in regions with frequent power outages.

2. Financial and Economic Support

SMEs often lack the financial resources for AI investment, requiring external financial support.

- Access to Credit and Grants – Governments, financial institutions, and NGOs should provide funding options for AI adoption. (Sharma et al., 2020)
- Flexible Payment Models – Subscription-based AI services (AI-as-a-Service) and leasing models reduce upfront costs.
- Tax Incentives and Subsidies – Governments can offer tax breaks or financial assistance to encourage AI adoption.

3. Skilled Workforce and Training Programs

Human capital is crucial for AI implementation and integration into business processes.

- AI Literacy and Digital Skills Training – SMEs need training programs to upskill employees on AI-related technologies. (World Economic Forum, 2018)
- Technical Support and AI Specialists – SMEs may require partnerships with AI service providers or hiring AI consultants.
- University and Industry Collaboration – Academic institutions can offer AI research, development, and workforce training programs.

4. Institutional and Policy Support

A conducive regulatory environment is essential for AI adoption.

- Clear AI Policies and Regulations – Governments should establish AI-friendly policies that ensure ethical use and data privacy. (OECD, 2019)
- Intellectual Property (IP) Protection – IP laws should safeguard AI-driven innovations created by SMEs.
- Public-Private Partnerships (PPPs) – Collaborative efforts between governments, private enterprises, and international organisations can support AI adoption.

5. Access to AI Ecosystems and Networks

SMEs need access to AI innovation hubs, industry networks, and collaborative platforms.

- Tech Hubs and Incubators – AI-focused incubators provide mentorship, funding, and business development support. (Brynjolfsson & McAfee, 2014)
- SME AI Communities – Peer-to-peer networks help SMEs share knowledge and best practices in AI adoption.
- Partnerships with Large Firms – Collaborations with larger corporations can provide access to AI expertise and technologies.

6. AI Ethics, Trust, and Cultural Acceptance

Building trust in AI among employees, customers, and stakeholders is critical for successful adoption.

- Awareness Campaigns – Educating SMEs about AI's benefits and addressing misconceptions can foster acceptance.
- Ethical AI Guidelines – Policies to ensure AI use is fair, unbiased, and does not harm vulnerable communities.
- Change Management Strategies – Businesses must address employee resistance through structured change management initiatives.

Successful AI adoption in SMEs in developing countries requires a holistic support system, including strong infrastructure, financial assistance, workforce training, policy support, access to AI networks, and cultural acceptance. Governments, private sector players, and international organisations must collaborate to create an enabling ecosystem for SMEs to leverage AI effectively. The data that was presented to answer RQ2 was gathered from a multiple case analysis approach, which aided in providing a holistic overview of the relevant support structures present and required.

Furthermore, Successful adoption of an AI system refers to the effective integration of AI technologies into an organisation's workflows, resulting in measurable improvements in efficiency, decision-making, and business outcomes while ensuring usability, ethical compliance, and sustainability. It is characterised by high user acceptance, tangible economic benefits, and alignment with strategic business goals (Davenport & Ronanki, 2018; Brynjolfsson & McAfee, 2014). Evaluating the success of AI adoption in SMEs requires a combination of qualitative and quantitative metrics that assess business impact, technical performance, and organisational integration. Below are the key dimensions of successful adoption,

1. Business Impact
    - Increased revenue and profitability (Brynjolfsson & McElheran, 2016).
    - Cost reduction due to automation and efficiency (McKinsey, 2017).
    - Enhanced decision-making and predictive capabilities (OECD, 2019).
2. Technical Performance
    - AI model accuracy, reliability, and scalability (Russell & Norvig, 2020).
    - Seamless integration with existing IT infrastructure (Westerman et al., 2014).
    - Minimal system downtime and high uptime rates (Deloitte, 2021).

3. User Adoption & Engagement
    - Employee acceptance and effective use of AI tools (Davenport & Kirby, 2016).
    - Customer engagement with AI-driven services (Sharma et al., 2020).
    - Reduction in resistance to AI adoption through training and change management (World Economic Forum, 2018).
4. Regulatory and Ethical Compliance
    - Adherence to data protection laws (e.g., GDPR, national AI policies) (Jobin et al., 2019).
    - Fair and unbiased AI decision-making (OECD, 2021).
    - Security measures ensuring data privacy and integrity (AI Now Institute, 2020).
5. Sustainability & Long-Term Viability
    - Continuous learning and improvement of AI models (McKinsey, 2018).
    - Workforce upskilling and adaptation to AI-driven workflows (Deloitte, 2021).
    - AI's contribution to long-term business resilience and market competitiveness (Brynjolfsson & McAfee, 2014).

Metrics to Assess AI Adoption Success

- Return on Investment (ROI)
- Operational Efficiency Gains
- Customer Satisfaction & NPS Scores
- Employee AI Adoption Rates
- Regulatory Compliance Metrics

Successful AI adoption is a holistic process that goes beyond technology deployment to include organisational readiness, workforce adaptation, and sustainable AI governance. Together with the key criteria for support structures and key dimensions of successful adoption, data from RQ1 part 1 was analysed to present comprehensive feedback on what business stakeholders, communities, public institutions, and governments could do and provide to support SMEs to successfully adopt an AI system in a developing country.

RQ3 used the collective primary data source as a multiple case analysis and used secondary data to form a framework to evaluate the multiple components of *qualitative value-creation* and *operational growth,* and various metrics that could be used as an evaluation criterion. The following metrics were used as a guideline to explore ***how*** the qualitative value-creation of AI concerning operational growth can be identified.

1. Business Performance Metrics

These metrics measure the overall impact of AI on business efficiency, revenue, and customer satisfaction.

- Return on Investment (ROI): Measures financial gains from AI adoption compared to the costs incurred.
    - Formula: $ROI = \frac{Net\ profit\ from\ AI}{Total\ AI\ Investment} \times 100$
- Revenue Growth: Increase in sales or revenue attributable to AI-driven efficiencies (e.g., better customer targeting, automation).
- Cost Savings: Reduction in operational expenses due to AI automation.
    - Example: AI-driven chatbots reducing customer support costs.
- Productivity Improvement: Measures AI's impact on labour efficiency.
    - Example: Percentage reduction in time spent on manual tasks.

2. AI System Performance Metrics

These assess how well the AI system functions in terms of accuracy, reliability, and efficiency.

- Algorithm Accuracy & Precision: Evaluates how well AI makes decisions.
    - Example: An AI fraud detection system's false positive rate.
- Model Performance (F1-score, Recall, Precision): Measures the balance between false positives and false negatives in AI outputs.
- Uptime & Reliability: AI system availability and resilience to failures.
    - Example: 99.9% uptime in cloud-based AI services.

3. User Adoption and Engagement Metrics

These assess how well employees and customers interact with the AI system.

- Employee Adoption Rate: Percentage of employees using AI tools in daily workflows.
- Customer Adoption Rate: Number of customers engaging with AI-powered services (e.g., chatbots, recommendation systems).
- Training & Skill Development Metrics: Number of employees trained on AI tools and their proficiency levels.

4. Customer Experience Metrics

These assess the AI system’s impact on customer interactions and satisfaction.

- Customer Satisfaction (CSAT) Score: Measures how satisfied customers are with AI-driven services.
    - Example: AI-driven customer service improves response times.
- Net Promoter Score (NPS): Measures customer loyalty and willingness to recommend AI-enhanced services.
- First Response Time (FRT) Reduction: Reduction in time taken to respond to customer queries using AI.

5. Compliance and Ethical Impact Metrics

These ensure AI adoption aligns with regulations and ethical standards.

- Regulatory Compliance Rate: Percentage of AI implementations meeting data protection and legal standards.
- Bias and Fairness Metrics: Measures how equitably AI treats different user groups.
- Data Security Incidents: Number of breaches or data mishandling cases.

6. Innovation and Competitive Advantage Metrics

This measures AI's role in driving new opportunities and market competitiveness.

- New Product Development: Number of AI-driven products or services launched.
- Market Positioning: Improvement in market share due to AI-driven differentiation.

By tracking these metrics, SMEs can assess whether their AI systems are delivering value, improving operations, and driving competitive advantage.

4.1.1. Application of the BMC–PESTEL Replication Framework

Each case study was analysed using the BMC–PESTEL replication protocol (Appendix C) to ensure consistency across internal and external factor evaluation. For example, the analysis of key partnerships, cost structure, and technological environment in Case Study 2 followed the replication protocol. This allowed comparison of AI readiness indicators across firms with different scales and industry contexts.

Summary derived from Appendix C

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10
Key Partners	✓		✓		✓		✓		✓	
Key Activities		✓		✓		✓		✓		✓
Key Resources	✓		✓		✓		✓		✓	
Value Proposition		✓		✓		✓		✓		✓
Customer Relationships	✓		✓		✓		✓		✓	
Channels		✓		✓		✓		✓		✓
Customer Segments	✓		✓		✓		✓		✓	
Cost Structure		✓		✓		✓		✓		✓
Revenue Streams	✓		✓		✓		✓		✓	
Political		✓		✓		✓		✓		✓
Economic	✓		✓		✓		✓		✓	
Social		✓		✓		✓		✓		✓
Technological	✓		✓		✓		✓		✓	
Environmental		✓		✓		✓		✓		✓
Legal	✓		✓		✓		✓		✓	

4.2. Study Results

Ten case studies were obtained from ten businesses; these businesses were situated in different countries, and for time-relevance purposes, most of the studies were conducted within the same periods to ensure that, for fair comparison and cross-referencing, macro-economic factors weren't drastically affected by real-time global occurrences that would affect the businesses and regions. All ten single case studies were created using information derived from the RQ 1 Model, which is as follows:

4.2.1. Case Study 1: AI Implementation in the Energy Industry in Namibia.

Introduction

This case study examined the impact of AI on a small business operating in Energy Trading and Solar Energy in Namibia. Using Business Model Canvas (BMC) and PESTEL analysis, this study explored how AI can optimise operations, enhance energy efficiency, and address economic, social, and technological challenges. Namibia, a geographically large country with a small population, is located on the western coast of Southern Africa. It has expansive landscapes and is rich in resource minerals, coupled with strong governance and institutions, as well as macroeconomic management that has assisted with poverty reduction in the country and has allowed Namibia to become an upper-middle-income country within the developing country criterion. With the many efforts from local government and partnerships, including increased funding and foreign investment, Namibia's renewable energy generation is projected to unlock future opportunities to trade power in the Southern Africa Power Pool, further encouraging large opportunities through expansion and digital transformation for emerging and existing SMEs in the energy industry.

Company Overview

The case focused on a Namibian-based SME involved in energy trading and solar energy solutions. The company provides renewable energy alternatives, has 11-25 employees and is structured as a Business-to-Business consumer model. Given Namibia's vast solar potential, AI integration is seen as a game-changer to enhance energy forecasting, optimise market transactions, and improve customer interactions.

Business Profile:

Name	N/A	Country	Namibia
Representative Role	Founder	Number of employees	11-25
Industry	Energy	Type of Business	B2B
Departments	Operations	Finance	Legal
	IT	Sales	Research and Development
	Customer Service		

To evaluate the impact that an AI project would have on this business, we analysed primary and secondary research sources and created the following models:

Table 3: Case Study 1 BMC

Key Partnerships	• Technology Providers: AI software developers, cloud computing services, and data analytics firms (Kaplan & Haenlein, 2019). • Regulatory Bodies: Namibian Electricity Control Board (ECB) and Namibia Energy Institute (NEI) to ensure compliance (Mupetami, 2021). • Renewable Energy Suppliers: Solar panel manufacturers and battery storage companies. • Financial Institutions: Banks and investors supporting AI-driven energy projects. • Universities and Research Institutions: Collaboration for AI model training and optimization.
Key Activities	• Predictive Analytics: Forecasting energy demand and pricing trends (Wang et al., 2022). • Automated Energy Trading: AI algorithms for real-time energy buying and selling (Schittekatte & Meeus, 2020). • Grid Optimization: AI-driven smart grids improving energy efficiency (Zhou et al., 2023). • Customer Relationship Management: AI chatbots and analytics for customer engagement. • Energy Consumption Monitoring: Smart metering and AI-driven demand response.
Key Resources	• AI Software & Algorithms: Machine learning and deep learning models for energy trading (Goodfellow et al., 2016). • Big Data & IoT Devices: Smart meters, weather data integration, and satellite-based solar forecasting. • Human Expertise: AI specialists, energy analysts, and business strategists. • Infrastructure: Cloud computing, servers, and blockchain for secure transactions.

Value Proposition	• Enhanced Energy Efficiency: AI optimizes energy generation and storage. • Cost Reduction: Predictive maintenance lowers operational costs (Kakran & Chanana, 2018). • Improved Energy Trading: AI enhances market intelligence and automation. • Sustainability: AI-driven optimization promotes renewable energy adoption. • Better Customer Experience: AI-driven insights improve service delivery.
Cost Structure	• AI Development & Maintenance Costs: Software updates, model training, and cloud computing. • Hardware & Infrastructure: IoT sensors, smart meters, and computing resources. • Regulatory Compliance & Licensing: Government approvals and cybersecurity measures.
Revenue Stream	• AI-Driven Energy Trading Fees: Commission on automated transactions. • Subscription-Based AI Services: Smart energy management tools for users. • Data Monetization: Selling anonymized energy usage data. • Government Incentives: Funding for renewable energy innovation.
Channels	• Online Platforms: AI-powered websites and mobile apps. • Partnerships: Collaborations with EV charging stations and solar energy providers.
Customers Relationships	• Personalized AI Recommendations: AI-based energy consumption insights for customers. • 24/7 Support: AI chatbots handling inquiries and complaints. • Data-Driven Loyalty Programs: Rewards based on sustainable energy usage.
Customer Segments	• Commercial & Industrial Users: Businesses adopting AI for energy optimization. • Energy Traders & Utilities: Entities leveraging AI for market predictions. • Government & NGOs: Institutions promoting renewable energy initiatives.

Table 3 provides a comprehensive overview of an AI project's impact on the business in the Energy industry in Namibia. It highlights the key partnerships and key resources that would be necessary to develop and implement an AI project, further looking at financial implications through the cost structure and revenue stream components. Considering that the business’s market approach is business-to-business, the customer relationships and customer segments that are mentioned are based on interacting with other businesses within commercial and industrial sectors, and other public and private institutions.

The next table, Table 4, provides an external evaluation of all the factors and their components that affect an AI project in Namibia within the energy industry. It briefly provides qualitative and quantitative factors, including affordability, accessibility, and skills factors.

Table 4: Case Study 1 PESTEL analysis

Politics	• Government Policies and Regulations: The Namibian government may have policies around the use of AI and its integration into industries like energy. While Namibia is investing in renewable energy and improving energy infrastructure, AI adoption might face regulatory hurdles that would require adaptation or licensing. • Government Support: Incentives & subsidies for solar AI solutions (Namibia Renewable Energy Policy). • Government Incentives & Policies: The Namibian government promotes renewable energy projects but has limited direct funding for AI adoption. However, policies such as tax incentives for technology investments could reduce the cost burden on SMEs.

	• Renewable Energy Funding: The Namibian government aims to have 70% renewable energy by 2030, allocating over N$1 billion ($55 million USD) for energy transition projects (Ministry of Mines and Energy, 2023). • AI Investment in Africa: AI funding for energy projects in Africa is expected to grow at a CAGR of 23.5%, reaching $1.3 billion by 2025 (African Development Bank, 2023).
Economics	• Cost Reduction: AI can lead to significant cost savings by optimizing energy production, distribution, and consumption, which is particularly beneficial for SMEs trying to remain competitive. - A study by McKinsey estimates that AI could contribute up to trillion to the global economy by 2030, with significant savings in energy production and consumption (McKinsey & Company, 2018). AI-driven optimization can reduce operational costs by up to 30% in energy sectors (Accenture, 2019). • Access to Capital: Namibia, as a developing economy, may face challenges accessing funding for advanced technologies like AI. However, investment from international organizations or private equity may be a potential source of capital. - According to the African Development Bank (2021), the financing gap for renewable energy in Africa, including Namibia, is estimated to be around $30 billion annually. • AI Project Cost: The cost of implementing AI-driven predictive maintenance in solar energy systems ranges between $50,000 and $500,000, depending on scale (McKinsey, 2022). • Return on Investment (ROI): AI-powered energy efficiency solutions can reduce operational costs by 15%–30%, resulting in annual savings of $20,000–$100,000 per SME (IEA, 2021). • Fluctuating exchange rates can impact the cost of AI-based solar technology, which is mostly imported. • Growing AI-based job market creates new employment opportunities in Namibia's renewable energy sector. • Brain drain: trained AI professionals may leave Namibia for higher-paying opportunities abroad.
Social	• Access to AI Technology: Limited AI expertise in Namibia may slow adoption (Zhou et al., 2023). • Skills Development: The integration of AI could spur demand for new skills. Training workers in AI and data analysis could create opportunities for upskilling in Namibia's workforce. - The Namibian government aims to train 90% of its workforce in digital skills by 2030 (Namibia National Development Plan 5, 2018). A report by the World Economic Forum (2020) indicates that 94% of business leaders expect employees to pick up new skills on the job due to AI technology. - Skill Development Costs: Training one AI specialist in Namibia costs approximately $5,000–$10,000 per year (Namibia University of Science and Technology, 2023). • Public Perception of AI: Namibians may have concerns about AI replacing jobs or eroding privacy. A strategic communication plan could help ease concerns by demonstrating AI's benefits in energy efficiency and cost savings. • Impact on Communities: AI could improve energy access in rural communities by optimizing distribution networks or providing off-grid solutions, contributing to social development in underserved areas. - Impact on Communities: Research shows that integrating AI and smart grid technology can increase access to energy in underserved areas by up to 20% (International Renewable Energy Agency, 2020).

	• Job Market Impact: AI adoption could reduce low-skill labour demand by 20% while increasing demand for AI-skilled professionals by 40% (World Economic Forum, 2023). • Public Acceptance: AI adoption in energy must be justified to consumers, especially in rural areas where affordability concerns are high.
Technological	• Energy Management and Optimization: AI technologies such as predictive analytics, smart grids, and demand-response systems can help energy providers optimize energy production, storage, and consumption, enhancing efficiency. - Energy Management and Optimization: According to the International Energy Agency (IEA, 2021), the adoption of AI and digital technologies in energy systems can lead to an estimated 30% improvement in efficiency for electricity generation and distribution. • AI-driven Solar Forecasting & Maintenance: Enhances efficiency & reliability of solar grids. • Renewable Energy Integration: AI can support the integration of renewable energy sources (solar, wind) by predicting fluctuations in supply and adjusting energy storage or distribution systems accordingly. • Technological Infrastructure: Namibia may face challenges in terms of technology infrastructure needed to support AI, including internet connectivity and access to cloud computing resources. • Cloud Computing Costs: AI cloud computing services cost approximately $1,000–$10,000 per month, depending on usage (Amazon Web Services, 2023). • Energy Grid Modernization: AI adoption requires smart meters and IoT integration, which can be costly. • Smart Grid Investment: Implementing AI-powered smart grids in SMEs could cost $100,000 to $500,000, depending on scale (IEA, 2021). • Cloud-based AI solutions make AI training accessible without needing expensive hardware. • Growing adoption of IoT & AI-powered smart grids increases demand for AI-trained solar energy professionals. • Partnerships with global AI leaders (Google, Microsoft, IBM) could introduce AI training programs in Namibia. • Limited AI research facilities in Namibia restrict skill development opportunities. • Lack of 5G & advanced internet infrastructure in rural areas makes remote AI training difficult. • High costs of AI software & computing resources can limit access to hands-on AI learning.
Environmental	• Sustainability and Energy Efficiency: AI can optimize energy usage, reducing waste and making energy consumption more sustainable, which is crucial for Namibia, as it continues to focus on renewable energy projects. - A report by the United Nations Environment Programme (UNEP, 2020) states that AI could help achieve energy savings of 15% to 30% globally by optimizing energy usage in various sectors, including power generation. • AI-driven battery management extends battery lifespan, reducing e-waste and maintenance costs. • Climate Change Mitigation: AI-driven energy management could aid Namibia's efforts to reduce its carbon footprint by enabling more efficient use of renewable resources. - AI applications in energy systems could reduce global CO_2 emissions by 1.5 gigatons by 2030 (Global Carbon Project, 2019). • Environmental Regulations: Namibia's environmental policies could influence how AI is deployed, particularly if it involves large-scale data collection or energy infrastructure changes that could impact the environment.

	• AI systems require energy-intensive computing (e.g., machine learning models for energy forecasting). • E-waste concerns arise from IoT sensors and AI-powered solar components that require disposal. • Water consumption for cooling AI data centres may conflict with Namibia's water-scarce environment. • AI can optimize solar energy efficiency, requiring skilled professionals to manage AI-powered grids. • E-waste concerns from AI-powered IoT devices - proper disposal training is needed. • AI computing's high energy consumption requires skilled professionals to optimize energy efficiency. • AI-based environmental compliance training is lacking in Namibia.
Legal	• Data Privacy and Security: The collection and processing of energy consumption data for AI systems might raise concerns about data privacy. Compliance with data protection laws and regulations would be necessary. - The General Data Protection Regulation (GDPR) emphasizes the importance of data privacy. The cost of non-compliance with data protection regulations can reach up to 4% of global revenue or €20 million, whichever is higher (European Commission, 2018). • Intellectual Property (IP): The SME would need to protect any AI algorithms, models, or proprietary technologies it develops to avoid intellectual property theft. • Liability and Accountability: Legal questions about liability may arise if AI-driven decisions lead to issues like system failures, incorrect energy distribution, or accidents. Clear legal frameworks around AI in energy would need to be developed. - As per a study by PwC, 74% of executives recognize that the lack of legal frameworks and standards regarding AI is a significant barrier to its adoption (PwC, 2018). • Renewable Energy Laws Favor Solar Growth: Government pushes for AI-enabled solar solutions. • Data Protection Laws Could Increase Compliance Costs: AI-driven energy data collection must comply with laws. • Regulatory Compliance Costs: Meeting AI-related legal requirements can cost SMEs \$20,000–\$100,000 annually (PwC, 2023). • Data Privacy Fines: Non-compliance with data regulations can result in fines of up to €20 million or 4% of annual revenue under GDPR (European Commission, 2023). • Namibia's renewable energy laws support AI investment in solar energy projects. • Data protection laws (Electronic Transactions and Cybercrime Act) promote secure AI-powered solar monitoring. • Legal frameworks for carbon credits encourage AI-driven energy efficiency programs. • Unclear AI regulations may slow AI adoption in the solar sector. • Data protection laws encourage AI cybersecurity training for solar energy professionals. • Complex licensing requirements for AI-based energy solutions may slow down AI skill adoption. • Few legal guidelines on AI ethics & bias in energy applications—professionals need training in ethical AI use.

The PESTEL analysis of the SME landscape and energy sector in Namibia provides an overview of some of the main strengths, weaknesses, threats, and opportunities that are present and potential for an AI project. These factors provide a clear and concise indication of which components to consider when analysing how affordable and accessible developing and implementing an AI project would be, and the skills that are required would be affected.

Using the BMC and PESTEL analysis to evaluate RQ1 part 2, the following figures illustrate the impact of AI in terms of affordability, accessibility, and skills that were derived from the model presented in RQ1 part 1.

Figure 8 is central to understanding how the three core adoption constraints - affordability, accessibility, and skills interact with internal and external business components. It served as a template for analysing each case study and guided data interpretation throughout RQ1.

Figure 8: Research Model 1 – Affordability, Accessibility, Skills

This figure presents the foundational model for RQ1, integrating components from the Business Model Canvas (BMC) for internal analysis and PESTEL for external analysis. The model visualises how affordability (green), accessibility (pink), and skills (orange) influence internal business structures (e.g., key partnerships, cost structure) and are impacted by external forces (e.g., political, technological environments). The directional lines indicate relational influence, and node sizes suggest the relative thematic weight derived from coding frequency in qualitative data.

The figures that have been presented above illustrate the impact of AI in terms of affordability, accessibility, and skills required. The model solved the following questions to support the findings of RQ1 part 2:

1. How will affordability impact an AI project in an SME in the energy industry in Namibia?
    - Internally, affordability will impact the key partnerships, cost structure, key resources and revenue stream of the AI project.
    - Externally, affordability will be impacted by the political, technological, environmental, and legal environments in Namibia.
2. How will accessibility impact an AI project in an SME in the energy industry in Namibia?
    - Internally, accessibility will impact the key partnerships and cost structure of an AI project.
    - Externally, accessibility will be impacted by the economic, technological, and legal environment in Namibia.
3. How will the skills required for an AI project impact the project in an SME in the energy industry in Namibia?
    - Internally, the skills required impact the key partnerships, key activities, and key resources of an AI project.
    - Externally, the skills required will be impacted by the economic, social, and technological environment in Namibia.

This answered RQ1 part 2 and presented what factors should be considered when developing and implementing an AI project. It showed the leading current factors that pose opportunities and potential risks that can be mitigated. With the high energy demand in Namibia and Southern Africa, AI proposes multiple opportunities that can assist the business in many ways. From enhancing internal operations to become more efficient and cost-effective, as well as upgrading current system offerings, to seizing external opportunities that are accessible to the business in the form of grants, training, and new technologies, AI has a solution to solve dynamic business challenges and optimize competitive advantages within the market and energy industry. Government subsidies and renewable energy incentives (e.g., through the Namibia Renewable Energy Policy) can offset AI software and hardware acquisition costs, stimulate AI use in diagnostics and grid optimization, and attract international investment for AI-driven sustainability projects. Government incentives such as tax breaks for green AI applications reduce capital burdens and supported predictive maintenance systems. This aligns with calls in the literature for public-private partnerships to unlock AI adoption in emerging sectors (Bughin et al., 2018).

4.2.2. Case Study 2: AI Implementation in the Telecommunications Industry in South Africa

Introduction

This case study explores how AI skills requirements impact a small South African SME operating in the Fibre network infrastructure industry. It evaluates the business's struggle with AI adoption, training costs, and workforce readiness while considering the broader political, economic, social, technological, environmental, and legal (PESTEL) factors. The SME provides services within the telecommunications industry, focusing on building Fibre Network Infrastructure in various local areas. For this study, the RQ1 Pilot Model was used to comprehensively identify and understand the vast business and social landscapes of South Africa and the dynamic factors that would impact an AI project internally and externally. Pertinent to the business culture that is prevalent in South Africa, SMEs and entrepreneurship are a vital part of this developing country's economy, supported by external factors such as the political, economic, and social environment. The move towards a digitised economic and social structure is rapid. However, the strong influence of digital transformation presents many "new" challenges and risks that SME's must overcome internally to compete in larger local markets. Digital transformation is reshaping the Fibre network infrastructure sector in South Africa. SMEs play a crucial role in expanding broadband connectivity, especially in underserved areas. However, the integration of Artificial Intelligence presents challenges, particularly in acquiring the necessary skills for AI implementation. At the forefront of digital transformation, especially AI development and implementation, fast and reliable connectivity is vital. The rollout of internet Fibre networks, as a key resource, has catalysed digital growth opportunities for all businesses, institutes, and households across the country, making internet connectivity accessible and affordable.

Company Overview

The case study was based on an SME in Johannesburg, South Africa. The company was acquired 22 years ago as an electronics services company and has pivoted and continuously adapted to the advancing needs of the rapidly growing technological business landscape of the country and is currently operating in the telecommunications industry. As a

Business–to–Business operating approach with 1-10 permanent employees, the business core team and offerings remain agile and customizable.

Business Profile:

Name	N/A	Country	South Africa
Representative Role	Director	Number of employees	1-10
Industry	Telecommunications	Type of Business	B2B
Departments	Operations	Marketing	HR

To evaluate the impact that an AI project would have on this business, we analysed primary and secondary research sources and created the following models:

Table 5: Case Study 2 BMC

Key Partnerships	• AI service providers (cloud computing, automation, and machine learning platforms). • Local tech startups and AI consulting firms. • Government and regulatory bodies providing AI adoption incentives. • Universities and research institutions for AI knowledge sharing. • Financial institutions offering AI adoption funding.
Key Activities	• Automation of repetitive tasks (e.g., customer service, data entry). • AI-driven marketing (predictive analytics, personalized campaigns). • AI-enhanced supply chain and logistics optimization. • Fraud detection and cybersecurity enhancements.
Key Resources	• AI tools (chatbots, CRM systems, automation software). • Skilled workforce trained in AI technologies. • Cloud computing and big data analytics infrastructure.
Value Proposition	• AI-driven personalized customer experiences. • Faster and more accurate decision-making. • Cost reduction through automated processes. • Enhanced data security and fraud prevention.
Cost Structure	• Initial investment in AI technology and training. • Subscription costs for AI tools (SaaS, cloud AI services). • Maintenance and updates for AI models. • AI adoption in fibre network SMEs can reduce operational costs by up to 30% (McKinsey, 2023). • 80% of SMEs in telecom report cost as the biggest AI adoption barrier (SME South Africa, 2023). • AI-driven automation in fibre networks could reduce operating costs by up to 30% (McKinsey, 2023).
Revenue Stream	• AI-powered subscription models (SaaS-based solutions). • Increased revenue from AI-enhanced marketing conversions.
Channels	• AI-driven digital marketing (SEO, social media, email automation). • AI-powered e-commerce recommendations. • Automated voice assistants for sales and support.

Customers Relationships	• AI-powered chatbots and virtual assistants. • AI-driven loyalty programs and customer segmentation. • Predictive analytics for personalized offers.
Customer Segments	• Urban and rural customers benefiting from AI-powered services. • Tech-savvy customers preferring AI-based interactions.

Table 5 highlights the main factors to consider from an internal perspective; these factors present a case for a generalised AI project and present an opportunity for further analysis of the impact of these factors. The AI impact of the key partnerships is stronger partnerships with AI developers; this increases accessibility to resources and skills and long-term affordability. The impact of key activities and key resources is increased efficiency in operations and decision-making, reduced manual workload and error rates, and better resource allocation with AI-powered analytics. Although the cost structure impact may present higher upfront costs, it does provide long-term savings and the reduction of operational expenses with automation.

Table 6 provides a PESTEL analysis that includes an affordability, accessibility, and skills analysis to evaluate the external impact that the macro-environment can have on an AI project.

