DETERMINANTS OF SME PERFORMANCE: THE MEDIATING ROLE OF AI ADOPTION AND MODERATING ROLE OF DIGITAL MARKETING WITHIN THE TECHNOLOGICAL, ORGANIZATIONAL AND ENVIRONMENTAL FRAMEWORK.

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ABSTRACT

Artificial Intelligence (AI) is transforming global business operations; however, its adoption among small and medium-sized enterprises (SMEs) in emerging markets remains relatively underexplored. Existing scholarship provides limited insights into the impact of AI adoption on SME performance in Pakistan. This study investigates the interrelationships among technological, organizational, and environmental factors, AI adoption, and SME performance within Pakistani manufacturing SMEs. Additionally, it examines the mediating role of AI adoption and the moderating effect of digital marketing strategies. Data were collected using judgmental sampling from 789 senior and middle-level managers across four manufacturing sectors in Pakistan: textiles, leather, sports goods, and surgical instruments. Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings reveal that relative advantage is the most influential driver of AI adoption in Pakistani manufacturing SMEs, followed by technology readiness, leadership vision, and trading partnerships. Further analysis shows that AI adoption significantly mediates the relationship between technological and environmental factors and SME performance. Moreover, digital marketing strategies strongly moderate this relationship, enhancing customer engagement and operational efficiency. These empirical results underscore the importance of perceived benefits and internal readiness as critical enablers supported by visionary leadership and collaborative partnerships. Theoretically, this study contributes by integrating the Technology-Organization-Environment (TOE) framework, the Diffusion of Innovation (DOI) theory, and the Resource-Based View (RBV) into a unified model specifically tailored for SMEs in an emerging economy. By analyzing the direct effect of technological, organizational, and environmental factors, mediating roles of AI adoption, and moderating roles of digital marketing, the research advances current knowledge in the field. Practically, the findings suggest that business leaders should prioritize AI-driven innovation and strategic digital marketing initiatives to enhance SME performance.

Keywords: AI Adoption, SME Performance, Digital Marketing Strategies, Technological Readiness, Relative Advantage

ABSTRAK

Kecerdasan Buatan (AI) sedang merevolusikan operasi perniagaan global; namun demikian, penerimaannya di kalangan perusahaan kecil dan sederhana (PKS) dalam pasaran negara membangun masih kurang mendapat perhatian kajian ilmiah. Penyelidikan yang sedia ada memberikan pandangan agak terhad mengenai kesan penerimaan AI terhadap prestasi PKS di Pakistan. Kajian ini meneliti hubungan antara faktor teknologi, organisasi, dan persekitaran dengan penerimaan AI serta prestasi PKS di kalangan perusahaan pembuatan di Pakistan. Selain itu, kajian ini turut mengkaji peranan perantaraan penerimaan AI dan kesan pemoderasian strategi pemasaran digital. Data dikumpulkan menerusi pensampelan pertimbangan melibatkan 789 pengurus kanan dan pertengahan daripada empat sektor pembuatan utama di Pakistan, iaitu tekstil, kulit, barangan sukan, dan instrumen pembedahan. Analisis data dilaksanakan menggunakan Pemodelan Persamaan Struktur Kaedah Kuasa Dua Terkecil (PLS-SEM). Hasil kajian menunjukkan bahawa kelebihan relatif merupakan pemacu utama penerimaan AI dalam PKS pembuatan di Pakistan, diikuti oleh kesediaan teknologi, visi kepimpinan, dan kerjasama perdagangan. Analisis lanjut mengesahkan bahawa penerimaan AI berfungsi sebagai pengantara yang signifikan dalam hubungan di antara faktor teknologi dan persekitaran dengan prestasi PKS. Selain itu, strategi pemasaran digital didapati memoderasi hubungan ini secara signifikan dengan meningkatkan penglibatan pelanggan dan kecekapan operasi. Dapatan empirikal ini menegaskan kepentingan manfaat yang dirasakan dan ketersediaan dalaman sebagai pemangkin kritikal, yang disokong oleh kepimpinan berwawasan serta kerjasama strategik. Secara teorinya, kajian ini menyumbang kepada bidang keilmuan dengan mengintegrasikan rangka kerja Teknologi-Organisasi-Persekitaran (TOE), Teori Penyebaran Inovasi (DOI), dan Pandangan Berasaskan Sumber (RBV) ke dalam satu model bersepadu yang disesuaikan khusus untuk PKS di ekonomi sedang membangun. Dengan menganalisis kesan langsung faktor teknologi, organisasi dan persekitaran, peranan perantaraan penerimaan AI, serta peranan pemoderasian strategi pemasaran digital, kajian ini memperkaya literatur sedia ada. Dari sudut praktikal, penemuan ini mencadangkan agar para pemimpin perniagaan memberi keutamaan kepada inovasi berasaskan AI dan pelaksanaan strategi pemasaran digital yang bersifat strategik bagi meningkatkan prestasi PKS.

Kata Kunci: Penerimaan AI, Prestasi PKS, Strategi Pemasaran Digital, Kesediaan Teknologi, Kelebihan Relatif

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LIST OF ABBREVIATION

AI	Artificial Intelligence
AIC	Akaike Information Criterion
AIDDM	Artificial Intelligence for Decision-Making
AIM	Artificial Intelligence in Marketing
AVE	Average Variance Extracted
DCT	Dynamic Capabilities Theory
ED	Entrepreneurial Development
ERP	Enterprise Resource Planning
GDP	Gross Domestic Product
GDPR	General Data Protection Regulation
GII	Global Innovation Index
HTMT	Heterotrait-Monotrait Ratio
ICSB	International Council for Small Business
ICT	Information and Communication Technology
IoT	Internet of Things
IS	Information Systems
IT	Information Technology
ML	Machine Learning
NLP	Natural Language Processing
OECD	Organisation for Economic Co-operation and Development

PLS	Partial Least Squares
RBV	Resource-Based View
ROI	Return on Investment
RRI&A	Research, Regulatory Insight & Advocacy Assistance for SMEs
SBP	State Bank of Pakistan
SCM	Supply Chain Management
SDG	Sustainable Development Goals
SECP	Securities and Exchange Commission of Pakistan
SMEDA	Small and Medium Enterprises Development Authority
SMEs	Small and Medium-sized Enterprises
SMIs	Small and Medium Industries
TOE	Technology-Organization-Environment
VRIN	Valuable, Rare, Inimitable, Non-substitutable
WIPO	World Intellectual Property Organization

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Small and medium-sized enterprises (SMEs) are vital to global economic development, contributing approximately 50% of global GDP and employing over 70% of the workforce (Brahmi et al., 2024; Wilczynska et al., 2024). Their agility and innovation capacity make them key players in industrial growth, especially in developing economies. However, despite their significance, SMEs often face structural barriers such as limited financing, digital infrastructure gaps, and regulatory inefficiencies (Manzoor et al., 2021).

Definitions of SMEs vary by country, typically based on criteria like number of employees, annual revenue, and total assets (Berisha & Pula, 2015). For instance, the European Commission classifies SMEs as firms with fewer than 250 employees (Milea et al., 2014), while the U.S. Small Business Administration applies a 500-employee threshold, adjusting for industry-specific differences (Han et al., 2017). In emerging markets like India or Brazil, definitions are tailored to local economic contexts (Dadwal et al., 2024).

In Pakistan, SMEs make up over 90% of all businesses, contribute 40% to GDP, and employ 70% of the non-agricultural workforce (Raza et al., 2018; SMEDA, 2022). They dominate key export sectors—textiles, leather, sports goods, and surgical instruments—

yet face persistent challenges in scaling operations and adopting emerging technologies. According to SMEDA (2022), SMEs are defined as follows:

Table 1.1
Definition of SME.

Classification of Enterprise Criteria	**Criteria** **Revenue from Annual Sales**
Small Business (SB)	Not exceeding 150 million Pakistani Rupees (PKR)
Medium-Sized Business (MSB)	Exceeding 150 million PKR but not more than PKR 800 Million
Start-up	Startup Defined as a SME within its first 5 years of operation, categorized accordingly as Startup SE or Startup ME.

(Source: SMEDA, 2022)

A substantial number of Pakistani SMEs remain informal, limiting access to institutional credit and technological infrastructure. Over 70% lack formal financing (Shaikh et al., 2011), while only 15% have adopted AI solutions—far below the global average of 35% (Shukla & Taneja, 2024). Barriers include high implementation costs, limited digital skills, infrastructure deficiencies (e.g., unreliable electricity and internet), and resistance to change (Heredia-Calzado & Duréndez, 2019; Rawashdeh et al., 2023).

The integration of Artificial Intelligence (AI) and digital marketing is becoming critical for SME competitiveness. AI tools—such as machine learning, predictive analytics, and process automation—enhance operational efficiency, decision-making, and customer engagement (Muminova et al., 2024; Brahmi et al., 2024). AI-driven marketing strategies, including automated campaigns and chatbots, improve customer targeting, sales performance, and brand visibility (Chatterjee et al., 2022).

Despite global momentum, Pakistani SMEs lag in AI adoption and digital transformation due to weak policy support, financial exclusion, and limited implementation capacity (Badghish & Soomro, 2024). This growing digital divide highlights the need for structured research on how technological, organizational, and environmental factors influence AI adoption and how digital strategies can enhance performance.

The Technology-Organization-Environment (TOE) framework offers a structured lens to examine these adoption drivers, categorizing them into technological readiness, organizational capabilities, and external pressures (Tornatzky & Fleischer, 1990). However, existing research largely focuses on large firms, with limited attention to SMEs in emerging markets. Similarly, the potential of digital marketing to amplify AI's benefits remains underexplored.

This study responds to these gaps by investigating how AI adoption mediates SME performance and how digital marketing moderates this relationship. Through an integrated framework combining TOE, Diffusion of Innovations (DoI), and the Resource-Based View (RBV), the study aims to provide actionable insights for boosting SME innovation, sustainability, and competitiveness in Pakistan.

1.2 Problem Statement

1.2.1 Technology Evolution in Pakistani SMEs

Artificial Intelligence (AI) is transforming business operations globally, offering opportunities for efficiency, automation, and strategic agility. While large firms have embraced AI at scale, Small and Medium-sized Enterprises (SMEs) now also stand to benefit from its applications—particularly in process optimization, predictive analytics, and digital marketing. Globally, 35% of SMEs have adopted AI technologies; however, in Pakistan, adoption remains critically low at just 15% (Kandeel et al., 2024; Shukla & Taneja, 2024). This disparity creates a widening technological divide, rendering Pakistani SMEs less competitive in increasingly digital global markets (Nazir et al., 2025).

AI's adoption in SMEs is shaped by a combination of technological readiness, organizational capability, and environmental support. The Technology-Organization-Environment (TOE) framework offers a useful lens to evaluate these dimensions (Ramdani et al., 2013). Yet, Pakistani SMEs continue to face systemic obstacles, including limited infrastructure, inadequate leadership commitment, lack of AI-trained personnel, and insufficient external policy support (Rawashdeh et al., 2023; Shinozaki, 2014).

The need for AI integration is especially critical given the recent contraction of Pakistan's manufacturing sector—particularly an 8.0% decline in large-scale manufacturing (LSM) in FY2023. Despite SMEs contributing 40% to GDP and 25% to exports, their competitiveness is declining due to digital lag and obsolete business models (SBP, 2023; SMEDA, 2022).

Table 1.2.
Industrial Production Growth in the Manufacturing Sector (FY19-FY23).

Fiscal Year	Overall Manufacturing Growth (%)	Growth in Large-Scale Manufacturing (%)	Growth in Small-Scale Manufacturing (%)
FY19	4.5	3.5	9.0
FY20	-7.8	-11.2	1.4
FY21	10.5	11.5	9.0
FY22	10.9	11.9	8.9
FY23	-3.9	-8.0	9.0

Source: (State Bank of Pakistan [SBP], 2023).

To remain viable in today's fast-evolving environment, SMEs must adopt AI-enabled tools like automation, business intelligence, and AI-driven marketing. However, gaps in policy, infrastructure, financing, and digital literacy remain substantial. While research has explored generic AI benefits, few studies investigate the specific drivers and barriers affecting AI adoption among SMEs in Pakistan's manufacturing sector.

1.2.2 Sector-Specific Challenges in Manufacturing SMEs

Manufacturing SMEs in Pakistan, especially in textiles, leather, surgical, and sports sectors, are foundational to economic activity but remain under-equipped to leverage AI and digital transformation. Challenges persist across three core areas:

- **Financial and Talent Limitations:** Over 70% of SMEs lack access to formal credit, and few can afford or retain AI-skilled talent (Manzoor et al., 2021;

Badghish & Soomro, 2024). High financing costs and limited digital literacy hinder technology adoption.

- **Infrastructure and Digital Access:** Weak internet connectivity, frequent power outages, and lack of access to cloud services obstruct AI-driven transformation (Rawashdeh et al., 2023).

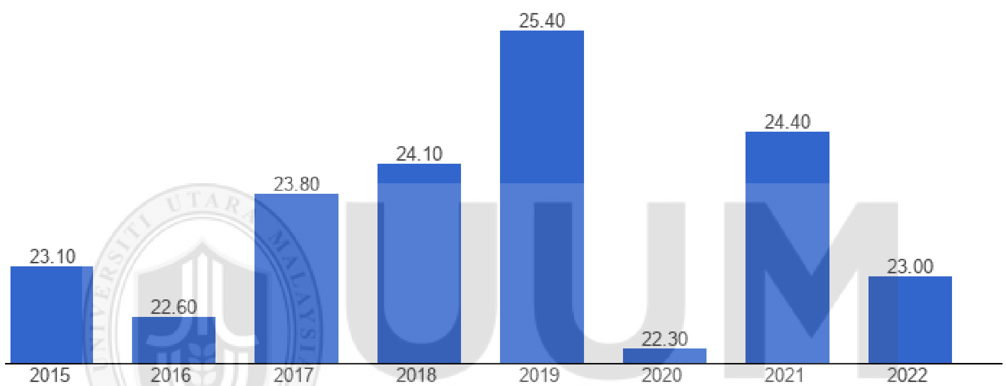

Figure 1.1.
Pakistan's Innovations Index (2011-2022).
Source: WIP, (2022)

- **Global Competitiveness and Export Constraints:** Pakistani SMEs face rising global demands for AI-integrated production, traceability, and sustainability compliance. Without AI-enabled quality control and logistics systems, local SMEs risk falling further behind (Rabby et al., 2021).

Digital marketing is also underutilized. AI-powered marketing tools—such as customer segmentation, predictive analytics, and automation—remain beyond the reach of most

SMEs due to skills gaps, cost barriers, and resistance to change (Enshassi et al., 2024; Chatterjee et al., 2022).

1.2.3 Theoretical Gap and Research Motivation

Although literature highlights AI's benefits in productivity and innovation, few studies offer a comprehensive framework combining technological, organizational, and environmental enablers for AI adoption in SMEs—especially within resource-constrained, emerging economies like Pakistan. Research is often fragmented, focusing narrowly on either infrastructure or operational outcomes, with limited attention to strategic interactions among internal and external factors (Nazir et al., 2025).

Moreover, prior studies have largely overlooked AI's role as a mediator between enabling conditions and performance, as well as the moderating influence of digital marketing strategies. Without understanding these mechanisms, the full potential of AI in SME competitiveness remains unrealized (Brahmi et al., 2024).

1.2.4 Bridging the Gap Through a Theoretical Framework

This study addresses the gap by integrating three theoretical perspectives:

1. Technology-Organization-Environment (TOE) Framework – Examines AI adoption from infrastructural, leadership, and environmental standpoints.

2. Diffusion of Innovation (DOI) Theory – Explains differential AI adoption behavior based on innovation attributes like complexity and perceived advantage.

3. Resource-Based View (RBV) – Positions AI as a strategic resource for sustainable competitive advantage.

This integrated framework investigates:

- The factors that influence AI adoption across Pakistani manufacturing SMEs;
- Whether AI mediates the relationship between TOE dimensions and performance;
- How AI-driven digital marketing enhances (moderates) this relationship.

By doing so, this study offers a structured and empirically tested framework for AI adoption and performance enhancement, tailored to the Pakistani SME context and its emerging market dynamics.

1.3 Research Questions

This study investigates how the adoption of Artificial Intelligence (AI) affects the performance of small and medium-sized enterprises (SMEs) in Pakistan's manufacturing sector. Drawing on the Technology–Organization–Environment (TOE) framework, the Diffusion of Innovations (DOI) theory, and the Resource-Based View (RBV), the research aims to explore both direct and indirect relationships among key organizational and environmental constructs, AI adoption, and firm performance.

The central research question guiding this study is:

"How do technological, organizational, and environmental factors influence AI adoption and, in turn, shape SME performance in Pakistan, considering the mediating role of AI and the moderating effect of digital marketing strategies?"

To address this overarching question, the study is further guided by the following sub-questions:

- **RQ1**: What is the influence of technological factors (e.g., compatibility, relative advantage, and technology readiness), organizational factors (e.g., leadership vision and change management capability), and environmental factors (e.g., competitive pressure and trading partnerships) on AI adoption among SMEs in Pakistan?
- **RQ2**: To what extent does AI adoption affect the performance of SMEs in the Pakistani manufacturing sector?
- **RQ3**: How does AI adoption mediate the relationship between the TOE factors (technological, organizational, and environmental) and SME performance?
- **RQ4**: How do digital marketing strategies moderate the relationship between AI adoption and SME performance?

These research questions are designed to comprehensively capture the multidimensional dynamics of AI adoption in resource-constrained environments, while also responding to key theoretical and practical gaps in the literature.

1.4 Research Objectives

The overarching aim of this study is:

"To examine how technological, organizational, and environmental factors influence SME performance in Pakistan, with Artificial Intelligence (AI) adoption as a mediating mechanism and digital marketing strategies as a moderating influence."

Based on this central aim, the study seeks to achieve the following specific objectives:

- **RO1**: To assess the extent to which technological, organizational, and environmental factors influence AI adoption in Pakistani manufacturing SMEs.
- **RO2**: To evaluate the influence of AI adoption on SME performance in Pakistan.
- **RO3**: To investigate whether AI adoption mediates the relationship between TOE factors (technological, organizational, and environmental) and SME performance.
- **RO4**: To determine the moderating effect of digital marketing strategies on the relationship between AI adoption and SME performance.

This structured objective design reflects the theoretical underpinnings of the TOE framework, Diffusion of Innovations (DOI), and Resource-Based View (RBV), while also emphasizing the practical significance of AI integration for SME competitiveness in an emerging economy context.

1.5 Scope of the Study

This study investigates the influence of Artificial Intelligence (AI) adoption and digital marketing strategies on the performance of small and medium-sized enterprises (SMEs) in Pakistan. The research is geographically confined to Pakistan—a representative emerging economy—yet the insights generated may offer contextual relevance to other developing nations with similar technological and institutional constraints. The scope is shaped by the practical and methodological consideration of applying digital technologies within a resource-constrained environment.

To maintain analytical depth, this study focuses exclusively on SMEs operating within the manufacturing sector, specifically targeting four key industries: textiles, leather goods, surgical instruments, and sports equipment. These sectors were selected based on their significant contribution to Pakistan's exports and GDP, as well as their vulnerability to declining competitiveness due to low AI adoption and outdated digital practices. While service-based SMEs are also influenced by AI and digital marketing, manufacturing SMEs were prioritized due to their critical industrial positioning, policy focus, and operational complexity—enabling more actionable insights within a bounded scope.

The research scope includes an examination of the technological dimensions of AI (compatibility, readiness, and perceived relative advantage), organizational enablers (leadership vision, change management capability), and environmental conditions (competitive pressure, trading partnerships) as per the Technology–Organization–

Environment (TOE) framework. In addition, the Diffusion of Innovation (DOI) theory underpins the innovation characteristics of AI adoption, while the Resource-Based View (RBV) informs the strategic implications of AI and digital marketing as firm-specific capabilities.

This study makes contributions across three domains:

- Theoretical Contribution: It integrates TOE, DOI, and RBV frameworks into a unified model of AI adoption in SMEs, providing empirical evidence on mediating and moderating mechanisms not adequately explored in existing literature.
- Practical and Managerial Implications: The findings offer actionable strategies for SME owners regarding AI deployment, digital marketing integration, and capability development.
- Policy Relevance: Recommendations are made to support SME digital transformation through policy measures related to financing, infrastructure, training, and AI innovation ecosystems.

Finally, while the findings are grounded in the Pakistani context, they may serve as a benchmark for comparative research across other emerging markets. The study also identifies pathways for future research, including AI adoption in service-based SMEs, cross-country comparisons, and longitudinal assessment of digital transformation outcomes.

1.6 Significance of the Study

The integration of AI in business operations is particularly transformative for SMEs in Pakistan, where resource constraints often hinder technological advancements. This study fills a critical gap in the literature by offering empirical evidence on AI's direct impact on SME performance. By exploring the mediating role of AI and the moderating role of digital marketing strategies, the study provides strategic insights tailored to the context of Pakistani SMEs. It addresses key questions about whether SMEs in Pakistan have the necessary resources—such as financial, infrastructural, and human capital—to successfully integrate AI into their operations. The findings have significant implications for policy formulation, guiding the development of supportive policies that foster AI adoption and innovation within the SME sector. Moreover, the study contributes to global academic discourse by providing a unique perspective from an emerging market, offering insights that can inform technological strategies for SMEs in similar contexts.

1.6.1 Theoretical Significance

This study provides a substantial theoretical contribution by integrating the Technological, Organizational, and Environmental (TOE) framework, the Diffusion of Innovations (DoI) theory, and the Resource-Based View (RBV) into the investigation of AI adoption among SMEs in Pakistan. These theoretical frameworks are employed to offer a holistic understanding of how AI technologies are adopted in a resource-constrained environment.

By adapting the TOE framework, the study delves into three critical dimensions that influence AI adoption:

- Technological factors, including AI readiness and compatibility, are examined to understand how SMEs evaluate and integrate AI technologies within existing business operations.
- Organizational factors such as leadership vision and change management capability are analyzed to assess how internal resources and organizational culture support or hinder AI adoption.
- Environmental factors, including competitive pressure and trading partnerships, are explored to determine how external market dynamics influence SMEs' decisions to adopt AI.

The study's contribution lies in its application of the TOE framework in the context of a developing economy, specifically Pakistan. The extension of the Diffusion of Innovations (DoI) theory in this study emphasizes AI as a critical innovation for SMEs, addressing both the facilitators and barriers to its adoption. The study examines how early adopters of AI technologies within SMEs can drive diffusion across the sector and identifies the factors that affect the speed and scope of AI adoption.

Further, by incorporating the Resource-Based View (RBV), the study positions AI as a strategic resource that can offer a competitive edge for SMEs. The research highlights the role of AI in enhancing firm-level capabilities, improving decision-making processes, and achieving operational efficiencies. The RBV framework is particularly relevant in this context, as it helps explain how SMEs, despite resource constraints, can leverage AI to differentiate themselves in competitive markets.

The theoretical extension of the RBV adds depth to the understanding of AI as a resource that can foster innovation and lead to sustainable competitive advantages. This study, therefore, enriches the existing literature by integrating multiple theoretical perspectives to capture the complexities of AI adoption in SMEs, particularly in emerging economies like Pakistan. The findings are pivotal for understanding the intersection of technology, organizational readiness, and external market conditions in shaping AI adoption pathways, making a significant contribution to both theory and practice in the field of AI and SME performance.

This multi-theoretical approach provides a comprehensive lens through which AI adoption can be understood, offering a robust framework for future research that seeks to explore AI adoption across different industries and geographic regions in emerging markets. By doing so, the study lays a solid theoretical foundation for examining how technology adoption can drive performance and innovation in the SME sector.

1.6.2 Practical Significance

The practical implications of this study are wide-ranging and provide actionable insights for various stakeholders, including SMEs, policymakers, and technology vendors in Pakistan.

For SMEs, the study offers valuable guidance on strategically adopting AI to enhance both operational efficiency and overall business performance. The findings emphasize the importance of technological readiness, leadership vision, and external partnerships as key drivers of successful AI adoption. SME managers can use these insights to make informed decisions about resource allocation, ensuring that investments in AI are aligned with their organizational goals and capabilities. The study underscores the need for SMEs to prioritize digital marketing strategies as an essential tool to maximize the benefits of AI, particularly in improving customer engagement and operational efficiency. These practical insights help SMEs navigate the complexities of AI integration, empowering them to compete more effectively in a digitalized business environment.

For policymakers, the study offers a roadmap for designing and implementing policies that support AI adoption in the SME sector. The findings highlight the specific challenges faced by SMEs, such as the lack of financial resources, inadequate digital infrastructure, and a shortage of skilled human capital. Policymakers can use these insights to craft financial incentives and develop capacity-building programs that address these challenges, thereby fostering a more AI-friendly business environment. Furthermore, the study emphasizes the importance of building a robust digital ecosystem, which includes improving access to high-quality digital infrastructure and developing AI literacy programs that can equip SMEs with the necessary skills to integrate AI technologies. Such interventions are critical for enhancing the competitiveness and sustainability of SMEs in Pakistan.

For technology vendors, the study provides a deeper understanding of the needs and challenges of Pakistani SMEs, helping them develop tailored AI solutions that address the specific requirements of this sector. The research highlights the importance of designing cost-effective and scalable AI technologies that can be easily integrated into the existing systems of SMEs. Vendors can use the findings to create AI solutions that cater to the unique needs of SMEs in Pakistan, focusing on enhancing their operational capabilities and customer management processes. Additionally, the insights from the study can guide vendors in developing AI tools that are aligned with the local business context and regulatory environment, ensuring that their products are both relevant and impactful for SMEs in emerging markets.

Overall, the practical contributions of this study serve as a blueprint for enhancing AI adoption and fostering innovation within the SME sector in Pakistan. By addressing the specific needs of SMEs, policymakers, and technology providers, the research facilitates the development of a supportive ecosystem that encourages technological innovation and promotes sustainable growth. This study not only contributes to improving the business practices of SMEs but also plays a crucial role in shaping the future of AI-driven entrepreneurship in Pakistan's evolving economic landscape.

1.7 Definition of Key Terms

In this research, the key terms are operationally defined as follows:

1.7.1 Artificial Intelligence (AI) Adoption

AI adoption is the process by which organizations implement AI capabilities to interpret, infer, and learn from data, thereby achieving predetermined goals (Mikalef & Gupta, 2021a). This study precisely denotes the implementation of AI technologies by SMEs in Pakistan to improve their operational effectiveness and performance.

1.7.2 Compatibility

Compatibility is conceptualized as the degree to which artificial intelligence (AI) technology corresponds with and can be integrated into an organization's existing IT framework, thereby supporting a smooth technological integration (Kurup

& Gupta, 2022).

1.7.3 Relative Advantage

Relative advantage is characterized by the perceived superiority and benefits of implementing AI compared to current methodologies or technologies within an organization (Kurup & Gupta, 2022; Yang et al., 2013)

1.7.4 Technology Readiness

Technology Readiness refers to an organization's preparedness to implement and support AI technology, considering human resources, data, financial aspects, and technological infrastructure (Kurup & Gupta, 2022).

1.7.5 Leadership Vision

Leadership Vision refers to the strategic perspective and dedication of the top management within an organization towards adopting and supporting AI (Kurup & Gupta, 2022; Yang et al., 2015).

1.7.6 Change Management Capability

Change management capability denotes the capacity of an organization to manage and adapt to the operational and structural changes brought about by AI implementation (Kurup & Gupta, 2022; Leyer & Schneider, 2021; Sai Ambati et al., 2020).

1.7.7 Competitive Pressure

Competitive pressure refers to the external impetus for organizations, the external impetus for organizations to adopt AI-driven by the need to maintain or improve competitive positioning (Chang et al., 2007; Kurup & Gupta, 2022; Porter & Millar, 1985).

1.7.8 Trading Partners

Trading partners refer to the influence of external business entities, such as suppliers and vendors, on an organization's decision to adopt AI (Dyer & Singh, 2018; Henderson, 1990; Kurup & Gupta, 2022).

1.7.9 Financial Performance

Financial performance refers to the measurable financial results of integrating AI, such as profitability, sales volume, and ROI, which reflect the direct economic benefits to the organization (Chen et al., 2022; Jain et al., 2014).

1.7.10 Non-Financial Performance

Non-financial performance encompasses the qualitative benefits derived from incorporating AI, such as enhanced client contentment, enhanced loyalty, and a more robust competitive advantage. These elements contribute a crucial role in the strategic and sustainable development of the organization (Chen et al., 2022; Diffley & McCole, 2015; Hernaus et al., 2012).

1.7.11 Digital Marketing Strategies

Digital marketing strategies consist of marketing efforts by organizations that utilize digital technologies to engage with commercial allies and clients. They integrate digital frameworks or infrastructures to create new value, fostering multiple interactions for customer data collection and communication (Wu et al., 2024).

1.8 Organization of the Thesis

The thesis is methodically structured into separate chapters, with each one fulfilling a unique role within the logical progression of the research process.

Chapter one sets the stage for the entire research. It unveils the background of the study, providing the context and relevance that anchors the research within a larger discourse. It articulates the problem statement, highlighting the existing gaps or challenges in the domain of AI, digital marketing strategies, and SME performance. The research questions are posed here, serving as the main queries guiding the research, accompanied by the research objectives that enumerate the goals set out to be achieved. The research's scope is clearly established, setting the parameters and confines of the study's operational field. The study's import is articulated, underscoring its potential impact and value within scholarly and applied realms. Moreover, the study acknowledges the possibility constraints or elements contributing could influence the interpretation of its results, thus outlining its limitations.

Chapter two delves deep into the existing body of literature, presenting an overview of prior studies, findings, and established knowledge in the domain. It discusses the TOE factors from the TOE framework and their interplay with the uptake of AI and the performance of small and SMEs. The RBV theory serves as the foundational framework for this research, scrutinized for its applicability and pertinence in evaluating SME performance. Furthermore, the DOI theory is rigorously analyzed, shedding light on its relevance to the study theme and furnishing the conceptual underpinning for the research.

Chapter three elucidates the research design, outlining the blueprint for conducting the research. It discusses the sampling technique, elaborating on the methods employed to select participants or units for the research. The gathering of data section outlines the instruments and methods employed in collecting data, while the data analysis section describes the statistical or quantitative techniques to be used in interpreting the collected data. The chapter also ensures the validity and reliability of the research, establishing the accuracy, consistency, and credibility of the research tools and findings.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter examines the key concepts relevant to the current investigation. It reviews previous studies and organizes the literature into distinct sections that form the foundation of the models used in this analysis. The chapter systematically explores the existing literature to establish the interconnections among AI adoption, digital marketing strategies, and SME performance. It identifies prevailing gaps and expands the understanding of the factors driving SME performance within the context of technological advancements. The chapter begins by defining and conceptualizing SME performance, followed by a review of the literature on the key variables influencing SME performance. The foundational theories pertinent to this study are outlined in the middle section, demonstrating the interconnected dynamics of the variables under examination. The chapter concludes with a summary of the hypotheses developed, which pertain to the research questions and objectives outlined in Chapter One.

2.2 SME Performance

Small and Medium Enterprises (SMEs) play a pivotal role in economic growth, employment generation, and innovation, but their performance remains complex, encompassing financial and non-financial dimensions influenced by both internal resources and external conditions. SME performance includes dimensions such as financial sustainability, operational efficiency, innovation capability, customer engagement, and environmental sustainability (Mikalef & Gupta, 2021; Wamba-Taguimdje et al., 2020). Each dimension is critically linked to technological adoption, particularly Artificial Intelligence (AI), which enhances SMEs' capability to achieve superior outcomes.

Firm performance (FP) in this study is conceptualized through a multidimensional perspective aligned with the Resource-Based View (RBV). RBV posits that firm performance hinges on leveraging valuable, rare, inimitable, and non-substitutable resources, including technological and human capabilities (Barney, 1991; Chatterjee et al., 2021; Mikalef & Gupta, 2021). Performance indicators adopted for this study encompass market growth, financial stability, product innovation, and AI's role in enhancing business outcomes (Bu et al., 2020; Chen et al., 2016)

2.2.1 Dimensions of SME Performance

SME performance is multidimensional, extending beyond traditional financial measures to incorporate operational efficiency, innovation, customer satisfaction, and sustainability compliance. Financial indicators, including profitability and liquidity, are crucial but insufficient to capture the broader aspects of business success (Feng et al., 2020; Cicea et al., 2019). Operational efficiency, supported by AI-driven automation and predictive analytics, significantly influences SMEs' competitiveness by streamlining processes and reducing costs (Bag et al., 2022; Denicolai et al., 2021).

Innovation capability is central to SME sustainability, enabling adaptability and market responsiveness through continuous product and service improvements. AI facilitates innovation by leveraging data-driven insights to anticipate market trends and personalize product offerings, enhancing competitive advantage (Huynh et al., 2020; Teece, 1986). Customer satisfaction, driven by AI-powered digital marketing, predictive analytics, and personalized interactions, further enhances SME market positioning and retention rates (Chatterjee et al., 2021; Pillai et al., 2020).

Environmental sustainability is increasingly relevant, given growing regulatory pressures and consumer expectations. AI supports SMEs in optimizing resource use, reducing waste, and meeting sustainability goals, thus reinforcing their long-term viability and market reputation (Dubey et al., 2020; Eccles et al., 2014).

Table 2.1 presents a summary of key indicators commonly used to assess SME performance.

Table 2.1
SME Performance Dimensions and Indicators

Performance Dimension	Indicators	Relevance to SMEs	Supporting References
Financial Performance	Profitability, Liquidity, ROI	Ensures financial sustainability	Cicea et al. (2019); Feng et al. (2020)
Operational Efficiency	Production speed, Quality control	Enhances cost-effectiveness	Shah & Ward (2003); Kim et al. (2021)
Innovation	R&D investments, New product launches	Drives competitive advantage	Schumpeter (1942); Teece (1986); Denicolai et al. (2021)
Customer Satisfaction	Retention rates, Service efficiency	Strengthens market positioning	Chien et al. (2020); Pillai et al. (2020)
Sustainability	ESG compliance, Resource efficiency	Reduces long-term risks	Eccles et al. (2014); Dubey et al. (2020)

Source: Adapted from Cicea et al. (2019); Feng et al. (2020); Kim et al. (2021); Chien et al. (2020); Dubey et al. (2020).

2.2.2 Measurement Approaches for SME Performance

Measuring SME performance combines objective financial metrics (profitability, ROI) and subjective managerial assessments (growth perceptions, market positioning). Objective measures provide quantifiable outcomes but may miss intangible performance aspects. Subjective measures, while susceptible to biases, effectively capture strategic insights in environments with limited financial transparency (Singh et al., 2015; Pucci et al., 2017).

Data availability remains challenging, especially in developing contexts where SMEs often lack robust financial records (Ahmad et al., 2021). AI-driven analytics and automation offer solutions by enhancing performance measurement capabilities, enabling more accurate and timely strategic decisions (Feng et al., 2020; Denicolai et al., 2021).

2.2.3 AI and SME Performance: A Multidimensional Perspective

The integration of AI into SME operations has transformed business processes across financial management, operational efficiency, innovation, customer engagement, and sustainability. AI-driven financial tools enhance cost optimization by automating budgeting, improving cash flow forecasting, and reducing fraud risks (Feng et al., 2020; Denicolai et al., 2021). The adoption of AI-powered automation has also improved operational workflows, enabling SMEs to enhance productivity, minimize errors, and optimize resource allocation (Bag et al., 2021; Chien et al., 2020).

AI is increasingly recognized as a driver of SME innovation, allowing businesses to leverage predictive analytics, big data insights, and smart manufacturing processes to enhance product development and market differentiation (Schumpeter, 1942; Teece, 1986). The ability to process large volumes of data enables SMEs to identify consumer trends, optimize pricing strategies, and develop targeted marketing campaigns, strengthening their competitive positioning (Keegan et al., 2022; Denicolai et al., 2021).

Customer engagement and personalization have also been significantly enhanced through AI applications in marketing and service delivery. AI-powered chatbots, recommendation algorithms, and automated customer feedback analysis improve response times and service efficiency, fostering brand loyalty and increased customer retention (Pillai et al., 2020; Chatterjee et al., 2021). SMEs utilizing AI-driven marketing strategies benefit from enhanced segmentation, higher conversion rates, and improved return on advertising spend (Keegan et al., 2022).

From a sustainability perspective, AI applications support SMEs in achieving ESG compliance through data-driven energy management, waste reduction, and environmental impact monitoring (Li et al., 2021; Dubey et al., 2020). AI-enabled resource optimization helps SMEs minimize operational costs while ensuring alignment with global sustainability goals, improving long-term business viability.

2.2.4 External Influences on SME Performance

SME performance is shaped not only by internal capabilities but also by external environmental factors, including regulatory frameworks, competitive market dynamics, financial accessibility, and infrastructural constraints. These factors can either enable or inhibit SME growth, particularly in developing economies like Pakistan. Understanding the external environment is crucial for SMEs to adapt and sustain long-term competitiveness in an AI-driven economy.

The regulatory environment plays a pivotal role in SME growth, influencing business ease, compliance costs, and access to government support. Favorable regulatory policies can enhance SME competitiveness, while bureaucratic inefficiencies, excessive taxation, and regulatory uncertainty can hinder business expansion (World Bank, 2022).

- Ease of Doing Business: Pakistan ranks low on the Ease of Doing Business Index, reflecting cumbersome bureaucratic processes, lengthy business registration procedures, and inconsistent regulatory enforcement (Ahmad et al., 2021). Simplifying business regulations and reducing administrative burdens can enhance SME formalization and promote AI-driven digital transformation.
- Taxation and Compliance: High taxation rates and complex tax structures discourage SME investment in AI and technological adoption (Raza et al., 2018). Studies highlight that excessive tax compliance costs divert financial resources away from innovation and technology investments (Dar et al., 2017).

- Government Policies and SME Support: While institutions like SMEDA (Small and Medium Enterprises Development Authority) and State Bank of Pakistan (SBP) provide SME financing schemes, policy inconsistencies and lack of enforcement limit the effectiveness of such programs (Manzoor et al., 2021).

Competition within the SME sector is intensifying due to globalization, digital disruption, and evolving consumer expectations. The Porter's Five Forces framework helps analyze how competitive forces shape SME performance (Porter, 1985):

- Industry Rivalry: High competition in textiles, manufacturing, and retail sectors compels SMEs to adopt AI-powered efficiency strategies, such as predictive analytics and automation, to maintain profitability (Bag et al., 2021).
- Bargaining Power of Customers: Digitalization has increased customer expectations for personalized services, putting pressure on SMEs to enhance digital marketing and AI-driven customer engagement (Keegan et al., 2022).
- Threat of New Entrants: Low barriers to entry in the SME sector create high market saturation, pushing SMEs to differentiate through AI-powered business intelligence and data analytics (Dubey et al., 2020).
- Supplier Bargaining Power: Dependence on imported raw materials exposes SMEs to currency fluctuations and supply chain risks, necessitating AI-driven supply chain optimization for cost efficiency (Huynh et al., 2020).
- Threat of Substitutes: The rise of e-commerce and digital platforms is reshaping market dynamics, forcing traditional SMEs to integrate AI-driven pricing strategies and automated service offerings (Pillai et al., 2020).

One of the greatest barriers to SME performance in Pakistan is limited access to financing. Despite SMEs constituting 90% of businesses, they receive only 7% of total bank lending due to high collateral requirements, lack of credit history, and risk-averse banking policies (Shaikh et al., 2011; Manzoor et al., 2021).

- Collateral and Creditworthiness: SMEs often struggle with collateral-based lending, restricting their ability to secure funding for AI adoption and digital infrastructure (Raza et al., 2018). Alternative financing models, such as venture capital and fintech lending, remain underdeveloped in Pakistan (Han et al., 2017).
- Interest Rates and Loan Accessibility: High interest rates disincentivize SMEs from seeking formal credit, pushing them towards informal borrowing with unfavorable repayment conditions (Dar et al., 2017). Government-backed microfinance initiatives could bridge this financing gap.
- Digital Finance and AI in Lending: AI-driven credit scoring models and blockchain-based lending could revolutionize SME financing by offering data-driven risk assessments, increasing SME financial inclusion (Kim et al., 2021).

A lack of robust infrastructure poses significant constraints on SME productivity and technology adoption. Pakistan's underdeveloped digital ecosystem, unreliable electricity supply, and inadequate internet penetration are major challenges for AI integration in SMEs (Raza et al., 2018).

- Power and Energy Constraints: Frequent power outages and high energy costs disrupt SME operations, making AI-driven automation costly and inefficient (Shaikh et al., 2011).
- Digital Infrastructure and Internet Access: While Pakistan's internet penetration has increased, broadband affordability and quality remain inconsistent, particularly in rural areas where many SMEs operate (Ahmad et al., 2021).
- Technological Readiness: Many SMEs lack digital literacy and technical expertise to implement AI and advanced digital solutions. Investments in digital upskilling and AI education programs are crucial for bridging this gap (Mikalef & Gupta, 2021).

External influences, including regulatory policies, competitive market pressures, financing constraints, and infrastructural limitations, play a critical role in shaping SME performance. While AI presents opportunities for enhancing financial efficiency, operational performance, and customer engagement, external barriers continue to hinder AI adoption. Addressing these challenges through policy reforms, financial inclusion initiatives, and digital infrastructure improvements is essential for SMEs to leverage AI for sustainable growth and competitiveness.

2.2.5 Theoretical Integration

The adoption of Artificial Intelligence (AI) and digital marketing in small and medium enterprises (SMEs) can be comprehensively understood by integrating three established theoretical frameworks: The Resource-Based View (RBV), the Technology–

Organization–Environment (TOE) framework, and the Diffusion of Innovations (DoI) theory. These models collectively explain how firms adopt and benefit from digital technologies, especially under the contextual constraints of emerging economies such as Pakistan. The integration of these perspectives provides a solid foundation to explore the mediating role of AI adoption and the moderating influence of digital marketing on SME performance.

The RBV emphasizes that firms gain sustained competitive advantage by leveraging resources that are valuable, rare, inimitable, and non-substitutable (Barney, 1991). Within this view, AI technologies are considered strategic resources that can enhance decision-making, innovation, and operational efficiency (Denicolai et al., 2021). When supported by internal capabilities—such as digital skills, leadership vision, and a culture of innovation—AI contributes significantly to SME performance (Mikalef & Gupta, 2021). In this study, SME performance is conceptualized as a multidimensional construct that includes financial sustainability, innovation output, operational efficiency, and customer responsiveness.

These outcomes are closely tied to how effectively SMEs deploy AI-enabled tools such as business intelligence, automation, and personalized marketing systems. However, the RBV also highlights that possession of AI tools alone is insufficient; firms must develop complementary internal capacities to realize their strategic value.

The TOE framework identifies the conditions that influence the adoption of innovation across three domains: technological, organizational, and environmental (Tornatzky &

Fleischer, 1990). This model provides a contextual lens to understand the varying adoption patterns observed in Pakistani SMEs.

Technological readiness—such as IT infrastructure, digital literacy, and system compatibility—forms the foundation for AI adoption. Organizational factors, including top management support, internal resource availability, and change readiness, are also critical. In the environmental domain, external pressures—such as competitive intensity, regulatory conditions, and customer expectations—either facilitate or hinder AI integration (Enholm et al., 2021).

In the Pakistani context, SMEs often face limitations across all three TOE dimensions: technological deficiencies, organizational inertia, and unfavorable policy environments (Raza et al., 2018; Manzoor et al., 2021). The TOE framework in this study enables the identification of such constraints and supports the investigation of how they shape AI-related decisions.

The DoI theory (Rogers, 2003) explains how new technologies spread across populations over time. It categorizes adopters into innovators, early adopters, early majority, late majority, and laggards, based on readiness, perceived risk, and social influence.

This theory is particularly relevant in the SME context, where digital maturity varies widely. Tech-savvy SMEs, such as those in fintech and e-commerce, tend to be early adopters. In contrast, others delay adoption due to high implementation costs, limited digital awareness, and uncertain returns (Ahmad et al., 2021; Wamba-Taguimdje et al., 2020). The DoI model highlights the progressive nature of AI integration and reinforces the need for both internal preparedness and external support mechanisms.

The integration of RBV, TOE, and DoI in this study allows for a multidimensional understanding of AI adoption and performance enhancement in SMEs. RBV offers an explanation of how AI acts as a strategic resource, TOE contextualizes adoption readiness, and DoI frames the adoption process as a gradual transition shaped by behavioral and systemic factors.

This combined framework strengthens the theoretical foundation of the study by enabling the exploration of:

- The determinants of AI adoption (via TOE),
- AI's mediating role in SME performance (via RBV),
- The moderating effect of digital marketing (through the lens of DoI and strategic capabilities).

In doing so, the study advances the literature by extending these theories to a new domain—AI-enabled SME transformation in emerging economies. It also provides practical insights for policymakers and business leaders seeking to foster digital adoption through capacity-building, infrastructure development, and regulatory reform.

Each variable included in the conceptual framework is grounded in established theoretical constructs. For instance, compatibility, relative advantage, and technology readiness are directly derived from the Diffusion of Innovations (Rogers, 2003) and TOE literature (Tornatzky & Fleischer, 1990; Ramdani et al., 2013). Organizational variables such as leadership vision and change management capability are informed by RBV principles, which emphasize the role of firm-specific intangible assets in shaping strategic capability (Barney, 1991; Mikalef & Gupta, 2021).

Similarly, environmental factors including competitive pressure and trading partnerships align with TOE's external dimension and reflect the institutional and market-driven constraints that SMEs face in developing economies (Wamba-Taguimdje et al., 2020; Enholm et al., 2021). The AI adoption construct as a mediator and digital marketing as a moderator are substantiated through their demonstrated influence in enhancing strategic resource leverage and customer engagement (Denicolai et al., 2021; Chatterjee et al., 2022). This structured justification ensures that each element in the model is logically supported by contemporary theoretical and empirical research.

This theoretical synthesis also carries significant practical implications. By clarifying how SMEs can translate AI capabilities and digital strategies into measurable performance outcomes, this study offers a decision-making framework for SME managers, industry stakeholders, and policymakers. It emphasizes the need for leadership development, digital training programs, and infrastructure investment to unlock AI's full potential. Furthermore, the model can guide government agencies such as SMEDA and SBP in designing sector-specific AI enablement policies, supporting sustainable SME transformation. Thus, the research bridges theoretical knowledge with actionable strategies for digital competitiveness in emerging economies like Pakistan.

2.3 Factors Influencing SME Performance

The performance of SMEs is influenced by a multitude of factors that span technological, organizational, and environmental domains. This section reviews the key factors that impact SME performance, drawing from recent empirical studies and theoretical frameworks.

Technological advancements play a crucial role in enhancing the operational efficiency and competitive advantage of SMEs. The adoption of new technologies such as AI, digital marketing tools, and cloud computing can significantly boost productivity, streamline operations, and open new market opportunities. According to recent studies, technological readiness and the availability of technical infrastructure are critical determinants of successful technology adoption in SMEs (Mikalef & Gupta, 2021a; Wamba-Taguimdje et al., 2020).

Organizational readiness, including leadership commitment, organizational culture, and human resource capabilities, is vital for improving SME performance. Effective change management and the ability to integrate new technologies into existing business processes are essential for leveraging technological innovations. Studies highlight the importance of organizational learning and adaptability in fostering a conducive environment for technological integration (Afiouni, 2019; Harfouche et al., 2022).

External environmental factors such as market competition, regulatory frameworks, and economic conditions also play a significant role in shaping SME performance. SMEs need to navigate complex regulatory landscapes and competitive pressures to maintain and enhance their market positions. The ability to respond to external pressures and capitalize on market opportunities is critical for sustaining growth (Gregory et al., 2020; Enholm et al., 2021).

While the primary focus of this study is on the factors influencing SME performance, AI adoption serves as a mediator that can amplify the effects of these factors. AI technologies enable better decision-making, enhance customer experiences, and optimize business operations. The integration of AI with digital marketing strategies can further enhance the precision and effectiveness of marketing campaigns, leading to improved customer engagement and higher conversion rates (Dellermann et al., 2019; Castillo et al., 2021).

To provide a comprehensive understanding of the factors influencing SME performance and the role of AI, this study leverages several theoretical frameworks. The table below highlights the prominent theories applied in recent research, detailing their descriptions, AI-related applications, and references.

Table 2.2
Theoretical Constructs in AI and SME Performance Research

Theory	Description	Application	Source
Contingency Theory	Posits that AI deployment is contingent on a variety of internal and external variables.	Adoption of AI within organizations.	(Chatterjee et al., 2022)
Dual Process Theory	Explores the mental mechanisms involved in making decisions in AI-related uncertain situations.	Utilizing AI to aid decision-making processes.	Dellermann et al. (2017)
Resource-Based View (RBV)	Details the critical assets that enterprises must develop to gain value from AI.	Generating business value via AI.	Mikalef and Gupta (2021a); Wamba-Taguimdje et al. (2020)
TOE Framework	Indicates that the embrace of AI is dictated by a blend of technological, organizational, and environmental determinants.	Integration of AI in organizations.	(Enholm et al., 2021)
Value Co-destruction	Highlights the intricate interplay between various stakeholders and the functions of AI applications in ascertaining AI's value.	Usage of AI on an individual level.	Castillo et al. (2020)
Organizational Learning Theory	Emphasizes the symbiotic relationship between AI's algorithmic learning and the amplification of organizational learning.	Leveraging AI for the improvement of organizational learning.	Afiouni (2019)
Theory of Artificial Knowledge Creation	Discusses how AI can enhance the formation and expansion of both implicit and explicit knowledge.	Facilitation of knowledge creation through AI.	(Harfouche et al., 2022)
Network Effect	Illustrates how the accumulation of user data augments the utility of AI platforms for each individual user.	Augmentation of the value of AI platforms.	Gregory et al. (2020)

2.5 Theoretical Foundations of AI in SMEs

2.5.1 Resource-Based View

The RBV offers a strategic perspective that is particularly relevant when examining the integration of AI into commercial activities. This perspective focuses on a firm's unique resources and capabilities, including technological infrastructure like advanced AI systems, employee expertise, and strategic allocation of financial resources towards AI investments. These resources, when evaluated through the RBV lens, are critical in determining the success and influence of AI adoption on SME performance.

At the heart of RBV is the principle that for assets to confer a lasting competitive edge, they must exhibit VRIN characteristics: they should be valuable, scarce, challenging to replicate, and not readily replaceable (Barney, 1991). In the realm of AI, this translates to a firm's technological assets, such as AI software and hardware, and the expertise of its personnel in these technologies. These are not merely supportive elements but are integral to the firm's strategic endeavors to enhance performance through AI.

AI's effectiveness in an organization significantly relies on the quality of its technological infrastructure, which includes hardware, software, and network capabilities. The sophistication of this infrastructure contributes a significant part in deciding how effectively AI can enhance organizational performance. Additionally, human resources, especially those with AI expertise, are invaluable. The specialized skills required for AI projects are crucial for their successful implementation and for driving SME performance improvements. The RBV also highlights the significance of organizational capabilities in efficiently coordinating and deploying these resources. This encompasses strategic planning, expertise in managing change, and promoting a culture of innovation, all vital for maximizing the benefits of AI.