Table 6: Case Study 2 PESTEL analysis

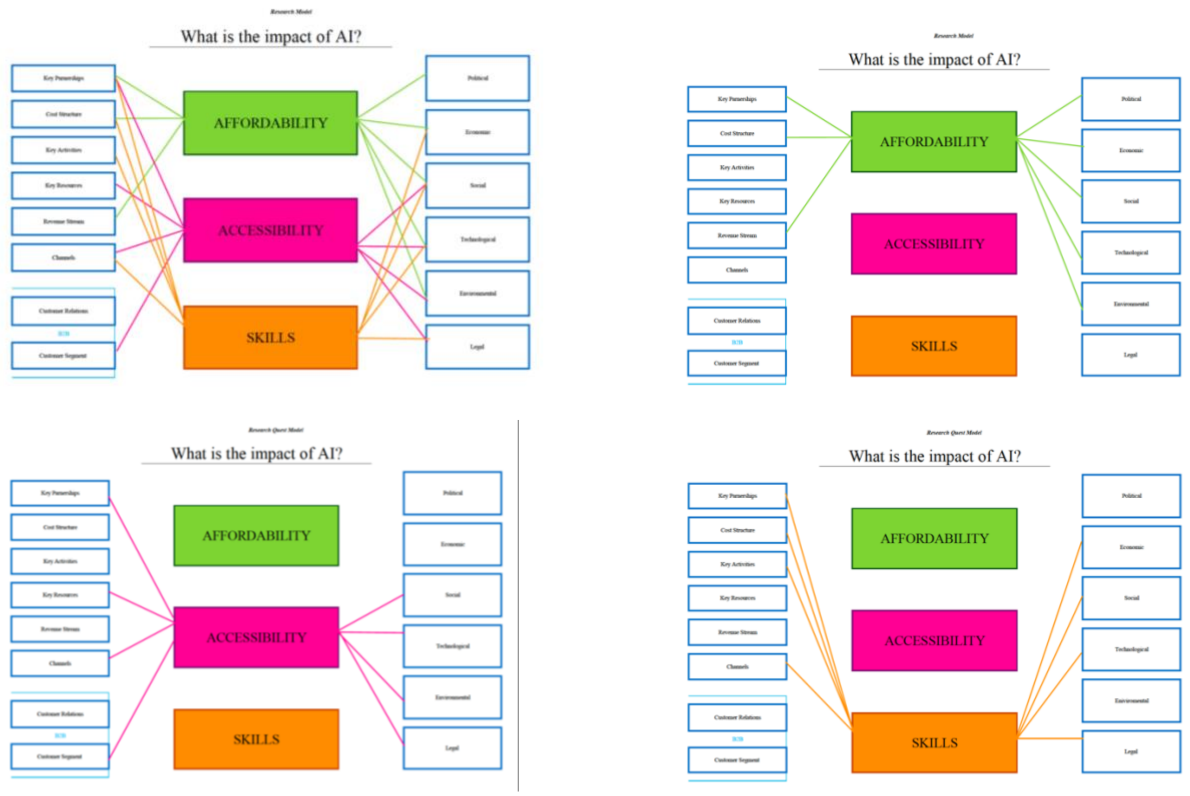
Politics	• The South African government is actively promoting AI through initiatives like the Artificial Intelligence Institute of South Africa (AIISA), which aims to support local businesses in AI adoption (DSI, 2023). • Only 12% of SMEs benefit from government AI training programs (Department of Labour, 2023). • 30% of telecom SMEs report a lack of clear AI training guidelines (ICASA, 2023). • Regulatory uncertainty remains a challenge, with AI governance and ethical concerns being debated at policy levels (Mhlanga, 2023). • Lack of AI-specific policies for telecom SMEs, creating uncertainty about required qualifications. • $77 million allocated by the government for AI research and innovation (South African Budget Review, 2023). • AI adoption in South Africa is expected to contribute up to 7.9% of GDP by 2030 (PwC, 2022). • R7.5 billion investment pledged for South Africa's digital infrastructure by 2025 (Department of Communications, 2023). • Only 20% of telecom SMEs receive government AI incentives (SME South Africa, 2023). • AI investment in telecoms projected to grow 20% annually in South Africa (ICASA, 2023).
Economics	• High initial costs of AI tools remain a barrier for small businesses, with cloud-based AI solutions offering affordability but requiring internet stability. • Economic downturns and inflation increase the cost of AI-powered equipment and services. • AI-driven automation could displace jobs but also create new digital economy roles. • Economic instability and power outages (load shedding) limit AI adoption, increasing operational risks. • 65% of South African SMEs cite financial constraints as the main barrier to AI adoption (SME South Africa, 2023). • AI-driven automation is expected to increase productivity by 20-30% in small businesses by 2025 (McKinsey, 2023). • South Africa ranks 59th in AI readiness globally (Oxford Insights, 2023). • 75% of SMEs in telecom report cost as the biggest AI adoption barrier (SME South Africa, 2023). • 67% of SMEs report difficulty hiring AI professionals due to high salary demands (Stats SA, 2023).

	• The average AI certification course costs R35,000 per employee (Coursera, 2023).
Social	• AI adoption faces trust issues, with concerns over bias and job losses. • 42% of South Africans express concern about AI replacing human jobs (World Economic Forum, 2023). • 58% of SME workers worry about AI replacing jobs (Deloitte, 2023). • AI chatbots and virtual assistants are enhancing customer service, improving response times. • Over 70% of consumers prefer AI-assisted services in e-commerce (Deloitte, 2023). • AI-driven network management improves customer satisfaction by 35% (Accenture, 2023). • Digital literacy is still low in rural areas, limiting AI accessibility. • Only 31% of rural SMEs have integrated AI tools into operations (Stats SA, 2023). • Limited AI skills among SME employees increases training costs. • Only 25% of telecom SMEs have AI-trained staff (Stats SA, 2023). • Lack of AI expertise among SME employees reduces accessibility, requiring costly external consultants. • AI-related job demand expected to grow by 42% in South Africa by 2027 (World Economic Forum, 2023). • Lack of localized AI training resources, with most material from international providers. • 85% of AI courses are provided by international platforms (ICT Africa, 2023). • Only 27% of South African telecom employees have AI-related skills (Stats SA, 2023). • 60% of rural SMEs lack the infrastructure needed for AI-based remote training (CSIR, 2023).
Technological	• AI innovation is accelerating, with South African startups leveraging machine learning for finance, retail, and healthcare. • The South African AI startup ecosystem has grown by 32% in the past 3 years (Startup Genome, 2023). • Cloud-based AI services are making AI more accessible to SMEs. • Cybersecurity risks are rising, requiring stricter AI data protection. • AI-powered fraud detection has reduced cybercrime losses by 25% in local businesses (CSIR, 2023). • Integration challenges with legacy fibre network systems. • Potential for improved efficiency through AI-driven diagnostics and automated troubleshooting. • Limited access to high-speed internet in rural areas affects cloud-based AI adoption. • 70% of AI solutions used by South African SMEs are from international providers (ICT Africa, 2023). • Only 30% of South African universities offer AI-focused courses (University of Pretoria, 2023). • 85% of SMEs struggle to find AI-skilled talent locally, leading to outsourcing (ICT Africa, 2023). • 60% of AI job postings in South Africa require at least five years of experience (LinkedIn Jobs Report, 2023).
Environmental	• AI is being used for smart energy management, helping SMEs reduce carbon footprints. • AI skills in green technology can help SMEs implement sustainable fibre network solutions. • AI-powered predictive maintenance is extending the lifespan of business assets. • Ethical concerns arise over AI's energy consumption, particularly with machine learning models. • AI-powered energy management systems reduce electricity usage by up to 18% (GreenCape, 2023). • South Africa's carbon emissions from AI computing are projected to grow by 12% annually (Department of Environmental Affairs, 2023). • AI-powered energy-efficient fibre network management can lower electricity consumption. • AI-driven network optimization cuts energy use by 22% (GreenCape, 2023). • AI helps optimize material use in fibre installations, reducing waste. • Load shedding causes 5-10% additional operational costs for AI-powered fibre infrastructure (Eskom, 2023).
Legal	• AI regulation is still evolving, with concerns about AI ethics, transparency, and liability. • Only 40% of AI-driven businesses in South Africa are fully compliant with data protection laws (Michalsons, 2023). • 65% of businesses report confusion over AI-related legal requirements (KPMG, 2023). • Compliance with AI-related telecom regulations adds to operational costs. • The Protection of Personal Information Act (POPIA) mandates strict compliance for AI-driven data collection and processing (Michalsons, 2023). • The POPIA Act regulates data privacy, impacting AI-driven marketing and analytics. • R20 million in fines issued for data privacy violations under POPIA in 2023 (South African Information Regulator, 2023). • Employment laws may need revision to address AI-related job changes. • South Africa ranked 67th globally in AI regulatory readiness (Oxford Insights, 2023). • ICASA regulations require telecom companies to maintain AI transparency and accountability. • South Africa has fewer than 500 certified AI ethics and compliance professionals (SA Business School, 2023).

Table 6 provides a concise analysis of all the external factors that may affect an AI project. It develops the base analysis to further dissect the data and evaluate which factors are affected by affordability, accessibility, and skills. The macroeconomic data presented paints a clear depiction of the business landscape within the telecommunications industry. It shows that AI accessibility remains a challenge for the Fibre network SMEs due to cost, lack of local solutions, and regulatory hurdles. Further emphasising the need for government incentives to be more SME-friendly, ensuring smaller businesses can afford AI tools, and improving the infrastructure in rural areas to provide affordable and reliable Fibre internet.

In Case Study 2, affordability was a moderate constraint, but a significant adoption inhibitor was the lack of accessible and affordable skills training. This figure illustrates those relationships visually, drawing from interview, survey, and document analysis data.

Figure 9: Case Study 2 impact of affordability, accessibility, and skills



This visual maps internal and external factors affecting AI adoption in a B2B SME operating in South Africa’s fibre network industry. Skills emerge as the most critical constraint, heavily influencing internal components like key partnerships and external dynamics such as regulatory compliance and technical training availability. Dashed arrows represent weaker influences, while solid arrows show dominant relationships derived from PESTEL and BMC coding. Figure 9 shows the relational impact between the internal factors and external factors that would affect an AI project within the telecommunications industry in South Africa.

Within this B2B operation, it can be identified that Customer Relationships are the least impacted, both internally and externally. This is attributed to the business's niche offering that is primarily contract-based within a monopolised Fibre infrastructure industry in South Africa. Research gathered through the survey, observation, and interviews has suggested that an AI project would best assist with managing resources and post-build Fibre-line servicing and maintenance. Skills required for a project have proven to be very impactful. This is due to the lack of formal AI skills available in the local economy, costly training, and few AI learning facilities. From an internal perspective, Key Partnerships has prevailed to be a common impactful factor regarding affordability, accessibility, and skills.

Partnerships in Case Study 2 were especially sensitive to external pressures, including political incentives and tech infrastructure gaps. This figure offers a visual summary of those drivers and their intensity.

Figure 10: Key Partnerships of Case Study 2

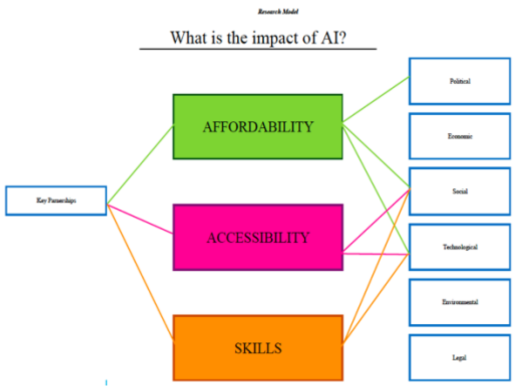


Figure 10 shows how key partnerships would be affected by various external factors within each scope. This figure illustrates how key partnerships are impacted by affordability, accessibility, and skills. For instance, external political support is linked to accessible funding schemes, while technological environments influence the availability of platforms for collaboration. These interdependencies show that successful AI implementation relies on a network of actors beyond the SME's internal control. If the business in the Fibre industry in South Africa were to begin an AI project internally, key partnerships would be impacted by affordability and from the external environment, it would be impacted by the political, social, and technological environments. Accessibility would impact the project due to external factors such as the social and technological environments. Lastly, key partnerships would impact the skills required to implement an AI project, which will also be impacted by the social and technological environment. Securing key partnerships would be vital for the successful implementation of an AI project in an SME that builds Fibre infrastructure in the telecommunications industry in South Africa.

Using the information that populated tables 5 and 6, and figures 9 and 10, RQ1 part two was presented and solved with the following proposed factors:

1. How will affordability impact an AI project in an SME in the telecommunications industry in South Africa?
    - Internally, affordability will impact the key partnerships, cost structure, and revenue stream of the AI project.
    - Externally, affordability will be impacted by the political, economic, social, technological, and environmental environment in South Africa
2. How will accessibility impact an AI project in an SME in the telecommunications industry in South Africa?
    - Internally, accessibility will impact the key partnerships, key resources, channels, and customer segments.
    - Externally, accessibility will be impacted by the social, technological, environmental, and legal environment in South Africa.
3. How will the skills required for an AI project impact the project in an SME in the telecommunications industry in South Africa?
    - Internally, the skills required impact the key partnerships, key activities, cost structure, and channels of an AI project.
    - Externally, the skills required will be impacted by the economic, social, technological, and legal environment in South Africa.

This solved for RQ1 part two, presenting the opportunities, risks, strengths and weaknesses that can be optimised and mitigated for the successful implementation of an AI Project. While the telecommunications industry shows significant growth in South Africa and plays a vital role in their Fourth Industrial Revolution and digitisation, the surge in 5G network technology and optical Fibre internet services remain integral to the technological, economic, and social advancement in the country. 54% of the population lives where at least one Fibre operator provides a service (ITWeb, 2024); these include urban areas and metropolitan townships. The remaining 46% who do not have access reside in areas that are city outliers and predominantly rural. By using AI, the business can use tools and systems that can optimise resource management and maintenance in existing areas that have Fibre infrastructure, as well as use AI systems that can plan optimal rollouts and infrastructure layouts in areas that are still in need of Fibre connectivity.

4.2.3. Case Study 3: AI implementation in the Fitness industry in South Africa

Introduction

The integration of AI in the fitness industry is transforming personal training services worldwide, offering data-driven insights, virtual coaching, and personalised workout programs. In developing countries like South Africa, where access to advanced fitness technology is growing, AI presents opportunities and challenges for SMEs. South Africa's fitness industry is valued at approximately ZAR 30 billion (USD 1.6 billion), with a projected annual growth rate of 5%–7% (Statista, 2023). The industry comprises over 1,000 commercial gyms and 30,000+ registered personal trainers, with an increasing demand for digital fitness solutions (Fitness Industry Report, 2023). AI is revolutionizing the fitness industry by enhancing personalization, efficiency, and client retention. AI-powered tools provide real-time movement analysis, injury prevention recommendations, and customized workout plans based on user data. In South Africa, AI adoption is still emerging, but personal trainers using AI tools see higher client retention and improved service differentiation (McKinsey, 2022). However, affordability and accessibility of AI tools remain challenges for SMEs in the fitness sector. This case study explores the impact of AI on a personal trainer operating at a gym in Johannesburg, South Africa, assessing how AI-driven technologies influence business operations, client engagement, and service offerings. The study applies the RQ1 Research Model to evaluate the affordability, accessibility, and skills required for AI integration.

Company Overview

The business under study is a business that offers personal training and operates within a mid-sized gym in Johannesburg, South Africa. As a Business-to-Consumer model, the business engages directly with gym members, it offers one-on-one fitness coaching, group classes, and customised training programs, targeting individuals seeking weight loss, strength training, and general wellness. The gym provides essential facilities, while the trainer operates as an independent contractor, generating revenue through session-based fees, membership referrals, and digital fitness consultations.

Business Profile:

Name	N/A	Country	South Africa

Representative Role	Founder	Number of employees	1-10
Industry	Wellness	Type of Business	B2C
Departments	Operations	Marketing	

To evaluate the impact that an AI project would have on this business, we analysed primary and secondary research sources and created the following models:

Table 7: Case Study 3 BMC

Key Partnerships	• Technology Providers: Partnerships with AI software developers to access fitness tracking, personalized training apps, and virtual coaching platforms. • Health and Nutrition Experts: Collaborations with nutritionists and health professionals to create comprehensive wellness programs that leverage AI insights. • Fitness Equipment Suppliers: Alliances with suppliers of smart fitness equipment that can track performance and provide data for AI analysis. • Medical Insurance Companies: Partnerships with health insurance providers to offer discounts or incentives for clients who engage in regular fitness training.
Key Activities	• Personalized Training Programs: Utilizing AI to analyze client data and create tailored fitness plans that adapt to individual goals and progress. • Performance Tracking and Analytics: Implementing AI-driven tools that monitor clients' performance in real-time, providing feedback and adjustments to training regimens. • Content Creation: Developing engaging content for online platforms, including workout videos, articles, and blogs that educate clients on fitness and wellness using AI-generated insights. • Client Engagement: Using AI chatbots and virtual assistants to enhance communication with clients, answer queries, and provide motivational support.
Key Resources	• AI Technology: Access to AI-driven software and applications that analyze data and offer personalized recommendations for fitness training. • Skilled Trainers: A team of certified personal trainers equipped with knowledge of AI tools to enhance client training experiences. • Client Database: A robust database of client information, preferences, and progress, which AI systems can analyze for better personalization. • Marketing Platforms: Digital marketing tools and social media channels for promoting services and engaging with clients.
Value Proposition	• Personalization: AI enables highly personalized training programs that cater to individual needs, enhancing client satisfaction and outcomes. • Data-Driven Insights: Clients receive real-time feedback and insights into their performance, helping them achieve their fitness goals more effectively. • Convenience: AI applications can offer clients flexible training options, including virtual sessions, which are particularly appealing in today's fast-paced environment. • Enhanced Engagement: Automated communication through AI helps maintain client motivation and engagement, leading to better retention rates.
Cost Structure	• Technology Costs: Expenses related to acquiring and maintaining AI software and applications. • Trainer Salaries: Compensation for additional personal trainers who provide tailored coaching and support. • Marketing Expenses: Costs associated with digital marketing campaigns to attract and retain clients.

Revenue Stream	• Personal Training Fees: Income generated from personalized training sessions, both in-person and virtual. • Subscription Services: Offering subscription-based access to training programs, nutrition plans, and AI analytics. • Merchandise Sales: Selling fitness-related products, such as workout gear, supplements, or equipment. • Corporate Wellness Programs: Providing tailored fitness programs for businesses aiming to improve employee health and productivity.
Channels	• Website and Mobile App: A user-friendly platform that provides access to training programs, performance tracking, and community features. • Social Media: Utilizing platforms like Instagram, Facebook, and TikTok to engage potential clients through fitness content and success stories. • Email Marketing: Sending personalized newsletters and updates to clients based on their training preferences and progress.
Customers Relationships	• Personal Coaching: Maintaining a strong personal connection with clients through regular check-ins, progress updates, and customized feedback. • Community Building: Creating a supportive online community where clients can share their experiences and progress, facilitated by AI-driven social features. • Loyalty Programs: Implementing AI-based loyalty programs that reward clients for achieving milestones and participating in training sessions.
Customer Segments	• Fitness Enthusiasts: Individuals looking for personalized training programs to enhance their fitness levels and achieve specific goals. • Beginner Fitness Seekers: Clients new to fitness who require guidance and support in starting their fitness journey. • Busy Professionals: Individuals with limited time who benefit from flexible training options and virtual coaching. • Health-Conscious Consumers: Clients interested in overall wellness, nutrition, and lifestyle improvements through fitness.

Table 7 highlights the main factors to consider from an internal perspective; these factors emphasize a consumer-centric approach as a driving growth factor. As a B2C (Business to Consumer) operations, client engagement and client experience are at the forefront of operations. The key partners provide access to the relevant customer segments – people who have an established interest in health, wellness, and fitness, by engaging with these key partners the business would be able to expand its customer reach without necessarily having to first persuade potential customers to take a vested interest in their health and fitness. With the existing key partner, the gym, and the proposed new key partners, customers are already filtered so that trainers can have direct access to people who have shared interests in their overall health and fitness. The Key activities, Key Resources, and Channels presents a new component to the current operations – content creation, marketing platforms, and digital client engagement, as currently all marketing and client engagements are done face-to-face and via word-of-mouth. By leveraging AI technologies, personal trainers can offer personalized and data-driven fitness solutions that cater to the diverse needs of their clients, ultimately fostering a more effective and enjoyable fitness experience. The BMC analysis highlights the key components necessary for success in this evolving market, emphasizing the importance of technology, skilled personnel, and strong customer relationships.

Table 8, as shown below, provides a PESTEL analysis that includes an affordability, accessibility, and skills analysis to evaluate the external impact that the macro-environment can have on an AI project.

Table 8: Case Study 3 PESTEL analysis

Politics	• Government Support: The South African government actively promotes health and fitness initiatives, which can enhance the demand for personal training services. Programs that support digital innovation in health and fitness, such as funding for tech startups, may also provide opportunities for AI integration in personal training (Department of Health, 2021). • Regulatory Environment: Regulations around fitness certifications and data privacy can influence how personal trainers utilize AI technologies. Compliance with the Protection of Personal Information Act (POPIA) is crucial for managing client data effectively (South African Government, 2013), and can incur additional expenses for small businesses (South African Government, 2013). • Government Support for Education and Training: The South African government promotes initiatives to enhance digital skills and literacy among the workforce. This includes funding and programs aimed at improving access to training in technology and AI, which can help personal trainers develop the necessary skills to use AI effectively (Department of Higher Education and Training, 2021). • Regulatory Standards for Professional Development: Regulations governing professional qualifications in the fitness industry may require trainers to undergo continuous education, including training in new technologies such as AI. This regulatory environment can impact the skill development landscape for personal trainers (Fitness Industry Association of South Africa, 2021).
Economics	• Market Growth: The fitness industry in South Africa is experiencing growth, driven by an increasing awareness of health and wellness. As disposable incomes rise, more consumers are willing to invest in personal training services (Statista, 2022). • Cost of AI Integration: While AI technology can enhance service offerings, the initial investment and ongoing costs of software and training for trainers may be prohibitive for small businesses. The economic environment can affect the ability of businesses to invest in such technologies, For small businesses, budget constraints may limit their ability to invest in advanced AI technologies (McKinsey & Company, 2021). • Market Size and Growth Rate: The South African fitness industry was valued at approximately ZAR 30 billion in 2021, with an expected annual growth rate of 4.4% through 2026 (Statista, 2022). This growth presents opportunities for AI-driven personal training services. • Consumer Spending on Fitness: In 2020, South African households spent an average of ZAR 4,500 per year on fitness-related services, which is projected to increase as the focus on health and wellness grows (Nielsen, 2020). • Market Demand for Skilled Trainers: As the demand for tech-savvy personal trainers increases, businesses that invest in skill development may gain a competitive advantage.

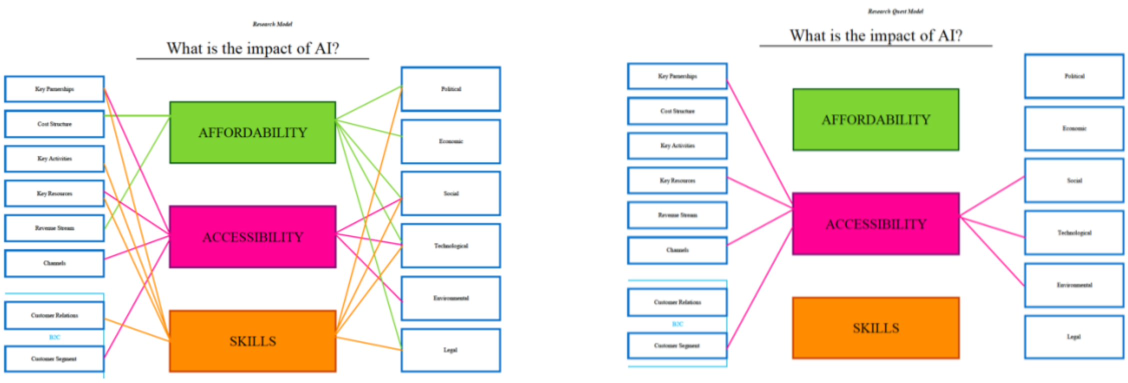
	This demand can drive economic opportunities for trainers who acquire AI-related skills (Statista, 2022).
Social	• Changing Attitudes Towards Fitness: There is a growing trend among South Africans to prioritize fitness and wellness, especially post-pandemic. This shift creates a greater demand for personalized fitness solutions that leverage AI (Fitness Industry Association of South Africa, 2021). • Consumer Willingness to Pay: The affordability of AI solutions may affect pricing strategies for personal training services. Clients are likely to demand personalized, technology-driven experiences, which may justify higher prices if they perceive value in AI-enhanced services (Fitness Industry Association of South Africa, 2021). • Demographic Trends: With a younger population increasingly tech-savvy, there is a higher acceptance of AI-driven fitness solutions. Tailoring services to meet the preferences of this demographic can enhance engagement (Pew Research Center, 2021). • Customer Demographics: According to recent data, approximately 40% of gym-goers in South Africa are aged between 18 and 34, a demographic that is more likely to engage with technology and AI-driven solutions (Pew Research Center, 2021). • Workforce Demographics: The younger, tech-savvy workforce is more likely to embrace AI technologies. This demographic shift can facilitate a quicker uptake of AI skills among personal trainers, making it easier for businesses to integrate AI into their offerings (Fitness Industry Association of South Africa, 2021).
Technological	• Advancements in AI: Rapid advancements in AI technology are enabling more sophisticated fitness tracking and personalization capabilities. Businesses must stay updated with these technologies to remain competitive (González et al., 2019). • Accessibility of Technology: The increasing availability of affordable AI solutions allows small fitness businesses to adopt these tools without significant financial burdens, enhancing service delivery (McKinsey & Company, 2021). • Advancements in AI and Mobile Technology: The rapid development of AI and mobile technology has significantly improved accessibility. Fitness apps that utilize AI for personalized training and progress tracking are readily available on smartphones, making it easier for clients to engage with personal training services (González et al., 2019). • Internet Connectivity: The availability and reliability of internet services across South Africa can impact accessibility. Improved internet infrastructure enables more clients to access AI-powered fitness solutions, particularly in urban areas (World Bank, 2021). • Technology Adoption Rates: A survey conducted in 2021 indicated that 60% of fitness enthusiasts in South Africa were interested in using AI-driven fitness applications (Fitness Industry Association of South Africa, 2021). This indicates a significant market for AI-integrated personal training services. • Integration Costs: While some AI tools may be affordable, integrating these technologies with existing systems can incur additional costs. Training staff to use new AI applications also contributes to overall affordability challenges (McKinsey & Company, 2021). • Training Costs: The average cost of AI training software for small businesses ranges from ZAR 2,000 to ZAR 10,000 annually, depending on the features and level of support (González et al., 2019). This investment must be considered when planning for AI integration. • Availability of Online Learning Resources: The proliferation of online courses and resources has made it easier for personal trainers to acquire AI-related skills. However, trainers must be motivated to engage with these resources, and access may still be limited for some individuals (McKinsey & Company, 2021).

Environmental	• Sustainability Trends: Consumers are becoming more environmentally conscious, which may influence their choice of fitness services. Personal training businesses that integrate sustainable practices into their operations, possibly through AI analytics for resource management, can attract eco-conscious clients (RICS, 2021). • Health Impacts of Environmental Factors: The effects of climate change on health and wellness can lead to an increased focus on fitness and outdoor activities, potentially boosting demand for personal training services (World Health Organization, 2021). • Sustainable Practices: Clients may prefer businesses that use technology to minimize environmental impacts. AI can optimize resource use and promote sustainable practices, enhancing the appeal of personal training services (RICS, 2021). • Health and Wellness Trends: Growing concerns about health and wellness in relation to environmental factors can increase the demand for accessible fitness solutions. AI-driven programs that promote physical activity can help address these concerns, making fitness more accessible to the population (World Health Organization, 2021).
Legal	• Data Privacy Regulations: Compliance with data protection laws, such as POPIA, is critical when collecting and processing client data through AI systems. Understanding these legal requirements is essential for risk management (South African Government, 2013). • Intellectual Property Rights: Businesses must be aware of the legal implications of using AI technologies, including software licensing and intellectual property rights, to avoid legal issues (WIPO, 2021).

Table 8 presents the external impacts that could affect an AI project in the fitness industry in South Africa. The political environment presents government support towards digitalization and health and fitness improvement as potential opportunities through grants, incentives, and programs. It highlights the economic, social, technological, environmental, and legal factors that would be impactful for the business.

Figure 11 demonstrates how affordability, accessibility, and skills affect both internal and external factors in a personal fitness SME in South Africa. The model identifies strong dependency on digital infrastructure and workforce development to enable successful AI adoption in a service-heavy context.

Figure 11: Case study 3 impact of affordability, accessibility, and skills



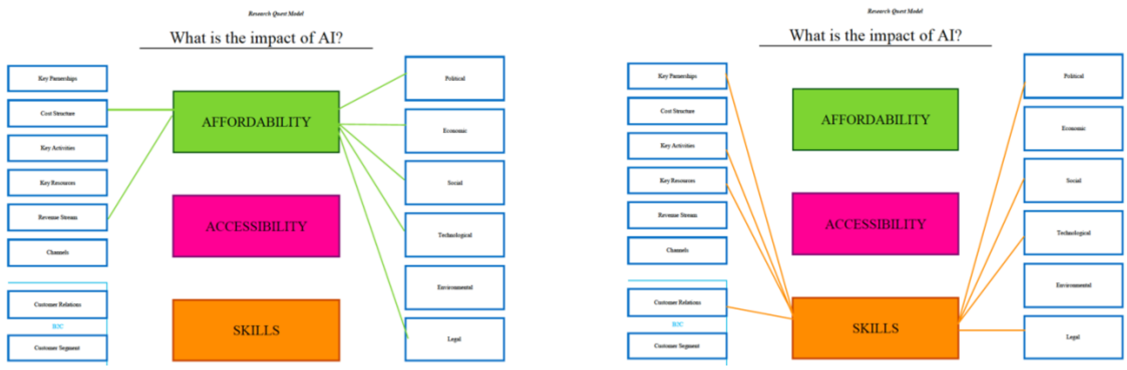
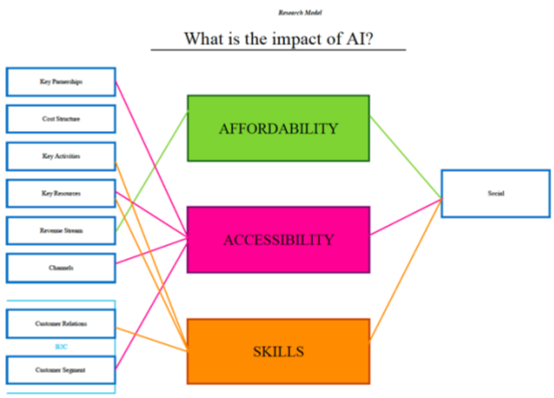


Figure 11 shows the relational impact between the internal factors presented on the left of each graph and the external factors that are presented on the right of each graph. The analysis demonstrates that the accessibility of AI has a profound impact on small B2C personal fitness training businesses in South Africa. Affordability of AI solutions has a multifaceted impact, including political support, economic growth, and technological advancements present opportunities for affordable AI integration and improved accessibility for both businesses and consumers. However, challenges such as regulatory compliance, related to training costs, ongoing skill development, and the need for reliable internet connectivity must be addressed to fully leverage the potential of AI in enhancing personal training services.

This figure explores the social factors influencing affordability, accessibility, and required skills in Case Study 3. It visualises how demographic shifts, fitness culture, and consumer expectations shape the SME's ability to integrate AI tools in a socially responsive way.

Figure 12: Case 3 Social Environment



A common environment that impacts affordability, accessibility, and skills is the Social Environment. Figure 12 illustrates the internal factors of each scope that are impacted by the external social environment. From Table 8 – Social, five factors are presented to consider during the planning and developing phase of an AI project in the fitness industry, these factors - Changing Attitudes to fitness, Consumer Willingness to Pay, Demographic Trends, Customer Demographics, and Workforce Demographics impact the affordability of the internal revenue stream component in table 7. Within the scope of accessibility, key partners – health and nutrition experts, fitness equipment suppliers, and insurance companies; key resources – marketing platforms and client databases; channels –website and mobile app, social media and email marketing, and customer segments – fitness enthusiasts, beginner fitness seekers, busy professionals, and health-conscious consumers are impacted by the social environment. In terms of skills required that are impacted by the social environment, the key activities – personalised training programs, content creation, and client engagement; key resources – skilled trainers; and customer relationships – personal coaching, community building, and loyalty programs show the need to have AI-related skills to enhance the consumer-centric approach.

Figure 13 focuses on technological conditions influencing the case study, such as access to platforms, data systems, and digital fitness applications. It reflects how internal BMC factors rely on external tech ecosystem maturity to drive AI readiness.