The capabilities associated with artificial intelligence, acknowledged as vital intangible assets, markedly boost the outcomes of businesses (Belhadi et al., 2021). These abilities encompass distinct resources known for their inherent value, uniqueness, difficulty to imitate, and non-substitutability, providing firms with an edge over competitors (Lou & Wu, 2020; Chaudhuri et al., 2022). Businesses employ these strategic assets as facilitators to enhance performance metrics (Mikalef and Gupta, 2021).

Creating value within firms through AI capabilities is pivotal, as such capabilities can substantially improve SME performance, a notion explored by Chatterjee et al. (2021). The RBV offers a comprehensive framework for grasping and leveraging the strategic value of AI (Barney, 1991). This study employs the RBV to further investigate these dynamics, concentrating on the development and application of AI capabilities to enhance SME performance, with insights from Chen and Lin (2021), Hossain et al. (2021), and Rahman et al. (2021).

The RBV's influence extends to informing organizations about the types of IT resources crucial for deploying investments within the organizational context (Wade & Hulland, 2004). It suggests that a company's competitive edge is influenced by its resource pool, which needs to be valuable, scarce, difficult to imitate, and irreplaceable. (Barney, 2001; Lockett et al., 2009). The RBV assumes optimal orchestration of these resources, enabling firms to outperform competitors (Palmatier et al., 2007).

The RBV is pertinent for this study as it provides insights into AI-specific assets that are critical to achieving a competitive edge. It can be integrated when compared to alternative theoretical viewpoints, like flexible capacities and capacity for absorption, to explain the business value derived from IT investments (Sirmon et al., 2010). Its extensive application in Information Systems research is evident in its utility for generating empirically testable hypotheses and advancing our understanding of the role of IS resources in organizational performance (Melville et al., 2004). Given this study's aim to identify key resources for creating AI capabilities leading to performance gains, the RBV serves as an appropriate theoretical underpinning.

2.5.2 Diffusion of Innovations (DoI) Theory

The DOI Theory, introduced by Everett Rogers in 1962 and refined over subsequent editions, stands as a foundational theory within social sciences, explaining how innovations gain traction and disseminate across social systems (Rogers, 1995; Zhang et al., 2015). Central to DOI is the notion that the spread of innovation is essentially a form of communication among the participants of a societal structure across time. Rogers (2003) posits that the diffusion process is critical for development and sustainability, with the adoption rate hinging on the perceived attributes of the innovation.

These attributes—relative advantage, compatibility, complexity, trialability, and observability—are crucial in shaping the adoption rate of innovations (Rogers, 1995). Innovations that are perceived as having a clear advantage are compatible with existing systems, are less complex, can be tried on a limited basis, and offer observable results that are more readily adopted. Rogers (2015) also categorizes adopters into groups ranging from innovators to laggards, each with distinct characteristics and requiring tailored strategies for effective innovation dissemination.

The DOI theory underscores the role of individual and organizational traits as predictors of how an organization innovates. For instance, leadership's attitude towards change, the internal structure of the organization, and external openness all impact adoption (Oliveira et al., 2014; Rogers, 2003). The spread of innovation is shaped by four primary factors: the type of innovation, communication mediums, the societal context, and the passage of time. These elements interact to influence the speed and extent of an innovation's adoption across a community.

Rogers' theoretical framework has been instrumental in shaping our understanding of organizational readiness for change—a concept that reflects the psychological and structural capacity of an organization to undertake changes (Weiner, 2009). Organizational readiness for change, according to Armenakis et al. (1993), involves the collective beliefs, attitudes, and intentions of individuals regarding the necessity of transformation and the organization's ability to successfully implement it. This readiness is not only about the resources and structural components but also the motivation and capacity to change, succinctly captured by Scaccia et al. (2015) in the formula $R = MC^2$, integrating general and innovation-specific capacities.

In sum, the DOI theory offers a thorough approach to understanding and managing the uptake of novel practices, emphasizing the significance of perceived innovation characteristics and the readiness of the organization to embrace and implement new technologies and processes. These concepts have been utilized in various fields, encompassing smart cities and big data, demonstrating the versatility and enduring relevance of Rogers' framework in guiding both theoretical exploration and practical application in the field of innovation diffusion.

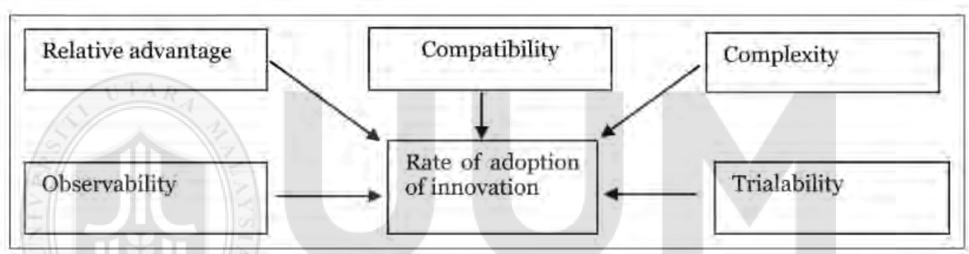

Figure 2.1.
Key Attributes of DOI
Source: Kurup & Gupta, (2022)

2.5.3 The Technology-Organization-Environment (TOE) Framework

The TOE framework, initiated by Tornatzky and Fleischer in the early 1990s, offers a comprehensive theoretical underpinning for the assimilation of information technology within various organizational contexts. It probes the synergy of organizational traits, technological dynamics, and environmental factors, highlighting their combined influence on the decisions surrounding IT adoption (Baker, 2011; Bala & Venkatesh, 2015; Bose & Luo, 2011). The framework has gained significant recognition in scholarly circles, especially for its broad approach to tackling the vast array of elements that impact IT adoption, with particular attention to the settings in developing nations (Chatterjee et al., 2021; Ghobakhloo et al., 2012; Lip-Sam & Hock-Eam, 2011; Oliveira et al., 2019).

In this study, the TOE framework is employed to clarify the intricate dynamics involved in the adoption of AI by SMEs. The framework identifies three critical aspects that influence technological innovation: the technological aspect, which includes both internal and external technological factors relevant to the firm; the organizational dimension, which focuses on the company's characteristics and assets; and the environmental aspect, which is concerned with market dynamics, competitive pressures, and regulatory issues (Tornatzky & Fleischer, 1990; Yang et al., 2013).

The TOE framework facilitates an enriched understanding of the Diffusion of Innovations (DOI) theory by encompassing these dimensions, thus explaining the spread of innovations within organizations (Hsu et al., 2006). It surpasses the constraints associated with industry type and company size (Wen & Chen, 2010). The comprehensive nature of the TOE framework allows for its widespread application in research to unearth the contextual elements that impact the adoption of new IT at the organizational level (Baker, 2011; Martins et al., 2016). Its effectiveness is particularly notable in scrutinizing the variables that determine the success of IT adoption across various organizational contexts (Chang et al., 2007; Chau & Tam, 1997; Kuan & Chau, 2001; Zhu et al., 2003).

In summary, the TOE framework stands as a valuable and comprehensive tool for exploring the multifaceted factors impacting IT adoption, particularly AI, in the context of SMEs, offering insights into how these enterprises can navigate and capitalize on technological innovations.

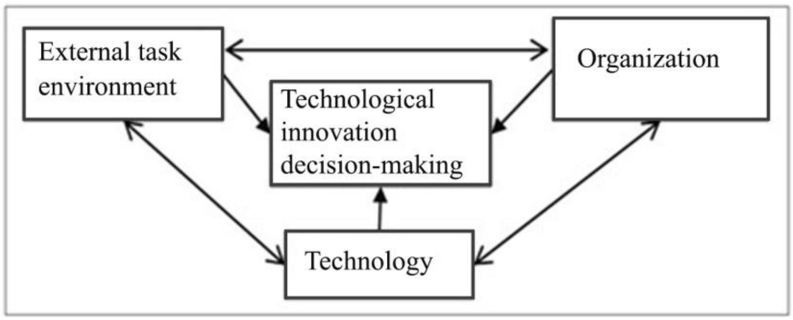

Figure 2.2
The Landscape of Technological Innovation.
Source: Kurup & Gupta, (2022)

2.5.4 Implications of TOE Framework and AI in SMEs

The integration of AI into SMEs is reshaping business operations and performance trajectories. This literature review focuses on the complex relationship between AI applications and SME performance, structured around three main elements: technological infrastructure, organizational characteristics, and environmental factors. AI adoption in SMEs manifests in two forms: immediate operational impacts (first-order effects) and long-term strategic outcomes (second-order effects). Understanding these effects requires examining the journey from initial AI deployment to operational changes and broader strategic implications. This exploration aims to provide a comprehensive perspective on the implications of AI's transformative role in SME performance, guided by relevant theoretical frameworks.

The illustration in Figure 2.3 provides a detailed depiction that encapsulates the intricate interactions between the utilization of AI applications and the performance outcomes of SMEs. The outlined framework sheds light on the fundamental components—technological infrastructure, organizational complexities, and external environmental factors—each of which is crucial in shaping an SME's ability to effectively utilize AI.

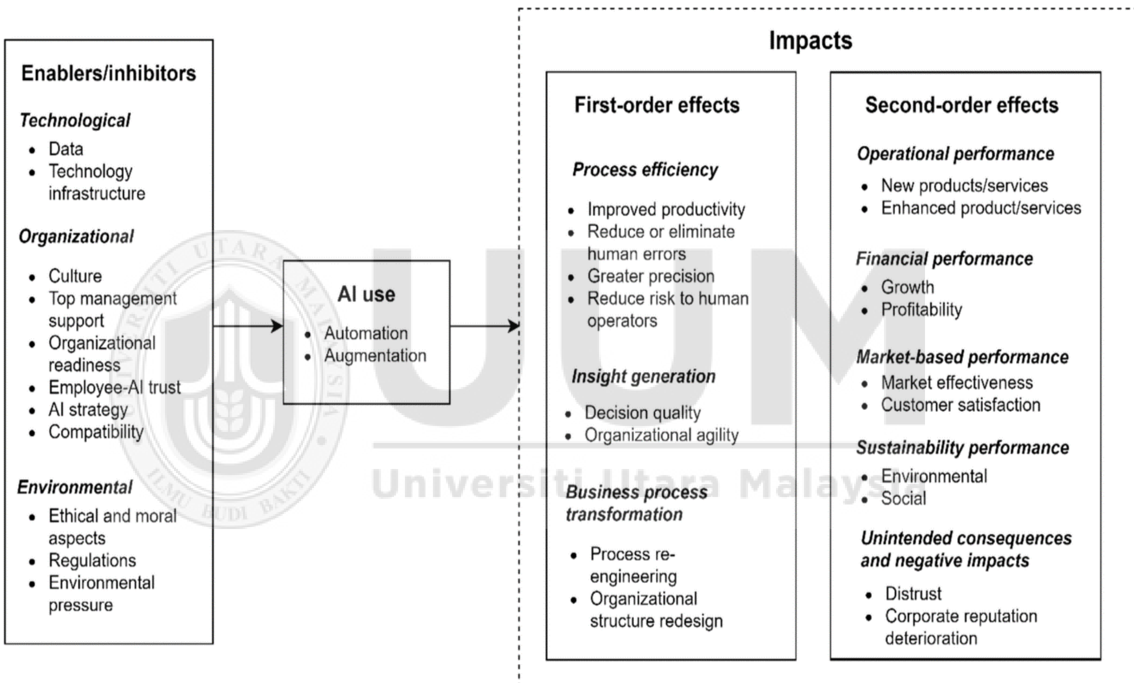

Figure 2.3
Visual representation of the enablers and inhibitors of AI use and its impacts.
Adapted from Enholm et al., (2021)

The integration of AI into small and SMEs involves tackling elements that either promote or obstruct this technological shift. Detailed examination and synthesis of the literature reveal that the facilitators and barriers of this process are intertwined within three key dimensions: technological, organizational, and environmental. This research is committed to a thorough investigation that highlights the complex elements that either support the integration of AI or pose challenges to its seamless adoption in SMEs.

Table 2.3
Various TOE aspects' influence AI adoption

Category	Aspect	Description	Cited Works
Technological	Data	- Accessibility of data	Afiouni (2019); et al.
		- Data Volume	Keding (2020); et al.
		- Speed at which data is processed	Gregory et al. (2020)
		- Diversity and variety of data	Wang et al. (2019)
		- Integrity and quality of data	Baier et al. (2019); et al.
Technology	Infrastructure	- Computational capacity	Wamba-Taguimdje et al. (2020); et al.
Infrastructure		- Cloud-based services	Borges et al. (2020); et al.
		- Algorithmic efficiency	Wamba-Taguimdje et al. (2020)
Organizational	Culture	- Organizational ethos and values	Pumplun et al. (2019); et al.
	Management Support	- Leadership and directive support	Alsheiabni et al. (2018); et al.
	Readiness	- Financial resource allocation	Pumplun et al. (2019)
		- Skillset of employees	Alsheibani et al. (2020); et al.
	AI Trust	- Confidence in AI among employees	Keding (2021)
	Strategy	- Strategic approach to AI integration	Keding (2021)
	Advantage & Compatibility	- Perceived benefits and fit with existing systems	AlSheibani et al., (2020)
Environmental	Ethics & Regulation	- Moral considerations and regulatory compliance	Baier et al. (2019)
	Industry Dynamics	- Norms and pressures within the industry	Coombs et al. (2020)
	Market Forces	- Competitive and consumer pressures	AlSheibani et al., (2020)

Source: Enholm et al. (2022)

2.5.5 Technological Influences on AI in SMEs

The AI within SMEs is significantly influenced by technological factors that determine their readiness and capacity to implement AI solutions. Central to this adoption is the accessibility of data, which acts as the critical fuel for AI engines. Data-rich environments are essential as they enable AI systems to enhance decision-making processes, providing insights that are often more precise than traditional rule-based logic (Pumplun et al., 2019; Schmidt et al., 2020). The "three Vs" of big data—volume, velocity, and variety—characterize the expansive datasets that AI applications rely on, although SMEs frequently face challenges related to the scarcity of quality training data (Baier et al., 2019; Gregory et al., 2020; Wang et al., 2019).

The quality of data is particularly paramount, as it informs the efficacy of AI predictions and decisions; thus, the data fed into AI systems must be accurate, unbiased, and clean to prevent the "Garbage-in, garbage-out" dilemma, necessitating a collaborative effort among data analysts and subject matter experts to address data quality issues (Ataman, 2023). In terms of technology infrastructure, SMEs require a strong combination of computing power, advanced algorithms, and extensive datasets to deploy AI successfully. The computational demands of complex AI algorithms make a powerful computing infrastructure indispensable (Wamba-Taguimdje et al., 2020). Recognizing the challenges SMEs may encounter in maintaining such resources, cloud-based machine learning solutions have been offered by leading technology firms, thus providing the necessary infrastructure to support AI adoption within these enterprises (Borges et al., 2020).

The technological readiness of a firm, which includes both the internal IT infrastructure and the availability of external AI solutions, is a critical determinant of an organization's operations and its capacity to implement AI effectively. For instance, in the domain of digital marketing, the ability to process large datasets and utilize advanced AI algorithms is essential for organizations to optimize their promotional strategies and compete efficiently in the market (Mikalef & Gupta, 2021a; Richey et al., 2007; Schmidt et al., 2020). This readiness not only influences a firm's operational capabilities but also its strategic positioning in leveraging AI to achieve a competitive advantage.

2.5.6 Organizational Dynamics

The dynamics within an organization are pivotal in shaping its approach to Artificial Intelligence (AI) integration. Organizational culture, particularly in SMEs, plays a crucial role, as a culture that embraces innovation and technological shifts can significantly influence the seamless integration and sustained use of AI technologies. Cultures that actively foster innovation and adaptability are better positioned to harness the potential of AI and maintain its usage in the long term (Mikalef & Gupta, 2021).

Moreover, the support of senior management is indispensable in the successful adoption of AI. Leaders in the organization must do more than merely approve AI initiatives; they need to actively foster an environment conducive to change and ensure the allocation of necessary resources (Alsheiabni et al., 2018). The readiness of the organization, both in terms of employee skills and financial resources, is also a critical factor for effective AI integration. For SMEs to integrate AI successfully, it is imperative to undertake a comprehensive assessment of their preparedness. This includes confirming that the workforce has the required competencies and that the financial resources of the firm are adequate to support the implementation of AI technologies (Pumplun et al., 2019).

Trust between employees and AI systems is another essential component of AI integration. Establishing a deep understanding of the operational dynamics of AI systems can build trust among employees, thereby enhancing the efficiency and effectiveness of AI integration (Makarius et al., 2020). A coherent AI strategy that outlines actionable plans and aligns with the organization's objectives is also crucial for successful AI adoption (Keding, 2020).

Compatibility of AI solutions with the existing systems and objectives of the firm is equally important. AI technologies should complement and enhance existing processes rather than disrupt them, to improve the potential for integration (Pumplun et al., 2019). The larger organizational context, including the firm's size, leadership vision, and the available resources for AI investment, are all significant factors that influence how effectively AI is adopted and utilized within an organization. The innovative culture of a firm and its leadership's vision for AI, particularly in enhancing digital marketing strategies, are vital for the successful implementation of AI-driven initiatives (Benbya et al., 2020). Thus, organizational dynamics form a crucial backdrop against which the possibility of AI to transform operational procedures and marketing strategies can be realized.

2.5.7 Environmental Considerations

Factors from the environment play a critical role in guiding the integration of Artificial Intelligence (AI) within entities, particularly within Small and Medium-sized Enterprises (SMEs). As AI technology progresses, adherence to ethical standards and norms is becoming more central, highlighting the need for these systems to commit to ethical practices. The distinction between human and AI capabilities is becoming increasingly nuanced, underscoring the necessity of ethically responsible AI applications (Coombs et al., 2020).

Moreover, regulatory frameworks are instrumental in shaping the ecosystem for AI within SMEs. Legislation such as the General Data Protection Regulation (GDPR) dictates the manner in which AI is implemented, necessitating businesses to employ adaptive strategies to ensure adherence to such regulations. These legal requirements are designed to safeguard personal data and privacy, and they exert a considerable impact on the deployment and utilization of AI in organizational contexts (Baier et al., 2019).

Moreover, environmental pressure, including the need to remain competitive and meet customer expectations, often drives SMEs towards the adoption of AI. The pressure to maintain a competitive edge amidst a swiftly evolving market landscape can make the integration of AI a strategic imperative. Businesses may embrace AI to cater to evolving market dynamics and customer preferences, which can be critical for their survival and growth (AlSheibani et al., 2020; Pumplun et al., 2019).

The broader environmental context, encompassing external influences such as industry characteristics, competitive pressures, and the regulatory climate, holds considerable sway in an organization's decisions regarding AI adoption. Industries undergoing rapid technological advancements may adopt AI to maintain or enhance their competitive position. This is particularly relevant in the field of digital marketing, where competitive pressures and market dynamics heavily influence how firms utilize AI for formulating efficient marketing tactics and enhancing customer engagement (Dubey et al., 2020; Porter & Heppelmann, 2014a). As such, understanding the environmental factors is crucial for firms, especially SMEs, as they navigate the intricate terrain of AI implementation and integration into their operations and marketing efforts.

2.6 Integrating RBV, TOE, and DoI for AI Adoption

The RBV offers a strategic perspective, highlighting the importance of an organization's distinct assets and competencies for maintaining a long-term competitive edge. This view gains additional depth when integrated with the TOE framework and the insights from

Everett Rogers' Diffusion of Innovations (DoI) theory. Such a combination yields a detailed comprehension of how firms adopt AI. The TOE framework's adaptability enriches the RBV by factoring in the company's intrinsic attributes and the influence of external elements on the decision-making process related to adopting technology, such as AI (Baker, 2011).

Rogers' DoI theory, with its inception in 1962, has been instrumental in explicating the social processes underpinning the assimilation of innovations within social systems, especially emphasizing the role of communication networks (Rogers, 2003; Zhang et al., 2015). This is particularly salient for AI adoption in SMEs, as DoI highlights the influence of perceived characteristics of the innovation—such as relative advantage and compatibility—on the adoption rate (Rogers, 2015; Greenhalgh et al., 2004; Tornatzky & Klein, 1982).

The integration model by Kurup and Gupta (2022) serves as a strategic roadmap for AI adoption in SMEs, synthesizing the principles of the RBV, TOE framework, and DOI theory. This model underscores the importance of internal capabilities and resources, as highlighted by RBV, along with the external and internal organizational factors from TOE and the nature of the AI innovation itself as described by DoI.

In this framework, the DOI theory is utilized for the integration of AI, underscoring the essential role of attributes like relative advantage, compatibility, complexity, trialability, and observability in dictating the pace at which AI is embraced by organizations (Yang et al., 2013). These attributes gauge an organization's capacity and willingness to assimilate AI technologies, particularly within the SME context.

The TOE framework further dissects the adoption process by examining the technological infrastructure, organizational readiness, and environmental influences that impact AI integration (Tornatzky et al., 1990). When paired with digital marketing strategies, AI's relative advantage and compatibility can significantly enhance an organization’s marketing effectiveness and its market performance. Leadership vision, organizational change management capabilities, and the ability to adapt to competitive pressures and leverage trading partnerships are all integral components of the AI adoption process. The interaction of these factors within the integrated model highlights how SMEs can strategically approach AI adoption, aligning their organizational culture and resources with the dynamic requirements of the digital marketing landscape.

By employing the unified model of RBV, TOE, and DoI theories, SMEs can attain a comprehensive grasp of the strategic importance of AI and leverage it to drive organizational performance. This approach not only aligns with the existing theoretical literature but also offers practical pathways for SMEs to efficiently maneuver the complexities of AI adoption and optimize their performance in the digital era.

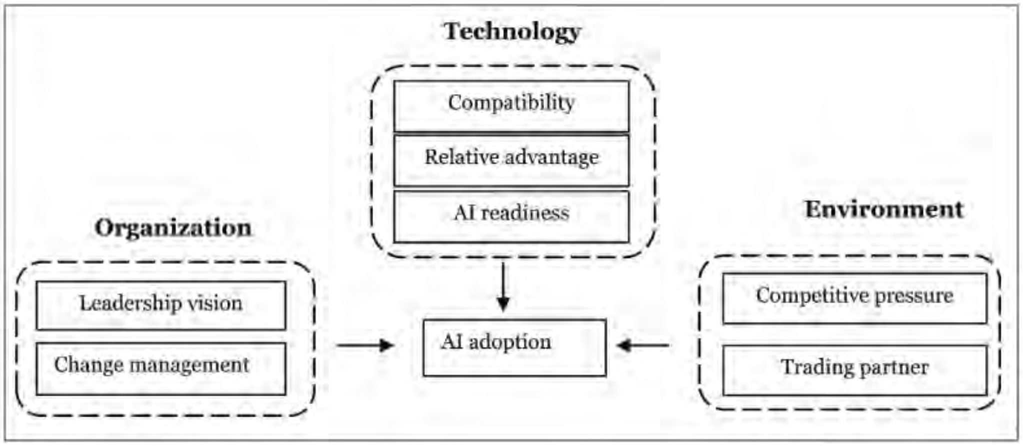

Figure 2.4.
Proposed Model for AI Adoption.
Source: Kurup & Gupta, (2022)

2.7 Technological Context

The technological environment within an organization is crucial in determining its readiness to adopt the latest technologies, such as AI. This concept encompasses the range and diversity of the organization's existing technology solutions, its capability for technical innovation, and the depth of technical know-how (Richey et al., 2007). Together, these factors form the foundation of a firm's capability to effectively incorporate and utilize AI technology.

Organizations use AI for various purposes, each demonstrating the technology's versatility and adaptability. For example, AI has been instrumental in anomaly detection in manufacturing, offering a higher level of precision and efficiency in identifying production irregularities (McKinsey & Company, 2018). In the realm of marketing, AI excels at customizing product recommendations and harnessing customer data to provide personalized experiences (Edelman & Abraham, 2022). Furthermore, AI plays a pivotal role in flagging suspicious transactions in financial services, showcasing its capability in pattern recognition and fraud detection (Brynjolfsson & Mcafee, 2017).

The integration and effective utilization of AI in an organization depend on several key factors. Seamless integration of AI technology with an organization's current infrastructure is vital for compatibility (Qi et al., 2007. Another critical factor is the relative advantage gained from implementing an AI solution, which involves evaluating the potential benefits AI can bring over existing processes or technologies (Yang et al., 2013). Additionally, an organization's readiness to implement AI, encompassing the necessary infrastructure, skilled personnel, and strategic alignment, is essential for successful adoption (Alsheibani et al., 2018).

In summary, the technology landscape within an organization is a multifaceted concept that significantly influences its capability to adopt and maximize the benefits of AI technology. It involves not just the presence of technology but also the organization's general readiness and capability to innovate and integrate new technological solutions like AI effectively.

2.7.1 Compatibility and AI Adoption

Compatibility, regarding the adoption of AI within organizations, refers to the ability of the current IT infrastructure of the organization to sustain AI technology. This compatibility is crucial for the seamless integration and effective functioning of AI systems. The deployment of technology solutions can vary among organizations, with some opting for on-premises solutions, others choosing cloud infrastructure, and some using a combined approach (Bibi et al., 2012). The necessary infrastructure for an AI system consists of libraries to facilitate AI algorithms, capabilities for data processing, and GPUs, which are crucial for the training of complex algorithms (Oh & Jung, 2004).

Organizations often prefer on-premises hosting for their IT solutions to mitigate risks associated with data security and control (Benlian & Hess, 2011). Conversely, cloud technologies, such as serverless computing, are gaining popularity for their ability to facilitate faster development of solutions (Chahal et al., 2020). Therefore, organizations are likely to favor AI solutions that are compatible with their existing infrastructure, whether it is on-premises or cloud-based.