Figure 13: Case study 3 Technological Environment

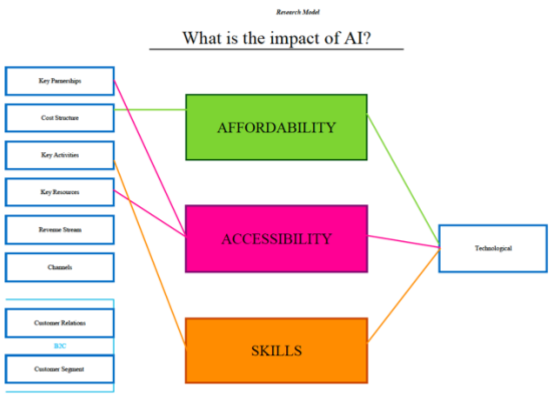


Figure 13 illustrates the connection between the internal factors that are impacted by the external technological environment. The cost structure of an AI project in the fitness industry in South Africa is impacted by the affordability of the technological requirements and external technological offerings available in the country, the technological environment impacts the technology costs related to acquiring and maintaining AI software and applications. Access to key partnerships – technology providers, and key resources – AI technology is impacted by the advancements in AI and accessibility technology in the technological environment. Key activities – performance tracking and analytics impact the skills required for the AI project, which is further impacted by the skill set within the technological environment.

Using the information that populated tables 8 and 8, and figures 11, 12, and 11, RQ1 part two was presented and solved with the following proposed factors:

1. How will affordability impact an AI project in an SME in the fitness industry in South Africa?
   - Internally, affordability will impact the cost structure and revenue stream of the AI project.
   - Externally, affordability will be impacted by the political, economic, social, technological, and legal environment in South Africa
2. How will accessibility impact an AI project in an SME in the fitness industry in South Africa?
   - Internally, accessibility will impact the key partnerships, key resources, channels, and customer segments.
   - Externally, accessibility will be impacted by the social, technological, and environmental environment in South Africa.
3. How will the skills required for an AI project impact the project in an SME in the fitness industry in South Africa?
   - Internally, the skills required impact the key partnerships, key activities, key resources, and customer relations of an AI project.
   - Externally, the skills required will be impacted by the political, social, technological, and legal environment in South Africa.

This solved RQ 1 part 2, showing that the integration of AI into a small B2C personal fitness training business in South Africa presents numerous opportunities to enhance service delivery, improve client engagement, and drive business growth. By leveraging AI technologies, personal trainers can offer personalised and data-driven fitness solutions that cater to the diverse needs of their clients, ultimately fostering a more effective and enjoyable fitness experience. The internal analysis highlights the key components necessary for success in this evolving market, emphasising the importance of technology, skilled personnel, and strong customer relationships. The external analysis shows that political support and regulatory frameworks, coupled with economic growth and changing consumer attitudes, create a favourable environment for AI adoption, and challenges related to costs, legal compliance, and the need for ongoing technological advancements must be addressed to fully leverage the potential of AI in the fitness industry. Overall, the affordability of AI technologies plays a crucial role in the business's ability to adopt these innovations. Although the initial investment in AI tools can be significant, the business has observed a growing market demand for tech-savvy personal trainers. By investing in AI skills development, the business would gain a competitive edge in the evolving fitness landscape.

4.2.4. Case Study 4: AI implementation in the Energy industry in Ghana

Introduction

The integration of AI in the renewable energy and electric vehicle (EV) industries has the potential to enhance efficiency, optimise resource allocation, and drive business innovation. As AI technologies become increasingly accessible, SME's in developing economies stand to benefit significantly (World Economic Forum, 2023). In Ghana, the renewable energy sector has gained momentum, driven by government initiatives to increase the share of renewable energy in the national energy mix to 10% by 2030 (Energy Commission, 2023). This growth presents significant opportunities for SME's in the renewable energy space as they play a crucial role in delivering sustainable energy solutions to local communities. Moreover, the landscape for AI adoption in Ghana is evolving, with increased investments in digital infrastructure and a growing emphasis on digital skills development. However, challenges such as limited access to funding, lack of awareness, and inadequate technical expertise continue to hinder the widespread adoption of AI among SMEs (World Bank, 2023). This business case study examines the accessibility, affordability, and skills required for AI implementation in a Ghana-based SME that specialises in solar energy solutions and EV technologies. This case study analyses the business's potential to adopt AI-driven innovations to enhance operational efficiency, improve customer engagement, and optimise energy management systems.

Company Overview

The business for Case Study 4 is a solar energy and electric vehicle company based in Ghana that operates on a Business-to-Consumer model. The company focuses on the supply, sale, commissioning, and installation of solar panels and electric vehicle solutions. With a workforce of 1-10 employees, the company leverages innovative renewable energy solutions to address Ghana's growing demand for sustainable energy and mobility.

Business Profile:

Name	N/A	Country	Ghana

Representative Role	Founder	Number of employees	1-10
Industry	Solar Energy and Electric Vehicle	Type of Business	B2C
Departments	Operations	Marketing	Sales
	Research & Development	Customer Service	

To evaluate the impact that an AI project would have on this business, we analysed primary and secondary research sources and created the following models:

Table 9: Case Study 4 BMC

Key Partnerships	• AI-based collaborations with software providers for predictive analytics in solar efficiency. • Partnerships with AI-driven EV charging network developers. • Integration with IoT and smart grid companies for real-time energy optimization.
Key Activities	• AI-driven demand forecasting for solar panel and EV sales. • Predictive maintenance for solar panels, inverters, and EVs. • AI-enhanced route optimization for EV rentals. • Automated customer service using AI chatbots.
Key Resources	• AI-driven data analytics for performance tracking. • Machine learning models for energy forecasting. • Skilled workforce trained in AI applications for solar and EVs.
Value Proposition	• Optimized energy efficiency and cost savings through AI-driven energy management. • Increased equipment lifespan due to AI-driven predictive maintenance. • Improved customer experience with AI chatbots and self-service options. • Smarter EV charging solutions reducing downtime and increasing convenience.
Cost Structure	• Investment in AI software, data analytics, and training. • Cost savings through AI-driven operational efficiencies. • Reduced maintenance and downtime costs.
Revenue Stream	• AI-based predictive maintenance service subscriptions. • Smart energy management solutions for customers. • AI-driven fleet optimization services for EV rentals.
Channels	• AI-optimized e-commerce platform for solar and EV products. • Smart mobile apps for energy monitoring and EV management. • Digital marketing using AI-driven customer insights.
Customers Relationships	• AI-powered CRM for personalized offers and proactive customer engagement. • Automated chatbots and virtual assistants for 24/7 support.
Customer Segments	• Households and businesses using solar energy. • EV owners and fleet operators. • Government and corporate clients seeking AI-optimized renewable energy solutions.

Table 9 shows the internal factors that are presented by the BMC analysis and highlights key points to consider for the adoption of an AI system. While the Key Partnerships mentions three varied types of partners, it also indicates further challenges that may arise regarding accessibility and affordability. For instance, AI-based collaborations with software providers pose the challenge of accessing suitable software providers. However, outsourcing is always an option, provided it is affordable. The other two partnership options that are mentioned are EV charging network providers and IoT – Smart grid companies; these two options would be solid and viable partners to have, if there is suitable infrastructure in the target market areas. The Key resources that are provided are highly dependent on the availability of adequate skills that meet AI analytics and machine learning functions, whether this can be navigated in-house is another factor to consider. Due to the nature of the business and its offerings, the customer segments are broad because it provides a market opportunity in both the public and private sectors and focuses on businesses and households that have building and vehicle assets that are part of their day-to-day lives and therefore are more willing to further invest in it for various reasons.

Table 10: Case Study 4 PESTEL analysis

Politics	• Government Support: The Ghanaian government has shown commitment to renewable energy initiatives, offering incentives for solar energy adoption and electric vehicle (EV) infrastructure (Ministry of Energy, 2021). Skills in navigating policy landscapes and engaging with government entities will be essential for project success. • Renewable Energy Targets: Ghana aims to achieve 10% of its energy from renewable sources by 2030, potentially offering incentives for AI-driven efficiency projects. • AI and Data Regulations: The absence of comprehensive AI regulations in Ghana provides a flexible environment for innovation but may lead to future compliance costs as policies evolve. • AI and Renewable Energy Support: Government support for AI in renewable energy varies across Africa, with some nations actively promoting AI-driven innovations. Policy inconsistencies may create barriers to accessibility (UNESCO, 2023). • Regulatory Frameworks: Limited AI-specific regulations can create challenges in data governance and accessibility, affecting AI deployment in renewable energy and EV industries (ITU, 2023). - Understanding regulatory requirements for AI implementation in energy systems is crucial. Skilled professionals will need to ensure compliance with local and international regulations (World Bank, 2020).
Economics	• High Initial Investment: AI projects require significant upfront capital for technology acquisition, data infrastructure, and skilled personnel. • Financing Challenges: Despite Africa's low loan default rate of 1.9%, financing costs remain high due to perceived risks, increasing the overall expense of AI projects. (LSE Africa at LSE, 2024) • Predictive Maintenance: AI can reduce maintenance costs by up to 20% through predictive analytics, enhancing equipment longevity.

	• Market Growth: The renewable energy market in Africa is expanding rapidly, driven by increasing demand for sustainable energy solutions (IRENA, 2022). Skills in data analysis and market forecasting will help prioritize AI projects that align with market trends. • Investment in Skills Development: The economic environment necessitates investment in workforce skills to integrate AI into renewable energy solutions. Organizations need to develop training programs to upskill employees (African Development Bank, 2021). • Energy Optimization: AI-driven energy management can lower operational expenses by optimizing energy consumption patterns. - Operational Efficiency Gains: AI can optimize energy consumption, reducing costs by up to 30% (IEA, 2023), making its long-term accessibility more feasible despite initial barriers.
Social	• Skill Development: Implementing AI necessitates investment in training programs to enhance digital literacy among employees, ensuring effective utilization of new technologies. • Employment Dynamics: While AI can automate routine tasks, it may lead to workforce displacement if not managed with reskilling initiatives. • Skill Gaps: Accessibility to AI depends on digital literacy levels; only 28% of Africa's population has necessary AI-related skills, limiting effective implementation (World Economic Forum, 2023). • Trust in AI: Building customer trust in AI-driven services is crucial, as acceptance varies and can impact market adoption rates. • Public Acceptance and Trust: Social trust in AI solutions varies, with rural communities facing higher resistance due to a lack of awareness and engagement (UNDP, 2023). • Public Awareness: Growing public interest in sustainability and clean energy creates a demand for innovative solutions (Baker & Markham, 2020). Professionals with communication skills will be vital in promoting AI-driven products and services. • Workforce Competence: The existing skill gap in AI and renewable energy sectors highlights the need for continuous education and training (Nduku, 2021). This necessitates the recruitment of personnel with advanced technical skills and experience in AI.
Technological	• Internet and Power Stability: AI systems demand reliable internet and electricity, yet approximately 900 million people in Africa lack internet access, and a similar number lack electricity, posing challenges for widespread AI adoption. (Africa News, 2024) • Compatibility Issues: Integrating AI with current operational systems may require additional investment to ensure seamless functionality. • AI Integration: Successful integration of AI in solar energy systems requires expertise in machine learning, data analytics, and software development (Sarker et al., 2021). Hiring or training skilled workers in these areas will be crucial for project implementation. • Innovation in EV Technology: As electric vehicle technology evolves, the need for expertise in AI for vehicle performance optimization and charging solutions will increase (Cebrián et al., 2020). Skilled technicians will be required to maintain and improve these systems.
Environmental	• Resource Efficiency: AI can enhance the efficiency of renewable energy systems, contributing to environmental sustainability and potentially attracting eco-conscious consumers. • Smart Grid Development: AI enhances accessibility by improving grid efficiency and energy distribution, crucial for remote areas (IEA, 2023). • Regulatory Adherence: Ensuring AI systems comply with environmental regulations may incur additional costs, particularly as standards evolve.

	• Carbon Footprint Considerations: AI-driven automation reduces emissions, making renewable energy adoption more accessible and sustainable (IPCC, 2023). • Sustainability Goals: Companies are increasingly held accountable for their environmental impact. Skilled professionals will need to develop AI solutions that enhance sustainability and minimize ecological footprints (Bohdanowicz et al., 2019). • Climate Change Adaptation: AI can assist in adapting renewable energy strategies to changing environmental conditions. Skills in climate data analysis will be essential for developing resilient energy systems (UNEP, 2020).
Legal	• Regulatory Landscape: The evolving nature of AI and data protection laws in Africa requires PPL to stay abreast of legal developments to ensure compliance, potentially leading to increased operational costs. • Data Protection Regulations: The absence of robust data governance laws in many African nations impacts AI's accessibility, particularly regarding cross-border data use (UNESCO, 2023). • Innovation Protection: Securing intellectual property rights for AI innovations involves legal expenses but safeguards competitive advantage. • Intellectual Property Rights: Legal uncertainties around AI innovations may deter companies from widespread adoption (World Bank, 2023). • Data Privacy Regulations: Compliance with data protection laws is vital, especially with AI systems that utilize personal data. Legal expertise will be required to ensure adherence to these regulations (European Commission, 2020)

Table 10 presents the PESTEL framework; it highlights external factors that may impact an AI project in the renewable energy market in Ghana. The Political factors show that the Ghanaian government realises the importance of renewable energy and has therefore launched initiatives to support both renewable energy projects and SMEs. However, the common challenge that is mentioned pertains to uncertainty around AI policies and regulations, this factor may intimidate the level of innovation and scope of data that supports the most optimised version of the AI project. The Economic factor provides potential high initial investment and financing challenges that should be considered, it also shows opportunities that could be economicly beneficial for the business, such as market growth and cost reductions.

Figure 14 presents a relational map for a renewable energy SME in Ghana, showing how accessibility and skills significantly affect internal operations, while affordability poses challenges across all external PESTEL dimensions

Figure 14: Case Study 4 impact of affordability, accessibility, and skills

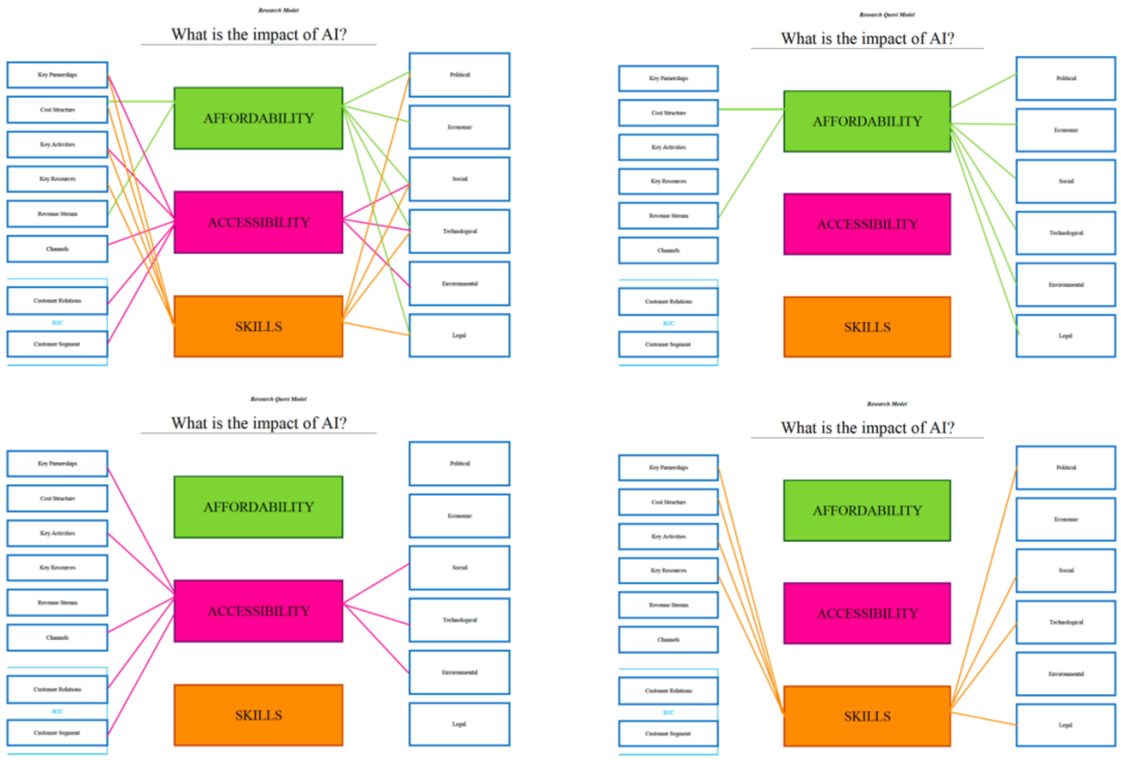


Figure 14 presents an interesting illustration of the relational impact of the internal and external components to consider, specifically in regards to affordability, accessibility, and skills. For an AI project in an SME within the renewable energy sector in Ghana, internal factors are heavily dependent on accessibility and skills. Five out of seven internal factors from the BMC model are impacted by accessibility, and four out of seven internal factors are impacted by skills. On the external side, affordability impacts all of the PESTEL factors. Highlighting the influence of government incentives, financial challenges, skills development, technological compatibility issues, regulatory adherence, and innovation protection. Arguably, although the Research Model illustrates that five out of six PESTEL factors are influenced by skills, various factors that impact the environment component of the model can be attributed to skills.

This figure isolates the impact of the social and technological environments on internal functions in Case Study 4. It demonstrates how socio-technological readiness, like workforce attitudes and infrastructure, modulates key partnerships and AI implementation strategies.

Figure 15: Case Study 4 Social and Technological Impact

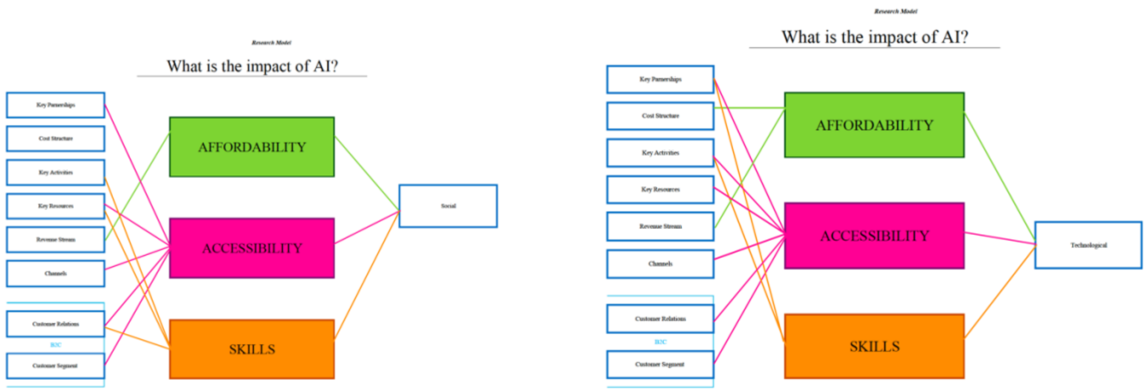


Figure 15 illustrates two key aspects: the internal relational impact of the external social environment and technological environment, based on affordability, accessibility, and skills. The social environment is impacted by affordability, accessibility, and skills, the internal factors that are attributed to key partnerships, key activities, key resources, revenue stream, channels, customer relations and customer segments. Retrieved from the information provided in table 10, the social environment is affected by factors such as skill development, employment dynamics, skill gaps, trust in AI, public acceptance and trust, public awareness, and workforce competence, all of which impacts seven out of the eight factors mentioned in the internal BMC analysis. Additionally, the technological environment impacts affordability, accessibility and skills concerning all eight factors from the internal BMC analysis.

Using the information that populated tables 9 and 10, and figures 14 and 15, RQ1 part two was presented and solved with the following proposed factors:

1. How will affordability impact an AI project in an SME in the Renewable Energy industry in Ghana?

- Internally, affordability will impact the cost structure and revenue stream of the AI project.
- Externally, affordability will be impacted by the political, economic, social, technological, and legal environment in Ghana.

2. How will accessibility impact an AI project in an SME in the Renewable Energy industry in Ghana?

- Internally, accessibility will impact the key partnerships, key activities, channels, customer relations and customer segments.

- Externally, accessibility will be impacted by the social, technological, and environmental environment in Ghana.

3. How will the skills required for an AI project impact the project in an SME in the Renewable Energy sector in Ghana?

- Internally, the skills required impact the key partnerships, cost structure, key activities and key resources of an AI project.
- Externally, the skills required will be impacted by the political, social, technological, and legal environment in Ghana.

This solved RQ1 part 2, showing that the integration of an AI project in an SME in the renewable energy industry in Ghana proposes the potential opportunity to expand the scope of service offerings and digital transformation through internal and external AI projects and partnerships, as well as the ability to cater for and participate in both the public and private consumer markets through targeting households, privately owned businesses, government institutions and all electric vehicle stakeholders and consumers. The internal analysis shows that while the integration of AI into the SMEs' operations presents opportunities for enhanced efficiency and cost savings, it also involves substantial initial investments and ongoing operational considerations. A thorough cost-benefit analysis, accounting for the factors outlined above, is essential to determine the project's overall affordability and strategic value. The External PESTEL analysis shows that the accessibility of AI in operations is influenced by multiple factors. While AI can enhance operational efficiencies and sustainability, barriers such as financial constraints, regulatory gaps, and digital infrastructure limitations hinder widespread accessibility. Addressing these challenges requires policy interventions, investment in digital literacy, and infrastructure development. Furthermore, the successful implementation of an AI project in an SME that specialises in renewable energy products and services in Ghana relies on both quantitative and qualitative skills across the PESTEL factors. Investment in workforce training and development, along with strategic partnerships and compliance with regulations, will be essential for harnessing the full potential of AI in renewable energy and electric vehicle sectors. The Ghanaian government's backing of renewable infrastructure and EV subsidy programs contributes to AI feasibility by supporting integration with IoT-enabled smart grid systems and facilitating partnerships with energy tech vendors through policy-aligned incentives. Ghana's energy subsidies indirectly enables AI integration in solar and EV forecasting. This case underlines the potential of sector-specific policies to create AI-friendly ecosystems for SMEs

(UNESCO, 2021; Mishra et al., 2021). The implementation of an AI project in an SME in Ghana presents significant opportunities for enhancing affordability, accessibility, and operational efficiency in the renewable energy and electric vehicle sectors. By leveraging the insights gained from the BMC and PESTEL analysis, the company can strategically navigate the challenges associated with AI integration and position itself for sustainable growth in the African market.

4.2.5. Case Study 5: AI Implementation in the Construction Industry in South Africa

Introduction

SMEs play a vital role in South Africa's construction industry, contributing significantly to employment, infrastructure development, and economic growth. According to the South African Department of Trade, Industry and Competition (DTIC), SMEs account for over 90% of businesses and contribute approximately 34% to GDP and 60% to employment in the construction sector (DTIC, 2020). Construction SMEs range from residential builders to civil works contractors and specialised service providers. Despite their importance, construction SMEs face persistent challenges, including access to finance, limited technical skills, regulatory compliance burdens, and productivity inefficiencies (CIDB, 2021). In recent years, AI has emerged as a transformative force that can address several of these obstacles by enhancing project planning, cost estimation, safety monitoring, and predictive maintenance.

Company Overview

This case study explores the impact of AI on a small business-to-business construction company in South Africa, specialising in commercial building projects. With a team of 11-25 employees, the company consists of two departments, mainly operations and finance.

Business Profile:

Name	N/A	Country	South Africa
Representative Role	MD	Number of employees	11 – 25
Industry	Construction	Type of Business	B2B
Departments	Operations	Finance	

To evaluate the impact that an AI project would have on this business, we analysed primary and secondary research sources and created the following models:

Table 11: Case study 5 BMC

Key Partnerships	• Technology Providers: AI software companies, cloud service providers. • Suppliers: Raw material suppliers, machinery suppliers with AI capabilities. • Contractors and Subcontractors: Specialized services such as electrical, plumbing, and HVAC. • Regulatory Bodies: Compliance with local construction regulations and safety standards.
Key Activities	• Project Management: AI can optimize project scheduling and resource allocation. • Design and Planning: AI-driven tools for Building Information Modeling (BIM) can enhance accuracy in design. • Quality Control: AI can help in real-time monitoring of construction quality and adherence to specifications. • Cost Estimation: Machine learning algorithms can provide accurate cost forecasts based on historical data.
Key Resources	• Human Resources: Skilled labor and project managers trained in AI tools. • Technological Resources: AI software, hardware, and cloud infrastructure. • Data Resources: Historical project data, client data, and performance metrics for AI training.
Value Proposition	• Increased Efficiency: AI can streamline operations, reduce waste, and optimize resource use. • Cost Savings: Improved project estimation and resource allocation lead to reduced costs. • Enhanced Safety: AI-powered safety monitoring can predict and mitigate risks on construction sites. • Better Decision Making: Data-driven insights allow for informed decision-making in project management.
Cost Structure	• Technology Investment: Initial and ongoing costs associated with AI software and hardware. • Training Costs: Investment in training staff to effectively use AI tools. • Operational Costs: Costs related to project management, labor, and materials.
Revenue Stream	• Project Fees: Revenue generated from completed construction projects. • Maintenance and Support Contracts: Ongoing income from clients for maintenance services. • Consultation Services: Offering expertise in AI implementation for other construction firms.
Channels	• Direct Sales: Direct engagement with clients through sales representatives and online platforms. • Partnerships: Collaborations with other businesses in the construction ecosystem for joint projects. • Online Marketing: Digital marketing strategies to reach potential clients effectively.
Customer Relationships	• Personalized Service: AI can analyze customer preferences and needs, allowing for tailored offerings. • Support Services: AI chatbots and automated customer service systems can provide 24/7 support.

	• Feedback Mechanisms: AI can facilitate customer feedback analysis to improve service quality.
Customer Segments	• Commercial Developers: Businesses looking for construction of office spaces, retail, or industrial facilities. • Government Contracts: Projects related to public infrastructure and development. • Private Clients: Smaller-scale construction projects for individual clients or small businesses.

Table 11 presents an internal BMC analysis of the key factors and considerations for each component mentioned above. The key partnerships provide a combination of four varied scopes of collaborations and the expertise that would be required for each of them. The dynamic of each partnership will vary based on the scope of the AI project. Key activities and key resources can be sourced as an in-house investment or outsourced, this is directly impacted by affordability, accessibility and skills. While each component presents a range of opportunities and challenges, it can also be identified that many components can be beneficial to each other. Channels can be impacted by the nature of key partnerships and customer segments, further integrating the customer relationship factors to feed back into the determination of which channels and collaborations are most viable.

Table 12: Case Study 5 PESTEL

Political	• Regulatory Environment: The South African construction industry is subject to various regulations, including the Construction Industry Development Board (CIDB) requirements and safety regulations. Compliance with these regulations can be streamlined through AI tools that ensure adherence to legal standards and quality checks (CIDB, 2021). - Policies that mandate the adoption of new technologies in the construction industry may require companies to invest in training programs to meet compliance, thus affecting the skills landscape (Construction Industry Development Board, 2021). • Government Initiatives: The South African government promotes infrastructure development through initiatives such as the National Development Plan (NDP). AI can enhance project planning and execution, making construction companies more competitive for government contracts (Republic of South Africa, 2020). • Government Funding and Support: The South African government may provide grants or incentives for small businesses adopting innovative technologies like AI. Accessibility to such funding can lower the financial burden of implementing AI solutions, making it more affordable for construction companies (Department of Trade, Industry and Competition, 2021).
Economic	• Economic Growth: South Africa's GDP growth impacts the construction sector. According to World Bank data, fluctuations in economic growth can affect investment in construction projects (World Bank, 2021). AI can optimize resource

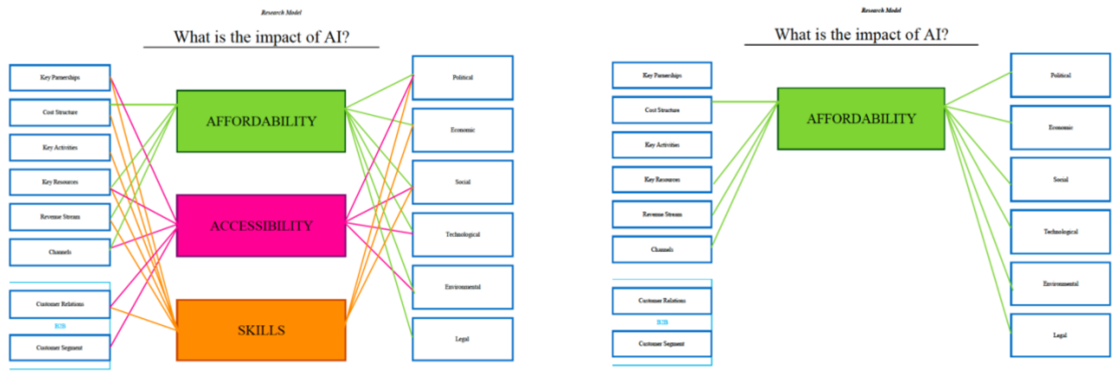
	allocation and reduce costs, allowing firms to remain profitable even in challenging economic conditions. • Labor Costs: Rising labor costs in South Africa necessitate efficient operations. - Affordability of AI solutions becomes crucial as companies seek to automate processes to mitigate high labor expenses (Statista, 2022). • Investment in Technology: Economic stability influences the ability of small businesses to invest in AI technologies. In a growing economy, increased capital availability can enhance accessibility to affordable AI solutions and cloud-based platforms (World Bank, 2021). • Cost of Technology: The affordability of AI tools significantly affects their accessibility. As AI technology becomes more cost-effective and available as a service (e.g., cloud solutions), it becomes easier for small construction businesses to adopt these technologies (McKinsey & Company, 2021). • Cost of Training Programs: The economic feasibility of investing in training programs to develop AI skills is a critical consideration. Companies must weigh the costs of training against potential gains in efficiency and competitiveness (Statista, 2022).
Social	• Skilled Workforce: The availability of a skilled workforce in AI and construction is critical. There is a growing emphasis on training programs in South Africa to bridge the skills gap (South African Government, 2021). • Health and Safety Concerns: The construction industry faces significant health and safety challenges. AI can be used to monitor site conditions and ensure compliance with safety regulations, reducing accidents and improving worker safety (López et al., 2020). • Technology Adoption Culture: The openness of the construction industry to adopt new technologies affects accessibility. A culture that embraces innovation will facilitate easier access to AI solutions, while resistance to change may hinder adoption (Nielsen, 2020). • Training and Workforce Development: Accessibility to AI also depends on the availability of training programs for employees. If there are affordable and accessible training opportunities, small businesses can effectively integrate AI into their operations (South African Government, 2021).
Technological	• Advancements in AI: The rapid development of AI technologies presents opportunities for the construction industry. • Integration with Existing Systems: The ease of integrating AI with current construction management systems can influence affordability. • Internet Connectivity: High-speed internet access is crucial for leveraging cloud-based AI tools. Areas with poor connectivity may face challenges in accessing these technologies, which can limit their utilization in construction projects (Statista, 2022).
Environmental	• Sustainability Practices: There is increasing pressure on the construction industry to adopt sustainable practices. AI can help optimize material usage, reduce waste, and improve energy efficiency in construction projects (Zhou et al., 2021). • Resource Availability: Economic challenges may impact the availability of resources for construction. Affordable AI solutions that help manage and allocate resources

	efficiently can be crucial for sustaining operations during challenging times (RICS, 2021). • Environmental Regulations: Compliance with environmental regulations can drive the need for accessible AI tools that assist in monitoring and managing sustainability practices in construction (RICS, 2021).
Legal	• Contract Law: Compliance with contract law is essential in the construction industry. • Intellectual Property Rights: Protecting innovations developed through AI is crucial for companies in the construction sector. • Compliance Costs: Adhering to legal requirements when implementing AI can incur additional costs.