A key factor in the compatibility of AI adoption is establishing a strong business rationale for choosing AI over existing technologies, which includes presenting a convincing case for the expected return on investment (ROI). The argument in favor of AI should clearly communicate the issues it aims to address and the ways it can boost process efficiency (Alsleihbani et al., 2020). This encompasses pinpointing particular areas where AI can enhance operations, cut costs, or spur innovation, ensuring that AI investments are in harmony with the strategic goals of the organization and yield measurable gains.

2.7.2 Relative Advantage and AI Adoption

Relative advantage, in relation to AI, refers to how adopting innovative technology like AI can transform an organization's situation relative to its existing state (Yang & Meyer, 2019). Relative advantage encompasses all benefits associated with adoption, such as increased revenues, operational efficiencies, and strategic effectiveness that AI adoption may bring - it also influences organizations' decisions to adopt such technologies (Mikalef & Gupta, 2021a).

Rogers (2003) notes the significant effect that perceived relative advantage has on an innovation's adoption intentions. When AI technologies clearly and unequivocally demonstrate advantages in enhancing both strategic and operational effectiveness, their adoption increases. Organizations may adopt cutting-edge information technologies like AI in response to fierce market competition and rapidly shifting business environments (Russell & Norvig, 2016).

AI offers solid computational power, sophisticated deep learning features, and smooth integration across borders, appealing to entities striving for innovation and competitive advantage (El Khatib et al., 2019). Uses of AI, such as chatbots for customer service, speech and voice recognition services, and the automation of network operations, have demonstrated their effectiveness in lowering operational costs while simultaneously elevating service quality, improving customer interactions, and increasing overall operational efficiency (El Khatib et al., 2019).

A pivotal advantage associated with AI adoption is cost savings. Numerous studies have pointed out this aspect as one of the primary drivers behind adopting innovative technologies (Martens & Teuteberg, 2012). For instance, cloud computing offers cost-cutting benefits by offloading server maintenance expenses (Oliveira et al., 2014; Senarathna et al., 2018), although actual savings may depend on an organization's current infrastructure and size.

AI adoption offers organizations cost savings while raising concerns over data security and privacy (Alkhater et al., 2018; Borgman et al., 2013). Cloud computing technologies often employ robust security protocols to mitigate these concerns (Alkhater et al., 2018). Establishing clear service level agreements and understanding third-party risk mitigation efforts are vital in mitigating any security threats related to AI adoption (Oliveira et al., 2014).

Perception of relative advantage (PRA), as part of DOI theory, has been employed as a significant variable construct in research on adoption decisions (Alshamaila et al., 2013). PRA plays an integral part in shaping organizations' decisions to adopt innovative technologies such as AI; its benefits may include increased revenue generation, reliability improvements, and overall efficiency gains. Therefore, in this study, relative advantage is utilized to gauge the perceived advantages of artificial intelligence (AI), specifically its benefits to Pakistani small and medium enterprises (SMEs).

2.7.3 Technology Readiness and AI Adoption

Technology readiness, a concept that encompasses both the infrastructure and human resources required for advanced technological initiatives, plays a crucial role in the successful deployment and utilization of Artificial Intelligence (AI) in organizations. This readiness is an amalgamation of tangible assets, such as hardware and software, and human capital, particularly IT professionals equipped with the necessary knowledge and skills to operate and manage Internet-related applications (Mata et al., 1995).

Regarding AI deployment, internal technological readiness refers to a firm's preparedness with the necessary infrastructure to implement AI. This infrastructure includes the hardware, software, and IT systems essential for AI integration. The alignment of current technological capabilities with the requirements for AI adoption is crucial (Richey et al., 2007; Schmidt et al., 2020; Pumplun et al., 2019). For SMEs, where data is a fundamental resource for AI, the transition from traditional rule-based approaches to data-driven methods enhances decision-making capabilities. The success of this integration depends significantly on the quality of data inputs and the presence of a skilled workforce familiar with AI technologies. External technological readiness, on the other hand, focuses on the market's readiness regarding the availability and accessibility of relevant AI technologies. This assessment involves a thorough consideration of various factors related to AI tools, platforms, and support services, which are essential for successful adoption and operational integration (Richey et al., 2007). For SMEs aiming to successfully deploy AI, a combination of robust computing infrastructure, sophisticated algorithms, and extensive datasets is essential (Fosso Wamba, 2022). Addressing the challenges faced by smaller firms, major technology companies have introduced cloud-based machine learning solutions, providing the necessary infrastructure for AI integration (Murray, 2022).

Therefore, merging IT infrastructure with human expertise, termed as technology readiness, is essential for comprehending the practical applications of AI in organizations. Delving into this synergy reveals both the challenges and prospects AI offers, particularly for SMEs, dependent on their level of technological preparedness. AI readiness signifies the level of readiness organizations hold for transformations involving AI and is a crucial component of AI deployment (Alsleihbani et al., 2018). Firms preparing for AI must have a range of resources like skilled personnel, data readiness, financial resources, and technical support (Jöhnk et al., 2020). This requires having AI specialists, process experts, and consultants who are skilled in AI to translate business needs into technical requirements, ensuring data and technology are in place for AI algorithms.

2.8 Organizational Context

In the realm of AI adoption, the organizational context plays a crucial role, encompassing both formal and informal frameworks within organizations (Keen, 1991; Yang et al., 2015). This context includes structured processes and activities defining task allocation and management, as well as informal interactions and behavioral dynamics contributing to task execution success (Keen, 1991). For organizations aiming to adopt AI, leadership vision is indispensable (Yang et al., 2015). Leadership vision refers to leaders' ability to foresee AI's benefits and challenges, cultivating an organizational culture receptive to change and innovation (Keen, 1991). Moreover, an organization's prior experience in managing change significantly affects AI adoption success (Yang et al., 2015). This experience, indicating proficiency in handling transitions, is pivotal in preparing the organization for systemic changes due to AI implementation (Keen, 1991).

In summary, the organizational context for AI adoption is shaped by formal structures and informal dynamics within an organization (Keen, 1991). It requires visionary leadership, understanding AI's potential, and guiding the organization through necessary changes, with previous change management experience influencing readiness and capability for effective AI integration (Yang et al., 2015).

2.8.1 Leadership Vision and AI Adoption

The role of leaders in AI adoption and implementation is critical, especially for emerging technologies like AI. Keen (1991) emphasizes the importance of leadership in shaping the vision and strategy for technology implementation. Leaders must articulate how AI aligns with organizational goals and ensure the allocation of necessary resources and budgets (Keen, 1991).

Moreover, leaders' understanding of AI is fundamental to the successful adoption of this technology (Mikalef & Gupta, 2021). They need to recognize the value AI can bring, along with its associated risks. Given that AI technology is comparatively recent and evolving, many pilot projects may initially fail. In such scenarios, leaders with a strategic vision for AI's role in the organization are crucial in sustaining AI initiatives through these early challenges (Mikalef & Gupta, 2021). Yang et al. (2015) further suggest that leaders should not solely concentrate on the technological aspects but also take into account the readiness of the organization from a user's perspective. This includes understanding how AI adoption fits within the existing organizational culture and user capabilities (Yang et al., 2015). In summary, effective leadership is essential for AI adoption in organizations, entailing a clear vision, resource allocation, understanding of the technology, and perseverance through initial setbacks (Keen, 1991; Mikalef & Gupta, 2021; Yang et al., 2015).

2.8.2 Change Management Capability and AI Adoption

AI technology markedly transforms work procedures at both the individual employee level and the broader process level. Ambati et al. (2020) emphasize the influence of adopting AI from the standpoint of the workforce, pointing out the necessity for organizations to be prepared for adjustments in workflow and job specifications. AI implementation can either fully automate tasks that were previously manual or augment human capabilities (Ambati et al., 2020). At the process level, Leyer and Schneider (2021) discuss how decision augmentation and automation with AI can be either a threat or an opportunity for managers. The shift towards AI-driven processes requires careful planning and adaptation to ensure smooth transitions (Leyer & Schneider, 2021).

McKinsey & Company (2018) emphasizes the importance of addressing the challenges AI and automation pose to the future of work. Their research points out ten crucial factors that organizations must consider for successful AI integration, including changes in IT and organizational culture (McKinsey & Company, 2018). Zheng et al. (2017) explore the concept of hybrid-augmented intelligence, where AI collaborates with and enhances human cognition. This approach underscores the symbiotic interaction between AI and human employees, highlighting the collaborative potential of AI in organizational processes (Zheng et al., 2017). Mikalef and Gupta (2021) discuss the organizational ramifications of AI implementation, with a focus on its influence on creativity and SME performance. They emphasize that AI capability is not just about technology but also involves understanding and adapting to the cultural and structural changes it brings (Mikalef & Gupta, 2021).

The capacity of an organization to handle and acclimate to the operational and structural shifts instigated by AI integration is vital. This involves a combination of technological proficiency and organizational agility to ensure that AI is integrated effectively into existing systems and processes (Ambati et al., 2020; Leyer & Schneider, 2021). In summary, the successful deployment of AI requires organizations to be prepared for changes at various levels. This includes adapting employee roles, reengineering processes, and fostering an organizational culture that embraces AI-driven innovation (Ambati et al., 2020; Leyer & Schneider, 2021; McKinsey & Company, 2018; Zheng et al., 2017; Mikalef & Gupta, 2021).

2.9 Environmental Context

The environmental context of an organization significantly influences its business operations, encompassing the assimilation of technological innovations like AI. This context is shaped by various factors at both global and national levels. Globally, competitive pressure is a crucial factor, especially in the context of AI adoption. In a fiercely competitive market, the imperative to embrace cutting-edge technologies such as AI is heightened to maintain or improve competitive positioning (Gibbs et al., 2003).

From an organizational perspective, the trading partner ecosystem is crucial in AI adoption, where the nature of an organization's interactions with vendors, suppliers, and other business partners significantly influences the decision to adopt AI. These partners can provide vital resources, insights, and support necessary for AI's successful implementation. Furthermore, when an organization's trading partners adopt AI, it can create a ripple effect, prompting its adoption across the network to ensure compatibility and efficiency in business processes (Gibbs et al., 2003). Therefore, within the environmental context of AI adoption, both the global competitive pressures and the dynamics of trading partner relationships play a pivotal role in shaping an organization's strategy towards AI integration into its operations.

2.9.1 Competitive Pressure and AI Adoption

Competition serves as a driving force for innovation and plays a critical role in encouraging businesses to embrace sophisticated technologies like Artificial Intelligence (AI). The concept of competitive pressure, characterized by the urgency to maintain market advantage, often drives organizations to embrace innovative solutions (Aboelmaged, 2010; Allam, 2016; Yang & Meyer, 2019). In today's dynamic socio-economic environment, external factors significantly sway corporate strategies and decisions, with AI adoption becoming increasingly crucial for businesses seeking a competitive edge (Hung et al., 2016; Coombs et al., 2020).

AI's transformative impact spans from improving decision-making processes to enriching customer interactions, marking it as a key component in contemporary business innovation (Fast & Horvitz, 2016; Hu et al., 2023). As market competition intensifies, the urgency to integrate AI into business operations grows, shifting its status from a mere technological advancement to a strategic necessity. This is particularly true in scenarios where the fear of falling behind competitors' spurs companies to prioritize AI adoption and integration.

This study recognizes the inherent correlation between competitive pressures and AI adoption rates. It seeks to investigate and elucidate how competitive forces influence organizational strategies and decision-making processes, specifically regarding AI implementation and their subsequent impact on SME performance. Through examining this relationship, the research aims to offer insights into the strategic significance of AI in sustaining and improving competitive positions within the business landscape.

2.9.2 Trading Partnerships and AI Adoption

In the context of SMEs, the environmental factor of trading partnerships serves a critical role in adopting innovative technologies, particularly e-commerce. The pressure exerted by business partners significantly influences SMEs, often driving their decisions to adopt new technologies. This influence is especially pronounced due to the interdependent nature of small enterprises and their reliance on trade partners for their survival and success. Research has shown that organizations tend to be inclined to embrace new technologies if their suppliers and partners possess higher levels of competency in these areas (Simatupang & Sridharan, 2005). The competence of these partners not only facilitates smoother operations but also ensures that both parties stay abreast of technological advancements, thereby maintaining a competitive edge in the industry.

Furthermore, research conducted by Gutierrez et al. (2015) and Sila (2013) suggests that the uptake of innovative technology in SMEs is notably affected by pressure from business partners. This observation underscores the significance of the external business environment in molding the technological path of SMEs. Additionally, Ching and Ellis (2004) discovered that business partner pressure significantly influenced the adoption of e-commerce by SMEs, emphasizing the crucial role played by external influences in the decision-making processes of these organizations.

In summary, the adoption of AI and other innovative technologies in SMEs is not solely a function of internal decision-making but is also deeply influenced by external factors, particularly the pressures and competencies of trading partners. This dynamic emphasizes the need for SMEs to consider their broader business ecosystem and the interplay of various stakeholders when planning their technological adoption strategies.

2.10 Artificial Intelligence and its Implications

Artificial Intelligence (AI), a major topic of debate and inquiry in recent years, is often used interchangeably with similar terms, leading to confusion (Jarek & Mazurek, 2019). AI refers to giving computers human-like abilities for tasks requiring human intelligence including comprehension, logical analysis, and problem-solving (Mikalef & Gupta, 2021a). Some scholars, like Enholm et al. (2022), envision ideal AI systems as operating autonomously, interpreting, learning, planning, and acting without following predetermined rules. Definitions of AI vary, ranging from a tool aiding human tasks (Enholm et al., 2022) to mimicking human cognitive processes (Tai, 2020). However, both perspectives agree that AI augments rather than replaces human capabilities. This review takes the perspective that AI is a practical field dedicated to furnishing systems with capabilities to interpret and derive insights from data, aiming to attain organizational and societal objectives (Mikalef & Gupta, 2021a).

Acknowledging the complex nature of AI is critical for a deep comprehension of the field. Artificial intelligence provides a strategic framework, with its technologies acting as the driving forces and its capabilities as the goals to be achieved. Each element, while part of a cohesive whole, contributes its own unique features and values. The continuous progression of AI and its components necessitates that those working within and studying the field stay informed about the evolving terminology and subtle distinctions that define it (Mikalef & Gupta, 2021).

Table 2.4
Artificial Intelligence Definitions from Existing Literature.

Reference(s)	**Definition**
Kolbjørnsrud et al. (2017)	AI is related to the ability of digital systems to perceive, interpret, respond, and learn from data inputs.
Afiouni (2019)	AI is the concept of computational systems performing tasks that demand the type of intelligence typically associated with humans, regardless of rule-based or other operational frameworks.
Lee et al. (2019)	AI involves the creation of intelligent entities capable of processing and analyzing data, as well as monitoring their environments to facilitate task performance without fixed algorithms.
Wang et al. (2019)	AI can be described as the core attribute of machine-based intelligence.
Makarius et al. (2020)	AI is defined by a system's ability to precisely interpret data from the environment, assimilate the information, and apply it to achieve adaptively determined goals and functions.
Schmidt et al. (2020)	AI seeks to replicate human cognitive skills and aptitudes using digital technologies.
Demlehner and Laumer (2020)	AI is indicative of a computational system's aptitude for perception, education, judgment, and strategy formation without constant reliance on predetermined rules or patterns.
Wamba-Taguimdje et al. (2020)	AI is presented as a collection of methods and strategies designed to construct devices that replicate intelligent behavior, minimally supervised by humans.
Mikalef and Gupta (2021b)	AI encompasses the ability of a system to recognize, generate, deduce, and integrate information to fulfill established objectives within both organizational and societal frameworks.

Certain academic elaborations emphasize AI's ability to function autonomously without the need for explicit programming directives for intelligent tasks (Demlehner & Laumer, 2020). The premise is that AI can sense, interpret, learn, and adapt — autonomously navigating its tasks without a stringent set of pre-defined rules (Demlehner & Laumer, 2020; Kolbjørnsrud et al., 2017; Wang et al., 2019). These AI platforms interpret external data, extract insights, and dynamically adapt these insights to fulfill predefined objectives (Makarius et al., 2020).

Different perspectives on AI fall into two main schools of thought. One sees AI as a tool crafted for precise functions that might challenge human capability, as suggested by sources like Demlehner and Laumer (2020) and Makarius et al. (2020). Alternatively, AI is perceived as a dynamic entity that simulates human cognitive functions, such as understanding, reasoning, and learning, a viewpoint shared by Mikalef and Gupta (2021). Both angles concur that AI is meant to augment rather than replace human expertise, enhancing efficiency in complex tasks (Mikalef & Gupta, 2021). Nevertheless, there are varying stances on this matter. Some argue that AI reflects human precision, as noted by Kolbjørnsmud et al. (2017) and Wang et al. (2019), while others maintain that AI might not fully capture the subtle intricacies of human thought as per Wamba-Taguimdje et al. (2020).

In considering AI, a clear divergence in perception arises, with some viewing it as an academic discipline (Schmidt et al., 2020) and others regarding it as an operational function within machines (Afiouni, 2019; Lee et al., 2019). These diverse viewpoints highlight the common and unique ways AI is conceptualized. This review posits that AI is a pragmatic field aimed at equipping systems with the capability to process, interpret, deduce, and evolve through data to meet the objectives of organizations and society at large.

Table 2.5
Recent researches on AI adoption.

Author (s) & Year	**Study Title**	**Theoretical Framework**	**Objective**	**Methodology & Locale**	**Key Findings**	**Direction for Future Research**
Bettoni et al. (2021)	An AI adoption model for SMEs: a conceptual framework.	AI Maturity and Adoption Model	Develop an AI adoption model for SMEs	Qualitative: Interviews with representatives from 39 companies	Created a framework to assist SMEs in AI integration, addressing adoption barriers	Expand AI adoption research in SMEs to include diverse industries and regions, refine assessment methodologies, and integrate ethical frameworks for comprehensive, adaptable models.
Denicolai et al. (2021)	Globalization, Digitization, and Sustainability in SMEs.	Readiness life cycle model	Investigate the impact of AI readiness on global SME performance	Quantitative: Survey with 438 SMEs, both domestic and international	Discovered a positive correlation between AI and global SME performance and the complex interplay with sustainability	Future research should explore digitalization's impact on sustainable competitive performance (SCP) in SMEs across different cultures and economies, employing longitudinal studies or mixed methods to address potential biases. Expanding the model to include other digital determinants like networks, platforms, and business models

						could further enrich understanding and practical implications.
Sharma et al. (2022)	Why Do SMEs Adopt Artificial Intelligence-Based Chatbots?	Technology-Organization-Environment (TOE)	Explore the motivations behind SMEs adopting AI chatbots	Quantitative: Online survey of 292 SMEs	Uncovered key factors driving SMEs towards AI chatbot adoption, including employee skills and financial backing	Future studies should broaden their scope through random and cross-national sampling, include actual adoption behavior, and explore AI chatbot adoption across various business sizes for deeper insights.
Chaudhuri et al. (2022)	Innovation in SMEs, AI Dynamism, and Sustainability: The Current Situation and Way Forward.	Expectation Disconfirmation Theory (EDT), Technology-Trust-Fit Theory (TTF), Contingency Theory	Assess AI's influence on the sustainability of SMEs	Quantitative: Survey of 343 SME managers	Found that organizational, technological, situational, and individual factors are crucial in AI adoption	Future research should expand the model by including a larger and more diverse respondent base, consider adopters as AI matures in Indian organizations, and enhance the model's explanatory power by integrating factors like privacy and security concerns to better understand automation predictors in firms.
Rawashdeh et al. (2023)	Determinants of artificial intelligence adoption in SMEs: The mediating role of accounting automation.	Technology-Organization-Environment (TOE)	Examine technological influences on AI adoption and the role of accounting automation.	Quantitative: Online survey with 40 SME managers and owners	Demonstrated the positive role of modern technologies linked with AI in SMEs	Future research should explore the mediating effect of accounting automation on AI adoption within a broader range of organizations, extending the TOE model literature by examining its influence alongside organizational and environmental constructs to enhance understanding of technology

						adoption processes.
Al-Zehhawi et al., 2022	The Effect of Artificial Intelligence on Job Performance in China's Small and Medium-Sized Enterprises (SMEs).	Descriptive method and Data analysis through SPSS	Analyze the effect of AI on job performance within Chinese SMEs	Quantitative: Questionnaire distributed among 220 SME managers	Found AI significantly impacts job performance, along with factors like gender and experience	Future research should extend beyond SMEs in China to include various sectors like the hotel, banking, and insurance industries to verify the applicability and robustness of this study's findings across different commercial contexts.
Heenkenda et al. (2022)	The Role of Innovation Capability in Enhancing Sustainability in SMEs: An Emerging Economy Perspective.	Knowledge creation Theory, Knowledge-Based view, Resource-Based view	Investigate innovation's impact on SME sustainability	Quantitative: Survey of 384 SMEs in Sri Lanka	Highlighted innovation's critical role in the long-term growth and sustainability of SMEs	Future research should expand beyond SMEs to include larger and international firms, encompass a wider geographic scope within and beyond Sri Lanka, employ diverse scales for measuring innovation capabilities and sustainability, and incorporate qualitative factors like government policies. Additionally, exploring other employee perspectives beyond owners and managers and including more mediators and moderators, such as business size and entrepreneurial abilities, could enrich understanding of the innovation-sustainability link.

2.11 AI Technologies and their Role

AI technologies are typified by computer systems equipped to imitate human intelligence operations such as learning and problem-solving (Heaton, 2018). These technologies include a variety of techniques, including machine learning, natural language processing, and computer vision (David Poole, 1998; Kaliszky et al., 2017). Machine Learning, a branch of AI, has risen to prominence because of the increase in data accessibility and developments in technology (Afiouni & Afiouni-Monla, 2019). It employs the training of machines to make data-driven decisions (Y. Wang et al., 2018). Advanced forms of machine learning, such as deep learning, employ neural network architectures to emulate human neurons, yielding precise results across various fields (Y. Wang et al., 2018). AI also integrates other technologies like natural language processing with machine learning in applications such as chatbots, facilitating their evolution and learning (Baby et al., 2017).

While the overarching definition of AI provides a broad perspective, diving deeper reveals an intricate web of techniques employed to achieve the set objectives. While the broad definition of AI offers a sweeping overview, a closer look reveals a complex array of techniques utilized to achieve specific goals. Our examination of the literature suggests a variety of avenues to attain these objectives, particularly highlighting applications in deep learning and machine learning. This section aims to clarify the key AI technologies, draw upon their definitions from existing literature, and highlight their distinct areas of application.

2.11.1 Machine Learning and Deep Learning

A pivotal element within the broader domain of AI technologies is machine learning (ML), which has gained prominence owing to the rapid expansion of data and advancements in computational power. ML's primary objective is to equip machines with the analytical prowess to derive insights from datasets, forecast outcomes, and unearth patterns that assist in decision-making (Afiouni, 2019). This technology is grounded in an inductive method where decisions are formulated based on statistical data analysis, allowing for nuanced decision rules to emerge (Wang et al., 2019; Schmidt et al., 2020).

Four main types categorize machine learning algorithms: supervised, unsupervised, semi-supervised, and reinforcement learning, as identified by Wang et al. (2019). In supervised learning, systems are trained with labeled data, which aids in pattern recognition and rule inference, a process described by Afiouni (2019). Unsupervised learning, on the other hand, does not use labeled data but rather relies on the data's intrinsic structure and statistics, resulting in its application in anomaly detection, clustering, and association mining (Schmidt et al., 2020). Semi-supervised learning incorporates data, both labeled and unlabeled, for training (Quinio et al., 2017). Learning through feedback from real-time environmental interaction, reinforcement learning distinguishes itself by not depending on historical data. (Quinio et al., 2017), aiming to fulfill specified goals, an approach discussed by Afiouni (2019).

Table 2.6
Machine Learning Definitions Across Existing Literature

Reference(s)	Definition
Wang et al. (2019)	Machine learning enables systems to independently learn and acquire insights, processing information through collection, examination, and projection.
Wang et al. (2019)	At its core, machine learning involves programming algorithms that empower systems to make accurate predictions, with a spectrum ranging from supervised to reinforcement learning methods.
Afiouni (2019)	As a branch of AI, machine learning excels at extracting data to make forecasts or decisions without relying on hardcoded instructions.
Schmidt et al. (2020)	Machine learning utilizes an inferential approach, formulating decision-making processes based on statistical analysis of data.
Wamba-Taguimdje et al. (2020)	Machine learning represents self-guided instructional processes where systems integrate and apply knowledge derived from provided data.

2.11.2 Other AI Technologies

In Information Systems research, although machine learning plays a pivotal role, various other AI technologies are gaining prominence in empirical studies. Machine learning or deep learning often intersects with these technologies to develop dynamic solutions that improve with experience. For example, Chatbots often employ a blend of NLP and ML techniques. NLP grants chatbots the ability to parse and engage in human languages, while ML algorithms facilitate these chatbots to refine their responses and functionalities while processing more data (Baby et al., 2017; Castillo et al., 2020). Table 2.7 will highlight additional AI technologies that are emerging as significant areas of study in Information Systems research.

Table 2.7
AI Technologies and their Definitions.

Technology	**Definition (Rephrased)**	**Reference(s)**
Natural Language Processing (NLP)	NLP enables machines to comprehend and process languages as humans do.	Jarrahi (2018)
Computer Vision	It involves the analytical processing and interpretation of visual data by computer systems.	Jarrahi (2018)
Expert System	These are systems that replicate human decision-making processes by using expertly derived knowledge to become a repository of specialized guidance for organizational use.	Afiouni (2019); Lichtenthaler (2019)
Planning and Scheduling	This refers to the crafting and ordered structuring of tasks to be carried out in the future.	Lichtenthaler (2019)
Speech Synthesis Systems	These systems are designed to convert text to spoken audio and vice versa, enabling textual information to be vocalized and spoken words to be digitized as text.	Lichtenthaler (2019); Damper et al. (1999); Ghadage and Shelke (2016)

2.12 AI Capabilities and its Spectrum

The evolving definition of AI capabilities within organizations has shifted focus from technologies to their effective use in businesses (Mikalef & Gupta, 2021a). AI capabilities encompass how organizations structure themselves to derive value from AI investments (Bytniewski et al., 2020; Schmidt et al., 2020; Y. Wang et al., 2018). AI Capability pertains to an organization's capability to leverage data, methodologies, processes, and personnel in ways that open up new avenues for automation, decision-making, and collaboration (Schmidt et al., 2020). The study by Wamba-Taguimdje et al. (2020) delves into the supplementary required resources to maximize the advantages of AI technologies, giving rise to the notion of AI capability, which pertains to how an organization harnesses AI-specific resources for value generation (Wamba-Taguimdje et al., 2020; Schmidt et al., 2020). AI capability extends beyond technical resources to encompass all organizational assets facilitating AI utilization (Mikalef & Gupta, 2021a).

In the context of SME performance, particularly within SMEs, AI's integration has significant implications. AI's diverse applications in areas like marketing, production, and customer service (Alsheibani et al., 2020; Jelonek et al., 2019) across the value chain can revolutionize key business aspects. AI's potential to automate complex tasks, previously considered challenging, like knowledge work and service work (Coombs et al., 2020), enhances business processes and operations. Additionally, AI's capacity to augment human decision-making by processing vast information beyond human cognitive capabilities (Jarrahi, 2018) is crucial for enhancing decision-making processes.

The integration of AI in SMEs profoundly affects SME performance across various dimensions. Operational efficiencies are improved through AI's role in automating tasks and augmenting human intelligence. Financial performance benefits from AI's implementation include increased revenue and cost reductions (Mikalef & Gupta, 2021a). AI's application in marketing enhances customer segmentation and targeting, improving overall marketing effectiveness and customer satisfaction (Riikkinen et al., 2018). Furthermore, AI drives sustainable business model innovation, supporting environmental and social responsibility initiatives (Toniolo et al., 2020). However, AI's adoption also presents challenges like potential biases and ethical concerns, requiring careful management and governance (Yudkowsky, 2008).

Table 2.8
Definitions of AI Capability Across Literature.

Author(s) & Year	Definition of AI Capability
Schmidt et al., (2020)	AI capability refers to the capacity of organizations to leverage data, methodologies, workflows, and human expertise to forge new avenues for automation, decision-making, and collaboration that surpass traditional methods.
Schmidt et al., (2020)	AI capabilities constitute the array of digital competencies that encompass AI-specific resources like algorithms and data for training, which together facilitate the generation of value.
Wamba-Taguimdje et al., (2020)	AI capabilities can be described as the company's proficiency in amalgamating organizational assets, skilled personnel, and AI tools to drive and realize business value and growth.

In summary, AI's implications for SMEs are extensive, impacting both process-level and firm-level performance. The multidimensional impacts of AI, from operational enhancements to financial gains and market competitiveness, highlight its pivotal role in a firm's success. However, navigating AI's potential challenges is equally important to ensure its ethical and effective integration in the business context.

2.13 AI Use and its Impact

AI has become a force of transformation across different sectors, including marketing, production management, and customer service, profoundly impacting the operational landscape of organizations (Abioye et al., 2021; Alsheiabni et al., 2018; Jelonek et al., 2019). The integration of AI throughout the firm's value chain herald’s significant advancements and modifications in conventional practices (Wamba-Taguimdje et al., 2020).

AI applications are categorized into two primary areas: automation and augmentation (Wamba-Taguimdje et al., 2020). In terms of automation, AI has expanded beyond traditional tasks, such as assembly line work, to include "Intelligent Automation." This form of automation involves AI systems engaging in continuous machine learning, thereby enhancing their performance and capabilities over time (Coombs et al., 2020). Examples of intelligent automation in action include virtual robots for email processing, AI-driven budgeting and inventory management in manufacturing, and AI chatbots in customer service, each contributing to enhanced operational efficiencies (Lee et al., 2019; Wamba-Taguimdje et al., 2020; Nuruzzaman & Hussain, 2018). Additionally, AI technologies like voice assistants and facial recognition systems are increasingly being used in everyday tasks, streamlining processes and improving user experience (Castillo et al., 2020; Prentice et al., 2020).

Conversely, AI's role in augmentation focuses on extending and enhancing human cognitive capabilities. This involves processing large volumes of information rapidly and effectively, capabilities that go beyond the natural abilities of humans (Jarrahi, 2018). Such augmentation is evident in various applications, including AI-assisted complex data analysis for managerial decisions and predictive analytics for strategic business maneuvers (Borges et al., 2020; Makarius et al., 2020). In healthcare, AI technologies contribute to the advancement of diagnostics and treatment by aiding in tasks such as the analysis of MRI images and the recognition of cancer patterns (Jarrahi, 2018). Furthermore, in the fields of public relations and marketing, AI plays a critical role in trend forecasting and customer segmentation, enabling more tailored and effective strategies (Galloway & Swiatek, 2018; Mishra & Pani, 2020).

In summary, the influence of AI on organizations encompasses both automation and augmentation, yielding substantial advantages such as increased efficiency, improved decision-making processes, and heightened adaptability to shifting business landscapes. The ongoing incorporation of AI across diverse sectors holds the potential to continue revolutionizing business operations and customer interactions.

2.14 AI and SME Performance

The impact of AI on SME performance spans across multiple dimensions. Operationally, it fosters the introduction of innovative products and services while simultaneously improving existing ones. Financially, firms implementing AI have seen gains in revenue and cost reductions, attributed to structured AI adoption strategies (Mikalef & Gupta, 2021a). In marketing, AI's application in customer segmentation and personalization leads to more effective strategies and improved customer satisfaction (Riikkinen et al., 2018). Furthermore, AI drives sustainable business model innovation, aiding in reducing environmental impacts while fostering social responsibility (Toniolo et al., 2020).

Nonetheless, the integration of AI poses certain obstacles. Issues such as biased outcomes, lack of transparency, and potential societal harm must be carefully managed.

Implementing effective AI governance practices is crucial to mitigate these risks and ensure ethical considerations are addressed (Yudkowsky, 2008).

2.15 AI's Impact on SMEs: A Multidimensional Analysis

AI has a substantial influence on SMEs across different levels., from process efficiency to broader SME performance, shaping competitive strategies and influencing operational dynamics. AI enhances efficiency and productivity by taking over tasks traditionally performed by humans, leading to streamlined processes and reduced operational costs (Balasundaram & Venkatagiri, 2020). Additionally, AI's capability to analyze vast data repositories offers invaluable insights, uncovering patterns and trends that aid in strategic decision-making (Mikalef & Gupta, 2021). This analytical power of AI drives the evolution of business processes, potentially reshaping organizational structures to be more efficient and adaptive to market demands (Mishra & Pani, 2020).

Within organizations, AI plays a significant contribution in enhancing both operational processes and financial results. For instance, firms such as Netflix and Spotify leverage AI to upgrade the quality of their content and tailor the experience to individual users (Netflix, 2020). Furthermore, AI is instrumental in helping businesses uncover fresh market prospects and roll out novel products or services (Mishra & Pani, 2020). Additionally, executives harness AI's analytical capabilities to refine the quality of current products and services, customizing them to meet customer preferences and ultimately enhancing the overall user experience. (Davenport & Ronanki, 2018).

Incorporating AI into business operations is associated with an increase in financial success (Eriksson et al., 2020). Companies that have adopted holistic AI strategies have witnessed enhancements in their financial performance (Mikalef & Gupta, 2021a). AI significantly improves marketing strategies through precise customer segmentation, enabling more targeted and relevant marketing efforts (Mishra & Pani, 2020). Additionally, AI-driven insights aid in anticipating and addressing customer needs, thereby fostering higher levels of customer satisfaction (Riikkinen et al., 2018).

AI also contributes to sustainability efforts by promoting energy conservation, pollution reduction, and enhancing workplace safety, thereby supporting both the environmental and social aspects of business operations (Borges et al., 2020; Toniolo et al., 2020). However, despite its benefits, AI holds the potential for unintended negative outcomes, such as biases and ethical challenges (Dastin, 2018; Vigdor, 2019). This necessitates effective governance practices and regulatory guidelines to guarantee transparency and accountability in AI applications (de Almeida et al., 2021).

In conclusion, AI's integration within SMEs profoundly affects SME performance at both the process and firm levels. Its capacity to enhance operational efficiency, generate strategic insights, and transform business processes is evident. However, alongside these benefits, SMEs must navigate AI's potential challenges responsibly, ensuring ethical and effective use in the business context. The dynamic nature of AI's impact on SMEs underscores the importance of a holistic approach to leveraging AI for sustainable business growth and innovation.

2.16 Digital Marketing

In the contemporary business landscape, digital marketing has arisen as a crucial approach for firms to interact with their customer base and expand their market reach. This aspect of marketing employs digital technologies, such as social media platforms, search engines, email services, and websites, to engage with both existing and prospective customers (Kannan & Li, 2017; Shah & Murthi, 2021). The digital era has revolutionized how businesses communicate with consumers, enabling them to utilize platforms like Facebook, Twitter, and Instagram for marketing campaigns (Govindarajan & Immelt, 2019).

In a rapidly evolving and competitive landscape, digital marketing strategies play a pivotal role for firms, particularly SMEs. These approaches facilitate streamlined digital interactions and interpretation of data, which is crucial for SMEs to tackle the complexities of digital transformation (Baiyere et al., 2020; Sebastian et al., 2017). Embracing digital marketing enables businesses to innovate across various domains, such as product launches, supply chain management, and customer engagement, thereby strengthening their market presence (Bharadwaj et al., 2012).

Moreover, digital marketing enables enterprises to adapt to changes in consumer behavior and market trends effectively. It offers platforms for interactive customer engagement, leveraging big data analytics and metric-based digital tools (Corral de Zubielqui & Jones, 2020; Kannan & Li, 2017). However, the dynamic nature of digital marketing also presents challenges, necessitating continual adaptation and innovation by businesses (Majchrzak et al., 2016; Sebastian et al., 2017).

2.17 The Evolution and Impact of Digital Marketing in SMEs

In the ever-changing business environment, digital marketing has become a vital strategy, leveraging online platforms to engage diverse audiences effectively. This field has evolved significantly with advancements in technology, particularly with the integration of AI, reshaping traditional marketing strategies (Verma et al., 2021).

Digital marketing, which initially focused on establishing an online presence and content curation, now employs AI to enhance decision-making, create personalized experiences, and optimize strategies (Verma et al., 2021). The integration of AI into digital marketing has resulted in notable enhancements in data-driven decision-making (Miklosik & Evans, 2020; Syam & Sharma, 2018), customer personalization (Bag et al., 2022; T. Davenport et al., 2020), and campaign optimization (Mikalef & Gupta, 2021a).

2.18 AI's Role in Enhancing Digital Marketing Strategies

AI's role in digital marketing extends across various functions, including social media mining for sentiment and trend analysis (J. Lee et al., 2019), real-time price optimization (Loureiro et al., 2021), and customer churn analysis (Pillai & Sivathanu, 2020). The utilization of AI in digital marketing not only boosts efficiency but also fosters enhanced customer satisfaction and loyalty (Stone et al., 2020; Syam & Sharma, 2018).

Table 2.9 lists the numerous ways AI has influenced traditional marketing strategies, reshaping them for the digital age and offering a roadmap for businesses aiming to harness the potential of AI in their marketing endeavors.

Table 2.9
The potential of AI in marketing endeavors.

Marketing Area	**Impact on Digital Marketing**	**Examples of AI Usage**
Overall Strategy	- Quick assembly and automation of decision-making information	- Analyzing outcomes and recommending strategies
	- Rapid decision-making based on alternative strategies	- Assisting in decision-making for optimal results
Business Model	- Using machine learning to reach look-alike audiences	- Quantifying and exploring the consequences of different models
Overall Branding and	- Tracking and shifting brand image using web and social media	- Identifying results of brand investments and recommending future investments
Proposition		- Developing new revenue streams
Ecosystem Management	- Identifying the most productive parts of the ecosystem and gaps	- Identifying gaps in ecosystem development and improving productivity
Competitive Strategy	- Identifying weak signals of impending competition	- Identifying weaknesses in own and competitor's strategy
Resource Management	- Rapid measurement and analysis of different strategies	- Analyzing risks, rewards, and planning scenarios

Branding	- Tracking brand image using web and social media	- Finding evidence of causes of brand shift and loss of market share
Product	- Customer input in product design and testing	- Synthesizing customer input and simulating new product designs
Proposition	- Customizing propositions and testing iteratively	- Identifying best propositions through customer feedback
Price	- Tailoring prices to different customers	- Resetting pricing strategies based on results and yield management
Advertising	- Digital advertising and programmatic approaches	- Choosing and designing content for different target markets
Direct Marketing	- Targeting specific segments and individuals	- Choosing appropriate channels, content, and contact types
Personal Selling	- Providing personalized responses to individuals	- Analyzing results and recommending personalization strategies
Public Relations	- Analyzing patterns and sentiment in word-of-mouth	- Identifying patterns, reasons, and actions based on word-of-mouth
Sales Promotion	- Identifying the most effective promotions	- Identifying best promotions for different customers/segments
Content	- Serving content to the right customers at the right time	- Customizing content to target segments and customers
People	- Providing marketing people with better information	- Identifying information gaps and assisting in decision-making
Marketing Analysis	- Accelerating analysis and applying it reactively	- Gaining insights and analyzing results of marketing research
Market Research	- Using online feedback and sentiment analysis	- Analyzing larger data sets and combining research results
Market Targeting	- AI-assisted accurate and timely market targeting	- Real-time changes to targeting strategies based on AI analysis
Data and Systems	- Using marketing automation and cloud-based systems	- Identifying opportunities to improve system deployment
Marketing Resource Management	- Optimizing resource allocation and forecasting	- Optimizing resource management and identifying planning scenarios
Content Management	- Managing and customizing content for different channels	- Developing tools for content delivery and optimization
Managing Marketing People	- Identifying high-performing marketers and resolving issues	- Providing tools and frameworks for better use of AI technology
Marketing Operating Model	- Optimizing the efficiency of the operating model	- Using machine learning for real-time decision

Source: (Stone et al., 2020)

2.19 Digital Marketing Strategies, Artificial Intelligence, and SME Performance

The integration of Artificial Intelligence (AI) into digital marketing marks a significant evolutionary step, providing businesses with innovative ways to enhance their marketing strategies and, consequently, their overall performance. The application of AI in this domain spans a variety of functions, including data-driven decision-making, customer segmentation, the generation of personalized marketing content, and predictive modeling, as highlighted by Nuruzzaman & Hussain (2018). This broad spectrum of applications enables businesses to harness large datasets for insight extraction and market trend prediction, thereby crafting more effective marketing strategies. The predictive power of AI not only allows businesses to respond to market changes more adeptly but also to anticipate and shape their marketing efforts through AI-driven insights, as noted by Huang & Rust (2021).

Furthermore, AI significantly enhances customer segmentation and the creation of personalized content, leading to highly targeted marketing campaigns. Such precision in marketing efforts results in increased customer engagement, higher conversion rates, and reinforced customer loyalty, according to Bag et al. (2022). AI-driven tools, including chatbots and customer service technologies, offer tailored experiences to consumers, addressing their specific needs and preferences. This bespoke approach to customer interaction not only boosts customer satisfaction but also cultivates long-term loyalty, which is essential for sustained business growth (Huang & Rust, 2021). Ultimately, the synergy between AI and digital marketing strategies holds the potential to substantially improve a firm's performance, offering companies a competitive edge that can lead to enhanced business outcomes and greater success in the marketplace.

2.20 Mediating Role of AI in Digital Marketing and SME Performance

2.20.1 AI as a Mediator between TOE Factors and SME Performance

Artificial Intelligence (AI) serves as a crucial mediator between TOE factors and SME performance. AI enhances decision-making through superior data-driven insights, aligning with the technological aspect of the TOE framework. Additionally, organizational readiness for AI adoption and its adaptability to external environments such as regulatory and competitive dynamics further accentuate its mediating role (Mikalef & Gupta, 2021b; Alsheibani et al., 2020; Coombs et al., 2020).

The idea of Artificial Intelligence Capability (AIC) emerges as a key intangible resource for business performance, mediating the relationship between resources and SME performance. AIC enhances firm capabilities, which is crucial for operational success, thus improving SME performance (Ghasemaghaei, 2021; Belhadi et al., 2021; Lou and Wu, 2021; Mikalef and Gupta, 2021; Yao et al., 2021; Chatterjee et al., 2021a).

2.20.2 Strategic AI Deployment and Its Impact on SMEs

The strategic integration of AI in SMEs significantly affects SME performance. By incorporating AI into core operations and marketing strategies, SMEs gain a competitive advantage through enhanced efficiency, productivity, and customer engagement. AI-driven analytics contribute to more effective and personalized marketing strategies, thereby impacting sales and customer satisfaction (Davenport & Ronanki, 2018; Mikalef & Gupta, 2021b). AI's effectiveness in SME performance relies on successful integration, adaptation, and complementary strategic innovations. The complexity of AI's role in SME performance highlights the need for a comprehensive strategy in AI integration, considering both technological and organizational dynamics (Barney, 1991; Chen and Lin, 2021; Hossain et al., 2021; Rahman et al., 2021).

Moreover, AI's mediation in the relationship between digital marketing strategies and SME performance is crucial. AI-driven digital marketing initiatives enable SMEs to target their audiences accurately, optimize marketing expenditures, and monitor performance metrics in real-time, leading to enhanced ROI and overall business outcomes (Belhadi et al., 2021; Lou and Wu, 2021). This strategic deployment of AI aligns with broader digital transformation goals, positioning AI as a strategic asset for long-term growth and sustainability (Haleem et al., 2022).

2.21 Moderating Influence of Digital Marketing Strategies

Digital marketing strategies refer to organizational marketing initiatives leveraging digital technologies for communication with both business partners and customers, thereby creating new value through integrated digital platforms and systems (Kannan & Li, 2017; Sridhar & Fang, 2019; Sommarberg & Makinen, 2019). These strategies enhance customer data collection and communication through multiple interactions, leveraging business intelligence tools. This approach not only augments marketing capabilities but also empowers enterprises to effectively forecast market trends, understand consumer preferences, and pinpoint emerging business opportunities, contributing to strategic decision-making and market adaptability (Bhimani et al., 2019; Frank et al., 2019; Luo et al., 2021).

2.22 Synergistic Effects of AI and Digital Marketing

The synergy between AI and digital marketing amplifies the benefits of each. AI enhances the precision and effectiveness of digital marketing strategies, while digital marketing provides a rich source of data for AI algorithms. This synergy improves marketing campaign efficiency and elevates the overall customer experience, contributing to enhanced SME performance and competitive advantage (Stone et al., 2020; Lee et al., 2019; Loureiro et al., 2021). Digital marketing's evolving nature, encompassing advanced digital technologies and social media platforms, transforms AI capabilities into actionable strategies directly influencing SME performance (Mangold, 2009; Rohm & Hanna, 2011).

2.23 Supporting Evidence of AI's Impact on Marketing Performance

The integration of AI in marketing has shown considerable benefits, including intelligent content creation, automated decision-making, efficient data analysis, and targeting the right customers. Research findings demonstrate that AI-based tools improve marketing processes and decision-making efficiency in SMEs, enhancing customer deliverance and market expansion (Kose and Sert, 2017; Jab? onska & Pólkowski, 2017; Kumar & Kalse, 2021; Kumar & Ayedee, 2021; OECD, 2021; Drydakis, 2022; Davenport et al., 2020; Rekha, Abdulla & Asharaf, 2016; Campbell et al., 2020; Lu et al., 2022).

AI technologies in marketing, such as augmented reality (AR) and machine learning, offer personalized marketing campaigns, improve online shopping experiences, and enhance targeting capacity (OECD, 2021). Machine learning algorithms like Support Vector Data Description (SVDD) optimize contact selection for direct marketing, demonstrating AI's potential to enhance various stages of the marketing planning process (Rekha, Abdulla & Asharaf, 2016; Campbell et al., 2020).

In conclusion, the moderating role of digital marketing in the AI-SME performance relationship is significant. The adoption of AI in SMEs enhances the firm's dynamic capabilities, allowing it to respond to emerging demands and improve customer service. This integration of AI with digital marketing strategies empowers SMEs to fully utilize the potential of AI, thereby fostering performance, innovation, and growth (Kose & Sert, 2017; Drydakis, 2022).

2.24 Hypothesis Development

Drawing from the extensive body of literature and aligned with the research objectives, this study constructs a series of hypotheses to guide the investigation. Initially, hypotheses H1 through H7 are established, forming a foundational understanding of the connection between AI adoption and a range of TOE factors within SMEs. Following these, hypothesis H8 is formulated to elucidate the direct impact of AI adoption on SME performance, serving as the study's primary focus. This hypothesis is pivotal as it explores AI's role as a transformative resource contributing to the operational success of SMEs. The research then progresses to examine the potential of AI as a mediator in the complex dynamics among the aforementioned factors and SME performance outcomes. Hypotheses H10 through H16 are devised to explore these mediating roles, providing insight into how AI adoption bridges initial adoption factors with enhancements in SME performance.

Moreover, the study expands its scope to examine the role of digital marketing strategies within this ecosystem. Hypothesis H9 investigates how AI adoption impacts SME performance in isolation, while hypothesis H17 posits that digital marketing strategies may moderate this relationship. This particular hypothesis suggests that robust digital marketing strategies can enhance the benefits of AI adoption, thereby boosting SME performance. Collectively, these hypotheses aim to establish a comprehensive framework that captures the various impacts of AI adoption on SME performance and the potential augmenting effects of digital marketing strategies. They seek to substantiate the theoretical framework presented in the study and provide empirical insights into the strategic deployment of AI within the SME sector.

2.25 Technological Factors to AI Adoption

2.25.1 Compatibility Relationship with AI Adoption

Compatibility, defined as the alignment between an organization's IT infrastructure and AI technology, is crucial for AI adoption. It encompasses the choice between on-premises, cloud, or hybrid solutions and requires infrastructure like AI algorithm libraries, data processing, and GPUs (Bibi et al., 2012; Oh & Jung, 2004). Preference varies on-premises for security (Benlian & Hess, 2011) and cloud for development speed (Chahal et al., 2020).

The business case for AI centers on ROI and improving process efficiency, aligning with strategic goals for operational and cost benefits (Alsheibani et al., 2020). Research shows a positive link between compatibility and the willingness to adopt new innovations, emphasizing the need for AI solutions to meet adopters' requirements and provide value (Rogers, 1995; Alsheibani et al., 2018; Ifinedo, 2005; Yang, 2015; Yan, 2009; Zahi, 2010; Chui, 2017). Based on this discussion, this study put forth that:

H1: Compatibility has a positive influence on AI adoption in Pakistani SMEs

2.25.2 Relative Advantage Relationship with AI Adoption

The principle of relative advantage is fundamental to technology adoption in organizations, emphasizing the importance of a technology's superiority over current processes. For Artificial Intelligence (AI), this advantage is multidimensional l, offering not just automation but also decision-making capabilities akin to human judgment and advanced data processing (Kurup & Gupta, 2022). The adoption of AI is thus a strategic decision underpinned by the potential for increased operational efficiency, productivity, and competitive positioning (Zhu & Kraemer, 2005).

This concept is supported by Rogers' DOI theory, which posits that the perceived benefits of an innovation play a crucial role in its adoption (Rogers, 2003). Empirical research across several developed countries aligns with this, showing that the relative advantage is a strong driver for adopting innovations in SMEs (Grandon & Pearson, 2004; Trainor et al., 2011).

AI's appeal lies in its capacity to enhance strategic and operational processes significantly. Its computational power and learning algorithms allow for innovations that can improve service quality and reduce costs, factors particularly crucial in competitive and rapidly changing business environments (El Khatib et al., 2019; Russell & Norvig, 2016). However, alongside the economic benefits, such as those offered by cloud computing, organizations must navigate concerns related to data security and privacy, making risk mitigation strategies vital (Martens & Teuteberg, 2012; Oliveira et al., 2014; Senarathna et al., 2018). Therefore, the perceived relative advantage, encompassing the expected financial and operational benefits, is essential in shaping organizations' decisions toward AI adoption (Alshamaila et al., 2013). In this vein, the proposed hypothesis is:

H2: Relative advantage has a positive influence on AI adoption in Pakistani SMEs.

2.25.3 Technology Readiness Relationship with the AI Adoption

Technology readiness is a critical determinant in the adoption of AI within organizations, reflecting the extent to which an enterprise is equipped with the necessary infrastructure and skilled personnel to implement and harness AI effectively. The concept covers not just the tangible assets such as hardware and software but also encompasses the expertise and knowledge base available to the organization (Mata et al., 1995; Zhu & Kraemer, 2005). For AI to be successfully adopted, especially within SMEs, there needs to be a harmonious integration of these technology assets with the data and human resources available (Pumplun et al., 2019; Richey et al., 2007; Schmidt et al., 2020).

AI readiness specifically refers to the organization's preparedness for AI-related transformations and is a key aspect of AI implementation. This includes the readiness of human resources, data, financial backing, and the specific technological support required for AI. Technical experts, process specialists, and consultants become vital as they translate business needs into technical requirements for AI applications (Kurup & Gupta, 2022). Given the importance of data quality and the availability of a skilled workforce in managing AI tools, internal technological readiness becomes a strategic priority. External technological readiness, on the other hand, relates to the market availability of AI technologies, tools, and services, which are critical for successful adoption and operational integration (Richey et al., 2007).