Tables 12 provides a PESTEL analysis that shows the external impactful factors that should be considered in the planning stages of an AI project in an SME in the construction industry in South Africa. The political environment suggests two routes that can be considered to address affordability, government initiatives such as the National Development Plan that assist SMEs involved in infrastructure development, and government funding and support for grants and incentives for SMEs adopting innovative technologies such as AI. Although the economic environment presents some challenges for affordability, highlighting the increased labour costs in the country, cost of technology and cost of training programs, it also presents opportunities that impacts accessibility through cloud-based AI services because of economic growth and investment in technology. The social and technological environment includes factors that impact the skills component of the skills required for an AI project, as well as the affordability and accessibility of training and infrastructure. Commonly, regulations, policies, and compliance pose challenges within the political, environmental, and legal environments.

Figure 16 maps the case of an SME in the construction industry, revealing how high training costs and uneven digital access restrict AI integration. Affordability emerges as a central bottleneck impacting internal efficiency and external engagement.

Figure 16: Case study 5 impact of affordability, accessibility, and skills.



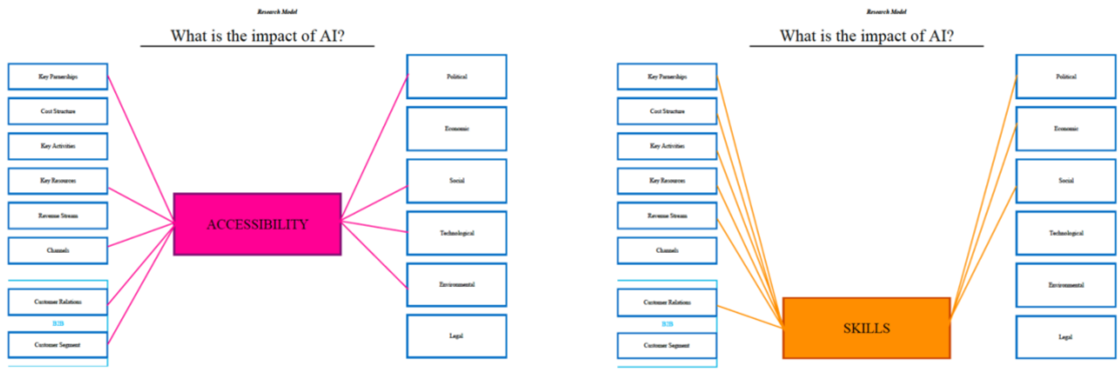
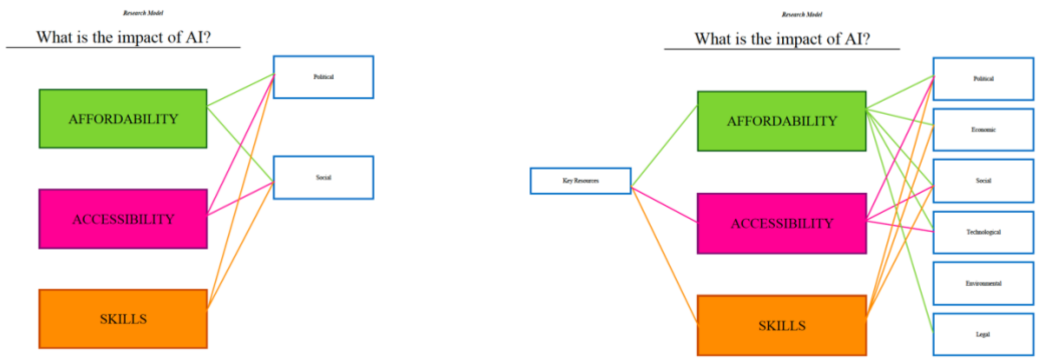


Figure 16 shows which factor of the BMC and PESTEL models impacts affordability, accessibility, and skills. It further presents individual illustrations for a clearer picture of the impacted factors and potential relational impact. Accessibility impacts key partnerships, key resources, channels, customer relationships, and customer segments, and is impacted by political, social, technological and environmental factors. Affordability impacts the cost structure, revenue stream and channels, and is impacted by all of the PESTEL factors. Skills impact most of the BMC components and are impacted by the political, economic, and social environment.

This figure drills into political and social enablers and constraints. It illustrates how key resources such as talent and content platforms depend on government support, societal trust in AI, and evolving regulations to ensure AI uptake.

Figure 17: Case study 5 impact of political, social environment, and key resources



The first diagram in Figure 16 presents the political and social environment, showing that it impacts all three of the scopes of study – affordability, accessibility, and skills. Government support and incentives play a critical role in providing solutions for the funding of capital investment and skills development. Skills are also a major challenge within the social environment and consequently impact the scope of the AI project in numerous ways. Key resources – human resources, technological resources, and data resources are impacted by affordability, accessibility and skills, which are impacted by the political, economic, social, technological, and legal environment in South Africa.

Using the information that populated tables 11 and 12, and figures 16 and 17, RQ1 part two was presented and solved with the following proposed factors:

1. How will affordability impact an AI project in an SME in the Construction industry in South Africa?
   - Internally, affordability will impact the key resources, cost structure, revenue stream and channels of the AI project.
   - Externally, affordability will be impacted by the political, economic, social, technological, environmental and legal environment in South Africa.
2. How will accessibility impact an AI project in an SME in the Construction industry in South Africa?
   - Internally, accessibility will impact the key partnerships, key resources, channels, customer relations and customer segments.
   - Externally, accessibility will be impacted by the political, social, technological, and environmental environment in South Africa.
3. How will the skills required for an AI project impact the project in an SME in the Construction industry in South Africa?
   - Internally, the skills required impact the key partnerships, cost structure, key activities, key resources, revenue stream and customer relations of an AI project.
   - Externally, the skills required will be impacted by the political, economic and social environment in South Africa

This solved RQ1 part 2, showing that the integration of an AI project in an SME in the Construction industry in South Africa has both many opportunities and challenges that influence the development and accessibility of necessary skills. Although economic growth presents accessibility to increased capital availability and technological investment that will assist SMEs, it also presents affordability challenges due to the increase in labour costs. This can be mitigated by leveraging the skills component of the AI project. The skills required for AI significantly impact a small B2B construction company in South Africa. The BMC and PESTEL analysis reveals that political support, economic conditions, social attitudes, technological advancements, environmental considerations, and legal frameworks. By understanding these factors and investing in skills development, construction companies can better prepare their workforce to leverage AI technologies and foster a culture of innovation, enhancing their competitiveness in the market. Within the South African Construction Industry context, affordability and accessibility can be addressed through various external opportunities.

4.2.6. Case Study 6: AI Implementation in the Restaurant Industry in Malawi

Introduction

SMEs play a vital role in Malawi's economy, contributing significantly to employment creation and income generation (International Trade Centre [ITC], 2022). SMEs in Malawi constitute approximately 90% of all businesses and contribute over 40% to GDP (Malawi Government, 2021). However, most SMEs struggle with limited access to finance, poor infrastructure, and low levels of technology adoption (ITC, 2022). These enterprises span diverse sectors including agriculture, retail, services, and hospitality. In the hospitality sector, particularly the restaurant industry, SMEs often face challenges including operational inefficiencies, high overhead costs, and inconsistent customer service. Recent advances in AI present a promising solution to these problems, offering tools for automation, data-driven decision-making, and personalised customer engagement (Bughin et al., 2018). Artificial intelligence is increasingly being adopted across sectors in Sub-Saharan Africa, albeit at a slower pace compared to developed economies. In Malawi, although the AI ecosystem is still nascent, digital literacy is improving, and the government is beginning to recognise the importance of integrating AI into national development plans (Ministry of Information and Digitisation, 2023). This case study examines how AI technologies are transforming operations at a mid-sized restaurant chain in Blantyre, Malawi.

Company Overview

This case study analyses the potential impact of an AI project in a local SME restaurant chain that offers a full menu of fast food meals and its own brand of frozen treats. Operating in Blantyre since 1991, it employs more than 50 staff and operates as a business-to-consumer model.

Business Profile:

Name	N/A	Country	Malawi
Representative Role	Founder	Number of employees	50+
Industry	Restaurant -Fast Food Chain	Type of Business	B2C

Departments	Operations	Finance	Marketing

To evaluate the impact that an AI project would have on this business, we analysed primary and secondary research sources and created the following models:

Table 13: Case Study 6 BMC

Key Partnerships	• Collaboration with local AI startups/Hospitality-tech solutions • Internet service providers • Digital payment platforms
Key Activities	• Core activities include data collection, machine learning model training • Digital marketing • Managing AI systems alongside traditional operations (Duan et al., 2019).
Key Resources	• Digital infrastructure, AI software tools (e.g., inventory systems, chatbots) • Skilled staff to manage the systems become critical resources (OECD, 2021).
Value Proposition	• AI-driven personalization (e.g., meal recommendations), faster service via chatbots, and consistent quality enhance customer satisfaction (Chatterjee et al., 2021).
Cost Structure	• Upfront costs include AI integration and staff training. However, long-term benefits include reduced labor costs, less food waste, and improved supply chain efficiency (Bughin et al., 2018).
Revenue Stream	• Increased online orders and optimized pricing through AI analytics lead to higher revenue. • AI also enables the introduction of new services like meal subscriptions (McKinsey, 2018).
Channels	• Introduction of AI chatbots on WhatsApp and social media expands digital ordering channels and provides 24/7 customer service (World Economic Forum, 2020).
Customer Relationships	• AI improves relationship management through automated follow-ups, loyalty tracking, and feedback analysis, promoting a personalized customer experience (Kraus et al., 2021).
Customer Segments	• AI enables more refined customer segmentation based on behavior, preferences, and order history. This allows for targeted marketing and tailored offerings (Bughin et al., 2018).

Table 13 presents the BMC analysis for an SME in the restaurant industry in Malawi, which shows the internal impact of an AI project. The key partnerships, activities, resources, and cost structure are primarily influenced by the affordability of tech solutions, the accessibility of infrastructure to support these solutions, and staff upskilling. Revenue stream, channels, customer relationships and segments are highly dependent on online accessibility for the business and its customers.

Table 14: Case Study 6 PESTEL

Political	• Government support for digital innovation: Malawi's government has initiated digital transformation strategies (Ministry of Information and Digitization, 2023), but practical support for SMEs is limited.

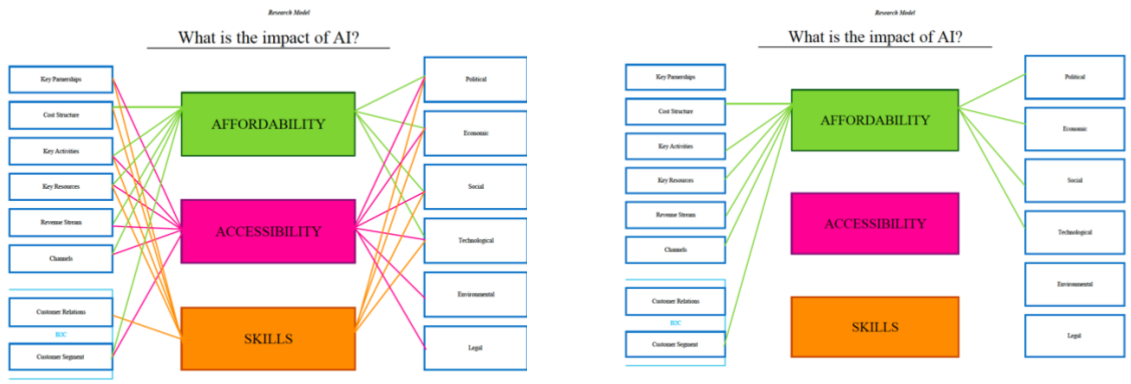
	• Only 15% of SMEs in Malawi receive government funding or grants for digital technology (ITC, 2022). • Only 8% of Malawi's annual ICT budget is allocated to SME-focused programs (Ministry of Information and Digitization, 2023). • Fewer than 3 government-supported digital innovation hubs exist nationwide (World Bank, 2023). • Less than 5% of national education funding is allocated to ICT or digital skills training (Ministry of Education, Malawi, 2023). • Policy stability: Political stability is relatively moderate but constrained by slow bureaucracy, delaying implementation of tech incentives, Malawi ranks 5.5/10 on political stability in the Mo Ibrahim Index (2022).
Economic	• Access to capital: Limited access to affordable credit, interest rates for SMEs average 24% per annum in Malawi (Reserve Bank of Malawi, 2023). • Cost vs. access: While AI tools like chatbots are relatively low-cost, cloud services and maintenance remain costly for many SMEs. • Availability of funding: Less than 20% of SMEs in Malawi report access to tech-specific loans or grants (ITC, 2022). • Cost of training: Training employees in AI or digital tools imposes significant costs on small businesses.
Social	• Digital literacy: Low digital literacy among staff may require additional training, increasing implementation costs. • Only 33% of Malawians have basic digital literacy; under 10% are familiar with AI or data tools (World Bank, 2021). • Low digital literacy among staff and customers limits AI usability, requiring training and onboarding efforts. • Consumer expectations: Younger demographics are increasingly tech-savvy and expect digital engagement like chatbots and online ordering. • Over 60% of urban Malawian consumers aged 18–35 use WhatsApp for business communication (GSMA, 2022). • Language and inclusivity: 74% of the Malawian population speaks Chichewa, yet only 39% are fluent in English (Ethnologue, 2023). • Education and vocational training: Only 2 universities in Malawi offer ICT degrees with AI components (UNESCO, 2022).
Technological	• AI accessibility: Availability of off-the-shelf AI tools (e.g., WhatsApp chatbots) reduces implementation cost. • Entry-level AI chatbots cost as low as $10/month (Statista, 2023). • Internet infrastructure: Intermittent connectivity in some parts of Lilongwe and Blantyre may hinder consistent AI functionality. • Internet penetration in Malawi is 23.1% as of 2023 (DataReportal, 2023). • Integration and support: Many SMEs lack IT support for integrating AI into daily operations. • Availability of training platforms: Online platforms (e.g., Coursera, Google AI) offer scalable options for AI skills development but require stable internet access. • 65% of rural SMEs report difficulty accessing e-learning platforms due to poor internet (DataReportal, 2023). • Only 30% of schools and SMEs have functional computer labs (Ministry of Education, Malawi, 2023).

Environmental	• Energy reliability: AI systems require consistent electricity; power outages can disrupt services and increase backup power costs. • Malawi experiences 3–4 power outages per week on average (World Bank, 2023). • Sustainability benefits: AI-driven inventory systems can reduce food waste by up to 30% (McKinsey, 2018). • Accessibility to green AI (e.g., low-energy models) remains limited in Malawi's market. • Sustainability training: There's growing interest in combining AI with sustainable business practices, but related training is lacking. • Less than 2% of training programs in Malawi incorporate sustainability or green AI content (UNEP, 2022).
Legal	• Data protection laws: Malawi has no dedicated data protection legislation as of 2024 (UNCTAD, 2024). • Malawi ranks "low" in the UNCTAD global e-commerce legislation framework readiness score (UNCTAD, 2024). • IP and tech ownership: 65% of SMEs do not verify software licensing in Malawi (ITC, 2022).

Tables 14 uses the PESTEL model to present the external impact that should be considered when implementing an AI project in the restaurant industry in Malawi. It shows that within the political environment, although the government has initiated digital transformation strategies that would potentially aid affordability, only 15% of SMEs have access to this opportunity which can be challenging to businesses in terms of accessibility. Despite affordability as an underlying challenge, accessibility is shown to be a prevalent challenge across the economic, social, technological and environmental environments. The Social environment presents challenges pertaining not only to the skills of employees but also highlights the low digital literacy rate across the community, therefore showing a risk of low social acceptance of the business's technological advancements.

Figure 18 outlines a restaurant SME's resource allocation challenges. It highlights how AI affordability is affected by procurement costs, while accessibility and skills gaps constrain AI-driven diagnostics and record management systems.

Figure 18: Case Study 6 impact of affordability, accessibility, and skills.



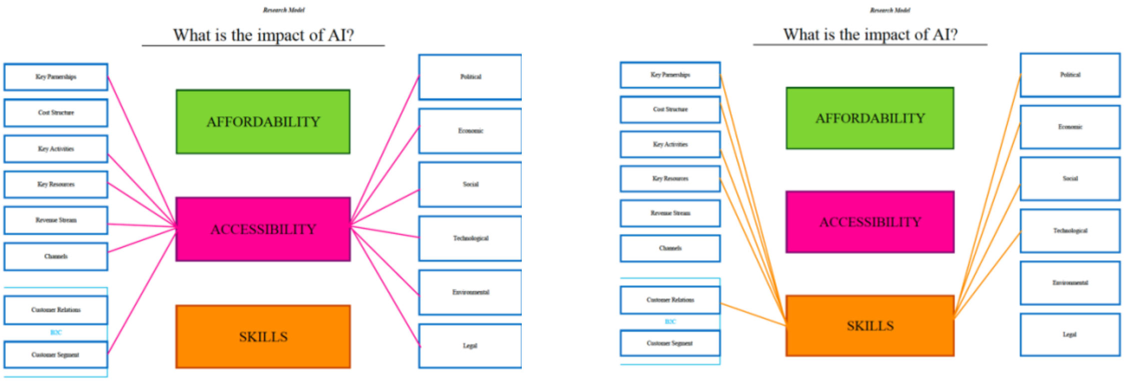


Figure 18 presents the impact of affordability, accessibility, and skills on an AI project in the Malawian restaurant industry. It shows that internally, affordability and accessibility are the most impactful factors to consider, and externally, accessibility is the most impacted factor. The skills required for an AI project impact the key partnerships, cost structure, key activities, key resources and customer relationships, and are impacted by the political, economic, social and technological environments.

This figure focuses on external regulatory and cultural elements influencing AI readiness. It illustrates how political will, social health norms, and data privacy frameworks collectively shape operational strategies in Case Study 6.

Figure 19: Case study 6 impact of political, social, and legal environment

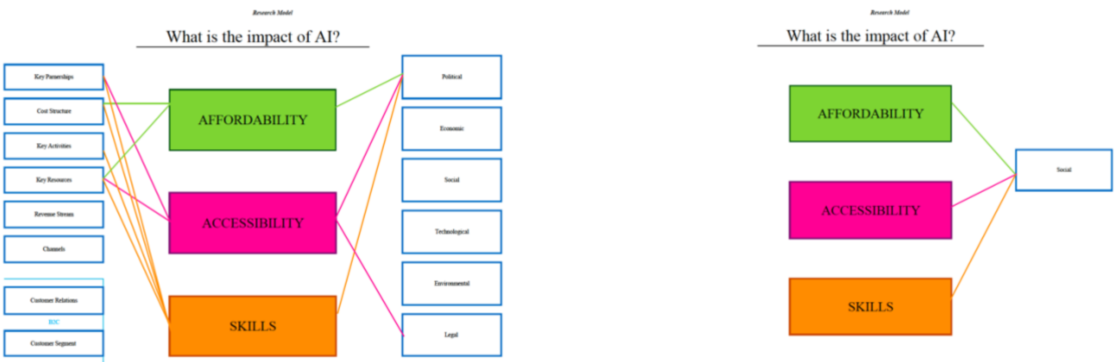


Figure 19 addresses how key partnerships, activities, resources and cost structure are impacted by affordability, accessibility, and skills, which are in turn impacted by the political and legal environment. This is directly attributable to government initiatives that are challenging to access, low funding for both SME programs and digital skills training, and constraints due to slow bureaucracy and a lack of strong regulations and data protection laws to support and protect businesses and consumers that are exposed to AI systems in Malawi.

Using the information that populated tables 13 and 14, and figures 18 and 19, RQ1 part two was presented and solved with the following proposed factors:

1. How will affordability impact an AI project in an SME in the Hospitality industry in Malawi?

- Internally, affordability will impact the cost structure, key activities, key resources, revenue stream, channels and customer segments of the AI project.
- Externally, affordability will be impacted by the political, economic, social, and technological environment in Malawi.

2. How will accessibility impact an AI project in an SME in the Hospitality industry in Malawi?

- Internally, accessibility will impact the key partnerships, key activities, key resources, revenue stream, channels and customer segments of an AI project.
- Externally, accessibility will be impacted by the political, economic, social, technological, environmental and legal environment in Malawi.

3. How will the skills required for an AI project impact the project in an SME in the Hospitality industry in Malawi?

- Internally, the skills required impact the key partnerships, cost structure, key activities, key resources and customer relations of an AI project.
- Externally, the skills required will be impacted by the political, economic, social and technological environment in Malawi.

This solved RQ1 part 2, showing that the integration of an AI project in an SME in the Hospitality industry in Malawi presents many internal opportunities to implement Ai-powered to improve customer experience and operational efficiency by including tools such as AI chatbot for online ordering and reservations, a machine learning model to predict customer preferences, and a basic inventory management system driven by AI algorithms. To optimise the AI capabilities of the system, the SME and developers should consider all factors that are impacted and impactful towards the affordability, accessibility, and skills required for the AI project. The BMC and PESTEL analysis provided insight into the internal and external landscape that would affect the project; notably, accessibility to public funding and government initiatives, and infrastructure, are impactful challenges to overcome. Because even if factors that impact the affordability of the project are mitigated through cloud services, outsourced tech-labour and cheaper mass customer engagement solutions such as WhatsApp are used, access to a stable internet connection and energy remains a deterrent factor for both the business and its customers. Table 14 mentioned low digital literacy among staff and customers, minimal funding for digital skills at school and tertiary levels, and language barriers as major impactful factors to consider. This presents challenges in regards to general usability skills and the skills required for staff to use the AI system optimally. Overall, this case study illustrates the potential of AI to address common SME challenges in Malawi's restaurant sector. By leveraging accessible AI tools, even modestly resourced businesses can improve efficiency, enhance customer satisfaction, and become more competitive. However, for broader adoption, there is a need for increased investment in digital infrastructure, capacity building, and supportive policy frameworks.

4.2.7. Case Study 7: AI Implementation in the Hospitality- Hotel Industry in India

Introduction

India's tourism industry is a vital pillar of the economy. According to the Ministry of Tourism, the sector contributed USD 194 billion to India's GDP in 2019, accounting for nearly 6.8% of the total economy and supporting over 39 million jobs (WTTC, 2020). The India Brand Equity Foundation (IBEF) reports that India aims to attract 100 million foreign tourists annually by 2047. Artificial Intelligence is increasingly reshaping how hospitality businesses in India operate, from chatbots for guest inquiries and AI-driven personalisation of services, to predictive analytics for occupancy planning. AI is helping hotels, especially smaller ones, become more competitive. A report by NASSCOM (2023) highlights that AI adoption in Indian hospitality can increase profitability by 10–15% through improved operational efficiency and guest satisfaction. This case study analyses the impact that an AI project will have on a boutique hotel in India.

Company Overview

A boutique hotel located in India offers bed and breakfast, a full restaurant, and concierge services that specialise in local tours and experiences. The hotel employs 11 to 25 staff members across hospitality, kitchen, housekeeping, and guest services. The core value proposition lies in combining authentic Indian wellness experiences with personalised attention.

Business Profile:

Name	N/A	Country	India
Representative Role	Owner	Number of employees	11 - 25
Industry	Hospitality - Hotel	Type of Business	B2C
Departments	Operations		

To evaluate the impact that an AI project would have on this business, we analysed primary and secondary research sources and created the following models:

Table 15: Case Study 7 BMC

Key Partnerships	• AI solution providers (SaaS platforms for hospitality) • Local tour/activity vendors integrated into upsell system • OTA platforms and payment gateways • Skill development platforms for AI literacy training
Key Activities	• Managing and training staff using AI tools • Monitoring AI insights to adjust operations and offers • Continuously updating AI algorithms and data inputs
Key Resources	• AI software (chatbot, CRM, inventory management, workforce scheduler) • Trained staff leveraging AI tools • Digital booking and payment infrastructure
Value Propositions	• Hyper-personalized stays (AI tailors meals, activities, room preferences) • Instant response to inquiries via AI chatbot • Seamless booking and communication • Consistent service through AI-enabled staff training
Cost Structure	• Initial AI setup and integration costs • Subscription fees for AI tools and maintenance • Staff training and change management • Cybersecurity and data protection costs
Revenue Stream	• Room bookings (optimized pricing via dynamic AI-based pricing models) • Upselling personalized packages (spa, workshops) • AI-based dynamic pricing can increase hotel revenue by 10-15% (EY, 2023).
Channels	• AI-powered booking engine (website, WhatsApp) • Social media ads targeting based on AI analytics • OTA platforms integrated with AI calendar availability
Customer relationships	• AI-enhanced CRM tracks preferences and follow-up schedules • Automated feedback collection and review generation • Loyalty program powered by AI behaviour tracking
Customer Segments	• Tech-savvy domestic and international wellness travellers • Repeat guests attracted by personalization • Corporate clients seeking AI-curated retreat experiences

Table 15 presents the BMC analysis for a boutique hotel in the Hospitality industry in India. The key Partnerships include SaaS (Software as a Service) and international OTA (Online Travel Agency) platforms, as well as local tour agencies, this provides an opportunity for the hotel to reach global customers seamlessly and connect them with local attractions and activities which expands interests that appeals to a broader target market of tourists. Key activities and resources emphasise the need to empower and train staff to be able to use AI systems optimally. Cost structure, revenue stream, and channels include the initial setup, ongoing maintenance and marketing platform costs.

Table 16: Case Study 7 PESTEL

Political	• India's government actively promotes AI adoption through policies like the National Strategy for AI (NITI Aayog, 2018) • Only 20% of Indian MSMEs have adopted AI due to cost concerns (NASSCOM, 2022). • Government Schemes (e.g., Startup India) may subsidize part of AI implementation • The Indian government provides up to 50% subsidies on AI adoption for MSMEs under various schemes (Startup India, 2023). • Tax on imported AI software/hardware can add 18-28% to costs (GoI, 2023). • Policies promote access to AI tools in rural/tier-2 areas • Government supported programs (e.g., FutureSkills Prime) • India's Digital India initiative allocated ₹8,000 crore for AI and digital transformation (MeitY, 2022). • The Indian government is promoting AI education through initiatives like the National Programme on AI and Skill India Mission • 60% of Indian MSMEs cite lack of AI expertise as a major barrier to adoption (NASSCOM, 2023).
Economic	• 80% of hotels in India lack AI-powered systems due to cost and technical barriers (NASSCOM, 2022). • AI accessibility in boutique hotels is affected by high initial costs of deployment • The affordability of AI depends on the availability of subscription-based AI-as-a-Service models, which allow businesses to avoid high capital expenditures (Kapoor et al., 2021). • Free online AI courses from Google, IBM, and Indian institutes are increasing accessibility (Kapoor et al., 2021). • SMEs in developing countries face financial constraints in AI investment (Kapoor et al., 2021). • AI implementation costs for small hotels range between ₹5-10 lakh for chatbot, CRM, and analytics integration (PwC, 2023). • AI training programs for hospitality staff cost ₹25,000 – ₹1,00,000 per employee (PwC, 2023). • AI upskilling investment can yield a 20-35% improvement in operational efficiency (McKinsey, 2022). • AI-enabled hotels report a 15% increase in revenue from personalized services (Statista, 2023). • AI adoption in India's hospitality sector is projected to grow at 13.6% CAGR from 2023-2028 (Statista, 2023).
Social	• Younger travellers prefer AI-driven personalization, while traditional customers may resist automation (Choudhary, 2023). • 72% of Indian travellers prefer AI-powered hotel services (Accenture, 2021). • 56% of hotel employees lack AI-related skills, creating an accessibility gap (LinkedIn, 2022). • Most AI training programs are focused on IT and engineering, with limited focus on hospitality applications (NITI Aayog, 2018). • Less than 10% of hospitality professionals in India have AI-related training (FICCI, 2022). • 90% of AI-driven customer service interactions are completed without human intervention (Salesforce, 2023). • Less than 30% of hotel staff feel comfortable using AI-driven tools (Accenture, 2021). • AI-based training programs in local languages increase adoption by 40% (Rana & Sharma, 2023).
Technological	• AI tools are becoming more accessible due to cloud computing and low-code AI platforms. • poor internet infrastructure in some regions limits the effectiveness of cloud-based AI solutions (Rana & Sharma, 2023). • 85% of AI solutions for SMEs are now cloud-based, reducing hardware costs (IBM, 2022). • Boutique hotels may struggle with legacy system integration, which can drive up costs. • Hotels with legacy systems spend 20-30% more on AI integration (EY, 2023). • Lack of technical expertise to integrate AI into existing operations, making seamless accessibility a challenge (Rana & Sharma, 2023). • 85% of AI solutions for SMEs are now cloud-based, lowering barriers to entry (IBM, 2022). • Only 40% of Indian hotels have AI-integrated PMS (Property Management Systems) (NASSCOM, 2023). • AI-powered voice assistants reduce manual work by 25% in hotels (PwC, 2022). • Integrating AI into existing hotel workflows requires specialized skills (IBM, 2022). • Hotels with trained AI staff report a 30% faster adoption rate (EY, 2023).
Environmental	• AI enhances sustainable practices by optimizing energy consumption, waste management, and water usage. • AI data centers require significant energy resources, raising concerns about environmental impact (Kumar et al., 2023). • AI-powered energy management systems reduce electricity costs by 20-30% (Schneider Electric, 2023). • AI-driven food waste tracking reduces kitchen waste by 15% (UNEP, 2022). • AI-powered sustainability management systems require knowledge of data analytics and energy monitoring.

	• Employees must be trained to use AI for energy efficiency, waste reduction, and carbon footprint tracking (Kumar et al., 2023). • AI-driven energy management training reduces electricity costs by 20% (Schneider Electric, 2023). • 70% of hotel staff require training to use AI for sustainability reporting (IEA, 2023).
Legal	• AI accessibility is influenced by regulatory compliance with India's DPDP Act (2023) and global laws like GDPR. • Data privacy laws - Digital Personal Data Protection Act (DPDP, 2023) • Failure to meet data privacy standards can result in hefty penalties, discouraging small businesses from AI adoption (GoI, 2023). • Fines for non-compliance with AI-related data laws in India can reach ₹250 crore (DPDP, 2023). • AI security solutions can increase operating costs by 15-25% (EY, 2023). • Employees must be trained on handling guest data securely, which adds to training costs (GoI, 2023). • 70% of AI-powered hotels must train staff in data protection (NASSCOM, 2022).

Table 16 provides a PESTEL analysis for the Hospitality -hotel industry in India. It shows the political environment's impactful factors to consider when planning an AI project, it shows that affordability can be impacted by the various government initiatives that have been launched to support AI adoption in startups and SMEs in India. The economic, environmental and social environment further addresses the constraints that impact affordability and skills, whereas the technological environment presents solutions that can impact accessibility.

Figure 20 captures AI integration in a hotel SME. It shows how limited cloud access and financial pressure undermine internal systems, with particular challenges in acquiring and retaining AI-skilled personnel.

Figure 20: Case study 7 impact of affordability, accessibility, and skills.

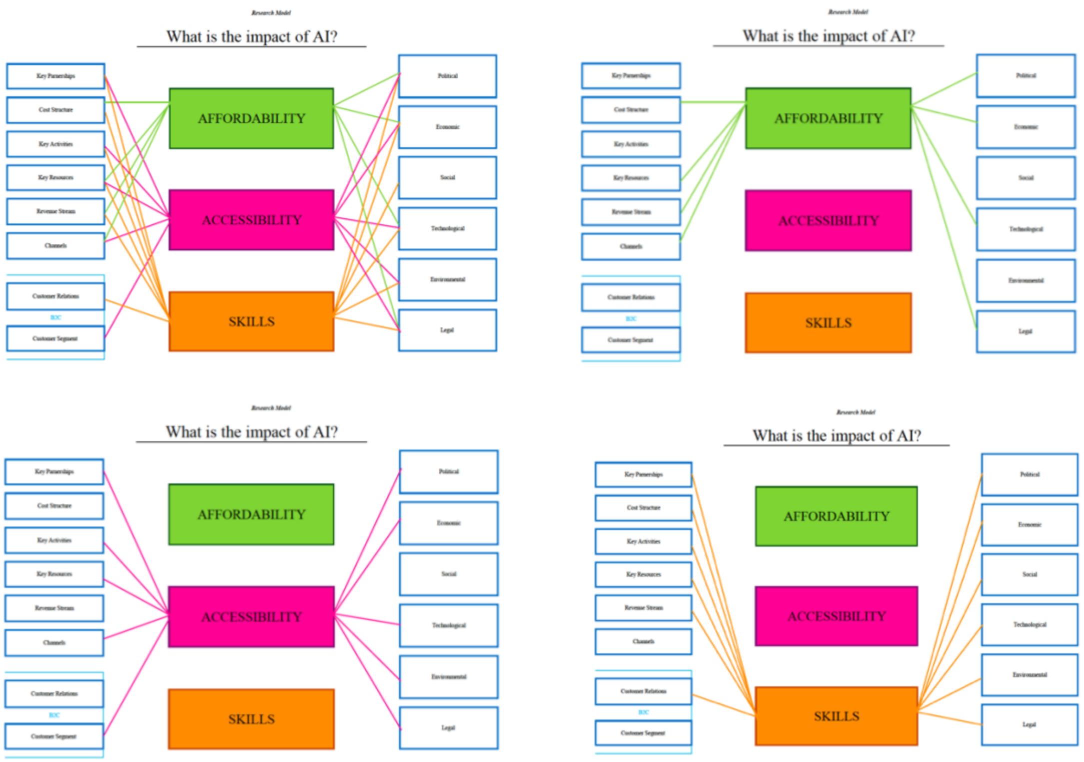


Figure 20 shows the correlation and impact of affordability, accessibility, and skills required for an AI project in the hospitality-hotel industry in India. On the internal and external side of the business, skills required impacts a potential AI project the most, followed by accessibility. This includes key activities - managing and training staff using AI tools and key resources - trained staff leveraging AI tools. Political, economic, and technological factors such as the tax on imported AI software and hardware can result in an additional cost of 18-28%, the implementation costs for AI in small hotels range between ₹5-10 lakh for integrating chatbot, CRM, and analytics systems and 85% of AI solutions for SMEs are now cloud-based, which helps to reduce hardware expenses, all of these factors impact the affordability of a potential AI project in a boutique hotel in India.

This figure compares how internal and external environments interact across the three core dimensions (affordability, accessibility, and skills), showing dynamic feedback loops between infrastructure development and workforce competency.

Figure 21: Case study 7, the impact of affordability, accessibility, and skills within the internal and external environment

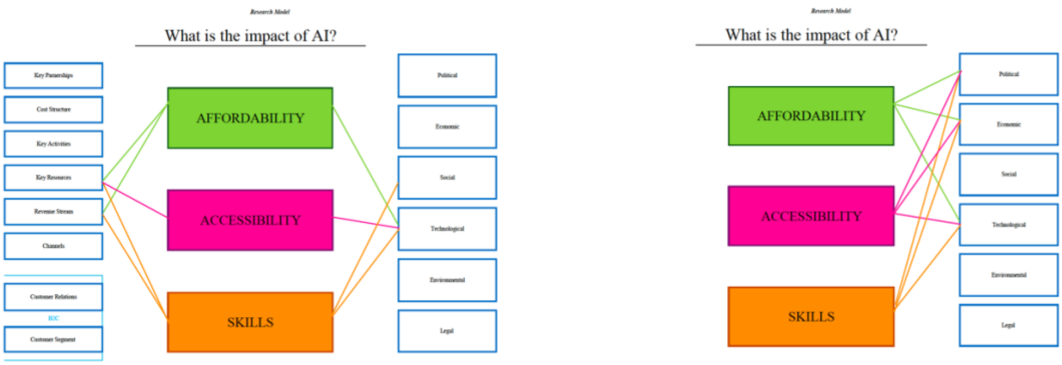


Figure 21 presents insights from Tables 15 and 16 on how affordability, accessibility, and skills impact the key resources and revenue stream of a potential AI project, and are impacted by the social and technological environment. The second diagram illustrates how the political, economic, and technological environment influences all three factors of scope—namely, affordability, accessibility, and skills. These factors include initiatives such as the Indian government providing up to 50% subsidies for AI adoption among SMEs under various schemes, the impact of high initial deployment costs on AI accessibility in boutique hotels, and the limitations imposed by inadequate internet infrastructure in certain regions on the effectiveness of cloud-based AI solutions.

Using the information that populated tables 15 and 16, and figures 20 and 21, RQ1 part two was presented and solved with the following proposed factors:

1. How will affordability impact an AI project in an SME in the Hospitality- Hotel industry in India?
   - Internally, affordability will impact the cost structure, key resources, revenue stream and channels of the AI project.
   - Externally, affordability will be impacted by the political, economic, technological and legal environment in India.
2. How will accessibility impact an AI project in an SME in the Hospitality- Hotel industry in India?
   - Internally, accessibility will impact the key partnerships, key activities, key resources, channels and customer segments of an AI project.
   - Externally, accessibility will be impacted by the political, economic, technological, environmental and legal environment in India.
3. How will the skills required for an AI project impact the project in an SME in the Hospitality - Hotel industry in India?
   - Internally, the skills required impact the key partnerships, cost structure, key activities, key resources, revenue stream and customer relations of an AI project.
   - Externally, the skills required will be impacted by the political, economic, social, technological, environmental and legal environment in India.

This solved RQ1 part 2, showing that the integration of an AI project in an SME in the Hospitality- Hotel industry in India presents many internal and external opportunities. It also exemplifies how thoughtful integration of digital tools can drive growth, enhance guest satisfaction, and build sustainable employment in tourism-dependent communities. As India's hospitality industry continues to digitise, boutique hotels have a unique opportunity to use AI not as a disruptor, but as a partner in delivering meaningful, memorable experiences. Accessibility of AI in boutique hotels is shaped by technological advancements, financial constraints, workforce skills, and regulatory compliance. While cloud-based AI tools are making integration easier, limited AI literacy, compliance costs, and initial investment barriers remain key challenges. To maximise AI accessibility and affordability, boutique hotels must leverage government incentives and subsidies, cloud solutions, workforce training programs, and energy-saving AI solutions. The affordability of AI for boutique hotels in India is influenced by high initial costs and taxation. The skills gap is a major barrier to AI adoption in boutique hotels. While government initiatives and online training programs are improving AI accessibility, cost constraints, language barriers, and workforce resistance remain challenges. Investing in AI training can enhance efficiency, reduce costs, and improve guest experiences. For the successful implementation of an AI system in a boutique hotel in India, the business would need a mix of technical, organisational, financial, and human support structures. These are critical to overcome challenges such as affordability, accessibility, and the skills gap.

4.2.8. Case Study 8: AI Implementation in the Tourism Industry in Vietnam

Introduction

The global tourism industry plays a vital role in economic development, contributing significantly to employment, foreign exchange earnings, and cross-cultural exchange (UNWTO, 2023). In Southeast Asia, tourism has been a key driver of economic growth, with Vietnam emerging as a major destination due to its rich cultural heritage, diverse landscapes, and government-led tourism initiatives (Nguyen & Tran, 2021). Operating across Vietnam, Cambodia, and Laos, the company employs a Business-to-Consumer (B2C) model, providing tailored travel experiences to international and domestic tourists. This case study examines the business model and offers insights into the factors contributing to the opportunities and the challenges it faced in a rapidly evolving tourism AI landscape.

Company Overview

This case study is based on a Vietnam-based tourism company that specialises in offering curated travel experiences in Vietnam, Cambodia, and Laos. With a workforce of over 50 employees spread across Vietnam, Cambodia, and Laos, the company has built a strong presence in the region's competitive tourism industry. The company operates on a B2C model, directly engaging with travellers to provide personalised services, including guided tours, accommodation bookings, transportation arrangements, and cultural experiences. The company's success is driven by its commitment to customer satisfaction, innovation in tour offerings, and adaptability to changing market demands.

Business Profile:

Name	N/A	Country	Vietnam
Representative Role	CEO	Number of employees	50+
Industry	Tourism	Type of Business	B2C

Departments	Sales		

To evaluate the impact that an AI project would have on this business, we analysed primary and secondary research sources and created the following models:

Table 17: Case Study 8 BMC

Key Partnerships	• AI technology providers for chatbot development and machine learning-based customer insights. • Local businesses and hotels for seamless integration of AI-powered bookings. • Government tourism boards and regulatory bodies ensuring compliance with AI-driven processes.
Key Activities	• Implementation of AI-driven chatbots for 24/7 customer support. • Personalization of travel recommendations using AI-based data analytics. • Integration of AI-powered pricing models to optimize tour package costs. • Automation of customer relationship management (CRM) and marketing campaigns.
Key Resources	• AI-powered CRM and chatbot software. • Data analytics tools for customer behavior prediction. • Trained workforce for AI system management and customer interaction.
Value Proposition	• Enhanced customer experience through AI-driven personalized recommendations and instant responses. • Cost savings through automation of administrative tasks and improved operational efficiency. • Competitive advantage by leveraging AI-driven insights for better decision-making and targeted marketing.
Cost Structure	• Initial investment in AI software and infrastructure. • Continuous maintenance and updates for AI-driven applications. • Employee training costs for AI system operation and management.
Revenue Stream	• Increased booking conversions due to AI-enhanced personalization. • Subscription-based premium AI-assisted travel planning services. • Partnerships with AI-integrated travel platforms for commission-based earnings.
Channels	• Website and mobile app featuring AI-driven booking recommendations. • Social media platforms utilizing AI for targeted advertising. • Online travel agencies (OTAs) integrating AI-powered customer support.
Customer Relationships	• AI-powered chatbots providing real-time assistance to customers. • Personalized email marketing and follow-up recommendations based on AI insights. • Enhanced user engagement via AI-driven content curation and sentiment analysis.
Customer Segments	• International travelers looking for customized experiences. • Budget-conscious tourists benefiting from AI-optimized pricing. • Repeat customers receiving tailored offers through AI-based loyalty programs.

Table 17 presents the BMC model, which highlights a customer-centric approach, offering personalised travel experiences across Southeast Asia through a B2C model. The integration of AI would support key activities such as customer service, marketing, and tour planning by enhancing personalisation and operational efficiency. However, the success of AI implementation depends on affordability, accessibility, and the skills required. As mentioned by the cost structure, AI offers long-term cost savings, however, the initial investment may be a barrier for SMEs, although cloud-based solutions can help reduce expenses. Additionally, the business must invest in upskilling its workforce to manage AI systems effectively to bridge the digital skills gap and ensure successful adoption.

Table 18: Case study 8 PESTEL

Political	• Government incentives for AI adoption in tourism may lower initial costs (Nguyen & Le, 2023). • Government-funded AI training programs can help bridge the skills gap (Nguyen & Le, 2023). • AI-related labor policies may require new certifications for employees handling AI systems.
Economic	• AI-driven automation reduces operational expenses, making services more affordable (Pham & Hoang, 2022). • High initial investment in AI infrastructure may be a financial challenge for SMEs. • AI-driven multilingual support increases market accessibility for non-English-speaking travelers. • Shortage of skilled AI professionals may drive up hiring and training costs (Pham & Hoang, 2022).
Social	• Affordability concerns among smaller travel operators may hinder AI adoption. • AI-enhanced accessibility features improve travel experiences for differently-abled tourists. • Digital literacy levels in rural areas may impact AI adoption and accessibility. • Workforce resistance to AI adoption due to fear of job displacement. • Need for continuous upskilling programs to adapt to evolving AI technologies.
Technological	• Cloud-based AI solutions offer cost-effective alternatives to on-premises installations. • AI-as-a-Service (AIaaS) models reduce upfront investment, making AI adoption more affordable for SMEs. • Open-source AI platforms reduce development costs for SMEs. • AI-based voice and text translation improve accessibility for international travelers. • Chatbots and virtual assistants offer 24/7 accessibility to travel services. • AI systems require skilled professionals for implementation, maintenance, and troubleshooting. • Advances in user-friendly AI tools may reduce the need for extensive technical expertise.
Environmental	• AI-optimized resource allocation can reduce operational waste, leading to cost savings. • Smart travel planning can minimize fuel consumption, reducing expenses for transportation partners. • AI-driven sustainability initiatives may require specialized training on eco-friendly travel solutions.
Legal	• Compliance with AI and data protection laws may increase legal costs (Tran & Vu, 2023). • AI-driven pricing strategies must adhere to fair competition laws. • Data security concerns may affect the accessibility of AI-driven travel recommendations. • Labor laws may mandate retraining programs to equip employees with AI-related skills (Tran & Vu, 2023).

Table 18 presents the PESTEL model for an SME in the tourism industry in Vietnam, which highlights key external factors influencing AI adoption. Politically, government support and digital transformation policies in Vietnam encourage AI integration, while legal frameworks require compliance with data protection laws. Economicly, affordability is a major consideration, as the initial costs of AI systems can strain SME budgets, though these may be offset by incentives and long-term efficiency gains. Technological advancements and the growing availability of cloud-based AI tools improve accessibility, but disparities in digital infrastructure, especially in Laos and Cambodia, may limit effective implementation. As mentioned in the social environment factor, increasing customer demand for tech-enabled services supports AI use, yet workforce readiness is a concern. The lack of AI skills may slow adoption, necessitating investment in training and upskilling programs, which impact the skills required for an AI project. Environmentally, AI can support more sustainable tourism practices, but specialised skills are needed to implement and manage such tools effectively.

Figure 22 depicts the implementation challenges in a tour agency SME. Poor affordability restricts access to AI-based management tools, while low digital literacy among local tour guides further constrains accessibility and skill deployment.

Figure 22: Case study 8 impact of affordability, accessibility and skills.

Figure 22 shows how affordability, accessibility and skills impacts and is impacted by the BMC and PESTEL model, further showing possible correlations that can be examined to understand the various extents of impacts. As per the BMC model, affordability, accessibility, and skills equally impact the internal factors that are presented by the model, each showing a correlation of 5 out of 8 factors. Similarly, the affordability and accessibility components illustrate a correlation of 5 out of the 6 PESTEL factors, and skills show a correlation with all the PESTEL factors, showing which external factors impact an AI project in the tourism industry in Vietnam.

This figure shows how AI adoption depends on social trust, cooperative platforms, and shared knowledge systems. It emphasizes the role of local partnerships in bridging skill and accessibility gaps.

Figure 23: Case study 8 Legal Impact and Key partnerships

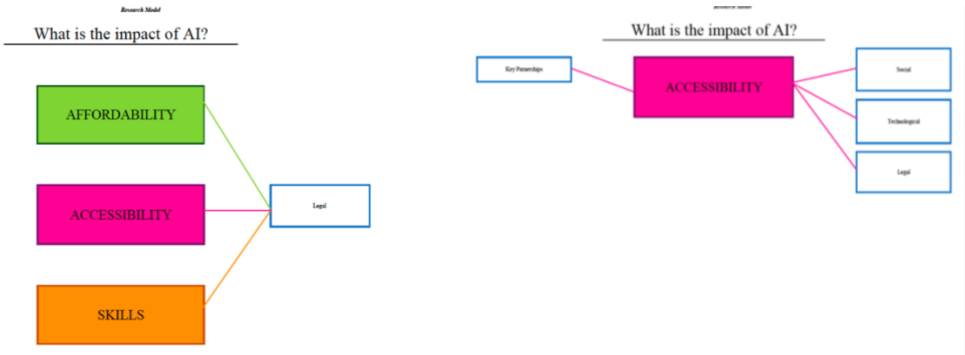


Figure 23 illustrates that for an AI project in the tourism industry in Vietnam, the legal environment impacts affordability, accessibility, and skills. This can be directly attributed by the following factors mentioned in table 18: Compliance with AI and data protection laws may increase legal costs (Tran & Vu, 2023), AI-driven pricing strategies must adhere to fair competition laws – Affordability; Data security concerns may affect the accessibility of AI-driven travel recommendations – Accessibility; Labour laws may mandate retraining programs to equip employees with AI-related skills (Tran & Vu, 2023) – Skills. The second illustration presented in Figure 23 shows how accessibility impacts the key partnerships and is impacted by the external social, technological, and legal environment. These factors include accessibility to key partnerships such as technology providers and local business and hotels, external factors such as socially- AI-enhanced accessibility features improve travel experiences for differently-abled tourists, technologically - AI-based voice and text translation improve accessibility for international travelers and chatbots and virtual assistants offer 24/7 accessibility to travel services, and legally – data security concerns that impacts accessibility.

Using the information that populated tables 17 and 18, and figures 22 and 23, RQ1 part two was presented and solved with the following proposed factors:

1. How will affordability impact an AI project in an SME in the Tourism industry in Vietnam?

- Internally, affordability will impact the cost structure, key activities, key resources, revenue stream and channels of the AI project.
- Externally, affordability will be impacted by the political, economic, social, technological and legal environment in Vietnam.

2. How will accessibility impact an AI project in an SME in the Tourism industry in Vietnam?

- Internally, accessibility will impact the key partnerships, key activities, key resources, revenue stream and channels of an AI project.
- Externally, accessibility will be impacted by the economic, social, technological, environmental and legal environment in Vietnam.

3. How will the skills required for an AI project impact the project in an SME in the Tourism industry in Vietnam?

- Internally, the skills required impact the cost structure, key activities, key resources, customer relations and customer segments of an AI project.
- Externally, the skills required will be impacted by the political, economic, social, technological, environmental and legal environment in Vietnam.

This solved RQ1 part 2, showing that the integration of an AI project in an SME in the Tourism industry in Vietnam has both opportunities and challenges pertaining to affordability, accessibility, and skills. The case study highlights the key drivers that could lead to competitive advantage, a viable response to market dynamics, and the broader implications for tourism enterprises operating in Southeast Asia. The integration of AI in the business's operations enhances both affordability and accessibility, driving efficiency and improving customer experience. While AI reduces operational costs and increases market reach, challenges such as compliance, initial investment, and workforce adaptation must be managed effectively. A strategic AI adoption approach will ensure maximum benefits while mitigating associated risks by leveraging AI for automation, personalisation and predictive analytics. The Key Takeaways of the PESTEL model are Political and Legal factors affecting compliance, funding, and partnerships for AI adoption, Economic factors that determine AI affordability and long-term financial benefits, Social factors that drive demand for AI-enhanced services and personalized experiences, Technological advancements enable AI-driven automation, efficiency, and innovation, Environmental concerns that influence AI-powered sustainability initiatives, and Legal concerns about data security and AI regulations.

4.2.9. Case Study 9: AI Implementation in the Retail Industry in India

Introduction

India's boutique retail clothing sector has experienced significant transformation in recent years, driven by rising disposable incomes, a growing middle class, and increasing demand for personalised fashion experiences (IBEF, 2023). Boutique clothing stores, often characterised by curated, artisanal collections and personalised customer service, face the dual challenge of maintaining uniqueness while competing with larger e-commerce players. Artificial intelligence (AI) has begun reshaping the retail landscape by enabling data-driven decision-making, enhancing customer personalisation, and optimising inventory management (Davenport & Ronanki, 2018). For small boutique retailers, AI presents opportunities to improve operational efficiency, elevate customer experience, and remain competitive in an increasingly digital marketplace. This case study explores the impact of AI implementation on a boutique clothing store in India, focusing on the affordability, accessibility, and skills required for effective adoption. It also examines the qualitative and quantitative value creation of AI through a PESTEL framework. The analysis aims to provide practical insights for small and medium-sized enterprises (SMEs) seeking digital transformation through AI.

Company Overview

This case study is based on a small business-to-consumer retail company based in Mumbai, India, specialising in luxury fashion, jewellery, and handcrafted products. The business has gained international recognition through its worldwide shipping services and personalised shopping experiences. They employ between 1 and 10 staff members and have a sales, marketing, and finance department.

Business Profile:

Name	N/A	Country	India
Representative Role	Founder	Number of employees	1-10
Industry	Retail- Clothing	Type of Business	B2C
Departments	Sales	Marketing	Finance

To evaluate the impact that an AI project would have on this business, we analysed primary and secondary research sources and created the following models:

Table 19: Case Study 9 BMC

Key Partnerships	• AI technology providers (Google Cloud AI, IBM Watson, Shopify AI)

	• Logistics and shipping companies (FedEx, DHL, Blue Dart) • Local artisans and jewelry manufacturers • Financial institutions offering AI-driven payment solutions
Key Activities	• AI-powered personalized product recommendations • AI-driven customer support (chatbots, virtual assistants) • AI-enhanced inventory management and demand forecasting • Automated fraud detection for online transactions • AI-driven marketing and social media optimization
Key Resources	• AI-powered e-commerce platform • Skilled workforce trained in AI operations • Secure payment and fraud prevention systems • AI-driven customer insights and analytics
Value Proposition	• Personalized AI-driven shopping experience • Faster and more efficient customer service • AI-optimized logistics for reduced shipping delays • Fraud prevention for secure transactions • Competitive pricing through AI-driven market analysis
Cost Structure	• AI software and maintenance costs • AI training and upskilling employees • Data security and compliance expenses • AI-powered logistics and automation tools
Revenue Stream	• Online sales via AI-optimized pricing strategies • Subscription-based AI-powered styling services • AI-driven targeted advertisements • Partnerships with AI-based retail influencers
Channels	• AI-enhanced e-commerce website • Social media platforms with AI-driven advertising (Instagram, Facebook, TikTok) • AI-powered mobile application • AI-integrated email and SMS marketing
Customer Relationships	• AI-powered chatbots for 24/7 customer support • AI-driven loyalty programs with personalized discounts • Virtual AI-assisted shopping consultations • Automated post-purchase follow-ups and recommendations
Customer Segments	• High-net-worth individuals seeking luxury products • International buyers looking for authentic Indian fashion and jewellery • Tourists purchasing souvenirs online • Millennials and Gen Z consumers engaging in digital shopping

Table 19 presents the BMC model for a boutique clothing store in the Retail industry in India. The BMC analysis reveals that implementing an AI project in the boutique retail clothing store enhances operational efficiency, customer experience, and global competitiveness. Key partnerships, resources and activities include AI vendors, logistics tech platforms, and digital marketing agencies that support the integration and operation of AI systems, skilled digital staff, and a robust IT infrastructure. For boutique clothing stores in India, strategic planning and partnerships can ensure affordable and accessible AI integration with the right skills in place. The channels, customer relationships and segments make use of a direct digital communication approach.

Table 20: Case Study 9 PESTEL

Political	• Government AI Initiatives: The Indian government supports AI adoption through Digital India and the National AI Strategy (NITI Aayog, 2018). • Regulations on AI and Data Privacy: Compliance with the Digital Personal Data Protection Bill, 2022 impacts AI-driven customer data handling (Government of India, 2022). • Trade Regulations: Global AI trade policies may impact AI-powered cross-border e-commerce transactions. • Public-private partnerships (e.g., AI training by NASSCOM and tech giants like Google) improve AI workforce development in India (NASSCOM, 2022).
Economic	• Cost of AI Implementation: AI adoption requires high initial investment but offers long-term cost savings through automation (McKinsey & Company, 2022). • AI-as-a-Service (AIaaS): Subscription-based AI services (Google Cloud AI, AWS AI) make AI affordable for small businesses (PwC, 2023). • Financial Incentives for AI: Government and private funding schemes can support AI integration. • Gig economy and outsourcing opportunities provide cost-effective access to AI expertise (Deloitte, 2022). • Digital payments and e-commerce growth in India enhance the affordability and accessibility of AI-driven payment processing and fraud detection systems (IBEF, 2023). • Currency fluctuations impact the cost of AI tools sourced internationally.
Social	• AI Literacy: Lack of AI skills among employees may require training investments (World Economic Forum, 2022). • Personalization Trend: Consumers prefer AI-driven customized shopping experiences. • Growing AI education in Indian universities increases the availability of entry-level AI talent (IBEF, 2023). • Urban-rural digital divide affects AI accessibility, as businesses in urban areas have better access to AI-powered logistics and marketing tools. • Retail Customers in India Are Digitally Engaged, driving demand for AI-driven personalization, loyalty programs, and automated customer support.
Technological	• Advancements in AI Tools: Cloud-based AI platforms make AI integration easier and more cost-effective (KPMG, 2021).

	• AI-Driven Marketing Automation: AI-based social media targeting and email marketing optimize customer outreach. • Cybersecurity Requirements: AI implementation requires secure data handling and fraud detection systems. • No-code and low-code AI platforms (e.g., Shopify AI, OpenAI's ChatGPT API) improve AI accessibility for businesses with limited technical expertise (KPMG, 2021). • AI-powered customer support tools (e.g., chatbots, recommendation engines) reduce the need for manual workforce expansion (NASSCOM, 2022). • High-speed internet and 5G adoption improve AI accessibility for businesses relying on AI-driven logistics and analytics (NASSCOM, 2022). • High Cost of Custom AI Development (~₹5–25 lakh for a custom AI system).
Environmental	• Green AI Adoption: Energy-efficient AI solutions reduce operational costs and align with sustainability goals (World Economic Forum, 2022). • AI-Optimized Logistics: AI helps reduce carbon footprint by optimizing supply chain routes and warehouse efficiency. • Eco-Friendly Consumer Preferences: AI can help track and promote sustainable products. • Limited awareness of green AI may result in businesses adopting inefficient AI models. - Knowledge of green AI and energy-efficient AI models is increasingly valuable (World Economic Forum, 2022). • Demand for AI sustainability expertise could drive new job roles in energy-efficient AI implementation.
Legal	• Data Protection Laws: Compliance with India's Personal Data Protection Bill, 2022, affects AI-based customer data processing (Government of India, 2022). • AI Bias and Ethical Regulations: AI must ensure fair pricing and unbiased product recommendations (European Commission, 2021). • Intellectual Property Laws: AI-generated designs and marketing content require compliance with IP laws. • International trade regulations on AI-powered e-commerce impact AI accessibility for businesses engaged in global shipping (European Commission, 2021).

Tables 20 presents the PESTEL analysis provides a comprehensive view of the external factors influencing the boutique clothing store's ability to adopt and benefit from an AI project in India. The political environment shows that Supportive government initiatives like the Digital India programme promote AI adoption among small businesses, improving accessibility and affordability. Furthermore, the political, social and technological environment analysis demonstrates that while AI adoption presents some financial and skill-related barriers**,** these are increasingly offset by government support, digital infrastructure growth, and a tech-savvy workforce**.** In terms of skills, the environmental and legal environment suggests that integrating sustainability-focused AI requires interdisciplinary expertise, and legal literacy around AI ethics and data usage is essential for implementation.

Figure 24 models how a retail store in India faces rising operational costs and inconsistent infrastructure. Skills training is central to mitigating these issues and scaling AI systems.

Figure 24: Case study 9 impact of affordability, accessibility, and skills

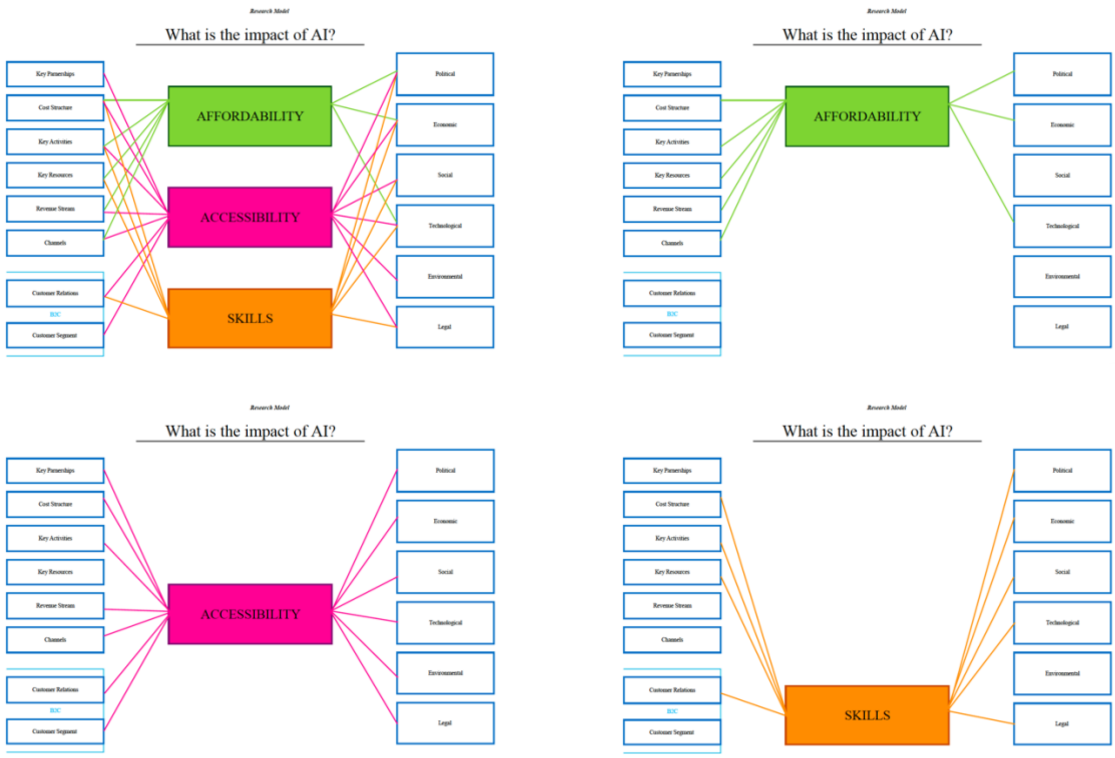


Figure 24 illustrates the correlation and impact between the internal and external variables presented by the BMC and PESTEL analysis to evaluate the impact of affordability, accessibility, and skills required to implement an AI project in a boutique retail clothing store in India. According to the diagrams, cost structure is impacted by affordability, accessibility, and skills, this can be attributed to the information presented in table 21, highlighting that AI introduces upfront costs (software, training, system integration), but over time reduces costs via automation of customer service, stock management, and marketing. Furthermore, the diagrams present that accessibility is the leading internal impact factor, impacting 7 of 8 BMC components, followed by affordability and then skills. Externally, accessibility is also the leading impacted factor, followed by skills and then affordability. As per the technological environment, tools are increasingly accessible online, which improves accessibility. Consequently, affordability, because cloud AI lowers the financial entry point, although conversely posing a challenge towards skills, because Complex AI still needs expert management.

This figure isolates the macro-environmental risks affecting AI investment. It shows that policy instability and unclear legal guidelines discourage small firms from scaling AI initiatives, regardless of technical capability.

Figure 25: Case Study 9 Impact of the political, economic and legal environment

Figure 25 illustrates that affordability, accessibility and skills required for an AI project are all impacted by the political environment. Government incentives reduce costs, Digital India expands AI access, and skill programs promote workforce readiness. However, Regulations on AI and Data Privacy impact AI-driven customer data handling and Trade regulations. Global AI trade policies may impact AI-powered cross-border e-commerce transactions. Economically, AI-as-a-Service, the gig economy, and digital payment platforms positively impact affordability, accessibility and skills, but the fluctuations of exchange rates negatively impact affordability. Legally, data protection laws and intellectual property laws impact the accessibility and skills required to maintain systems that adhere to these laws. International trade regulations on AI-powered e-commerce also impact AI accessibility for businesses engaged in global shipping.