Acknowledging the vital role played by technology companies in providing cloud-based machine learning services, these resources enable SMEs to integrate AI into their operations by offering the essential infrastructure required (Borges et al., 2020; Wamba-Taguimdje et al., 2020). Thus, technology readiness, incorporating both the IT infrastructure and human resource expertise, is posited to have a significant positive influence on AI adoption in SMEs. Furthermore, AI readiness, encompassing the organizational preparedness for AI, is posited to positively impact AI adoption in organizations. Hence, the following hypotheses are proposed for SMEs in Pakistan:

H3: Technology readiness has a positive influence on AI adoption in Pakistani SMEs.

2.26 Organizational Factors to AI Adoption

2.26.1 Top Leadership Vision Relationship with the AI Adoption

The role of top management and leadership vision is pivotal in the adoption and integration of AI within organizations, particularly SMEs in Pakistan. Research has consistently demonstrated that top management's commitment significantly influences the successful deployment of new technologies (Burgess, 2017; Skafi et al., 2020). This support goes beyond mere approval of initiatives; it involves actively shaping and steering the organization's strategic direction toward AI integration and fostering a culture that embraces technological advancement (Yang & Meyer, 2019).

Leadership vision in the context of AI is not just about endorsing AI-related projects but also about comprehensively understanding the technology's potential value and the risks involved. Given the nascent stage of AI and the possibility of initial setbacks, such as the failure of pilot projects, a strong leadership vision is crucial. Leaders with a clear strategic vision for the role of AI are instrumental in supporting and sustaining AI initiatives, even in the face of early-stage challenges (Kurup & Gupta, 2022).

Top management's role encompasses defining the AI vision, ensuring the allocation of necessary budgets, and providing the requisite resources. This support is a cornerstone for both the initial adoption and the ongoing development of AI capabilities, which is essential for maintaining long-term competitive advantages and continuous improvement of AI within business processes (Stone et al., 2020). Reflecting on the critical influence of top leadership vision on AI adoption, the following hypothesis is proposed for SMEs in Pakistan:

H4: Leadership vision has a positive influence on AI adoption in Pakistani SMEs.

2.26.2 Change Management Relationship with the AI Adoption

Change management capability is essential when adopting Artificial Intelligence (AI), as it significantly alters both employee roles and business processes. AI implementations can lead to complete task automation or the augmentation of human tasks, which necessitates organizational adaptability to change (Ambati, Bishop & Bishop, 2020). Research indicates that adapting to changes in both information technology (IT) infrastructure and organizational culture presents hurdles for AI business propositions, with company culture often cited as resistance to AI implementation (Leyer & Schneider, 2021; McKinsey & Company, 2018).

Organizations with a history of successful change are better equipped to anticipate and navigate the challenges that come with AI adoption. Their prior experience with change enables them to foresee potential pitfalls and effectively manage the transition to new AI-driven processes (Mikalef & Gupta, 2021; Zheng et al., 2017). Based on the insights from various studies, it is evident that an organization's change management capability is crucial for the successful adoption of AI. This hypothesis underscores the importance of organizational readiness for change as a determinant of successful AI adoption and implementation. Hence, the study proposes the following hypothesis:

H5: Change management capability has a positive influence on AI adoption in Pakistani SMEs.

2.27 Environmental Factors to AI Adoption

2.27.1 Competitive Pressure Relationship with AI Adoption

In the corporate landscape, competitive pressure is a key driver of innovation. This pressure is particularly intense in the sphere of Artificial Intelligence (AI) adoption, where maintaining a competitive advantage is crucial (Aboelmaged, 2010; Allam, 2016; Yang & Meyer, 2019). For Pakistani SMEs, the need to stay abreast of rapidly changing global markets and internal strategic imperatives has made the adoption of AI not just a value-added choice but a strategic necessity (Coombs et al., 2020; Fast & Horvitz, 2016; Hu et al., 2023).

Kurup and Gupta (2022) align with this view, emphasizing that competitive pressure can significantly impact the rate at which organizations adopt new technologies. In the realm of AI, capabilities like natural language processing and generation become essential as they are the backbone of chatbots and voicebots, which are increasingly becoming industry standards. As organizations implement these AI-driven services to enhance customer service, there is a ripple effect wherein competitors feel compelled to adopt similar AI solutions to meet customer expectations and remain competitive.

Thus, within the competitive landscape of Pakistani SMEs, there is a clear link between competitive pressure and the urgency to adopt AI. The adoption of AI is seen as a strategic response to the competitive forces at play, which can enhance SME performance and secure a strong market position. This hypothesis underscores the idea that the adoption of

AI is a strategic move influenced by the competitive environment, with organizations adopting AI to maintain or enhance their competitive positioning. Reflecting these insights, the study proposes the following hypothesis for SMEs in Pakistan:

H6: Competitive pressure has a positive influence on AI adoption in Pakistani SMEs.

2.27.2 Trading Partnerships Relationship with the Use of AI

The concept of trading partners encompasses vendors, suppliers, or traders that engage in commerce with an organization. These partnerships are pivotal in helping organizations obtain assets, collaborate on critical machinery, cultivate Intellectual Property, and foster organizational knowledge, which may be challenging to achieve independently (Melville, Kraemer, & Gurbaxani, 2004). Such collaborative relationships are strategically formed to enhance coordination, achieve shared goals, and develop competitive advantages that are often difficult to replicate (Sambamurthy, Bharadwaj, & Grover, 2003).

Trading partners significantly contribute to AI adoption by furnishing essential data for processing and facilitating process automation. As organizations strive for agility and innovation, the collaborations they forge with their trading partners can become a driving force for adopting new technologies like AI, as these partnerships can facilitate the exchange of resources and capabilities that underpin the AI integration process (Dyer & Singh, 1998; Henderson, 1990).

Kurup and Gupta (2022) further reinforce this perspective, emphasizing that trading partners play a pivotal role in AI adoption by providing essential data and enabling process automation. The capacity of these partners to both supply and effectively use AI-generated data and outputs significantly influences an organization's ability and decision to adopt AI technologies (Grover, Kar, & Dwivedi, 2022). This interdependency is a key driver in the AI adoption process, as partnerships facilitate the exchange of the resources necessary for successful AI integration. This hypothesis suggests that the presence of supportive and collaborative trading partners is conducive to the adoption of AI technologies. Strong partnerships can provide the resources, data, and knowledge that are essential for successfully implementing AI and leveraging its full potential to maintain a competitive edge in the market. In line with the relational view that emphasizes the strategic benefits of cooperative strategies, the study proposes the following hypothesis:

H7: Trading partners had a positive influence on AI adoption in Pakistani SMEs.

2.28 AI Adoption Relationship with SME Performance

The incorporation of AI within organizations, particularly SMEs, signifies a transformative evolution in operational paradigms reminiscent of the influence of e-commerce on business landscapes. Empirical studies consistently illustrate a beneficial correlation between e-commerce implementation and improved SME performance (Sunayana & Parveen, 2019; Wardoyo, Irani, & Kautsar, 2018), implying that AI adoption could similarly, if not more profoundly, enhance SME efficiency.

AI's impact is multi-dimensional. Its first-order effects bring about process-level enhancements, improving efficiency, accuracy, and productivity—elements essential to operational excellence. AI-driven automation accelerates tasks, reduces error rates, and enables more precise operations (Lichtenthaler, 2019). Moreover, AI's capacity to analyze large datasets and uncover patterns undetectable by humans sharpens decision-making, enhancing market responsiveness and competitive edge.

At the organizational level, AI catalyzes business process transformation, fostering job creation, potentially introducing new roles, and reshaping organizational dynamics. This comprehensive transformation often leads to significant improvements in organizational performance, including operational and financial metrics, market positioning, and sustainability (Makarius et al., 2020). AI also revolutionizes product and service innovation, enabling organizations to explore new markets and elevate customer experiences. Its role in marketing is particularly noteworthy, where AI's data-driven insights lead to more targeted strategies and personalized customer interactions, enhancing satisfaction and retention (Davenport & Ronanki, 2018; Riikkinen et al., 2018).

However, the path of AI adoption is fraught with challenges. Potential biases, ethical dilemmas, and social implications necessitate stringent governance to ensure AI is used responsibly and ethically (Yudkowsky, 2008). This hypothesis posits that strategic deployment of AI in SMEs could markedly enhance various performance metrics, thus positioning these organizations for greater success in a swiftly changing business landscape. Considering these factors, the study puts forward the following hypothesis for SMEs in Pakistan:

H8: AI adoption has a positive influence on SMEs performance in Pakistan.

2.29 Digital Marketing Strategies Relationship with SME Performance

The correlation between digital marketing strategies and SME performance has become increasingly significant pertaining to the integration of AI. AI's role in transforming digital marketing is multi-dimensional, enhancing data-driven decision-making, personalizing customer experiences, optimizing marketing campaigns, and elevating customer satisfaction. These advancements, ranging from social media analysis to dynamic pricing, have fundamentally altered how businesses engage with their audience (Miklosik & Evans, 2020; Syam & Sharma, 2018; Verma et al., 2021).

AI's integration into digital marketing not only improves front-end customer interactions but also streamlines different facets of marketing strategy, including customer behavior analysis and campaign effectiveness evaluation (Lee et al., 2019; Loureiro et al., 2021). This comprehensive enhancement, attributable to AI, contributes significantly to SME performance, particularly when aligned with organizational objectives and technological capabilities. Considering these transformative impacts of AI in digital marketing, the proposed hypothesis is:

H9: Digital marketing strategies have a positive influence on SMEs performance in Pakistan.

2.30 Mediating Role of AI Adoption

In exploring the mediating role of AI within SMEs, it's crucial to consider how AI bridges the gap between various TOE factors and their impact on SME performance. The following hypotheses integrate these considerations, each supported by relevant literature:

2.31 Technological Factors and SME Performance

2.31.1 Compatibility

AI's ability to integrate with existing IT infrastructure is a key mediator in enhancing SME performance. This encompasses how AI aligns with and complements current technological assets (Grover, Kar, & Dwivedi, 2022).

2.31.2 Relative Advantage

AI's capacity to offer superior benefits over existing processes is a significant mediator. The greater the perceived benefits of AI, the more pronounced its impact on SME performance (Zhu & Kraemer, 2005).

2.31.3 Technology Readiness

The readiness of an organization in terms of infrastructure and skills for AI adoption is a crucial mediating factor in achieving enhanced performance (Mata, Fuerst, & Barney, 1995). The proposed hypothesis is as follows:

H10: AI adoption mediates the relationship between compatibility and SMEs performance in Pakistan.

H11: AI adoption mediates the relationship between relative advantage and SMEs performance in Pakistan.

H12: AI adoption mediates the relationship between technology readiness and SMEs performance in Pakistan.

2.32 Organizational Factors and SME performance

2.32.1 Leadership Vision

The vision and support of top management for AI adoption play a mediating role in impacting SME performance (Burgess, 2017).

2.32.2 Change Management Capability

An organization's capability to manage the changes brought by AI adoption is another mediator impacting SME performance (Mikalef & Gupta, 2021). The proposed hypothesis is as follows:

H13: AI adoption mediates the relationship between leadership vision and SMEs performance in Pakistan.

H14: AI adoption mediates the relationship between change management capability and SMEs performance in Pakistan.

2.33 Environmental Factors and SME performance

2.33.1 Competitive Pressure

The pressure exerted by industry competition can be a driver for AI adoption, with AI acting as a mediator to translate this pressure into enhanced SME performance (Allam, 2016).

2.33.2 Trading Partnerships

The relationships and interactions with trading partners influence AI adoption, where AI mediates this relationship to improve performance (Dyer & Singh, 1998). The proposed hypothesis is as follows:

H15: AI adoption mediates the relationship between competitive pressure and SMEs performance in Pakistan.

H16: AI adoption mediates the relationship between trading partnerships and SMEs performance in Pakistan.

In summary, these hypotheses underscore the mediating role of AI in translating various technological, organizational, and environmental inputs into substantial improvements in SME performance, thereby highlighting the multifaceted impact of AI adoption in the Pakistani SME context.

2.34 Moderating Role of Digital Marketing Strategy

Digital marketing strategies consist of marketing initiatives within organizations that utilize digital tools and platforms to engage and interact with commercial allies and clients. They integrate digital frameworks or infrastructures to create new value, fostering multiple interactions for customer data collection and communication (Kannan and Li, 2017; Sommarberg and Makinen, 2019; Sridhar and Fang, 2019). By employing business intelligence tools, digital marketing strategies improve marketing capabilities and enable enterprises to predict market trends, evaluate consumer preferences, and identify business opportunities (Bhimani et al., 2019; Frank et al., 2019; Luo et al., 2021).

Enterprises use digital marketing platforms to understand customer needs, applying innovative technologies like big data (Ferraris et al., 2019; Ghasemaghaei and Calic, 2019; Lin and Kunnathur, 2019) and the Internet of Things (IoT) (Bresciani et al., 2018). However, integrating new technologies into digital marketing poses significant challenges and has led to fragmented and controversial research in this domain (Kolloch and Dellermann, 2018; Scott et al., 2019; Verhoef and Bijmolt, 2019).

The incorporation of AI into digital marketing strategies marks a critical point for enhancing SME performance. The RBV theory suggests that strategic resources like AI can provide unique capabilities and competitive advantages when effectively leveraged (Barney, 1991; Wernerfelt, 1984). The integration of AI improves the efficiency and effectiveness of marketing campaigns by providing personalized content and optimizing marketing spend, which can lead to improved customer engagement and performance indicators such as sales growth, market share, and profitability (Bharadwaj, 2000; Huang & Rust, 2021). Thus, the study proposes the following hypothesis:

H17: Digital marketing strategies moderate the relationship between AI adoption and SMEs performance in Pakistan.

2.35 Implications for the Current Study's Hypotheses and Framework

The extensive literature review conducted for this study underscores the transformative potential of AI in augmenting the operational, financial, and marketing performance of SMEs. The integration of AI, particularly in digital marketing, has become a crucial element in modern business strategies. The review reveals the multifaceted role of AI as a mediator and enabler in optimizing SME performance, especially when synergized with digital marketing strategies.

The review highlights AI's significant impact on SMEs, showcasing its ability to automate processes, provide data-driven insights, and enhance decision-making. Research works like those by Davenport & Ronanki (2018) and Mikalef & Gupta (2021b) exemplify the wide array of AI applications in SMEs. The connection between digital marketing strategies and AI has been identified as a critical factor in elevating SME performance. The integration of AI into digital marketing strategies enhances the efficiency and efficacy of marketing campaigns, leading to better customer engagement and improved business outcomes.

A notable literature gap is the limited focus on AI adoption in SMEs within emerging economies, particularly in Pakistan. This presents an opportunity for further research to understand the unique challenges and potentials in these contexts. The review supports the formulation of hypotheses centered around the influence of AI across different aspects of SME performance. These hypotheses could explore the direct effects of AI on operational efficiency, marketing effectiveness, and financial performance, as well as the mediating role of AI between various organizational factors and outcomes.

Table 2.10
Summary of Research Hypothesis:

Research Questions	**Research Objectives**	**Statement of Hypotheses**
Q1: What is the influence/relationship between technological factors (i.e., compatibility, relative advantage, and technology readiness), organizational factors (i.e., top leadership vision and change management capability), and environmental factors (i.e., competitive pressure and trading partnerships) on AI adoption in Pakistani SMEs?	Objective 1: To examine the influence of technological factors (i.e., compatibility, relative advantage, and technology readiness), organizational factors (i.e., top leadership vision and change management capability), and environmental factors (i.e., competitive pressure and trading partnerships) on AI adoption in Pakistani SMEs.	H1: Compatibility has a positive influence on AI adoption in Pakistani SMEs. H2: Relative advantage has a positive influence on AI adoption in Pakistani SMEs. H3: Technology readiness has a positive influence on AI adoption in Pakistani SMEs. H4: Leadership vision has a positive influence on AI adoption in Pakistani SMEs. H5: Change management capability has a positive influence on AI adoption in Pakistani SMEs. H6: Competitive pressure has a positive influence on AI adoption in Pakistani SMEs. H7: Trading partners have a positive influence on AI adoption in Pakistani SMEs.
Q2: To what extent does AI adoption influence SMEs' performance in Pakistan?	Objective 2: To investigate the influence of AI adoption on SMEs performance in Pakistan.	H8: AI adoption has a positive on SMEs performance in Pakistan.
Q3: Does AI adoption mediate the relationship between technological factors (i.e., compatibility, relative advantage, and technology readiness), organizational factors (i.e., top leadership vision and change management capability), and environmental factors (i.e., competitive pressure and trading partnerships) and SMEs performance in Pakistan?	Objective 3: To investigate the mediating role of AI adoption in the relationship between technological factors (i.e., compatibility, relative advantage, and technology readiness), organizational factors (i.e., top leadership vision and change management capability), and environmental factors (i.e., competitive pressure and trading partnerships) and SMEs performance in Pakistan.	H10: AI adoption mediates the relationship between compatibility and SMEs performance in Pakistan. H11: AI adoption mediates the relationship between relative advantage and SMEs performance in Pakistan. H12: AI adoption mediates the relationship between technology readiness and SMEs performance in Pakistan. H13: AI adoption mediates the relationship between leadership vision and SMEs performance in Pakistan. H14: AI adoption mediates the relationship between change management capability and SMEs performance in Pakistan.

		H15: AI adoption mediates the relationship between competitive pressure and SMEs performance in Pakistan. H16: AI adoption mediates the relationship between trading partnerships and SMEs performance in Pakistan.
Q4: Do digital marketing strategies moderate the relationship between AI adoption and the performance of SMEs in Pakistan?	Objective 4: To ascertain the moderating role of digital marketing strategies in the relationship between AI adoption and SME performance in Pakistan.	H9: Digital marketing strategies have a positive influence on SMEs performance in Pakistan. H17: Digital marketing strategies moderate the relationship between AI adoption and SMEs performance in Pakistan.

2.36 Synthesis of Literature

The reviewed literature consistently highlights the potential for transformation offered by AI in enhancing the efficiency, productivity, and market competitiveness of SMEs. Studies indicate that AI's integration, particularly in digital marketing and operational processes, leads to improved decision-making and customer engagement (Davenport & Ronanki, 2018; Haleem et al., 2022; Mikalef & Gupta, 2021b). The role of AI as a mediator in SME performance is emphasized, particularly in its interaction with TOE factors within the TOE framework (Mikalef & Gupta, 2021b; Alsheibani et al., 2020; Coombs et al., 2020). Furthermore, AI's strategic deployment within SMEs is shown to significantly influence SME performance, underscoring the synergy between AI and digital marketing efforts (Davenport & Ronanki, 2018; Belhadi et al., 2021; Lou and Wu, 2021).

2.37 Identification of Research Gaps

Despite the growing body of literature on AI in SMEs, significant gaps remain, particularly regarding AI's adoption and impact in emerging economies like Pakistan. The current research landscape is heavily skewed toward developed countries, leaving a noticeable void in studies on regions such as Pakistan, Bangladesh, or Sri Lanka. Scholars like Bunte et al. (2021) and Rawashdeh et al. (2023) have underscored the pressing need for more focused investigations within these emerging markets. This oversight limits the identification of unique opportunities and challenges faced by SMEs in less examined economies, hindering a global understanding of AI's potential. While the integration of AI in sectors such as healthcare and manufacturing has received considerable attention, there is a notable lack of comprehensive studies on its impact across other sectors within Pakistan. This research gap, highlighted by Strusani & Houngbonon (2019) and Mhlanga (2021), suggests a need for broader sectoral analyses. Additionally, technological illiteracy and traditional mindsets within SMEs pose significant barriers to facilitating the effective adoption and utilization of AI technologies in Pakistan. Sources like ThinkConnects (2021) and SouthAsiaIndex (2022) emphasize the need for educational reforms and a paradigm shift in attitudes towards technology.

Furthermore, although AI's role in revolutionizing various business processes is recognized, there's a notable gap in understanding its impact on integrated marketing communication within Pakistani SMEs, as pointed out by Shahid & Li (2019). The dominance of quantitative research designs in existing studies points to a necessity for qualitative research to gain a deeper understanding of the particular challenges and opportunities encountered by Pakistani SMEs in adopting AI. This need is echoed by Abid et al. (2019) and Ahmed et al. (2022). Moreover, while sectors like healthcare and security in Pakistan are beginning to adopt AI, more focused studies on strategic AI implementation across various industries are needed. In conclusion, the research on AI in SMEs, especially in emerging economies like Pakistan, needs to expand to cover the specific challenges, opportunities, and impacts of AI adoption across diverse sectors. Employing both qualitative and quantitative methods provides a comprehensive understanding of this dynamic field. Future studies could reveal critical insights into sector-specific challenges and opportunities of AI adoption, enriching the global narrative on the transformative potential of AI in SMEs.

2.38 Proposed Research Framework

The integrated model we propose synthesizes elements from the RBV, DoI, and TOE frameworks, offering a multifaceted perspective on Artificial Intelligence (AI) adoption in SMEs. This model aligns AI as a strategic resource, echoing Barney (1991), while concurrently analyzing AI adoption through DoI's lens, focusing on characteristics that influence its acceptance and diffusion as identified by Rogers (2003). Moreover, it includes both internal and external factors from the TOE framework, thus providing a comprehensive overview of the forces driving or hindering AI adoption in SMEs.

The model considers key factors influencing adoption, including technological factors such as compatibility, relative advantage, and technology readiness. Compatibility assesses the degree to which AI technology can integrate with existing IT infrastructure (Qi, Wu, & Li, 2007), while relative advantage focuses on the perceived benefits of adopting AI (Yang, Kankanhalli, Ng, & Lim, 2013). Technology readiness involves assessing an organization's preparedness to implement and support AI, including aspects like human resources, data, financial support, and technological infrastructure (AlSheibani et al., 2018; Jöhnk et al., 2021).

In terms of organizational factors, leadership vision, and change management capability are crucial. Leadership vision relates to the strategic commitment of top management towards adopting and supporting AI (AbuAkel & Ibrahim, 2023; Keen, 1991; Yang et al., 2015), while change management capability reflects the organization's ability to adapt to the operational and structural changes brought by AI implementation (Ambati, Bishop, & Bishop, 2020; Leyer & Schneider, 2021).

Environmental factors, such as competitive pressure and trading partnerships, also play a significant role. Competitive pressure stems from the need to maintain or improve competitive positioning (Porter & Millar, 1985; Zhu & Kraemer, 2005), and trading partners influence an organization's decision to adopt AI (Dyer & Singh, 1998; Sheikh et al., 2018).

Integrating RBV, TOE, and DoI for AI Adoption The RBV theory provides a strategic vantage point, focusing on a firm's unique resources and capabilities as pivotal for sustained competitive advantage. When combined with the TOE framework and Everett Rogers' Diffusion of Innovations (DoI) theory, a more granular understanding of AI adoption within firms is achieved. The TOE framework, with its flexibility, complements the RBV by considering both the internal characteristics of the firm and the impact of the external environment on technological adoption decisions, such as those needed for AI integration (Baker, 2011).

Rogers' DoI theory, with its inception in 1962, has been instrumental in explicating the social processes underpinning the assimilation of innovations within social systems, especially emphasizing the role of communication networks (Rogers, 2003; Zhang et al., 2015). This is particularly salient for AI adoption in SMEs, as DoI highlights the influence of perceived characteristics of the innovation—such as relative advantage and compatibility—on the adoption rate (Rogers, 2015; Greenhalgh et al., 2004; Tornatzky & Klein, 1982).

The integration model by Kurup and Gupta (2022) serves as a strategic roadmap for AI adoption in SMEs, synthesizing the principles of RBV, TOE, and DoI. This model underscores the importance of internal capabilities and resources, as highlighted by RBV, along with the external and internal organizational factors from TOE and the nature of the AI innovation itself, as described by DoI.

DoI theory is applied to AI adoption, emphasizing the critical role of perceived attributes such as relative advantage, compatibility, complexity, trialability, and observability in influencing the rate at which AI is adopted within organizations (Yang et al., 2013). These attributes assess the potential and readiness of an organization to integrate AI technologies, especially in the context of SMEs.

The TOE framework further dissects the adoption process by examining the technological infrastructure, organizational readiness, and environmental influences that impact AI integration (Tornatzky et al., 1990). When paired with digital marketing strategies, AI's relative advantage and compatibility can significantly enhance an organization's marketing effectiveness and its market performance.

Leadership vision, organizational change management capabilities, and the ability to adapt to competitive pressures and leverage trading partnerships are all integral components of the AI adoption process. The interaction of these factors within the integrated model highlights how SMEs can strategically approach AI adoption, aligning their organizational culture and resources with the dynamic requirements of the digital marketing landscape.

By employing the unified model of RBV, TOE, and DoI theories, SMEs can gain a holistic understanding of the strategic importance of AI and leverage it to drive organizational performance. This approach not only aligns with the existing theoretical literature but also offers practical pathways for SMEs to effectively navigate the complexities of AI adoption and optimize their performance in the digital era.

AI adoption mediates the relationship between TOE factors and SME performance by facilitating more efficient and effective operations. For instance, technology readiness and compatibility can significantly enhance AI integration, which in turn improves decision-making, operational efficiency, and innovation capabilities within SMEs (S. Alsheibani et al., 2020).

Digital marketing strategies act as a moderating variable, potentially amplifying the positive effects of AI adoption on SME performance. Effective digital marketing can enhance the reach and engagement of SMEs, leveraging AI-driven insights to tailor marketing efforts and improve customer acquisition and retention (Dubey et al., 2020). This synergy between AI and digital marketing enables SMEs to optimize their market presence and operational strategies.