Using the information that populated tables 18 and 19, and figures 24 and 25, RQ1 part two was presented and solved with the following proposed factors:

1. How will affordability impact an AI project in an SME in the Retail industry in India?
   - Internally, affordability will impact the cost structure, key activities, key resources, revenue stream and channels of the AI project.
   - Externally, affordability will be impacted by the political, economic, and technological environment in India.
2. How will accessibility impact an AI project in an SME in the Retail industry in India?

- Internally, accessibility will impact the key partnerships, cost structure, key activities, revenue stream, channels, customer relations and customer segment of an AI project.
- Externally, accessibility will be impacted by the political, economic, social, technological, environmental and legal environment in India.

3. How will the skills required for an AI project impact the project in an SME in the Retail industry in India?

- Internally, the skills required impact the cost structure, key activities, key resources, and customer relations of an AI project.
- Externally, the skills required will be impacted by the political, economic, social, technological, and legal environment in India.

This solved RQ1 part 2, demonstrating that integrating an AI project in a retail SME in India presents both opportunities and challenges related to affordability, accessibility, and skills. The integration of AI in a small B2C retail business in India that offers worldwide shipping has a transformative impact across all aspects of the BMC. AI enhances operational efficiency, customer experience, and profitability by automating processes, optimising logistics, and personalising customer interactions. As AI technology continues to advance, businesses that leverage its capabilities will gain a competitive edge in the global e-commerce landscape. AI affordability is influenced by multiple PESTEL factors, including government incentives, economic conditions, technological advancements, and regulatory costs. While AI adoption requires significant initial investment, cloud-based and open-source AI solutions make it more accessible for small businesses. Investment in scalable AI tools can ensure cost-effective implementation while maintaining compliance with legal and environmental regulations, and can overcome accessibility barriers and enhance their competitiveness in global e-commerce markets. Although AI-as-a-Service and no-code AI platforms reduce skill dependencies, businesses still require foundational AI knowledge to implement AI-driven automation, customer support, and logistics optimisation. Strategic investments in AI training, outsourcing AI functions, and leveraging cloud-based AI solutions can help small businesses overcome AI skills gaps while maintaining operational efficiency and global competitiveness.

4.2.10. Case Study 10: AI Implementation in the Business Industry in Chile

Introduction

SMEs play a crucial role in the global economy, particularly in developing and emerging markets. In Chile, SMEs represent approximately 98% of all enterprises and contribute significantly to employment and GDP (OECD, 2022). In Latin America, Chile has emerged as one of the more digitally advanced nations, ranking high on regional indices for innovation and internet penetration (IDB, 2021). The Chilean government has introduced the National AI Policy to encourage ethical and inclusive AI adoption, with a focus on SMEs and public services. The Chilean government has introduced the National AI Policy to encourage ethical and inclusive AI adoption, with a focus on SMEs and public services. Business consulting in Chile is a dynamic sector, supporting companies across areas such as strategic management, digital transformation, financial advisory, and operations. B2B consulting SMEs cater to local businesses needing expertise to improve performance or navigate complex environments, especially in sectors like mining, retail, and agriculture (ProChile, 2022). This case study examines the integration and impact of AI in a Chilean B2B consulting SME, exploring how AI reshapes consulting practices, client engagement, and business outcomes.

Company Overview

This case study evaluates a small-medium B2B consulting firm based in Chile, the company offers strategic and operational consulting to SMEs. Employing 1-10 staff members, it has a sales, IT and Finance department.

Business Profile:

Name	N/A	Country	Chile
Representative Role	CEO	Number of employees	1-10
Industry	Business	Type of Business	B2B
Departments	Sales	IT	Finance

To evaluate the impact that an AI project would have on this business, we analysed primary and secondary research sources and created the following models:

Table 21: Case Study 10 BMC

Key Partnerships	• AI technology providers (e.g., software vendors, cloud services) • Universities and research institutions for talent and R&D collaboration

	• Government and development agencies offering AI grants and incentives • Strategic alliances with data analytics firms
Key Activities	• Client advisory and strategic planning • Data analysis, risk assessment, and solution design • AI-driven forecasting and modelling • Training and change management services • Enhanced scenario modelling and predictive consulting (Davenport & Ronanki, 2018)
Key Resources	• Skilled consultants (now also including AI/data specialists) • AI software tools and platforms • Proprietary datasets and client data - Increased value of data as a strategic resource (Brynjolfsson & McAfee, 2017) • Training infrastructure
Value Proposition	• Tailored, data-driven strategic advice • Faster decision-making support using predictive AI • Improved accuracy in market and risk analysis • Competitive edge through technology-led consulting - Enhanced client value through automation and personalization - Differentiation through AI-powered insights (Chui et al., 2018)
Cost Structure	• Staff salaries (including new AI roles) - Initial investment in AI tools and upskilling • AI infrastructure and software subscriptions - Long-term cost savings through process automation (Bughin et al., 2018) • Data management and compliance costs • Training and change management programs
Revenue Stream	• Consulting fees (hourly/project-based) • Subscription models for AI-powered tools or dashboards • AI training and implementation services • Performance-based revenue linked to client success
Channels	• Direct interactions (meetings, webinars) • Digital platforms (consulting portals, AI dashboards) - Expansion into digital and real-time service delivery • AI chatbots and virtual assistants for client support - Improved self-service channels using AI tools (Ransbotham et al., 2017)
Customer Relationships	• Long-term strategic partnerships • Personalized client engagement via CRM AI tools • Proactive issue resolution using predictive analytics
Customer Segments	• SMEs and large corporations seeking digital transformation • Public sector organizations • NGOs and international agencies in Latin America

Table 21 shows that an AI project in a business consulting firm in Chile can transform the firm's business model by enhancing value propositions through data-driven insights and predictive analytics. Key activities shift toward AI-enabled services, requiring new skills and digital infrastructure. While upfront costs rise due to AI tools and training, long-term efficiencies lower operational expenses. Customer relationships become more personalised via AI-powered tools, and new digital service channels emerge. Overall, AI enhances competitiveness but demands careful attention to affordability, accessibility of technology, and availability of skilled personnel to ensure sustainable integration and growth.

Table 22: Case Study 10 PESTEL

Political	• Government support for AI initiatives through the National AI Policy can facilitate funding and resources for AI projects. Stability in government policies encourages investment in technology. - Increased public spending on digital transformation in Chile is expected to rise by 15% annually, leading to potential subsidies or grants for SMEs implementing AI (OECD, 2022). • According to the OECD (2022), investments in digital infrastructure in Chile are projected to increase by 12% annually, indicating improved accessibility for SMEs seeking to adopt AI solutions. • The Chilean government has invested approximately USD 10 million in AI education programs and training initiatives aimed at SMEs (Gobierno de Chile, 2021), which can improve the availability of skilled workers for AI projects.
Economic	• The overall economic health of Chile influences the spending capacity of SMEs. A growing economy typically leads to increased demand for consulting services and investment in technology. - According to the World Bank (2023), Chile's GDP growth rate is projected to be 3% in the next year, indicating a moderate increase in business investment capacity. The cost of AI project implementation is estimated at USD 50,000 for initial setup and training. • Chile's GDP per capita is expected to reach approximately USD 18,000 by 2025 (World Bank, 2023), indicating a potential increase in disposable income for SMEs, which can enhance accessibility to AI tools and services. • According to the World Economic Forum (2023), the demand for AI and machine learning skills in Latin America is expected to grow by 20% annually, indicating a rising need for skilled professionals in the coming years.
Social	• Growing acceptance of AI among businesses can enhance the willingness to invest in AI solutions. The workforce's adaptability to technology influences training costs and project success. - Surveys show that 70% of Chilean SMEs are open to adopting AI solutions, reflecting a cultural shift toward digital transformation (IDB, 2021). This openness can result in higher client engagement, justifying investment costs. • Surveys indicate that 60% of Chilean SMEs report a lack of knowledge about AI technologies (IDB, 2021). Addressing this knowledge gap through training could improve accessibility for many businesses.

	• Surveys show that 75% of employees in Chilean SMEs express interest in receiving training in AI and data analytics (IDB, 2021). This enthusiasm can facilitate the development of necessary skills within the organization.
Technological	• Rapid advancements in AI technologies can reduce the cost of implementation over time. Increased availability of cloud-based AI solutions lowers entry barriers for SMEs. - The cost of AI technology is declining, with cloud services expected to reduce operational expenses by 25% for small businesses by 2025 (McKinsey, 2021). • The market for AI tools is expected to grow at a compound annual growth rate (CAGR) of 25% in Latin America, indicating a broader range of accessible tools for SMEs by 2025 (McKinsey, 2021). • The rapid evolution of AI technologies necessitates continuous learning and adaptation. Organizations must invest in ongoing training programs to keep skills up to date.
Environmental	• Implementing AI-driven solutions for sustainability may require an additional 10-20% of the AI project budget (World Bank, 2023). • Environmental considerations may not directly impact the skills required for AI projects; however, skills related to sustainability and green technologies may become increasingly important as businesses adopt AI for environmental monitoring and compliance. - Skills in environmental analytics and sustainable practices are projected to account for 15% of the total skills demand in AI projects by 2025 (World Bank, 2023). This could require additional training investments.
Legal	• Compliance with data protection regulations in Chile can increase the cost of AI projects due to the need for robust security measures. However, it also builds trust with clients. - Compliance costs can constitute approximately 10-15% of the total project budget. For an AI project estimated at USD 50,000, this translates to USD 5,000 to USD 7,500, which can be a barrier for SMEs with limited budgets (OECD, 2022).

Table 22 presents a PESTEL analysis for a business consulting firm in Chile, which shows that Political support for digital transformation in Chile improves accessibility to AI through public-private initiatives and grants. Whereas, Technological advancements lower barriers, improving accessibility**,** but also demand up-to-date infrastructure. The economic environment suggests a growth in the overall economy, increasing spending capacity and leading to a higher demand for consulting services and technology investment, promoting the affordability of AI. Due to the nature of the business, Environmental concerns have minimal direct impact but may shape the budget for data centre options. The social and legal environment shows that social attitudes toward technology influence skills adoption, and legal frameworks around data privacy increase the need for skilled personnel to manage compliance. Overall, PESTEL factors highlight that while Chile offers growing AI opportunities, affordability, skills development, and infrastructure access are critical to success.

Figure 26 explores AI use in a B2B Management Consulting SME in Chile, it underscores how high AI licensing fees and limited connectivity curb adoption, despite moderate digital proficiency among staff.

Figure 26: Case Study 10 impact of affordability, accessibility, and skills

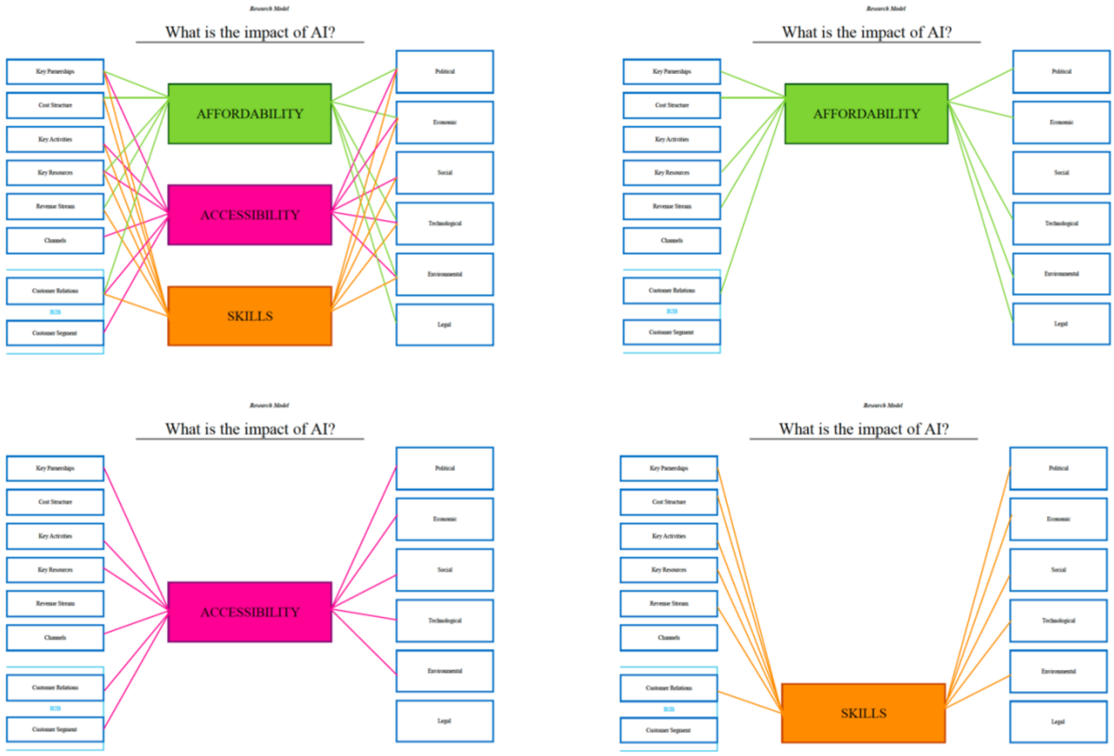


Figure 26 illustrates the impact of affordability, accessibility and skills required for an AI project using the BMC and PESTEL analysis. Internally, accessibility and skills are highly impactful, followed by affordability. Externally, affordability, accessibility, and skills are equally impacted. Key resources, customer relations, and the political and economic environment are common factors. This can be attributed to key resources such as skilled consultants, AI software tools and platforms, proprietary datasets and client data, and customer relationships being enhanced by AI CRM tools and predictive analysis, as well as government investment into AI education and training and an increase in demand for skilled professionals.

This figure focuses on how affordability, accessibility, and skills affect customer-facing operations. It shows that AI adoption can enhance personalized marketing and service delivery, but only when affordability and digital literacy barriers are overcome.

Figure 27: Case study 10 Impact of customer relations and segments

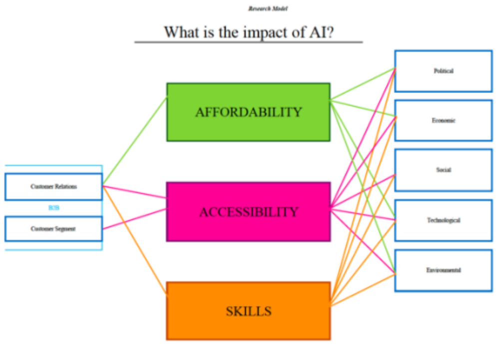


Figure 27 illustrates the correlation between the external factors that impact affordability, accessibility, and skills that consequently impact customer relations and customer segments. Internally, table 22 shows that an AI project impacts customer relations due to Long-term strategic partnerships, personalised client engagement via CRM AI tools, proactive issue resolution using predictive analytics, and customer segments due to SMEs and large corporations seeking digital transformation, public sector organisations, NGOs and international agencies in Latin America. The external factors that correlate to the impact are economic - a growing economy typically leads to increased demand for consulting services and investment in technology, social - surveys show that 75% of employees in Chilean SMEs express interest in receiving training in AI and data analytics (IDB, 2021), technological - the market for AI tools is expected to grow at a compound annual growth rate (CAGR) of 25% in Latin America, indicating a broader range of accessible tools for SMEs by 2025 (McKinsey, 2021), and environmental - Implementing AI-driven solutions for sustainability may require an additional 10-20% of the AI project budget (World Bank, 2023), and political - government support for AI initiatives through the National AI Policy can facilitate funding and resources for AI projects. Chile’s National AI Policy provides a practical example of how public policy can directly facilitate SME AI adoption. The consulting SME in this case can benefit from Government grants and incentives for AI integration, strategic partnerships with universities and research institutions supported by state funding, participation in national digitalisation programs focused on SME transformation. These measures help reduce implementation costs and attract technical talent, addressing both affordability and skills barriers. This case illustrates how national digital strategies such as Chile's AI policy can tangibly reduce SME entry barriers into AI transformation. Government funding supported partnerships with AI providers and subsidised staff training. These mechanisms align with broader findings that targeted state intervention enhances both the affordability and availability of AI tools (Mazzucato, 2018; OECD, 2022).

Using the information that populated tables 21 and 22, and figures 26 and 27, RQ1 part two was presented and solved with the following proposed factors:

1. How will affordability impact an AI project in an SME in the Business Consulting Industry in Chile?
    - Internally, affordability will impact the key partnerships, cost structure, key resources, revenue stream and customer relations of the AI project.
    - Externally, affordability will be impacted by the political, economic, technological, environmental, and legal environment in Chile.
1. How will accessibility impact an AI project in an SME in the Business Consulting industry in Chile?
    - Internally, accessibility will impact the key partnerships, key activities, key resources, channels, customer relations and customer segment of an AI project.
    - Externally, accessibility will be impacted by the political, economic, social, technological, and environmental environment in Chile.
2. How will the skills required for an AI project impact the project in an SME in the Business Consulting industry in Chile?
    - Internally, the skills required impact the key partnerships, cost structure, key activities, key resources, revenue stream and customer relations of an AI project.
    - Externally, the skills required will be impacted by the political, economic, social, technological, and environmental environment in Chile.

This solved RQ1 part 2, demonstrating the impact of an AI project in a business consulting SME in Chile related to affordability, accessibility, and skills. The case study illustrates how AI can enhance the competitiveness of consulting SMEs in Chile by enabling data-driven services and operational efficiencies. However, successful adoption requires not only technological investment but also strategic change management, talent development, and client education. The affordability and accessibility of an AI project are influenced by various external factors as identified in the PESTEL analysis. Politically, supportive policies can lower barriers and enhance digital access. Economicly, GDP growth can enhance the firm's capacity to invest. Socially, education and awareness are crucial for increasing accessibility, social acceptance of AI solutions boosts market potential, and employee interest in AI education can facilitate internal skill development. Technologically, the necessity for ongoing learning underscores the need for training budgets, however, technological advancements reduce costs, while environmental considerations may slightly increase initial investments. Legal requirements for compliance also need to be factored into the project budget, and compliance with regulations necessitates specific skill sets to ensure ethical AI use. As Chile continues to foster its AI ecosystem, firms can be well-positioned to drive innovation within the SME sector.

4.3. Multi-Case Study A

To determine RQ2, the support structures that are required to successfully adopt an AI system, a multi-case study was developed by amassing and inferring data gathered from single case studies 1 to 10. As per the dimensions and criteria set in Chapter 3 Operationalization of Theoretical Constructs, seven dimensions were implemented as a guideline to analyse each case study's BMC model that was compiled for RQ1 results.

4.3.1. Project Planning and Preparations – Value proposition, Key Activities, and Key Resources

KPI Development and Strategic Alignment

The basis of KPI development is forming an AI-aligned strategic roadmap with clear business objectives and clearly defining them for AI impact. The value propositions can be used to determine the main purposes of the AI system and, consequently, what factors to evaluate to determine if the system is meeting its objectives. The case studies presented value propositions that highlighted cost reduction, enhanced AI-driven customer experience, faster and more accurate decision making and enhanced security. To ensure that these key objectives are met, stakeholder alignment meetings can be held to ensure that project goals support the firm’s value proposition, and a Business case can be developed showing ROI expectations and risk mitigation. For this stage, support structures would consist mainly of human capital in terms of stakeholder engagement on multiple levels and thorough research and historical evaluations.

4.3.2. Infrastructure Development – Key Partnerships and Key Resources

Technical Readiness and Data Availability

The key partnerships and resources that were mentioned in all the case studies were related to tech-providers for both software and hardware components that would be required to develop an AI system. In the context of technical readiness, support structures for this would be scalable cloud or on-premises computing infrastructure and support structures for data availability would be secure data storage and processing systems, and clean, structured, and accessible datasets for training AI models, and Investment (financial or skill based) in data governance frameworks and compliance tools.

4.3.3. Workforce Engagement – Key partnerships, Key Activities, and Key Resources

Skills Development and Change Management

The key partnerships that are related to skills development and change management are AI Tech Providers and Consultants, and government and development agencies that offer AI training grants and incentives. Furthermore, by analysing the key activities such as data analytics and forecasting, and key resources such as CRM, AI software tools and platforms and training infrastructure, the support structures that can be implemented are upskilling programs in data literacy, AI tools, and ethical AI usage. To support change management and knowledge exchange, and training, cross-functional AI teams blending technical and domain expertise can be utilised, as well as internal AI champions or change agents to lead transformation, and regular change management workshops to address fears and resistance.

4.3.4. Implementation Process – Key Activities and Channels

Technical Deployment and Process Integration

Based on the case studies, data analytics and automation are core activities of any AI system, and channels include online platforms and AI-enabled chatbots. For this, knowledge of the existing processes, systems, and customers must be integrated. A support structure for this would be a dedicated AI project management team that can use agile methodologies to roll out AI features in stages, develop process mapping and workflow redesign to integrate AI seamlessly, and deployment of API systems and automation tools for integration with existing platforms.

4.3.5. Measurable Outcomes – Value Propositions and Revenue Streams

Operational Efficiency and Decision-making Enhancements

The intended value proposition and revenue stream objectives can be identified as measurable outcomes for an AI system. Deduced from the value propositions and revenue streams presented in all the case studies, operational efficiency is commonly associated with reduced costs and data analytics, and revenue streams from optimised service offerings and customer service experiences. To support the development of measurable outcomes, support structures are tools for monitoring AI performance metrics, dashboards for real-time decision-making insights, client feedback loops to validate improvements in service delivery and regular impact reviews (e.g., before-and-after productivity metrics).

4.3.6. Sustainability – Cost Structure and Revenue Streams

Scalability, Maintenance and Support

To ensure that the system is sustainable in terms of its ongoing life cycle and adaptability to future enhancements, scalability, maintenance, and support must be accommodated. Despite the variety of industries presented by the case studies, the cost structure component involves AI infrastructure and skills training, and the revenue stream is based on multiple-tier revenue streams. In this regard, the support structures required are scalable AI platforms that grow with business needs, dedicated teams for ongoing AI system updates and model retraining, cost models that plan for long-term AI maintenance and support, and modular AI architecture allowing reuse across services and clients.

4.3.7. Ecosystem Engagement – Key Partnerships, Customer Segments, and Customer Relationships

Partnerships and Regulatory Compliance

The common key partnerships that were emphasised in the case studies were governments and institutional support, which aimed at improving skills and training and the AI regulatory framework and governance. The support structures for ecosystem engagement are strategic partnerships with AI vendors, universities, and R&D centres, engagement with government programs promoting AI adoption, compliance frameworks aligned with local and international AI/data regulations, and participation in industry AI forums to stay updated on ethical and legal standards.

4.4. Multi-Case Study B

To determine the qualitative value creation of AI concerning operational growth, value creation and operational growth were analysed. Drawing from ten case studies across diverse sectors and geographies, the analysis is structured using four key constructs. By integrating the BMC elements with PESTEL, the framework provides a multidimensional understanding of AI's impact within specific operational environments. The analytical framework that is used for each case study is analysed using the four key constructs: Industry- sector-specific AI use cases and operational challenges, location- geographic and infrastructural considerations, social-cultural structures - language, digital literacy, and cultural adaptability, and PESTEL- broader macro-environmental conditions influencing AI adoption and effectiveness. The case study analysis to determine the value creation is as follows:

4.4.1. Renewable Energy – Namibia

The AI-driven energy forecasting and diagnostics industry will successfully reduce maintenance costs and enhance energy reliability in Namibia, efficiently serving both rural and urban areas. User-friendly interfaces, designed to accommodate low digital literacy and multiple languages, will significantly increase adoption rates. Politically, government incentives will support the integration of renewable energy and AI technologies. However, the limited local research and development efforts will necessitate reliance on imported AI systems. Despite this reliance, technological advancements will contribute to improved grid reliability, better rural access, and overall energy sustainability. This approach will create value by enhancing resilience, improving energy access, and providing user-focused service models.

4.4.2. Telecommunications – South Africa

The telecommunications industry in South Africa is expected to experience significant improvements through AI-optimised network traffic and automated customer service, which will collectively elevate service quality. This technological advancement is anticipated to facilitate effective urban-rural network deployment and robust performance management. Moreover, AI will likely bridge digital literacy gaps through the implementation of chatbots and mobile interfaces, contributing to enhanced network reliability and more equitable digital access. The competitive market is expected to drive continuous innovation in this sector, while data privacy regulations will influence AI design. This approach is projected to create an inclusive digital infrastructure and automated service delivery, making significant strides in value creation.

4.4.3. Construction – South Africa

In the construction industry in South Africa, AI has significantly supported cost estimation, project tracking, and safety compliance, enabling agile resource management in fast-growing urban centres. AI-assisted training has addressed labour skill shortages, increasing project efficiency, reducing downtime, and empowering the workforce. Environmentally, AI contributes to sustainable construction through energy modelling, while politically, the government's focus on infrastructure creates demand for these technologies. This approach has led to value creation in the form of faster project cycles, safer work sites, and green compliance.

4.4.4. Fitness – South Africa

The fitness industry in South Africa will benefit from AI through personalised workout plans and automated scheduling, which can be expected to significantly increase client retention. A hybrid model combining physical and digital services will achieve location-focused support for urban clients. Culturally, custom health recommendations will resonate well with local health goals, leading to value creation in the form of personalised services, enhanced client engagement, and operational flexibility. From a PESTEL perspective, the rising health consciousness in the social sector can support the adoption of AI fitness technology, while the technological sector will benefit from the widespread use of mobile devices, facilitating the use of AI fitness apps. This will culminate in improved personalised wellness, greater client engagement, and better outreach within urban areas.

4.4.5. Renewable Energy – Ghana

In Ghana, AI-enabled performance prediction and fault detection in solar installations can be expected to extend energy access to underserved rural areas. AI applications incorporate local language support for broader accessibility, contributing to energy democratisation, proactive maintenance, and educational impact. Politically, policy shifts toward decentralisation support the technology, while economically, energy cost savings improve the return on investment (ROI) on AI systems. This approach can lead to improved uptime and decentralised energy access.

4.4.6. Restaurant – Malawi

The restaurant industry in Malawi has the opportunity to see significant advancements with AI forecasted demand and optimisation of procurement and logistics. This technology can help mitigate the effects of unreliable infrastructure and supply chains. Moreover, menus and ordering systems can be adapted to local dietary preferences and languages, contributing to waste reduction, improved supply consistency, and enhanced customer satisfaction. From a PESTEL perspective, the economic sector faces limitations due to the informal economy, while the social sector sees traditional food practices shaping AI customisation. Ultimately, the integration of AI can lead to operational stability, waste reduction, and cultural resonance.

4.4.7. Retail – India

In India, the retail industry has seen substantial improvements through AI-powered inventory management and customer targeting, which have significantly increased sales efficiency. The technology can enable high-volume, precision retail operations in urban settings, support small retailers and diverse consumers with multilingual AI tools. This leads to operational optimisation, market inclusivity, and tailored consumer outreach. From a PESTEL perspective, high mobile adoption supports AI commerce, while emerging e-commerce laws affect algorithmic transparency, resulting in smart inventory, increased sales, and SME inclusion.

4.4.8. Hotel – India

In the hotel industry in India, AI has the ability to facilitate automated bookings, customised guest services, and streamlined facility management. This technology provides scalability during peak tourism seasons in major cities, enhanced management of high-volume guest interactions. Respecting cultural customs through hospitality, AI results in improved guest satisfaction, fostering service excellence, guest personalisation, and operational scalability. From a PESTEL perspective, the economic recovery of tourism has boosted AI investment, while legal frameworks around consumer protection demand greater transparency in AI applications. The integration of AI in the hotel industry has led to significant value creation in terms of service efficiency, personalised experiences, and demand forecasting.

4.4.9. Tourism – Vietnam

In Vietnam, the tourism industry has seen significant advancements with the integration of AI, which has curated itineraries, managed bookings, and predicted tourist trends. This technology supports multilingual services, catering to both international and domestic tourists. The inclusion of culturally sensitive content enhances local immersion and tourist satisfaction. Consequently, AI can lead to improved planning, cross-cultural engagement, and a better overall customer experience. From a PESTEL perspective, AI also helps manage overtourism and sustainability, while the social demand for unique experiences drives further personalisation. Ultimately, this results in local immersion, eco-tourism, and better visitor planning.

4.4.10. Management Consulting – Chile

In the management consulting sector in Chile, AI provides real-time analytics, automated reports, and insight generation, which enables consultants to serve clients across Chile's diverse geography. Tools adapted to SME needs enhance communication and relevance, creating data-driven consulting, client-tailored insights, and geographic reach. From a PESTEL perspective, pro-business policies encourage tech adoption, while data protection laws shape AI implementation. This approach can result in scalable insights, strategic agility, and regional equity.

4.4.11. Cross-Case Synthesis

Across all cases, three consistent patterns of qualitative value emerged. Firstly, efficiency gains are evident, as AI streamlines routine tasks, improves resource allocation, and reduces human error across sectors. Secondly, contextual adaptation plays a significant role, with AI tools being localised in language, interface, and cultural content, which greatly improves adoption and effectiveness. Lastly, operational resilience and reach are enhanced, particularly in remote or infrastructure-deficient locations, allowing SMEs to expand their reach and maintain continuity. These qualitative value creation patterns demonstrate several key points: alignment with industry-specific applications of AI drives efficiency and relevance; AI expands operational capabilities in underserved areas; cultural and linguistic adaptation is essential for adoption; and PESTEL sensitivity, where political incentives, legal frameworks, and economic pressures heavily influence the feasibility and sustainability of AI deployments.

AI has demonstrated substantial qualitative value in promoting operational growth within SMEs in developing countries. When AI is aligned with industry-specific requirements, geographic limitations, and cultural norms, it becomes a strategic catalyst for resilience, innovation, and inclusive development. This analysis highlights the importance of localised AI deployment strategies to maximise impact in the SME ecosystem in developing countries. Integrating PESTEL analysis into the BMC-based framework reveals that the operational value of AI for SMEs is not only driven by internal efficiency but is also influenced by the broader external environment. The true potential of AI in developing economies lies in its ability to tailor solutions to local contexts, align with policy and regulatory frameworks, and adapt to societal expectations. To ensure that SMEs fully benefit from AI, it is essential to harmonise both micro-level strategies and macro-level enablers.

4.5. Theoretical Framing of Results

The case study results were interpreted through the lens of three core theoretical frameworks: Diffusion of Innovations, Technology Acceptance Model (TAM), and Digital Divide Theory. These theories provided a nuanced understanding of the primary adoption barriers —accessibility, skills, and affordability for AI in SMEs in developing countries.

Diffusion of Innovations and Accessibility

Rogers' Diffusion of Innovations theory explains how innovations spread through social systems, highlighting stages such as knowledge, persuasion, decision, implementation, and confirmation. In this study, accessibility barriers, particularly infrastructure limitations and the digital ecosystem, reflect a delayed or obstructed diffusion process.

Example from case studies:

SMEs in rural regions of Namibia and Malawi reported long delays in adopting AI tools due to unreliable internet access and a lack of exposure to new technologies. These cases illustrate the early-stage diffusion gap where "knowledge" and "persuasion" stages are incomplete due to infrastructural constraints.

Thus, the Diffusion of Innovations theory clarified why accessibility challenges persist despite perceived benefits; these SMEs may be effectively stuck at earlier stages in the innovation adoption lifecycle.

TAM and Skills

The Technology Acceptance Model posits that perceived ease of use and usefulness drive technology adoption. The availability of skills, both technical and managerial, deeply influences these perceptions.

Case study insight:

Firms in India and South Africa that have prior exposure to digital platforms (e.g., CRM, ERP) are more willing to experiment with AI tools. Their leaders cited confidence in team capabilities and perceived AI systems as “manageable,” reflecting higher perceived ease of use and usefulness.

Where technical skills are absent, AI systems can be seen as intimidating or impractical, regardless of affordability, showing how TAM principles help explain variation in perceived feasibility of AI across skill levels.

Digital Divide Theory and Affordability

The Digital Divide theory sheds light on how disparities in economic and technological resources create unequal access to innovations. This was evident in how affordability shaped adoption decisions.

Case study insight:

SMEs in Ghana and Vietnam are faced with high upfront costs and a lack of access to affordable financing options. Even when infrastructure and skills are adequate, affordability remains a gating factor, underscoring the persistent structural inequities outlined in digital divide frameworks.

This theory helped contextualise why even well-informed and skilled SMEs are unable to adopt AI; structural cost barriers effectively excluded them from participating in digital transformation.

Theoretical Integration into Framework Use

These theories also reinforced the rationale for combining the Business Model Canvas (BMC) and PESTEL frameworks:

BMC internal components (key resources, cost structure, value proposition) are directly aligned with TAM (skills/skills perception) and Digital Divide (financial constraints).

PESTEL external factors (infrastructure, education policy, internet penetration) supported analysis from the Diffusion and Digital Divide perspectives. By integrating these theoretical models, the study not only uncovered operational insights but also contributed to extending these theories in resource-constrained, non-Western settings, where adoption dynamics are shaped by infrastructure scarcity, capability gaps, and systemic inequality.

4.6. Quantitative Indicators of AI Adoption Constraints in SMEs

To complement the qualitative insights gathered from the case studies, this section introduces quantitative benchmarks (gathered from secondary sources) related to AI training costs, infrastructure expenses, and SME budget allocation patterns. These figures help gauge the relative burden that affordability, accessibility, and skills development place on SMEs in developing countries and improve the generalisability of findings.

Estimated AI Training Costs

Across several case studies (e.g., Case 2 – South Africa, Case 7 – India), it can be noted that technical training and AI-related digital upskilling are one of the largest barriers to adoption. Based on international benchmarks:

- The average cost for entry-level AI training for SMEs ranges from \$2,000 to \$5,000 USD per employee (World Bank, 2021; Mishra et al., 2021).
- For SMEs in the study, this represents 15–40% of their annual per-employee training budget, depending on firm size and revenue.

Skill development is often the most expensive component of AI adoption for SMEs in low-income settings, especially when bespoke or vendor-supported solutions are required (OECD, 2022).

Infrastructure and Software Licensing Costs

AI integration often requires cloud services, broadband access, and digital platforms. Case studies in Ghana and Malawi highlighted issues in broadband affordability and reliability, and software licensing. Data from ITU and GSMA show:

- Average monthly broadband cost in Sub-Saharan Africa = US$30–US$50 representing up to 5–10% of monthly SME turnover.
- SME licenses for AI CRM or analytics platforms cost $100–$300/month, excluding setup and support (Accenture, 2023).

These figures align with interview responses where SMEs reported deferring adoption due to ongoing overhead costs.

Adoption Rates and Investment Gaps

According to the World Bank (2021), only 16% of SMEs in developing economies currently use AI or advanced data analytics tools. In contrast, 53% of large firms report at least one AI use case.

- In this study, only 2 out of 10 case SMEs had fully integrated AI systems.
- Most others operated in AI-curious or pilot phases, confirming barriers in readiness and affordability.

These disparities highlight a measurable digital maturity gap between SME tiers and larger enterprises, reinforcing the need for policy-driven resource reallocation and support schemes.

4.8. Summary

This chapter presents the findings derived from a multi-case study analysis of ten SMEs across developing countries, with insights structured around the BMC, the PESTEL framework, and qualitative reviews. The results directly address the three core research questions guiding this study.

RQ1: What is the impact of AI on SMEs in developing countries in terms of affordability, accessibility, and skills?

The findings demonstrate that the adoption of AI within SMEs in developing countries is largely shaped by three interrelated factors:

Affordability: Many SMEs can leverage cloud-based or modular AI systems that reduce upfront costs. The subscription or pay-as-you-go models are especially effective in sectors like retail and hospitality (India), where capital investment is a barrier. BMC insights show that such cost structures can enhance the Cost Structure and Value Proposition elements.

Accessibility: SMEs in remote or underserved regions (e.g., Ghana, Namibia) can benefit from AI tools designed to function in low-connectivity or offline environments. The PESTEL analysis highlights that technological infrastructure and geographic location significantly influence accessibility, particularly for SMEs in rural areas.

Skills: A significant barrier remains the digital skills gap. However, AI systems with user-friendly interfaces and embedded training modules can enable basic adoption even in contexts with low technical expertise (e.g., construction and restaurants in South Africa and Malawi). The Key Resources and Customer Relationships segments of the BMC are notably influenced by local skill levels.

RQ2: What support structures are required to successfully adopt an AI system in an SME in developing countries?

Support structures that emerged as critical include digital infrastructure, policy and regulation, training and capacity building, and AI vendor ecosystems. Reliable internet and mobile access are foundational, as seen in countries like Vietnam and Chile, where robust infrastructure enables more complex AI integrations. Government incentives and legal frameworks, particularly the political and legal dimensions of the PESTEL analysis, are enablers in sectors such as renewable energy and telecom in Namibia and South Africa. Capacity-building programs, often provided through public-private partnerships, are pivotal in preparing SMEs for AI adoption. These programs are especially important in sectors like fitness and retail, where AI is embedded into daily client interactions. Additionally, local tech providers and consultants serve as intermediaries, simplifying the adoption process. These actors function as Key Partners in the Business Model Canvas (BMC), offering not only technical services but also strategic integration support.

RQ3: How can the qualitative value creation of AI concerning operational growth be identified?

AI's qualitative contributions to operational growth can be identified through four consistent themes: Efficiency Improvements, where AI-enabled automation and predictive capabilities reduce downtime and manual errors in sectors like energy in Ghana and construction in South Africa. Service Personalisation, which allows SMEs to tailor offerings to individual needs, improving customer experience and loyalty, as seen in fitness routines and tourism itineraries. Geographic and Cultural Adaptability, where AI systems that localise language, content, and interfaces see higher adoption, addressing the Customer Segments and Channels components of the BMC. Lastly, Resilience and Scalability in contexts of political or economic uncertainty, such as Malawi and Chile, where AI-supported continuity and scalability enhance operational stability and long-term growth.

The synthesis of BMC and PESTEL revealed that operational value is not purely technological; it is socioeconomicly embedded. AI becomes transformative when tailored to the firm's operational realities and external environmental conditions. In conclusion, the results provide robust evidence that AI, when accessible, affordable, and supported by appropriate infrastructure and training, can significantly contribute to the operational growth of SMEs in developing countries. Qualitative value creation is best understood through a multi-construct lens that includes internal business models and external macro-environmental forces. These insights lay the foundation for actionable recommendations in Chapter 5.

CHAPTER 5
DISCUSSION

5.1. Interpretation of findings

The analysis of the BMC and PESTEL reveals a multifaceted impact of AI on SMEs in developing countries. These insights offer a deeper understanding of how AI transforms business models while also highlighting the external contextual factors that shape AI adoption. Chapter 4 presented ten single-case studies to solve for RQ1 and further adapted the individual case studies into two multi-case studies to solve for RQ2 and RQ3, respectively.

The ten single-case studies were compiled within the same period to ensure that all the data were time-sensitive and could be fairly adapted for the multi-case study with information that was relevant and up-to-date in terms of global events. To maintain the integrity of the sample to accurately represent *Developing Countries*, the SMEs that were selected were from countries that are acknowledged as "developing" by the United Nations Developing Countries register, Furthermore, the total sample consisted of participants from multiple countries across three continents. Table 23 displays a list of the participants and information that was used as variables for the research questions.

Table 23: Participant Details

Case Study	Country	Industry	Operations	Number of Employees	Model	Business Departments
CS 1	Namibia	Renewable Energy	Solar Power Solutions	11 – 25	B2B	Operations, Finance, Legal, IT, sales, R&D, Customer Service
CS 2	South Africa	Telecommunications	Internet Fibre Infrastructure Development	1 – 10	B2B	Operations, marketing, HR
CS 3	South Africa	Health and Wellness	Fitness Training	1 -10	B2C	Operations, Marketing
CS 4	Ghana	Renewable Energy	Renewable Energy & Electric Vehicle resource supplier	1 – 10	B2C	Operations, Marketing, sales, R&D, customer service
CS 5	South Africa	Construction	Building Construction	11 – 25	B2B	Operations, finance
CS 6	Malawi	Food & Hospitality	Restaurant Chain	50+	B2C	Operations, finance, marketing
CS 7	India	Hospitality	Boutique Hotel	11 - 25	B2C	Operations

CS 8	Vietnam	Tourism	Tour Agency	50+	B2C	Sales
CS 9	India	Retail & Clothing	Clothing Boutique	11 - 25	B2C	Sales, marketing, Finance
CS 10	Chile	Business Services	Business Management Consulting	1 -10	B2B	Sales, IT, finance

Table 23 captures the details of the SMEs that were used to develop the single-case studies. For RQ1, the country, industry and operations were the key variables that were used to develop the business cases. To solve for RQ1, what framework can SMEs utilise in their strategic planning to evaluate the impact of AI, internally and externally? (Scope of reference: Affordability, Accessibility, Skills), The questions were broken down into two parts. Part 1 developed the framework that was adapted to analyse the impact of AI internally and externally. To analyse the internal impact, the components from the Business Model Canvas were used, namely: Key partnerships, Cost Structure, Key Activities, Key Resources, Revenue Stream, Channels, Customer Relationships, Customer Segments. And to analyse the external impact, the PESTEL framework was used, namely: Political, Economic, Social, Technological, Environmental, Legal. Upon compiling the above information in tabular format, to solve for part 2, the impact in reference to affordability, accessibility, and skills, the components were evaluated in relation to the scope to determine which components directly impact and are impacted by each component of the scope, this was further presented in the form of relational diagrams. Overall, the information provided developed the *RQ1 Model,* which was applied to each case study. To solve RQ2, what support structures are required to successfully adopt an AI system? The internal components presented by the BMC part of the model were used to identify short-medium term structures that would enable the ease of AI deployment, mitigating and reducing risks that would otherwise hinder successful adoption. Lastly, to solve for RQ3, how can the qualitative value-creation of AI concerning operational growth be identified? A Multiple-case study was developed, cross-referencing factors presented by the RQ1 Model and secondary research sources, while considering how *value-creation and operational growth* differ across regions. Culminating the overall results and key considerations, the results can be interpreted as follows:

Firstly, looking at the data presented for RQ1 part 1 and 2, it can be inferred that by combining the components from the BMC and PESTEL frameworks into a clear and concise model, stakeholders can identify potential risks that may prevail and actively work towards mitigating or developing contingency plans to support the planning, development, and ongoing maintenance of an AI project in an SME in a developing country. This solution model comprehensively highlights all the internal factors that are impacted by an AI project and all the external factors that impact the AI project. It allows stakeholders in SMEs in developing countries to apply real-world factors of consideration that are present in their region, and problems that may arise that are exclusive to their circumstances, which existing strategic models don't comprehensively cater for, because they're tried and proven in developed countries that have more accommodating resources for digital transformation opportunities. In this context, the digital transformation opportunities that are referred to are SMEs in developed countries being able to afford implementing projects through government support, financial institutions, investors, and other partnerships.

Secondly, using the supporting model created, the reference scope presented multiple factors to consider regarding affordability, accessibility, and skills required for an AI project in an SME in a developing country. By synthesising the BMC and PESTEL framework, internal and external factors, the analysis presented a holistic approach by highlighting both key success factors and challenges. For example, within the scope of affordability, the BMC presented long-term cost savings via automation as an opportunity, but PESTEL presented high upfront costs and limited funding access as constraints. Internally, cloud-based AI tools and expanded digital channels enhanced accessibility; however, externally, infrastructural limitations and uneven internet penetration constrain accessibility. And regarding skills required, the internal opportunity that is presented is enhanced value creation via skilled AI teams, and the external constraint presented is factors such as national skills gap and a lack of AI training programmes. Therefore, the model suggests that to interpret data that is presented, all factors must be considered and their relation to one another must be acknowledged, which can be illustrated by the relational flow diagrams presented in each case study. Overall, this concludes that AI can significantly boost innovation, operational efficiency, and competitiveness in SMEs, but only where economic, infrastructural, and human capacity conditions are supportive.

To determine which components were the most and least impacted, the total number of times each component was impacted was calculated by adding all the factors of impact mentioned in each case study.

$$Total\ number\ of\ times\ impacted\ (X) = CS1\ (afX, acX, skX) + CS2(afX, acX, skX) \ldots + CS10\ (afX, acX, skX)$$

X- RQ1 Model Factor

af – Affordability

ac- Accessibility

sk- Skills

Each case study has the potential to impact each component up to 3 times (scope). Thus, in this research study, each component has the potential to be impacted up to 30 times. Of the 14 components identified as impactful in the RQ1 Model, Key Resources were most affected internally, scoring 21 out of 30, while externally, technology was most affected with a score of 27 out of 30. In this sample, the implementation of an AI project in an SME in a developing country is influenced by internal capacity (key resources) and the external technological environment. These two factors are critical because they form the basis for the adoption, deployment, and scaling of AI systems. Without them, AI strategies may not succeed. Key Resources refer to the internal people, data, and tools necessary for running and maintaining AI systems. The Technological Environment includes infrastructure, platforms, and networks required for deployment and scaling.

In the context of SMEs in developing countries, within this research sample, customer segments and the environmental environment are the least impactful factors in the initial implementation of AI. Customer segment scored 10 out of 30, and the environmental environment scored 16 out of 30. Their influence is generally indirect, long-term, or dependent on other, more immediate enablers like infrastructure, skills, and capital. While they may shape long-term strategy or ethical positioning, they do not present major barriers or enablers for adoption. Instead, internal resources, technological infrastructure, and skills availability are the critical success factors that must be prioritised to achieve meaningful AI integration.

The overall impact of affordability, accessibility, and skills in relation to this study was calculated by adding the total number of times each component of the scope was impacted by each component of the RQ1 Model.

$$\text{AF, AC, Skills} = \frac{\text{Sum of Impact}}{14\ (\text{RQ1 Model component}) * 10\ (\text{number of case studies}) * 3\ (\text{number of scopes})}$$

Figure 28 provides a summary of the internal BMC and external PESTEL factors that impact affordability, accessibility, and skills in each case study.

Figure 28: Impact of Affordability, Accessibility, and Skills Matrix

		CS1 Namibia			CS2 South			CS3 South			CS4 Ghana			CS5 South			CS6 Malawi			CS7 India			CS8 Vietnam			CS9 India			CS10 Chile		
		AF	AC	SK	AF	AC	SK	AF	AC	SK	AF	AC	SK	AF	AC	SK	AF	AC	SK	AF	AC	SK	AF	AC	SK	AF	AC	SK	AF	AC	SK
Business Canvas Model (BMC)	Key partnerships	X	X	X	X	X	X		X	X		X	X		X	X		X	X		X	X		X			X		X	X	X
	Cost Structure	X	X		X		X	X			X		X	X		X	X	X		X		X	X		X	X	X	X	X		X
	Key Activities			X			X			X		X	X			X	X	X	X		X	X	X	X	X	X	X	X		X	X
	Key Resources	X		X		X			X				X	X	X	X	X	X	X	X	X	X	X	X	X	X		X	X	X	X
	Revenue Stream	X			X			X			X			X		X	X	X		X		X	X	X		X	X		X		X
	Channels					X	X		X			X		X	X		X	X		X	X		X	X		X	X			X	
	Customer relationships									X		X			X	X		X				X			X		X	X	X	X	X
	Customer Segments					X			X			X			X		X		X		X				X		X			X	
PESTEL	Political	X			X			X		X	X		X	X	X	X	X	X	X	X	X	X	X		X	X	X	X	X	X	X
	Economic		X	X	X		X	X			X			X		X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
	Social			X	X		X	X	X	X	X	X	X	X	X	X	X	X	X			X	X	X	X	X	X	X		X	X
	Technological	X	X	X	X		X	X	X	X	X	X	X	X	X		X	X	X	X	X	X	X	X	X		X	X	X	X	X
	Environmental	X			X				X			X		X	X	X			X		X	X		X	X		X		X	X	X
	Legal	X	X				X	X		X	X		X	X					X	X	X	X	X	X	X		X	X	X		

Index: X AF - Affordability X AC - Accessibility X SK - Skills

Figure 28 shows the degree of impact of affordability, accessibility and skills. Affordability scored 86, accessibility scored 90, and skills scored 92. These scores reflect the frequency and strength of thematic intersections within the BMC and PESTEL frameworks.

Synthesising findings from all case studies, Figure 29 reveals that skills represent the most recurring and critical challenge. This supports the TAM theory's emphasis on perceived ease of use and reinforces the need for targeted upskilling as a prerequisite for accessible and affordable AI adoption.

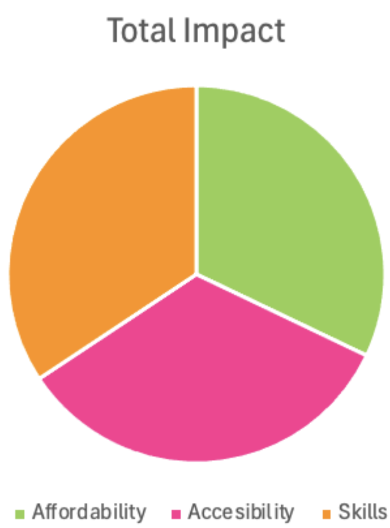


Figure 29: Impact of Affordability, Accessibility, and Skills

In Figure 29, the navy bar signifies more dominant barriers as experienced by SMEs in real-world AI implementation contexts. Suggesting that within the scope, skills are the most impactful factor for an AI project in an SME in a developing country. This is likely because they act as the gateway between technological potential and actual business transformation. Without the right skills, even the most affordable and accessible AI solutions cannot be effectively deployed, managed, or scaled. AI requires an understanding of data science, machine learning, model training, and algorithm selection. Unfortunately, in developing countries, SMEs often lack staff with technical literacy, even for simpler tools, let alone advanced AI. Furthermore, without internal skills, SMEs must outsource AI tasks, which increases costs, delays, and security risks. In contrast, upskilling or hiring internally builds institutional knowledge and long-term AI capability. Socially, the introduction of AI frequently encounters resistance stemming from concerns about job displacement and a lack of understanding. Consequently, employees who possess digital confidence are more inclined to embrace and trust AI tools. Skills training plays a crucial role in fostering a culture of innovation, thereby facilitating the human aspect of digital transformation. Without a workforce that can plan, deploy, operate, and sustain AI systems, all other enablers, like affordability, accessibility, or infrastructure, have limited value.

To solve for RQ2, determining the support structures for successful adoption of an AI project in an SME in a developing country, seven dimensions were explored in conjunction with the BMC component of the RQ1 Model. The multiple-case study, drawing on SMEs in developing countries across industries (e.g., consulting in Chile, solar energy in Namibia, fitness in South Africa), reveals that the successful adoption of AI hinges on the presence and alignment of support structures across strategic, operational, and environmental dimensions. These structures ensure that AI projects are not only launched but sustained, scaled, and embedded into the business model. A brief interpretation of each dimension is as follows:

- Project Planning & Preparation: Strategic Alignment

All case studies emphasise the need for clear KPIs, AI use case definitions, and measurable goals before implementation. Without structured planning, AI projects risk being experimental with no real value creation. SMEs should develop a business-driven AI roadmap to ensure greater success in aligning AI with core functions.

- Infrastructure Development: Technical Readiness & Data Availability

SMEs with basic digital infrastructure (e.g., cloud access, data storage, cybersecurity) and structured datasets are likely to advance further in AI adoption. AI readiness depends on having accessible, clean, and actionable data. SMEs without infrastructure face delays and dependency on external vendors.

- Workforce Engagement: Skills Development & Change Management

The most consistent success factor across all cases can be identified as investment in staff training, digital literacy, and cultural readiness. AI is a socio-technical system. Resistance, fear, or lack of understanding can derail adoption unless employees are engaged and empowered.

- Implementation Process: Technical Deployment & Process Integration

Case studies show that AI must integrate seamlessly into existing workflows to be useful (e.g., chatbot integration in consulting or CRM upgrades in fitness SMEs). When AI tools are poorly integrated, they add complexity rather than solve problems. Agile, phased deployment worked best.

- Measurable Outcomes: Operational Efficiency & Decision-Making

Success is more evident where SMEs can measure and visualise impact, time saved, customer satisfaction, and sales growth. Tangible metrics help justify continued investment and secure internal buy-in. Lack of ROI visibility can cause disillusionment in some cases.

- Sustainability: Scalability & Maintenance

SMEs that budgeted for ongoing maintenance, data updates, and model retraining sustained results longer. AI is not a one-time investment. Its sustainability depends on an evolving support system, updates, monitoring, and adaptation.

- Ecosystem Engagement: Partnerships & Regulatory Support

Public-private partnerships, government AI strategies, and vendor ecosystems (e.g., Microsoft for Startups or Google Cloud credits) accelerate adoption. SMEs in isolation struggle. Connection to a broader AI ecosystem, technical, financial, and policy-related, lowers barriers.

The multiple-case study emphasises that AI success in SMEs depends on thorough planning, infrastructure, people, and ecosystem engagement. Support structures in these areas are crucial for turning AI into a practical reality. In developing countries, resource constraints make these structures even more important for achieving successful implementation.

To address RQ3, a multiple-case study evaluated how SMEs in developing countries identify qualitative value-creation of AI for operational growth. The study covered cases from Chile, Namibia, South Africa, Malawi, India, and Vietnam. Common drivers included process automation, which reduces manual tasks, saving time and boosting productivity; decision-making enhancement, providing better data insights for faster, more accurate decisions; customer experience improvements through personalization and engagement via chatbots, recommendation engines, and CRM tools; employee empowerment by assisting staff, enhancing confidence, skills, and job satisfaction; and reputation and innovation boosts that enhance credibility and perceived innovation in competitive markets.

Furthermore, Operational Growth is more visible where infrastructure and AI awareness are higher. Where digital basics are lacking, growth is often confined to internal efficiencies rather than market expansion. The case studies indicate that AI-driven growth differs by region based on infrastructure, economic maturity, and digital readiness. In Latin America, particularly in Chile, growth is linked to efficiency in client delivery and brand perception through analytics tools. Southern Africa, including Namibia and South Africa, experiences growth in time savings and task automation, though it is hindered by infrastructure gaps. In South Asia, notably in India, AI can enhance customer interaction, especially in hotels and retail, through effective natural language processing. In Southeast Asia, Vietnam sees AI facilitating scalability in tourism, improving bookings and client interactions in fragmented markets. Additionally, Cultural norms significantly influence how AI’s value is perceived, accepted, and applied. In some African and Asian regions, scepticism about AI's accuracy limits its use, while concerns about job security in areas with high unemployment decrease workforce buy-in. Conversely, in Chile and Vietnam, AI is associated with progress and competitiveness, which aids adoption. Traditional business structures, such as those in India, where decisions remain top-down, can slow the uptake of AI technologies.

While the primary focus of this study has been on the structural and operational barriers to AI adoption, namely affordability, accessibility, and skills, there is an equally important layer of ethical and legal challenges that emerged during cross-case analysis. These include data privacy concerns, algorithmic bias, transparency, and compliance with evolving regulations.

- Data Privacy and Compliance

Several SMEs, particularly in retail (Case 9, India) and consulting services (Case 10, Chile), may face uncertainty around handling client or patient data through AI tools. This is particularly concerning given the global shift toward stronger data protection regulations, such as the General Data Protection Regulation (GDPR) in the EU and the Protection of Personal Information Act (POPIA) in South Africa. These frameworks require that personal data be collected transparently, stored securely, and used only with informed consent. SMEs with limited legal or IT capacity often struggle to comply with these standards, risking legal exposure or reputational damage (Taddeo & Floridi, 2018). In several cases, fear of non-compliance acts as a deterrent to AI experimentation, especially where data-driven personalisation is a core feature. AI systems require ethically grounded design and deployment, particularly in SMEs where institutional checks are often weak (Jobin, Ienca, & Vayena, 2019)

- Algorithmic Bias and Fairness

Algorithmic bias, where AI systems reinforce historical inequalities due to biased training data, is an implicit concern in sectors such as fitness and telecommunications. For example, if Case Study 6 (Malawi) uses chatbot technologies for customer service but lacks diversity in training datasets, it potentially disadvantages non-native English speakers or neurodiverse users. These concerns are especially salient in SMEs lacking internal data science capabilities, where pre-built AI models are deployed without local calibration or auditing mechanisms. As Mittelstadt et al. (2016) argue, SMEs may unwittingly propagate ethical risks due to “opaque, unaccountable automation”.

In summary, the qualitative value-creation of AI in SMEs across developing countries is real, multifaceted, and context-dependent. The benefits of AI, such as automation and enhanced decision-making, are universally acknowledged. However, the extent and perception of growth vary significantly based on regional infrastructure, digital readiness, cultural beliefs about innovation and job security, and the internal organisational maturity. Understanding these factors is crucial for aligning AI strategies with local values and long-term growth goals, ensuring that AI becomes a transformative force for SMEs globally.

5.2. Limitations of the study

While this multiple-case study provides meaningful insights into how affordability, accessibility, and skills affect AI adoption and value creation in SMEs across developing countries, several limitations should be acknowledged to ensure academic rigour and interpretive clarity.

The diversity of socio-economic, cultural, and political environments in developing nations means that the findings may not be universally applicable. Despite its methodological strengths, this study acknowledges several limitations that may influence the interpretation and generalizability of the findings. The SMEs examined may not represent all SMEs in their respective sectors or countries, warranting a contextualised interpretation of the results. Furthermore, the research relies heavily on qualitative methods, which, while rich in depth, may lack the statistical robustness required for policy modelling or large-scale forecasting. Additionally, the study primarily examines the short- to mid-term effects of AI implementation, thus lacking a long-term perspective on sustainability and adaptation. Another important factor to consider is that the SMEs studied are at varying stages of AI maturity, making direct comparisons challenging. Some firms are still in the exploratory phase, while others are scaling operational systems. This disparity necessitates a nuanced approach to analysis. Also, data availability and validation pose challenges, as some SMEs lacked formal KPIs and consistent reporting. Consequently, the findings may reflect perceived impact rather than measurable outcomes, with self-reported data potentially overstating business performance.

One key limitation is the reliance on self-reported data collected through semi-structured interviews and online surveys. Participants, primarily SME owners and managers, may have unintentionally overstated AI benefits, underreported implementation challenges, or provided incomplete financial and operational data. This potential for response bias is well-documented in qualitative research and can skew findings, particularly on sensitive topics like cost, technological capacity, or staff readiness (Podsakoff et al., 2003).

To mitigate this limitation, the study employed triangulation techniques, as described in Section 3.6. Self-reported data were cross-validated with objective sources, such as company financial documents (where accessible), third-party industry reports, and publicly available infrastructure data (e.g., national internet penetration rates). In cases where triangulation was not feasible, member checking was used to ensure participant accuracy and confirm interpretations (Lincoln & Guba, 1985). Additionally, probing techniques were integrated into interview protocols to elicit more precise and reflective responses from participants, particularly regarding affordability, accessibility, and skills-related issues.

Another limitation is the non-random, purposive sampling used to select SMEs, which, while appropriate for exploratory case study research, limits statistical generalizability. The findings are intended to provide theoretical generalisations applicable to similar settings rather than predictive insights across all SMEs. Furthermore, variations in AI maturity, regional infrastructure, and sector-specific dynamics may influence how findings transfer to other contexts.

Cultural and cognitive biases further influence the responses, with local attitudes toward technology, hierarchy, and risk shaping how AI is described and valued. Additionally, the rapidly evolving AI landscape means that the findings may quickly become outdated as technologies and national AI strategies progress.

The decision to adopt a qualitative-only design was deliberate and grounded in the need for depth over breadth. Given the lack of prior empirical research in the Global South on this topic, a qualitative strategy allowed for theory building and context-sensitive exploration. However, this also means that findings are not statistically generalizable. That said, the study's value lies in its transferability, not generalizability. The ten SMEs, though diverse in geography and sector, share common characteristics with many SMEs across developing countries: limited financial resources, uneven digital infrastructure, and a shortage of AI-capable staff. These shared features make the insights applicable to other small firms facing similar constraints, provided contextual adaptation is considered (Patton, 2015; Miles et al., 2014). Future research should explore opportunities for quantitative validation and scale-based comparison, particularly where common indicators (e.g., investment cost ratios or training hours) are already established.

In conclusion, a comprehensive understanding requires considering the unique contexts and evolving dynamics of AI adoption across different regions. Despite these limitations, the study remains credible due to its use of a robust, transparent framework, multiple data sources, and strategies to enhance trustworthiness, such as triangulation, audit trails, and thick descriptions (Miles, Huberman, & Saldaña, 2014; Yin, 2018). The hybrid BMC–PESTEL framework and its use of measurable constructs allow for broader analytical replication. Future research can explore how these components function in different regional or sectoral settings, testing their relevance while adapting them to local realities. This positions the framework as a foundational tool for SME strategy under digital transformation pressure, even outside the original sample contexts.

5.3. Summary

Chapter 5 discusses the implications of the study's findings on the adoption of AI in SMEs in developing countries, emphasising affordability, accessibility, and skills as critical dimensions. The discussion highlights that skills are the most influential factor in AI implementation, with the lack of technical expertise and digital literacy significantly constraining adoption. However, SMEs that invested in employee training or received external support demonstrated higher success rates. Affordability, while a common barrier, is not insurmountable; many SMEs mitigate financial constraints through incremental adoption strategies, use of cloud-based solutions, and collaborative partnerships. Accessibility, particularly in terms of digital infrastructure and data availability, strongly influences implementation outcomes, with more digitally connected regions showing better integration. The study also finds that AI creates substantial qualitative value by enhancing decision-making, operational efficiency, customer engagement, and organisational innovation. Furthermore, cultural and regional factors such as perceptions of technology, hierarchical structures, and trust in innovation significantly shape how AI is adopted and the value it delivers. These findings suggest that effective AI adoption in SMEs requires not only technical readiness but also comprehensive support structures and sensitivity to local contexts.

CHAPTER 6
SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS

6.1. Summary of Study

This study aimed to identify and understand the impact of Artificial Intelligence on Small-Medium Enterprises in Developing Countries. SMEs in developing countries face many challenges, among these challenges is the need to be able to adapt and innovate to stay competitive; ideally, this can be supported by digital transformation. However, this solution consequently presents its challenges that stakeholders are usually unprepared for. For this, strategic and comprehensive planning, development, and implementation of an AI project are critical. Therefore, to sufficiently plan for this and be able to optimise and mitigate the risks presented, stakeholders should evaluate how affordability, accessibility, and skills impact the internal environment and are impacted by the external environment. To solve for this, this study presented a research model that synthesises the Business Model Canvas and PESTEL (Political, Economic, Social, Technological, Environmental, Legal) framework. This dual approach enabled a comprehensive evaluation of internal business dynamics alongside external environmental influences (Osterwalder & Pigneur, 2010; Johnson et al., 2017).

The Research Model (referred to as the RQ1 Model in the previous chapters) aims to address the gap in strategic AI planning frameworks that currently exist and are predominantly created by and for organisations in developed countries who have access to more opportunities through financial support, infrastructure, and access to skills development. Additionally, the Research Model is presented in a comprehensive yet concise manner that is broadly understandable by stakeholders without previous training and business backgrounds, to accommodate the professional and educational dynamics in developing countries.