In summary, the proposed framework integrates RBV, DoI, and TOE to examine AI adoption in SMEs comprehensively. It analyzes the relative advantage of AI, its technological readiness, and the support from top management, along with competitive pressures and government support, each influencing AI usage and affecting SME performance. This integrative approach provides valuable insights into strategic implementation within the SME context, aligning with the critical need to enhance the theoretical framework through a multidimensional analysis of AI adoption, digital marketing strategies, and SME performance. This comprehensive approach not only enhances the credibility and depth of the research but also offers valuable insights into how AI and digital marketing strategies can be effectively leveraged to improve SME performance in Pakistan. By thoroughly examining the technological, organizational, and environmental dimensions and critically analyzing their interactions and implications, this research provides a nuanced understanding of the factors influencing AI adoption and its subsequent impact on SME performance.

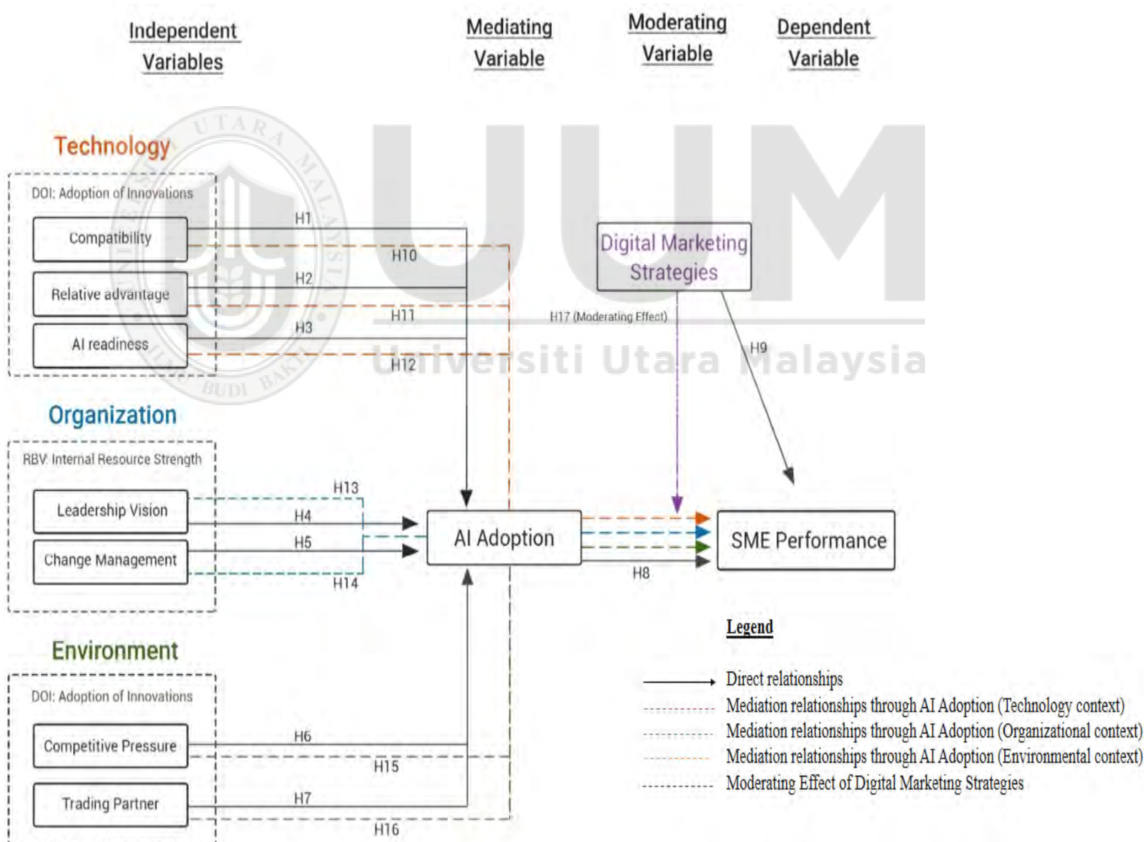

Figure 2.5.
Proposed research framework.

2.39 Chapter Summary

The literature review provided a thorough examination of AI's role and impact within SMEs, focusing primarily on the influence of AI adoption on SME performance against the backdrop of technological, organizational, and environmental factors. It explored the critical importance of SMEs in fostering economic development, shedding light on the hurdles these entities encounter in adopting new technologies. The narrative positioned AI as a pivotal tool for boosting SME operations and enhancing their competitive edge, with a special emphasis on its transformative potential in emerging economies, including Pakistan. The review dissected the TOE framework, offering a nuanced understanding of how AI adoption in SMEs is shaped by the intricate interaction between technological capabilities, organizational readiness, and external pressures.

Furthermore, the chapter underscored the significance of AI in digital marketing, framing it as a crucial moderator capable of elevating SME performance through refined marketing strategies and heightened customer engagement. It pinpointed a notable research gap in the study of AI adoption among SMEs situated in emerging markets, advocating for an in-depth exploration of the unique challenges and opportunities present in such environments. By synthesizing existing literature, the review formulated hypotheses concerning AI's effect on SME performance, attributing technological, organizational, and environmental factors as essential influencers. It suggested that AI could bridge these factors and SME performance, improving operational efficiency, marketing efficacy, and overall market competitiveness. Conclusively, the chapter heralded the transformative capacity of AI and digital marketing strategies in propelling SME growth and innovation, calling for a more concentrated research effort on AI integration within SMEs, especially within the framework of emerging economies.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

In this chapter, the methodology employed to explore the effects of AI adoption in SMEs is presented. It explains the research paradigm, design, and the targeted population for investigation. The chapter describes the sampling methods and units of analysis, along with the procedures for measuring and operationalizing key variables, including firm performance and AI adoption constructs within the TOE Framework. Additionally, it covers the constructs associated with TOE factors and their measurement. The chapter discusses the questionnaire design, data collection methods, and data analysis techniques, particularly highlighting the role of Structural Equation Modeling (SEM) in model validation. Ethical considerations and a summary of the chapter's main points are also included.

3.2 Research Paradigm for the Study

This study adopts a positivist research paradigm, grounded in the belief that reality is objective, measurable, and governed by laws that can be discovered through systematic observation and empirical analysis (Creswell & Creswell, 2018). Positivism is well-suited for studies that aim to test theoretical relationships using structured instruments, statistical methods, and quantifiable data. Consistent with this paradigm, the study follows a hypothetico-deductive approach, whereby hypotheses are derived from well-established theoretical frameworks—namely the Technology–Organization–Environment (TOE) framework, the Resource-Based View (RBV), and Diffusion of Innovations (DoI) theory—and are subsequently tested through empirical analysis (Hair et al., 2019; Park et al., 2020).

The adoption of a quantitative methodology is justified by the research objective, which is to empirically examine the mediating role of Artificial Intelligence (AI) adoption and the moderating effect of digital marketing strategies in the relationship between TOE factors and SME performance. This approach allows for hypothesis testing, validation of causal relationships, and generalization of findings across a broader population of SMEs—outcomes that would be less feasible with qualitative or mixed-method designs (Saunders et al., 2019; Creswell & Clark, 2011).

Table 3.1
Philosophical Assumptions of the Research Paradigm.

Philosophical Assumptions	Positivism/Quantitative
Ontology	Reality is objective, fixed, and can be observed and described from an external perspective.
Epistemology	Knowledge is obtained through detached observation and quantification of phenomena. The researcher is independent of the participants and uses objective measures to test hypotheses.
Axiology	Research is conducted in a value-free manner, aiming to remain impartial and objective throughout the study.
Methodology	Emphasizes the use of structured, standardized instruments, such as surveys or existing databases, with statistical analysis to quantify relationships and test hypotheses.

In accordance with these assumptions, this study operationalizes the constructs TOE factors, AI adoption, digital marketing strategies, and SME performance using validated measurement scales. Quantitative data were collected using structured surveys distributed across SMEs in the Pakistani manufacturing sector.

This design facilitates replication, generalizability, and statistical validation of findings—key hallmarks of positivist research (Bryman, 2016). The quantitative approach is particularly apt for this study, as it enables the modeling of complex relationships—including mediation and moderation—within a theory-driven framework using techniques such as Partial Least Squares Structural Equation Modeling (PLS-SEM) (Hair et al., 2021; Sarstedt et al., 2022).

Furthermore, the adoption of positivism ensures that the study adheres to high standards of empirical rigor, making its findings applicable for both academic theory-building and practical policy guidance. The generalizable insights derived from this study are expected to inform decision-making among policymakers, SME owners, and digital transformation practitioners.

3.3 Research Design

The research design serves as a structured blueprint that guides the collection, measurement, and analysis of data to answer the research questions outlined in Chapter 1. Aligned with the positivist paradigm, this study adopts a quantitative, cross-sectional survey design, enabling the systematic investigation of hypothesized relationships among TOE factors, AI adoption, digital marketing strategies, and SME performance. This approach is appropriate for validating theoretical constructs and assessing mediating and moderating effects in a structured model (Creswell & Creswell, 2018; Hair et al., 2019).

A cross-sectional design was selected due to its efficiency in capturing data from a large population at a single point in time. It enables the examination of current patterns and associations between variables without the time or cost constraints associated with longitudinal studies (Saunders et al., 2019). Furthermore, a quantitative method is particularly well-suited for hypothesis testing, generalizability, and replicability—key goals of this study and hallmarks of positivist research (Bryman, 2016).

The data were collected using a standardized structured questionnaire that measured core constructs such as technological readiness, organizational capabilities, environmental factors, AI adoption, digital marketing practices, and firm performance. Measurement items were adapted from validated sources in the literature to ensure construct reliability and validity (Bu et al., 2020; Zeng et al., 2022; Kurup & Gupta, 2022). Each item used a seven-point Likert scale, capturing the degree of agreement or perception of respondents.

The questionnaire was disseminated electronically via Google Forms to maximize accessibility and cost-efficiency. Respondents were selected using a judgmental sampling approach, focusing on SME managers and decision-makers with relevant knowledge of AI-related initiatives. This method allowed the study to specifically target firms that are either currently implementing or actively exploring AI technologies—a focus aligned with the research objectives (Etikan et al., 2016). A multi-channel outreach strategy was employed using LinkedIn InMails, WhatsApp groups, and email invitations, based on contact information sourced from the Pakistan Export Directory.

To enhance participation, reminders were sent after two weeks to non-respondents using the same channels. Data collection spanned three months, allowing sufficient time for follow-ups and reducing non-response bias.

The quantitative data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 3, which is suitable for analyzing complex models involving both mediating and moderating effects (Hair et al., 2021). This technique is robust to small sample sizes, does not assume multivariate normality, and is ideal for exploratory research with latent constructs (Sarstedt et al., 2022).

In summary, the research design—characterized by a cross-sectional survey, quantitative data collection, structured instrumentation, and SEM analysis—ensures methodological rigor, validity, and alignment with the positivist paradigm. It facilitates empirical testing of the theoretical framework and provides actionable insights into how AI and digital marketing strategies influence SME performance in Pakistan's manufacturing sector.

3.4 Population

Defining the target population is a foundational step in any empirical investigation, as it shapes the sampling strategy, data collection process, and the generalizability of research findings (Sekaran & Bougie, 2016). In this study, the population comprises Small and Medium Enterprises (SMEs) operating in the manufacturing sector of Pakistan, with a specific focus on export-oriented firms. This population was selected due to the critical role manufacturing SMEs play in the country's economic development and international trade competitiveness.

According to the Small and Medium Enterprises Development Authority (SMEDA, 2022), SMEs represent approximately 90% of all registered businesses in Pakistan, contributing around 40% to GDP, 25% to exports, and employing nearly 78% of the non-agricultural labor force. Among them, manufacturing SMEs hold strategic importance, accounting for nearly 70% of the country's total manufacturing output. These firms are also among the earliest segments to engage with technology adoption initiatives, including artificial intelligence and digital transformation (Raza et al., 2018; Ahmad et al., 2021).

To ensure the research aligns with its objectives—namely, to examine AI adoption and digital marketing strategies as mediators and moderators of SME performance—the study focuses on export-oriented manufacturing SMEs. These firms are most likely to face international competitive pressure, regulatory compliance demands, and evolving digital expectations, making them an ideal context for applying the TOE framework and associated constructs.

The population frame was derived from the Pakistan Export Directory (Exportsinfo, 2020), which lists 6561 registered export-focused manufacturing SMEs. These firms are distributed across four key sectors, which also align with Pakistan's major export domains:

Table 3.2 provides a detailed enumeration of these industries, representing the industry-wise segmentation of the study's population.

Table 3.2.
The population of the study.

Category of Manufacturing SMEs	Quantity of SMEs
SMEs in Textiles	1304
SMEs in Leather Products	1540
SMEs in Sporting Goods	2071
SMEs in Surgical Equipment	1646
Aggregate Total	**6561**

Source: Exportsinfo, (2020)

These industries were selected for two primary reasons:

1. Economic Contribution – Together, they constitute a significant share of Pakistan's export revenue and industrial employment.

2. Technological Relevance – These sectors are increasingly integrating AI-enabled tools (e.g., for predictive maintenance, smart logistics, customer analytics), which aligns with the research focus on digital innovation and performance.

This industry-level segmentation enables the study to provide nuanced insights into how external pressures (e.g., export market demands), internal capabilities, and technology-readiness levels influence AI adoption and performance outcomes.

By focusing on this population, the study ensures contextual relevance, industry diversity, and practical significance. The selection also provides a rich environment to explore how TOE factors, mediated by AI adoption and moderated by digital marketing, contribute to SME competitiveness in emerging economies.

3.5 Sampling Technique

The sampling strategy adopted in this study is aligned with its hypothetico-deductive approach, which is grounded in testing theory-driven hypotheses through structured empirical inquiry. Given the study's objective to validate the mediating role of AI adoption and the moderating effect of digital marketing strategies on SME performance within the TOE framework, the research required participants with relevant insights and exposure to technological adoption within Pakistani SMEs. Hence, judgmental (purposive) sampling was used to target SME decision-makers most capable of providing meaningful and contextually rich responses.

The target population comprised 6,561 export-oriented SMEs operating within Pakistan's four primary manufacturing sectors—textiles, leather goods, sports goods, and surgical instruments—as identified from the Pakistan Export Directory (Exportsinfo, 2020). The selection of these sectors was based on their significant contribution to Pakistan's economy and export performance and their increasing need for technological transformation to remain competitive.

Although statistical generalizability is not the primary goal of judgmental sampling, the study drew from best practices to ensure adequate response volume for robust analysis using PLS-SEM. Based on previous studies indicating an average SME response rate of 46% in the Pakistani context (Beh & Shafique, 2016), a total of 789 questionnaires were distributed across the four sectors to achieve a minimum valid sample size above the threshold recommended by Hair et al. (2019) for PLS-SEM modeling.

While the initial approach was proportionate stratified random sampling based on the distribution of SMEs across four major sectors, the actual data collection adopted a purposive sampling method. This shift was necessitated by limited access to a complete and randomized SME database. Respondents were accessed through professional networks, SME forums, and digital platforms (LinkedIn, WhatsApp groups), aligning with common practices in SME research in emerging economies (Creswell & Clark, 2017). As such, generalizability is cautiously framed, emphasizing theoretical replication over statistical representativeness.

The table 3.3 below illustrates the distribution of questionnaires across the sectors, based on proportional segmentation of the population:

Table 3.3
Questionnaire Distribution by Sector (Judgmental Sampling)

Strata	**Population (N)**	**Proportionate Fraction**	**Questionnaires Distributed**
Textile SMEs	1304	1304/6561 = 0.198	156
Leather SMEs	1540	1540/6561 = 0.234	184
Sports SMEs	2071	2071/6561 = 0.315	249
Surgical SMEs	1646	1646/6561 = 0.250	200
Total	**6561**		**789**

Source: Exportsinfo, (2020)

This approach ensured that each key sector was adequately represented based on its proportion in the total population, while the use of judgmental sampling allowed for the selection of respondents best positioned to assess the adoption and impact of AI and digital marketing. The survey was administered electronically via Google Forms, providing convenient access for respondents. Follow-up reminders were issued two weeks after the initial distribution to enhance response rates. The data collection period extended over three months, ensuring sufficient time for engagement and participation.

Furthermore, the sampling strategy addressed potential non-response concerns by leveraging a multi-channel outreach strategy, including LinkedIn InMails, WhatsApp professional groups, and direct emails. The distribution method was designed to optimize reach and relevance, ultimately supporting the theoretical generalizability and empirical rigor of the study’s findings.

3.6 Unit of Analysis

In this study, the unit of analysis is the organization, specifically small and medium-sized enterprises (SMEs) operating in Pakistan's manufacturing sector. These firms are the focal entities whose characteristics, behaviors, and performance outcomes are being investigated in relation to artificial intelligence (AI) adoption and digital marketing strategies.

To gather relevant insights at the organizational level, managers and owners—particularly those occupying top and middle management positions—served as the key informants. This selection is justified by their strategic involvement in decision-making processes concerning technology adoption and performance management. As noted by Sekaran and Bougie (2016), the unit of analysis refers to the major entity being studied, while the unit of observation (in this case, managerial staff) provides the data necessary to reflect organizational-level constructs.

This approach aligns with recommendations by Rea and Parker (2005), who emphasize that the unit of analysis should correspond to the level at which the research questions are framed and the data are aggregated. Given that the hypotheses and theoretical framework are conceptualized at the organizational level (e.g., AI adoption by firms, SME performance), focusing on the SME as the unit of analysis is methodologically appropriate.

By engaging SME managers as informants, the study captures strategic and operational perspectives on AI adoption, organizational capabilities, and external influences. This ensures that the findings reflect organizational realities, rather than individual-level perceptions alone.

In summary, the unit of analysis in this research is the organization (SME), while top and middle-level managers or owners serve as the informants, enabling a valid and reliable assessment of AI adoption and its impact on performance within the Pakistani SME context.

3.7 Instrumentation and Construct Operationalization

This study adopted a rigorous approach to the development and operationalization of instruments, grounded in the TOE, RBV, and DoI theoretical frameworks. The aim was to ensure that all constructs—technological, organizational, and environmental factors, along with AI adoption, digital marketing strategies, and SME performance—were measured with theoretical precision, empirical reliability, and contextual relevance.

To convert abstract theoretical constructs into quantifiable variables, a seven-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree) was employed. This scale was selected due to its increased variance capture, reduced central tendency bias, and higher discriminatory power compared to shorter scales, thereby enhancing the sensitivity of responses (Krosnick & Fabrigar, 1997; Dawes, 2008; Sekaran & Bougie, 2016).

Moreover, it aligns with the statistical assumptions of PLS-SEM, allowing for robust latent variable modeling.

Each construct was operationalized using reflective multi-item measures sourced from peer-reviewed empirical studies known for their psychometric robustness. Instrument sources were selected based on conceptual alignment with the study's framework and established validity in prior SME and technology adoption research. This ensured theoretical consistency and reinforced construct validity.

For instance, technological readiness, compatibility, and relative advantage were operationalized using scales developed by Kurup and Gupta (2022). AI adoption was measured using indicators adapted from Zeng et al. (2022), while digital marketing strategies were captured through items developed by Wu et al. (2024). SME performance—a central dependent variable—was conceptualized as a multidimensional construct comprising market, financial, innovation, and AI-related outcomes. This operationalization, adapted from Bu et al. (2020) and Chen et al. (2016), is rooted in RBV theory, which advocates for evaluating performance through both tangible and intangible strategic resources.

To ensure measurement validity and contextual appropriateness, the instrument development process involved several critical steps:

- **Expert Review and Content Validation**: Three subject-matter experts in AI adoption, SME management, and digital marketing evaluated the draft instrument for conceptual relevance, clarity, and contextual applicability. Their feedback led to refinements in item wording and construct framing, especially for AI and marketing-related constructs within the Pakistani SME environment.

- **Pilot Testing and Face Validity**: A pilot test involving 88 SME managers across the selected industries was conducted to evaluate clarity, comprehensibility, and cultural sensitivity. Based on the feedback, minor linguistic and contextual revisions were made—especially in items referencing AI applications and digital marketing practices—to ensure cultural and semantic consistency.

- **Contextual Sensitivity**: Recognizing Pakistan's unique technological and business environment, special attention was given to localizing the instrument while preserving theoretical intent. Terminologies were adapted without altering the construct meaning, ensuring both construct equivalence and contextual resonance.

The reliability and validity of the constructs were confirmed through rigorous analysis during the PLS-SEM stage. Convergent validity was evaluated using Average Variance Extracted (AVE), and discriminant validity was assessed through both the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio. Internal consistency was measured using Cronbach's alpha and Composite Reliability (CR), all of which surpassed the recommended thresholds (Hair et al., 2019; Henseler et al., 2015), confirming the measurement model's robustness.

The finalized instrument includes ten constructs measured through multiple items, enabling a comprehensive and reliable reflection of the conceptual model. A structured questionnaire design was utilized to suit the reflective measurement model recommended for PLS-SEM studies, facilitating accurate estimation of both direct and indirect paths. Descriptions of the variables are presented in Table 3.4

Table 3.4
Instruments description.

Variables	**Items**	**Sources**
SME performance	4	Bu et al. (2020)
AI Adoption	7	Zeng et al. (2022)
Digital Marketing Strategy	4	Wu et al. (2024)
Compatibility (Technological Factor)	4	Kurup and Gupta (2022)
Relative Advantage (Technological Factor)	4	Kurup and Gupta (2022); Rogers (2003)
Technology Readiness (Technological Factor)	5	Kurup and Gupta (2022)
Leadership Vision (Organizational Factor)	4	Kurup and Gupta (2022)
Change Management Capability (Organizational Factor)	3	Kurup and Gupta (2022)
Competitive Pressure (Environmental Factor)	3	Kurup and Gupta (2022)
Trading Partnerships (Environmental Factor)	3	Kurup and Gupta (2022)

3.7.1 Firm Performance Construct

Firm Performance (FP) was treated as a second-order, multidimensional construct representing the cumulative impact of strategic capabilities like AI and digital marketing. Drawing from RBV, FP encompasses both tangible (e.g., sales growth, financial health) and intangible (e.g., innovation, technological agility) performance dimensions (Barney, 1991; Mikalef & Gupta, 2021; Chatterjee et al., 2021b). As recommended by Arias-Pérez and Vélez-Jaramillo (2022) and Chen et al. (2022), firm age and size were included as control variables due to their influence on performance outcomes in technology-intensive environments.

Four items—market share growth, financial soundness, innovation in offerings, and AI-enabled improvement—were adapted primarily from Bu et al. (2020) and Chen et al. (2016) to reflect firm-level strategic outcomes.

Each item was rated on a seven-point Likert scale to capture SME decision-makers' perceptions of performance improvements attributable to AI adoption and digital marketing practices.

A summary of all instruments and sources is presented in Table 3.4, while Table 3.5 provides a detailed breakdown of the firm performance construct, its reliability metrics, and item descriptions.

Table 3.5
Measurement Scale of Firm performance adapted from Chen et al. (2016) and Bu et al. (2020).

Construct: Firm performance (FP)	**Code**	**Scale Items**	**Reliability (Cronbach's Alpha)**	**Internal Consistency**
FP	FP1	Our market share is on an upward trajectory.	0.839	0.809
	FP2	Our company is not facing any financial challenges currently.		
	FP3	We are consistently rolling out new products and services.		
	FP4	The integration of AI is contributing to our business growth.		

The reliability and internal consistency values are reflective of the overall measurement scale, indicating that the items provide a reliable assessment of Firm performance. Each item is assessed on a seven-point Likert scale from 1 (strongly disagree) to 7 (strongly agreed)" to capture the subjective assessment of Firm performance in relation to AI adoption.

3.7.2 AI Adoption Construct

AI adoption in SMEs integrates technologies like computer vision and machine learning to enhance operational efficiencies and capitalize on unique strengths, improving customer services and fostering solution-oriented approaches across various functions (Chatterjee et al., 2021). This transformation extends to marketing, recruitment, and financial management, enhancing firms' profitability, productivity, and customer loyalty while reducing risks (Cham et al.., 2022).

AI technologies replace tasks needing human expertise with advanced analytical and computational processes, blurring the lines between machine capabilities and human expertise and facilitating the redesign of business practices (Chatterjee et al., 2021; Yablonsky, 2019). Recent advancements in AI contribute to the creation of innovative products and services, enhancing data analysis in competitive environments and fostering digital technology applications in tech firms (Arias-Pérez & Vélez-Jaramillo, 2022; Mondal, 2020; Ochmann & Laumer, 2019). AI adoption also advances digital innovation in firms through improved data storage and sharing, re-programmability, user experience integration, and the creation of innovative products and services (Cubric, 2020).

The AI adoption instrument specifically measures respondents' perceptions based on their experiences with AI in their organizations. This ensures the data collected is directly relevant to the practical implementation of AI within their operational contexts. The items in the questionnaire are designed to capture specific aspects of AI adoption, such as cost efficiency, time reduction, and decision-making improvements, aligning with the constructs discussed in the literature review.

Table 3.6
Measurement of AI Adoption Based on Zeng et al. (2022).

AI Adoption (AIA) Item Code	**Scale Items**	**FL**	**T-Value**	**Alpha**	**CR**	**AVE**
AI Adoption	Overall AI Adoption Construct		-	0.83	0.92	0.64
AIA1	Implementing AI is more cost-efficient compared to alternative technologies.	0.84	15.47	-	-	-
AIA2	AI implementation reduces costs and time associated with alternative methods.	0.77	14.23	-	-	-
AIA3	Adopting AI decreases the time, effort, and expenses needed for advantageous outcomes.	0.81	14.57	-	-	-
AIA4	AI integration aids HR managers in the candidate selection process.	0.82	15.45	-	-	-
AIA5	AI adoption enables more informed and effective decisions regarding recruitment and selection.	0.81	14.55	-	-	-
AIA6	Integrating AI enhances the efficiency of technology-related tasks.	0.80	14.21	-	-	-
AIA7	AI implementation offers improved control and quicker decision-making in security matters.	0.76	13.55	-	-	-

The measurement framework, based on Zeng et al. (2022), provides a reliable assessment of AI adoption in SMEs. High factor loadings and Composite Reliability indicate strong internal consistency, while the Average Variance Extracted reflects the construct's explanatory power. The construct is assessed on a seven-point Likert scale from 1 (strongly disagree) to 7 (strongly agreed)

3.7.3 TOE Framework Constructs for AI Adoption Measurement

The TOE framework is leveraged in this research to explore the determinants of AI adoption within organizations. Constructs are adapted from Kurup & Gupta (2022), ensuring robust reliability and validity through comprehensive statistical analysis. Each construct is assessed on a seven-point Likert scale from 1 (strongly disagree) to 7 (strongly agreed).