The study focuses on three key research questions:

RQ1: What framework can SMEs utilise in their strategic planning to evaluate the impact of AI, internally and externally, particularly concerning affordability, accessibility, and skills?
RQ2: What support structures are required to successfully adopt an AI system?
RQ3: How can the qualitative value-creation of AI concerning operational growth be identified?
To address these questions, the research applies an integrated analytical framework combining the BMC and the PESTEL frameworks, I.E., Research Model (RQ1 Model). This dual-framework approach enabled a detailed assessment of both internal (e.g., key resources, cost structures, value propositions) and external (e.g., political, economic, technological, and social) factors influencing AI adoption. A total of 10 single case studies were conducted to explore strategic AI planning in SMEs (RQ1), while multiple-case analysis was used to examine required support structures (RQ2) and qualitative value-creation (RQ3). Case studies were drawn from diverse SME sectors across developing regions, including Latin America, Sub-Saharan Africa, South Asia, and Southeast Asia, allowing for a contextualized understanding of AI's role in varying socio-economic environments (Yin, 2018).
The cases that were covered are from Chile, Namibia, South Africa, Malawi, India, and Vietnam. The study is organised into five chapters: Chapter 1 introduces the research purpose and context; Chapter 2 reviews literature on AI in SMEs, strategic planning, and digital transformation in developing economies; Chapter 3 outlines the qualitative, single-case and multiple-case research design; Chapter 4 presents the findings from the BMC and PESTEL analyses within the context of each research question; Chapter 5 discusses the interpretations of findings, focusing on key enablers such as skills development, infrastructure, and ecosystem partnerships, and limitations of the study. The research contributes to the growing body of knowledge on digital transformation in SMEs and offers a practical framework for strategic AI evaluation in resource-constrained settings. Brief chapter summaries are provided below:

Chapter 1 sets the foundation for the study by outlining the growing relevance of AI in SMEs in developing countries. While AI offers transformative potential for improving efficiency, innovation, and competitiveness, SMEs in the Global South often lack the financial, infrastructural, and human capital resources necessary for successful adoption. The chapter highlights the disconnect between AI implementation strategies in developed economies and the realities faced by SMEs in under-resourced regions. To address this gap, the study focuses on three critical factors, affordability, accessibility, and skills, and formulates three research questions aimed at evaluating suitable strategic frameworks, required support structures, and qualitative value-creation outcomes. To respond to these research questions, the study proposed a hybrid framework combining the Business Model Canvas and PESTEL analysis. This integrated approach helps SMEs assess both internal operations and external environmental influences on AI adoption. The framework is designed to be inclusive and practical, accounting for regional disparities, social dynamics, and the varying levels of business acumen among stakeholders. Ultimately, Chapter 1 positions the research as a response to the need for context-specific planning tools that can guide SMEs in developing countries through AI implementation in a sustainable, scalable, and impactful manner.

Chapter 2 provides a comprehensive literature review that establishes the theoretical foundation for the study by examining how affordability, accessibility, and skills influence the adoption of AI in SMEs in developing countries. The literature review explores theories such as the Diffusion of Innovations (Rogers, 2003), Technology Acceptance Model (Davis, 1989), Digital Divide Theory, and Resource Dependency Theory, among others, to explain how economic, infrastructural, and social barriers affect AI adoption. The review also highlights the importance of internal and external factors, such as financial capacity, leadership, government policy, and global supply chains, in shaping AI affordability and accessibility. With regard to skills, the chapter emphasises the importance of technical, managerial, and soft skills, as well as the role of partnerships and global knowledge transfer in closing the skills gap. Lastly, the chapter discusses how AI value creation can be measured qualitatively through improved decision-making, innovation, and stakeholder satisfaction, reinforcing the need for a multi-dimensional evaluation strategy in assessing AI impact.

Chapter 3 outlines the research methodology adopted to explore the impact of AI on SMEs in developing countries, focusing on the dimensions of affordability, accessibility, skills, successful adoption, value creation, and operational growth. The chapter reiterates the research problem and the need for a structured approach to evaluate AI's influence on SMEs in resource-constrained environments. The study addresses three research questions, each guided by a specific design: ten single-case studies were used to explore RQ1, a multi-case study design was employed for RQ2, and a multi-case approach (Yin, 2018) with a cross-case synthesis approach was applied for RQ3. The theoretical constructs were clearly defined and operationalised. Affordability was assessed in terms of financial resources available for AI adoption, accessibility referred to technological infrastructure and digital tools, and skills encompassed workforce capabilities in AI technologies. Successful adoption was defined by integration outcomes, value creation by qualitative improvements, and operational growth by enhanced efficiency and decision-making. Furthermore, A purposive sampling strategy was employed to select SMEs that varied in sector, geographic region, and digital maturity to ensure contextual richness. Data collection involved both primary sources, including semi-structured interviews and online surveys and secondary sources, such as academic literature, global reports, and historical data (Creswell & Poth, 2018). This mixed-methods approach ensured comprehensive coverage of internal and external factors affecting AI adoption. Data analysis followed a strategy with insights categorized according to the BMC and PESTEL frameworks. For multi-case and cross-case synthesis, pattern matching and comparative analysis were used to identify shared themes across different contexts (Braun & Clarke, 2006; Yin, 2018). To ensure research rigour, the study applied qualitative criteria including credibility, dependability, transferability, and confirmability through triangulation, member checking, detailed audit trails, and reflective analysis (Lincoln & Guba, 1985).

Chapter 4 presents the findings from the empirical investigation of how AI impacts SMEs in developing countries. The data were collected through interviews, surveys, and secondary sources across 10 single case studies, followed by two levels of multi-case analysis to explore broader themes related to AI adoption, support structures, and qualitative value-creation. The single-case study results provide rich, contextual insights into AI implementation across diverse sectors and geographies—including renewable energy (Namibia and Ghana), telecommunications and construction (South Africa), fitness (South Africa), hospitality and retail (India), tourism (Vietnam), restaurants (Malawi), and consulting (Chile). Each case was analyzed using the integrated Business Model Canvas (BMC) and PESTEL frameworks to assess internal capabilities (e.g., affordability, accessibility, and skills) and external influences (e.g., infrastructure, policy, and social factors) (Osterwalder & Pigneur, 2010; Johnson et al., 2017). The first multi-case analysis (4.3) synthesizes the findings from RQ1, revealing that the affordability of AI tools is often constrained by upfront costs, but mitigated through phased implementation, cloud-based solutions, and vendor partnerships. Accessibility varied depending on digital infrastructure and internet penetration, while skills emerged as a critical enabler across all cases. Regions with stronger educational support and external collaboration saw smoother adoption. The second multi-case analysis (4.4) addresses RQ3 by identifying qualitative value-creation outcomes, including improvements in operational efficiency, decision-making accuracy, customer service, and innovation capacity. Each case demonstrated unique forms of growth influenced by local context and cultural attitudes toward AI. For example, in Chile's consulting sector, AI enhanced data analysis and client reporting, whereas in Vietnam's tourism industry, it improved service personalization and booking management. A cross-case synthesis (4.4.11) highlighted common success factors such as leadership support, workforce engagement, ecosystem collaboration, and policy alignment (Yin, 2018). The chapter concludes by summarizing key insights: that AI adoption is context-sensitive, requires strong internal and external support structures, and delivers its most significant impact in the form of qualitative operational improvements—particularly in SMEs that overcome barriers related to skills and accessibility.

Chapter 5 interprets the findings of the study in relation to the research questions and theoretical framework, while also acknowledging the limitations of the research. The discussion emphasizes that skills availability emerged as the most impactful factor influencing AI adoption in SMEs, as it directly affects implementation, integration, and long-term sustainability. Without sufficient internal expertise or access to training resources, even affordable and accessible AI tools cannot be effectively utilised (Davenport & Ronanki, 2018). In contrast, affordability and accessibility, while important, were found to be secondary barriers manageable through phased investments, cloud-based solutions, or external ecosystem support. The study also found that AI delivers qualitative value in the form of improved operational efficiency, enhanced decision-making, customer engagement, and innovation, even when direct financial returns were not immediately evident. These insights are particularly relevant for SMEs in developing countries, where budget constraints are high, but the operational demands are equally complex. Furthermore, the discussion highlights that regional differences such as infrastructure maturity, cultural attitudes toward technology, and policy support significantly influenced the pace and perception of AI adoption (World Bank, 2021; UNCTAD, 2021). Cultural beliefs also played a role in shaping employee acceptance and organisational readiness, with innovation often being perceived as a risk rather than an opportunity in more traditional environments. In terms of limitations, the study acknowledges the constraints of generalizability due to its qualitative nature and focus on ten case studies across specific countries. The diversity of industries and AI maturity levels made direct comparison challenging, and the rapidly evolving AI landscape may limit the long-term applicability of the findings (Yin, 2018). Additionally, some findings relied on self-reported data, which may carry response bias. Despite these limitations, the study offers a valuable framework for understanding the complex interplay between strategic readiness and external environmental conditions in AI adoption among SMEs in developing economies.

6.2. Implications

This study provides meaningful insights into how artificial intelligence (AI) can be successfully adopted by small and medium-sized enterprises (SMEs) in developing countries, with a particular focus on the role of affordability, accessibility, and skills. The implications span several domains:

1. Practical Implications for SMEs

- SMEs must take a strategic approach to AI adoption, aligning implementation with business objectives through structured planning tools like the Business Model Canvas (BMC) and environmental scanning via PESTEL.
- The findings show that AI creates qualitative value, such as operational efficiency, improved decision-making, and customer engagement, even without immediate financial returns (Davenport & Ronanki, 2018).
- SMEs can begin with low-cost, modular AI solutions (e.g., chatbots, CRM analytics) and scale based on measurable outcomes, reducing the perceived barrier of affordability.

2. Policy and Ecosystem Implications

- Governments and policymakers must recognise that infrastructure, training, and digital inclusion are foundational to equitable AI adoption.
- Public-private partnerships, subsidized AI tools, and national digital strategies can improve access to affordable technologies and upskill the workforce (World Bank, 2021).
- Regulatory frameworks should ensure data privacy and ethical AI use, while also being flexible enough to encourage innovation among SMEs.

While AI adoption barriers remain significant in developing countries, this study identified direct policy impacts that facilitated SME transitions to AI. For instance, in Chile, national AI subsidies supported SME partnerships and lowered AI entry costs, enabling B2B firms to scale their consulting services. Similarly, in Namibia, sector-specific government incentives helped energy SMEs invest in AI-based grid solutions. These findings affirm that targeted public support, aligned with industry needs, can accelerate AI diffusion among SMEs.

Case-Backed Policy Proposals:

- Tax Credits for AI Training and Implementation

SMEs in Chile leveraged tax-backed funding to access AI specialists and university labs. Such schemes reduce skill acquisition costs and promote local capacity building. Public investment in innovation ecosystems has proven effective in building SME resilience and digital maturity (Mazzucato, 2018; Brynjolfsson & McAfee, 2014).

- Subsidised Cloud Access for Low-Income Regions

Namibia's solar SMEs adopted AI via subsidised access to clean energy data systems. Similar strategies could apply to cloud AI platforms.

- Government-Facilitated Innovation Hubs

Cases in Ghana and Chile highlight the importance of collaborative R&D ecosystems. Innovation hubs can incubate locally relevant AI tools. Public-private collaborations within national AI strategies offer scalable SME pathways (Zhang et al., 2020; Manyika et al., 2017).

- Frameworks for Ethical AI in Low-Resource Settings

To mitigate these risks, ethical frameworks must be tailored to low-resource environments. The OECD AI Principles (2019) and UNESCO's Recommendation on the Ethics of AI (2021) emphasize inclusivity, accountability, and human rights compliance. Key pillars include:

•Transparency: SMEs should document AI decision-making processes, especially in customer-facing tools.

•Accountability: Assign human oversight roles for AI outputs to ensure fallback mechanisms exist.

•Fairness and Inclusion: AI systems must be tested for demographic bias, particularly in multilingual or low-literacy populations.

Adoption of these principles—even in lightweight form—can help SMEs avoid ethical pitfalls while building trust among users, regulators, and partners.

These policy recommendations are grounded in empirical insights and supported by established academic literature, providing a clear roadmap for governments seeking to enhance digital competitiveness in SME sectors. Policy support, when well-aligned with business needs, can act as a force multiplier, transforming AI from a niche innovation into a broad-based enabler of inclusive economic growth.

3. Academic and Theoretical Implications

- The integration of BMC and PESTEL provides a novel, multidimensional framework to assess AI readiness in resource-constrained settings, contributing to both entrepreneurship and innovation literature (Osterwalder & Pigneur, 2010).
- This approach encourages a context-specific understanding of AI adoption that moves beyond technology-centric models and accounts for cultural, economic, and structural realities in the Global South (UNCTAD, 2021).
- The study provides a replicable template for future comparative research across regions and industries, particularly in under-researched emerging markets.

4. Systemic Insight

- AI adoption is not just a technological upgrade, it is a transformational process that requires ecosystem support, cultural readiness, and organisational adaptation.
- SMEs should not be viewed as isolated actors; their success with AI depends on interconnected systems involving vendors, institutions, regulators, and educational bodies.

The findings from Chapter 4 demonstrate how affordability, accessibility, and skills gaps manifested differently across the case study SMEs. For example, in the fitness SME in South Africa, accessibility challenges stemmed from limited access to cloud-based infrastructure, while in the consulting SME in Chile, affordability was a concern due to the high licensing fees of AI platforms. Similarly, the restaurant SME in Malawi struggled with low digital skills among staff, affecting both adoption and acceptance of AI tools.
To address these challenges, ecosystem-level solutions are necessary:

- Regional AI Hubs: Establish government- or university-supported AI innovation hubs that provide shared access to infrastructure, data, training, and affordable AI-as-a-service tools.
- Cross-border Knowledge Networks: Facilitate partnerships among SMEs, tech firms, and research institutions across developing countries to share case studies, software, and skills development programs.
- Subsidised AI Programs: Collaborate with international development organisations to fund AI pilot projects in SMEs through grants or low-cost licensing schemes.
- Such initiatives can significantly reduce adoption barriers by creating collaborative, accessible environments where SMEs can learn, experiment, and grow together.

The findings of this study provide actionable guidance for SMEs navigating AI adoption, particularly in developing country contexts. However, the diversity of industries and regional challenges necessitates sector- and geography-specific recommendations. Below is a set of tailored implications based on the empirical cases examined:

Sector- and Region-Specific Recommendations

- Hospitality SME (India): Affordability is a critical barrier, particularly for customer engagement tools. SMEs should adopt cloud-based AI chatbots through subscription-based platforms to reduce upfront investment. Partnerships with tech startups or digital marketing agencies can also extend functionality at low cost.
- Renewable Energy SME (Namibia): Skills shortages remain a key inhibitor. Collaborating with local universities or vocational institutions to deliver government-funded AI literacy programs tailored to energy management and predictive maintenance can bridge this gap. Incentives for training through development grants should be explored.
- Retail SME (India): Accessibility issues, especially infrastructure readiness, affect cloud integration. SMEs should prioritise hybrid AI tools (offline-compatible solutions) and engage with local digital inclusion initiatives supported by telecom providers.
- Consulting SME (Chile): Here, value creation from AI is linked to decision-making enhancement. The SME should prioritise internal analytics tools for project evaluation and leverage global networks for knowledge transfer, especially via open-source AI platforms.
- Restaurant SME (Malawi): Low digital literacy calls for simple, intuitive tools. Partnerships with local NGOs for hands-on digital training, combined with mobile-based inventory and POS systems enhanced by basic AI analytics, could offer a starting point.

These sector-anchored solutions offer a more granular roadmap for SME owners and policymakers. They reinforce the need for localised implementation strategies that reflect not just broad development categories but sectoral dynamics and community realities (Patton, 2015).

Theoretical Integration and Empirical Findings

To strengthen the theoretical foundation of this research, this section explicitly maps the three guiding theories - Diffusion of Innovations (Rogers, 2003), Technology Acceptance Model (Davis, 1989), and Digital Divide Theory (van Dijk, 2020), to the core AI adoption constraints identified across the case studies: accessibility, skills, and affordability. These linkages helped guide data interpretation and shape actionable policy recommendations.

Table 24 provides a summary of how each theory informed the analysis of specific barriers encountered by SMEs in the Global South. This triangulation supports both conceptual depth and empirical relevance.

Tables 24 Summary of theoretical analysis of specific barriers

Theory	**Affordability**	**Accessibility**	**Skills**
Diffusion of Innovations (Rogers, 2003)	Initial investment burdens deter entry, stalling late-stage adopters.	Explains slow AI uptake due to lack of infrastructure, weak awareness, and incomplete diffusion across the social system.	Limited exposure delays knowledge/decision stages of innovation adoption.
Technology Acceptance Model (Davis, 1989)	Cost-benefit evaluation impacts perceived usefulness and willingness to adopt.	Access to AI tools influences perceived ease of use.	Skills directly shape perceived ease of use and usefulness.
Digital Divide Theory (van Dijk, 2020)	Structural inequalities in internet, hardware, and digital content access	Educational disparities impact digital skills	Resource scarcity and financial exclusion inhibit adoption capability

These frameworks shaped how case study results were interpreted. For instance, Diffusion theory explained the stalled adoption pathways in Malawi and Ghana, where AI knowledge had not penetrated SME ecosystems. TAM clarified why SMEs with higher digital literacy perceived AI as less complex and more beneficial, particularly in South Africa and India. Digital Divide theory contextualised affordability challenges, especially in rural regions lacking basic infrastructure.

By integrating these theories, the study supports policy designs targeting ecosystem improvements (Diffusion), skill development (TAM), and financial inclusion (Digital Divide), thereby reinforcing the relevance of context-specific interventions (Mishra et al., 2021; OECD, 2022).

6.3. Recommendations for future researchers

Based on the findings and limitations of this study, several key recommendations are proposed for future researchers to expand and deepen the understanding of AI in SMEs in developing countries.

1. Conduct Longitudinal Research: Future studies should adopt a longitudinal approach to track AI adoption over time, allowing researchers to assess the sustainability and long-term impact of AI on operational performance, innovation, and workforce transformation. Such research would help distinguish short-term efficiencies from enduring strategic benefits.
2. Develop Metrics to Quantify Qualitative Value: This study emphasised qualitative value-creation (e.g., improved decision-making and customer engagement). Future research should focus on developing quantitative indicators or mixed-method frameworks to measure these outcomes more systematically, enhancing the ability to evaluate AI's non-financial impact. Mixed-methods design should be able to track cost–benefit outcomes, including AI ROI over time and economic multipliers in low-resource sectors. Including such quantitative indicators supports triangulation of findings and helps policymakers design data-informed incentives, such as AI tax credits or grants proportionate to SME turnover.
3. Broaden Sectoral and Regional Scope: Researchers are encouraged to explore additional sectors, such as agriculture, education, and health, as well as underrepresented regions like Central Asia, the Caribbean, or remote parts of Africa. This would provide a more inclusive and comprehensive view of how contextual factors shape AI adoption across diverse environments, and further to test the transferability of the proposed framework across cultural and infrastructural contexts.
4. Investigate Gender and Inclusion Dynamics: Future studies should explore how AI adoption affects inclusivity within SMEs, particularly regarding gender equity, youth participation, and marginalised groups. This would contribute to a more socially responsible understanding of AI deployment in developing countries.
5. Compare Regulatory and Policy Frameworks: There is a need for comparative studies that evaluate how different national policy environments support or constrain AI adoption in

SMEs. Identifying best practices across countries can inform more effective public sector interventions.

6. Examine AI Ethics and Governance in SMEs: As ethical considerations in AI gain prominence, future research should investigate how SMEs in developing contexts handle data privacy, algorithmic bias, and compliance with local and international AI regulations. This line of inquiry would contribute to more responsible and transparent AI adoption.

7. Evaluate Ecosystem-Based Support Models: Future research should assess the effectiveness of ecosystem-based interventions, such as public-private partnerships, academic collaborations, and incubator programs, in facilitating AI adoption. Understanding the role of support networks could help design more scalable and sustainable AI solutions for SMEs.

8. Contextual Adaptation Studies: Examine how SMEs in unstudied sectors or geographies can tailor the framework to fit their specific needs, possibly by adjusting affordability indicators or redefining skill requirements based on local education and labour markets.

These recommendations would not only validate and refine the present findings but also contribute to a more scalable, equitable, and practical understanding of AI's role in the transformation of SMEs in resource-constrained environments.

6.4. Scalability and Adaptability of the Framework

Although this study was focused on AI adoption in SMEs within developing countries, the integrated Business Model Canvas (BMC)–PESTEL framework demonstrates strong potential for scalability and adaptation across various organizational contexts.

1. Startups in Emerging Economies

Startups often operate with leaner structures but face similar AI adoption challenges as SMEs, including skills gaps and limited financing. However, startups are typically more agile and innovation-driven.

- The BMC elements (e.g., value proposition, customer segments, and key resources) are especially relevant for startups seeking product–market fit using AI technologies.
- Startups can benefit from PESTEL analysis to assess the regulatory and infrastructural landscape before launching AI products.

For example, AI-focused agritech startups in Kenya and Nigeria can use this model to identify external enablers such as policy support or mobile infrastructure availability.

Startups in the Global South must navigate complex socio-political ecosystems(Nambisan et al., 2019). Frameworks like BMC–PESTEL offer strategic clarity in early-stage AI deployment.

2. Public Sector and Government Services

Governments increasingly explore AI for public service optimization, such as automating welfare systems, predictive policing, or healthcare diagnostics.

- The BMC can be adapted to public service delivery models, replacing revenue streams with "public value creation" metrics and modifying customer segments to reflect citizen groups or departments.
- PESTEL dimensions become even more critical for governments due to high exposure to legal and social implications of AI (e.g., bias, accountability).
- This framework can assist local government units in designing ethical AI interventions, especially where digital public infrastructure is weak.

Public-sector AI adoption demands hybrid models that balance innovation with legitimacy and accountability (Wirtz et al., 2019; Mikhaylov et al., 2018).

3. Large Enterprises and MNCs

Although beyond the SME scope, larger firms operating in developing economies may use the framework to localize AI strategies for regional markets. This includes tailoring AI models to low-resource environments or integrating inclusive design principles.

Framework Modifications for Scalability

Dimension	**Adaptation Example**
Revenue Streams	Replaced with public value in government usage
Customer Segments	Adjusted to stakeholders or departments
Legal (PESTEL)	Expanded to include AI ethics, algorithm audits
Key Activities	Modified for mission-driven or regulatory roles

Practical Utility and Framework Replicability

A key contribution of this study is the development of a replicable AI readiness assessment tool based on the BMC–PESTEL framework. The replication protocol was designed for immediate use by SMEs, policymakers, and researchers, allowing for strategic self-assessment and cross-case comparison. The protocol can be adapted for startups, NGOs, or public-sector entities exploring AI integration. A full checklist is provided in Appendix C, supporting scalability and operationalisation in diverse contexts.

6.5. Conclusion

This study set out to explore the impact of Artificial Intelligence (AI) on small and medium-sized enterprises (SMEs) in developing countries, with a focus on the strategic challenges and opportunities related to affordability, accessibility, and skills. By applying an integrated framework combining the Business Model Canvas (BMC) and PESTEL (Political, Economic, Social, Technological, Environmental, Legal) analysis, and using both single-case and multiple-case study designs, the research has demonstrated that AI adoption among SMEs is context-dependent and driven by a complex interaction of internal capabilities and external conditions. Key findings show that skills availability is the most critical enabler of AI adoption, as it influences not only the initial implementation but also long-term integration, value creation, and sustainability. While affordability and accessibility remain persistent challenges, they can be addressed through ecosystem support, cloud-based solutions, and incremental adoption strategies. The study further reveals that AI delivers substantial qualitative value, such as improved decision-making, customer experience, and operational growth, even in resource-constrained environments. Ultimately, the research offers both a practical contribution through its proposed evaluative framework and a theoretical one by extending the conversation on digital transformation into underrepresented Global South contexts. The implications for practitioners, policymakers, and researchers underline the importance of investing in human capital, infrastructure, and ecosystem collaboration to ensure inclusive and sustainable AI adoption. While the study has its limitations, it provides a foundation for further research and action aimed at enabling SMEs in developing countries to harness AI as a tool for growth, resilience, and innovation.

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APPENDIX A

Appendix A: Sample Interview and Survey Questions

This appendix provides examples of interview and survey questions used in the study, tailored for SMEs operating in diverse sectors and regions. The instruments were adapted during pilot testing to reflect cultural norms, economic constraints, sector-specific terminology, and technological maturity.

A.1 Sample Semi-Structured Interview Questions

General (All Sectors)

1. Can you describe how your business currently uses (or plans to use) AI technologies?
2. What challenges have you encountered (or anticipate) in adopting AI in your organisation?
3. How has the cost of AI tools impacted your decision-making?
4. How would you describe your team's digital and technical skills related to AI?

Sector-Specific Tailoring
• **Renewable Energy (Namibia, Ghana):** "Have you explored AI for energy forecasting or smart grid optimisation? What infrastructure challenges do you face?" • **Hospitality and Tourism (India, Vietnam):** "Have you used AI-driven chatbots or recommendation engines to personalise customer experiences? How has the cultural perception of automation influenced uptake?" • **Construction (South Africa):** "Are there AI tools in use for project risk forecasting or equipment maintenance? What digital infrastructure do you rely on at job sites?"

Regionally Sensitive Probes
• How reliable is your internet connectivity, and how does it affect your ability to adopt AI tools? • In your country, are there government or private support programs helping SMEs with digital transformation?

- How do staff typically react to the idea of automation—do they see it as helpful or threatening?

A.2 Sample Online Survey Questions

1. Demographics
2. Is your business considered an SME in your country?

   ☐ Yes☐ No
3. Type of business

   ☐ B2B ☐ B2C
4. Country: [Dropdown list]
5. Sector: [Dropdown list]
6. Size of enterprise:

   ☐ Micro (1–9 employees) ☐ Small (10–49 employees) ☐ Medium (50–249 employees)
7. Departments:
8. ☐ Operations ☐ Finance ☐ Marketing ☐ HR ☐ Legal ☐ IT ☐ Sales ☐ R&D ☐ Customer Service

Affordability Indicators

1. Approximate total investment in AI tools (USD): __________
2. Do you have access to financing or subsidies to support AI adoption?

   ☐ Yes ☐ No

Accessibility Indicators

1. Do you have access to stable internet capable of supporting cloud-based AI tools?

   ☐ Yes ☐ No
2. Which of the following do you currently use?

   ☐ Cloud storage ☐ SaaS platforms (e.g., CRM, analytics) ☐ None
3. Are there AI-related support programs (e.g., incubators, training hubs) available in your region?

   ☐ Yes ☐ No ☐ Not sure

Skills Indicators

1. How many employees in your organisation have basic knowledge of AI or data analytics?

   ☐ None ☐ 1–3 ☐ 4–10 ☐ More than 10

2. Have employees received formal AI-related training in the past 12 months?

   ☐ Yes ☐ No

3. Do you currently rely on external consultants for AI implementation?

   ☐ Yes ☐ No

APPENDIX B

Appendix B: Figure Explanations

This appendix provides detailed contextual explanations for Figures 8 through 28. Each explanation includes the purpose of the figure, its construction, and the analytical relationships it aims to visualize, enhancing clarity and supporting the theoretical and empirical findings presented in Chapter 4.

Figure	Title	Description
Figure 8	Research Model 1	Foundational model, integrates BMC and PESTEL analysis, maps influence of affordability, accessibility, and skills across SME environments.
Figure 9	Case Study 2 Impact	SME operations in telecommunications (South Africa), affordability moderate, skills critical adoption barrier.
Figure 10	Key Partnerships of Case Study 2	Influence of political and technological infrastructure on internal business partnerships, AI adoption shaped by ecosystem engagement.
Figure 11	Case Study 3 Impact	Fitness-focused SME, AI potential high but constrained by inconsistent internet access and staff upskilling needs.
Figure 12	Case 3 Social Environment	Social factors like fitness culture, digital familiarity, and customer attitudes toward AI personalization.
Figure 13	Case Study 3 Technological Environment	Technological readiness including app integration, wearables, and broadband availability, weak digital infrastructure limited AI system reliability.
Figure 14	Case Study 4 Impact	Ghanaian renewable energy SME, accessibility and skills barriers overshadow affordability issues.
Figure 15	Case Study 4 Social and Technological Impact	Community perceptions of AI, limited technical platforms, need for trust-building and tailored training programs.
Figure 16	Case Study 5 Impact	Construction sector, affordability major challenge, accessibility especially hardware availability in rural areas greatest obstacle.
Figure 17	Case Study 5 Political, Social, and Key Resources	Government funding programs and social narratives around AI influenced partnerships and employee readiness.

Figure 18	Case Study 6 Impact	Restaurant SME, cost-intensive AI tools posed affordability challenges, accessibility to training and compliance support core adoption bottlenecks.
Figure 19	Case Study 6 Political, Social, and Legal Environment	Political landscape around data, privacy, and national digital strategies shaped adoption ability, weak regulatory clarity increased risk.
Figure 20	Case Study 7 Impact	Hotel SME, high implementation costs and digital access gaps, workforce skilling initiatives seen as solution.
Figure 21	Case Study 7 Internal and External Environment Impact	Feedback loop model, improving internal digital competencies amplified external connectivity benefits.
Figure 22	Case Study 8 Impact	Tour-agency SME, affordability and skills deficits linked, accessibility to mobile-based AI central to feasibility.
Figure 23	Case Study 8 Social Impact and Key Partnerships	Social trust, engagement, and government tourism board partnerships determining factors.
Figure 24	Case Study 9 Impact	Indian retail SME, high growth potential limited by access to funding and trade regulations, moderate internal AI fluency.
Figure 25	Case Study 9 Political, Economic, and Legal Environment	Policy environment around data storage, cybersecurity, and AI ethics played critical role, legal uncertainty created barriers.
Figure 26	Case Study 10 Impact	Management Consulting SME in Chile, need for affordable AI marketing tools, accessibility especially reliable infrastructure hampered progress.
Figure 27	Case Study 10 Customer Relations and Segments	AI influenced customer segmentation and personalization capabilities, unlocking benefits depends on solving affordability and access issues.
Figure 28	Summary Matrix	Impact of Affordability, Accessibility, and Skills Matrix, summary of all 10 case studies.
Figure 29	Comparative Impact	Synthesizing across all 10 case studies, skills most critical, followed by accessibility and affordability.

APPENDIX C

This practical checklist guides SMEs in applying the integrated Business Model Canvas (BMC) and PESTEL framework to assess readiness for AI adoption. It ensures a structured evaluation of internal capabilities and external environmental factors.

Replication Protocol: BMC–PESTEL Checklist for SMEs Adopting AI	
	1. Business Model Canvas (Internal Assessment)
☐	Key Partners: Do we have access to AI vendors, consultants, or academic institutions?
☐	Key Activities: Which operations could benefit most from AI (e.g., customer service, logistics)?
☐	Key Resources: Do we have staff with digital or technical skills?
☐	Value Proposition: How could AI improve our product/service offering?
☐	Customer Relationships: Could AI enhance personalization or support?
☐	Channels: Are our current digital channels AI-compatible (e.g., CRM, web analytics)?
☐	Customer Segments: Which customer groups would benefit most from AI innovation?
☐	Cost Structure: What are the upfront and recurring costs of AI tools/training?
☐	Revenue Streams: Could AI create new sources of income or increase efficiency?
	2. PESTEL Analysis (External Environment)
☐	Political: Are national AI strategies, subsidies, or incentives available?
☐	Economic: Is our sector experiencing growth that could justify AI investment?
☐	Social: Are employees and customers open to AI-enhanced services?
☐	Technological: Do we have access to adequate internet, cloud services, and hardware?
☐	Environmental: Could AI help us optimize energy use or reduce waste?
☐	Legal: Are we compliant with data privacy laws (e.g., GDPR, POPIA)?

SMEs should revisit this checklist at multiple stages—initial exploration, pilot testing, and scaling. It can also be used during stakeholder planning sessions to identify alignment or gaps in readiness.