3.8 Technological Factors

3.8.1 Compatibility Construct

Compatibility refers to the degree to which an innovation can provide value and fulfill the requirements of its prospective adopters (Rogers, 1995). Chui (2017) stressed the importance of having a strong AI business case and alignment with current strategies for effective AI integration. Ifinedo (2005) noted that a closer alignment between the adoption process and the diffusion of technological innovation facilitates smoother adoption. Numerous studies have indicated a positive correlation between compatibility and the intention to adopt new innovations (Ifinedo, 2005; Yang, 2015; Yan, 2009; Zahi, 2010).

Table 3.7
Measure of Compatibility Adapted from Kurup and Gupta (2022).

Compatibility (C) Item Code	**Scale Item**	**Loading (Standardized Regression Weights)**	**Cronbach Alpha**
C1	AI systems align well with our existing communication and network setup.	0.868	0.935
C2	AI systems are in harmony with our existing hardware setup.	0.890	0.935
C3	AI systems are congruent with our current infrastructure.	0.915	0.935
C4	AI systems are well-integrated with our digital data processing resources.	0.869	0.935

The scale, adapted by Kurup and Gupta (2022) and initially validated by Chen (2019), efficiently gauges the compatibility of AI technology with an organization's framework current IT infrastructure., highlighting the importance of alignment between AI applications and organizational capabilities for successful AI adoption.

3.8.2 Relative Advantage Construct

The Relative Advantage construct assesses the superiority of AI over existing processes, particularly in solving business problems and offering benefits over manual processes. Central to technology adoption in organizations, it underscores AI's multidimensionality, providing automation, decision-making capabilities, and advanced data processing (Kurup & Gupta, 2022). AI adoption, therefore, becomes a strategic decision for increased operational efficiency, productivity, and competitive positioning (Zhu & Kraemer, 2005).

Rooted in Rogers' diffusion of innovations theory, the relative advantage is recognized as a crucial factor in the adoption of innovations, especially in SMEs (Grandon & Pearson, 2004; Rogers, 2003; Trainor et al., 2011). AI's computational power fosters service quality improvement and cost reduction, which is critical in competitive business environments (Russell & Norvig, 2016; El Khatib et al., 2019). However, alongside economic benefits, issues like data security and privacy are significant, necessitating risk mitigation strategies (Martens & Teuteberg, 2012; Oliveira et al., 2014; Senarathna et al., 2018). The perceived relative advantage, including expected financial and operational benefits, is vital in influencing organizations' AI adoption decisions (Alshamaila et al., 2013).

Table 3.8
Measure of Relative Advantage Construct – Adapted from Kurup and Gupta (2022).

Relative Advantage (RA) Item Code	Scale Items	Cronbach Alpha	Loading (Standardized Regression Weights)	R^2
RA1	AI systems enhance employee output efficiency.	0.869	0.741***	0.549
RA2	AI systems contribute to the enhancement of customer support.		0.740***	0.548
RA3	AI systems optimize the employment of IT assets.		0.834***	0.695
RA4	AI systems facilitate increased adaptability and system integration.		0.851***	0.725

Table 3.8 encapsulates the Relative Advantage constructs items, their respective standardized regression weights (loadings), R^2 values, and the overall Cronbach Alpha value of 0.869. It underscores the construct's internal consistency and its role in assessing AI's superiority over existing processes, as adapted from Kurup and Gupta (2022).

3.8.3 Technology Readiness Construct

Technology readiness, crucial for Artificial Intelligence (AI) deployment, involves both infrastructure and human resource capabilities. It encompasses tangible assets like hardware and software and human capital, notably IT professionals proficient in Internet-related applications (Mata et al., 1995). Internal technological readiness refers to a firm's infrastructure readiness for AI, including essential hardware, software, and IT systems (Pumplun et al., 2019; Richey et al., 2007; Schmidt et al., 2020). For SMEs, transitioning to data-driven methods from traditional rule-based approaches is key for decision-making, relying on quality data and skilled AI workforce.

External technological readiness assesses the market's preparedness for AI technology, focusing on the availability of AI tools, platforms, and services (Richey et al., 2007). For successful AI deployment, SMEs require robust computing infrastructure, advanced algorithms, and extensive datasets (Wamba-Taguimdje et al., 2020). Cloud-based machine learning solutions by major tech companies offer vital infrastructure for AI integration (Borges et al., 2020).

AI readiness is an organization's preparedness level for AI-related changes, encompassing human resources, data readiness, financial and technological support (AlSheibani et al., 2018; Jöhnk et al., 2021). It requires technical experts, process experts, and consultants for effective AI implementation. In this study, Technology Readiness is conceptualized as an organization's capability to leverage AI and digital marketing strategies, including both technological assets and expertise for strategic SME goals.

Table 3.9
Measure of Technology Readiness – Adapted from Kurup and Gupta (2022).

Relative Advantage (TR) Item Code	Scale Items	Loading
TR1	Our organization possesses the necessary resources to develop AI applications.	0.834
TR2	Our organization allocates resources promptly for the deployment of AI.	0.830
TR3	Our organization employs consultants with expertise in AI and sector-specific knowledge.	0.799
TR4	Our organization maintains resources dedicated to model surveillance and response.	0.769
TR5	Our organization upholds a centrally coordinated practice for AI management.	0.732

Table 3.9.1
Construct Reliability and Validity – Adapted from Kurup and Gupta (2022).

Construct	AVE	CR	Cronbach's α
Technology Readiness (TR)	0.630	0.895	0.855

3.9 Organizational Factors

3.9.1 Leadership Vision Construct

The influence of top management and leadership vision is crucial in adopting and integrating Artificial Intelligence (AI) within organizations, especially SMEs in Pakistan. Research indicates that the commitment of top management is crucial for the successful deployment of new technologies, including AI (Burgess, 2017; Skafi et al., 2020). Their role is not limited to approving AI initiatives but also actively directing the organization's strategy towards AI integration and promoting a culture receptive to technological advances (Yang & Meyer, 2019).

Leadership vision in AI involves not only endorsing AI-related projects but also thoroughly understanding the technology's potential and associated risks. This is particularly important given the early stage of AI development and the potential for setbacks, such as failed pilot projects (Kurup & Gupta, 2022). Leaders with a strategic vision for AI play a crucial role in supporting and sustaining AI initiatives, even when facing initial challenges.

Top management's responsibilities include defining the AI vision, allocating budgets, and providing necessary resources. This support is fundamental for both the initial adoption and ongoing development of AI capabilities, which are key to maintaining competitive advantages and continuously improving AI applications in business processes (Stone et al., 2020).

Table 3.10
Measure of Leadership Vision– Adapted from Kurup and Gupta (2022).

Leadership Vision (L) Item Code	**Scale Items**	**Loading**
L 1	Management within our organization is prepared to embrace the risks associated with integrating AI.	0.800
L 2	The leadership in our organization views IT proficiency as a strategic asset.	0.773
L 3	Executives in our organization are committed to the utilization of AI technology.	0.764
L 4	The leadership is of the opinion that AI adoption is crucial for maintaining our competitive edge in the industry.	0.736

Table 3.10.1
Construct Reliability and Validity.

Construct	**AVE**	**CR**	**Cronbach's α**
Leadership	0.591	0.852	0.791

3.9.2 Change Management Capability Construct

Change management capability within organizations, particularly concerning the integration of new technologies such as AI, entails effectively transitioning from previous processes and technologies to new ones. This capability is critical for ensuring that organizations can adapt to and leverage technological advancements effectively. It assesses an organization's ability to implement changes, especially concerning technology transitions. It considers the organization's prior experience with business process changes. Scales are leveraged by Mikalef and Gupta (2021a).

Table 3.11
Measure of Change Management Capability – Adapted from Kurup and Gupta (2022).

Change Management Capability (CMC) Item Code	**Scale Items**	**Loading**
CMC 1	In our organization, there are business areas that have previously undergone process transformation.	0.942
CMC 2	Certain departments within our organization have effectively transitioned from legacy technologies to modern solutions.	0.936
CMC 3	Our organization has a track record of successfully executing changes in operational processes.	0.674

Table 3.11.1
Construct Reliability and Validity

Construct	**AVE**	**CR**	**Cronbach's α**
Change Management Capability (CMC)	0.739	0.893	0.816

3.10 Environmental Factors

3.10.1 Competitive Pressure

Competitive pressure represents a notable environmental aspect affecting the adoption of AI within organizations. This pressure typically stems from the pace of innovation in operational procedures, the introduction of new products or services, and the integration of AI technologies by competitors in the sector. Additionally, it encompasses elements of price and quality competition within the industry.

Table 3.12
Measure of Competitive Pressure– Adapted from Kurup and Gupta (2022).

Competitive Pressure (CP) Item Code	**Scale Item**	**Loading (Standardized Regression Weights)**	**R^2**	**Cronbach Alpha**
CP1	The pace of introducing novel operational procedures and offerings in our sector has escalated significantly.	0.697***	0.485	0.830
CP2	Adopting AI technologies for innovation within our industry would compel our firm to follow suit.	0.769***	0.591	0.830
CP3	Our industry is characterized by intense competition on pricing.	0.920***	0.847	0.830

3.10.2 Trading Partnerships

This construct evaluates the influence of trading partners on AI adoption, focusing on their AI integration and understanding.

Table 3.13
Measure of Trading Partnerships - Adapted from Kurup and Gupta (2022).

Item Code -Trading Partnerships (TP)	**Scale Item**	**Loading (Standardized Regression Weights)**
TP1	Our organization is cognizant of the results produced by the applications our trading partners utilize.	0.871
TP2	We are informed about applications that process information from our trading partners.	0.838
TP3	We are knowledgeable about applications that integrate our IT systems with those of our trading partners.	0.648

Table 3.13.1
Construct Reliability and Validity.

Construct	**AVE**	**CR**	**Cronbach's α**
Trading Partnerships (TP)	0.627	0.832	0.691

The items for each construct are carefully designed to capture the specific aspects of AI adoption pertinent to each domain within the TOE framework. The high levels of reliability and validity across the constructs underscore the robustness of the measurement instruments utilized for this study, enabling a thorough examination of the factors influencing AI adoption. For a detailed understanding of the specific items associated with each construct, here's how they align with the constructs and the reliability and validity measures as reported by Kurup & Gupta (2022):

Table 3.14
Measures of the Study for TOE Framework Constructs in AI Adoption.

Construct		**No. of Items**	**Reported Reliability**	**Sources**
Technological Factors				
Compatibility (C)	Degree to which AI integrates with existing IT infrastructure	4 (C1 - C4)	Cronbach Alpha: 0.935	Kurup & Gupta (2022)
Relative Advantage (RA)	Perceived benefits of AI over existing processes	4 (RA1 - RA4)	Cronbach Alpha: 0.869	Kurup & Gupta (2022)
Technology Readiness (TR)	Organization's readiness for AI technology	5 (TR1 - TR5)	Cronbach Alpha: 0.855	Kurup & Gupta (2022)
Organizational Factors				
Leadership Vision (L)	Role of leadership in adopting and integrating AI	4 (L1 - L4)	Cronbach Alpha: 0.791	Kurup & Gupta (2022)
Change Management Capability (CMC)	Ability to transition to new technologies	3 (CMC1 - CMC3)	Cronbach Alpha: 0.816	Kurup & Gupta (2022)
Environmental Factors				
Competitive Pressure (CP)	Market-driven need for AI adoption	3 (CP1, CP2, CP3)	Cronbach Alpha: 0.830	Kurup & Gupta (2022)
Trading Partnerships (TP)	Influence of trading partners on AI adoption	3 (TP1 - TP3)	Cronbach Alpha: 0.691	Kurup & Gupta (2022)

3.11 Digital Marketing Strategy Construct

In the empirical study conducted by Wu et al. (2024) on digital marketing strategies and performance in SMEs, the construct of digital marketing strategies was meticulously analyzed. This construct is composed of various scale items that evaluate how companies leverage digital media for customer relationship management, customer preference prediction, channel member relationship management, and customer attraction.

Table 3.15.
Digital Marketing Strategies Construct – Wu et al.'s (2024).

Item Code	**Scale Item**	**Mean**	**SD**	**Standardized Loading (St.load)**
DMS1	Our company orchestrates customer interactions via digital channels.	5.7	1.8	0.87
DMS2	Our company utilizes digital channels to forecast customer inclinations.	5.4	1.5	0.73
DMS3	Our company administers its connections with distribution partners through digital platforms.	5.1	1.6	0.82
DMS4	Our company leverages digital marketing strategies to draw in customers.	5.3	1.8	0.86

Table 3.15.1
Measures of Construct Reliability.

Measures Construct	**Cronbach's Alpha (α)**	**AVE**
Digital Marketing Strategy	0.91	0.86

Table 3.15.1 highlights the reliability and robustness of the digital marketing strategies construct. The high Cronbach's Alpha of 0.91 indicates excellent internal consistency, and the AVE of 0.86 further confirms the construct's validity.

3.12 Questionnaire Development

The efficacy of a questionnaire is a critical determinant in the reliability of the data gathered from respondents. An effective design aids in minimizing measurement errors and enhances the precision of the information collected. According to Sekaran and Bougie (2016), a questionnaire must be easily understandable and written in the language familiar to the participants. Therefore, the current research has employed English for questionnaire construction, acknowledging its status as the business lingua franca in the global corporate environment, which is pertinent to the SMEs under study.

The questionnaire for this study is structured in a closed-ended format and comprises two main sections. The first section collects demographic data concerning the respondents and their firms, while the second section focuses on evaluating the constructs pertinent to the study's framework.

Section A (Demographic Profile of Respondents): This section seeks to collect demographic details that provide context to the responses. There are six items in this section that capture personal and professional details such as gender, age, highest educational qualification, and current role within the organization. Additionally, information regarding the industry category of the SME and the extent of AI and digital marketing experience is requested.

Section B (Perceptions on AI): In the construct assessment section, respondents evaluate and provide insights on various constructs that are fundamental to the research study's framework.

The structure is as follows:

Part A: Technological Factors - Focuses on the integration and application of AI within the SME, examining its alignment with existing processes and infrastructure.

Part B: Organizational Factors - Reviews the internal organizational elements that either support or challenge AI adoption, including leadership vision and change management.

Part C: Environmental Factors - Considers the external influences on the organization, such as market competition and partnerships, that could impact AI and digital marketing strategy implementation.

Part D: Digital Marketing Strategies - Evaluates the strategies used by the SME in digital marketing, their breadth, and depth, and their strategic importance.

Part E: SME performance - Gauges the organization's performance metrics, particularly how they have been affected by the adoption of AI and digital marketing initiatives.

Each of these parts is essential to the comprehensive analysis of the role of AI and digital marketing in shaping SME performance within the context of technological, organizational, and environmental factors. In line with previous empirical studies, a seven-point Likert scale is utilized for responses, ranging from "1 = strongly disagree" to "7 = strongly agree" (Rahman et al., 2021; Kurup & Gupta, 2022). This scale allows for a detailed measurement of perceptions and attitudes across various dimensions, including independent, mediating, moderating, and dependent variables.

3.13 Data Collection Procedure

Data for this study were collected using a structured, pre-validated questionnaire targeted at top and middle-level managers from manufacturing SMEs in Pakistan. These respondents were selected based on their strategic roles and direct involvement in technology adoption and marketing decision-making, making them suitable informants for the research objectives.

Each questionnaire was accompanied by a cover letter clearly explaining the purpose, significance, and voluntary nature of the study. The letter also assured respondents of confidentiality and anonymity, outlining that participation was entirely optional and data would be used strictly for academic research purposes. This ethical protocol was designed to enhance trust and encourage accurate, thoughtful responses.

The questionnaire utilized a seven-point Likert scale, anchored from "1 – Strongly Disagree" to "7 – Strongly Agree", which allowed for nuanced responses across the constructs of interest. Items captured perceptions related to technological, organizational, and environmental factors, as well as AI adoption, digital marketing strategies, and multidimensional SME performance.

The survey was administered electronically via Google Forms for ease of access, time efficiency, and to facilitate centralized data management. A multi-channel distribution strategy was employed to maximize reach and improve response rates. This included:

- **Official email invitations** using addresses obtained from verified members of registered chambers of commerce (e.g., Karachi Chamber of Commerce and Industry),
- **LinkedIn InMails** to connect with SME decision-makers professionally,
- **WhatsApp groups** specifically involving SME managers and industry professionals.

Follow-up reminders were sent two weeks after the initial distribution to enhance participation. The data collection spanned approximately three months, ensuring ample time for outreach, follow-up, and comprehensive coverage of the targeted sample.

3.14 Data Quality Control

To ensure the reliability of the data, Cronbach's Alpha is computed, offering a measure of the internal consistency of the survey instrument and the stability of the constructs. Validity is examined through a series of tests designed to confirm the research instrument's capacity to measure the intended constructs, a crucial step in corroborating the theoretical framework of the study (Sekaran & Bougie, 2016).

3.15 Pilot Study

The initiation of a comprehensive pilot study was pivotal in ascertaining the validity and reliability of the questionnaire designated for the primary survey. This fundamental phase, emphasized by Creswell & Clark (2011), was strategically aimed at refining the survey instrument to guarantee its precision in capturing the intended data. The selection of participants, who closely represent the characteristics of the target demographic, as advised by Keyton (2015), was instrumental in procuring essential feedback. This feedback played a crucial role in the modification of the questionnaire's wording, structure, and overall length, subsequently enhancing its clarity and relevance for the intended audience.

Table 3.16
Preliminary Reliability and Validity Assessment of Constructs (n=88).

Construct	**Number of Items**	**Cronbach's Alpha (α)**
Technological Factors	13	0.920
- Compatibility	4	0.935
- Relative Advantage	4	0.869
- Technology Readiness	5	0.855
Organizational Factors	7	0.880
- Leadership Vision	4	0.791
- Change Management Capability	3	0.816
Environmental Factors	6	0.850
- Competitive Pressure	3	0.830
- Trading Partnerships	3	0.700
AI Adoption	7	0.920
Digital Marketing Strategy	4	0.910
Overall Reliability (Total Alpha)	30	0.910

3.16 Analysis of Reliability and Validity

The reliability and validity of the measurement model underwent thorough evaluation through factor analysis, with a focus on reflective constructs. This assessment adhered to the rigorous standards outlined by Hair et al. (2014) and followed a primer on partial least squares structural equation modeling (PLS-SEM), wherein Cronbach's alpha served as the primary metric for reliability assessment, with a benchmark of >0.7 indicating acceptable reliability. This study placed a significant emphasis on high correlations between measures of identical concepts, a vital procedure for affirming both convergent and discriminant validity, thereby ensuring the accuracy of the measurements.

The statistical examination conducted using SPSS software corroborated the internal consistency and reliability of the constructs under consideration. The values of Cronbach's Alpha, spanning from 0.691 to 0.935, exceeded the stipulated standard of 0.7, illustrating a comprehensive reliability across all constructs. Furthermore, the Kaiser-Meyer-Olkin (KMO) measure, with values ranging from 0.52 to 0.65 for the various constructs, surpassed the recommended threshold of 0.5. This not only signifies the suitability of factor analysis for the collected data but also bolsters the constructs' validity within the conceptual framework of the study.

This pilot study efficaciously established the questionnaire's reliability and validity in examining the effects of AI adoption and digital marketing strategies on SME performance, particularly within the context of Pakistan. The favorable outcomes from the reliability and validity evaluations provide a robust foundation for advancing to the main study. They ensure that the subsequent research is poised to offer profound insights into the strategic adoption of AI and digital marketing within SMEs, thereby making a significant contribution to the existing body of knowledge.

3.17 Techniques for Data Analysis

This study employs a combination of descriptive and inferential statistical methods to explore relationships among constructs and validate the proposed theoretical model. Descriptive statistics, conducted using SPSS version 25, include measures such as means, standard deviations, and frequency distributions, offering insights into the demographic and organizational characteristics of the respondents.

For inferential analysis, the study utilizes Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS version 3.3.2, which is well-suited for predictive modeling, theory development, and complex models involving mediation and moderation (Hair et al., 2019; Sarstedt et al., 2014). PLS-SEM was selected over covariance-based SEM due to its flexibility in handling non-normal data, suitability for smaller sample sizes, and focus on variance explanation, which aligns with the study's objectives.

The measurement model was evaluated for internal consistency, convergent validity, and discriminant validity using Composite Reliability (CR), Average Variance Extracted (AVE), and HTMT ratios (Hair et al., 2021; Ramayah et al., 2017). For the structural model, path coefficients, t-statistics, and p-values were calculated using bootstrapping (5,000 resamples) to test hypotheses. Additionally, effect sizes (f^2), coefficient of determination (R^2), and predictive relevance (Q^2) were reported to assess the strength and explanatory power of the model.

PLS-SEM, while robust and widely used in social science research, operates under certain assumptions and limitations. It does not require multivariate normality, making it suitable for this study where normality tests indicated mild deviations. However, multicollinearity must be addressed by ensuring Variance Inflation Factor (VIF) values remain below the threshold of 5.0. The model's predictive rather than confirmatory orientation implies a focus on maximizing explained variance rather than testing model fit indices such as RMSEA or CFI (Hair et al., 2019; Sarstedt et al., 2022). This limitation is acknowledged and justified in light of the study's exploratory and theory-extending goals.

Table 3.17
Data Analysis Methods Summary.

Objective	**Data Analysis Methods**
Descriptive Analysis	Mean, Standard Deviation, Data Trend
Reliability Assessment	Cronbach's Alpha
Validity Testing	Confirmatory Factor Analysis
Model Validation	SEM (RMSEA, CFI, TLI)
Mediation Analysis	Bootstrapping Techniques
Moderation Analysis	Interaction Term Analysis
Sampling Adequacy	KMO & Bartlett's Test

Each step of the analysis process is framed to ensure that the data's reliability and validity are rigorously tested, thereby providing a solid foundation for the conclusions drawn from the study. The cited methods and references are interwoven to give the methodology a coherent structure and scholarly depth.

3.18 Ethical Considerations

The study strictly adhered to ethical standards. Respondents were assured confidentiality and anonymity, and informed consent was explicitly obtained through clear statements provided at the beginning of the electronic questionnaire. Participation was voluntary, and respondents were free to withdraw at any point without consequences (Zikmund et al., 2013).

Figure 3.1 summarizes the step-by-step methodological process clearly, providing a visual anchor for enhanced readability and comprehension

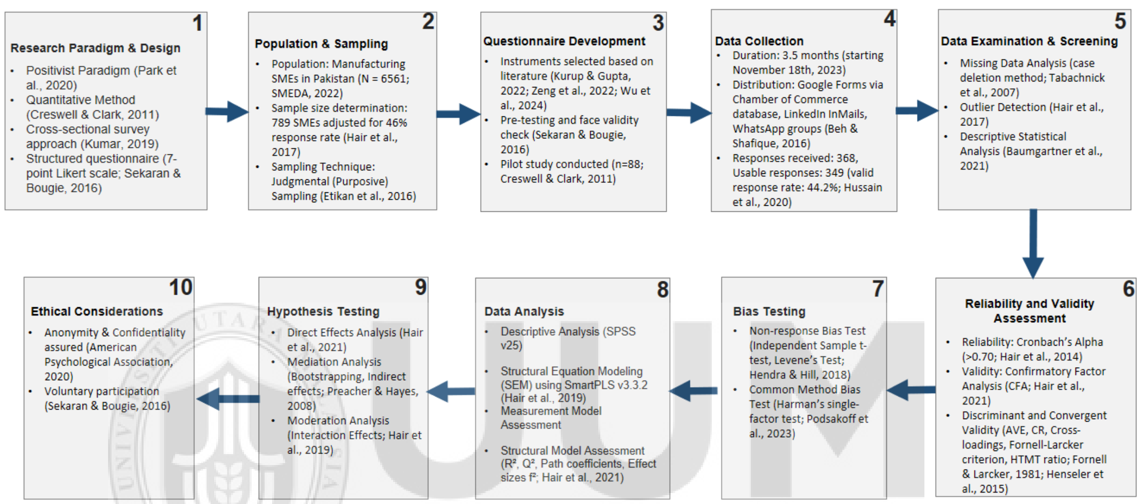

Figure 3.1
Methodological Flow of the Study

3.19 Chapter Summary

This chapter has delineated the research methodology utilized in this study, elucidating the research paradigm, design, and the specific type of research conducted. It provided a comprehensive explanation of the instrument designs, including the constructs for firm performance, AI adoption, and various factors within the TOE Framework. The chapter also discussed the size and scope of the population and sampling techniques alongside the unit of analysis used to gather data. The procedures for data collection and analysis were clearly presented, mentioning the software tools that facilitate this analysis. Furthermore, it highlighted the steps taken to ensure the research's reliability and validity, particularly through the development and testing of the questionnaire. The chapter concluded by explaining the factor tests that is conducted to assess the constructs' validity and the overall research methodology's soundness, ensuring a robust foundation for the study's empirical investigation.

CHAPTER FOUR

ANALYSIS AND FINDINGS

4.1 Introduction

This chapter opens with a thorough explanation of the data collection methods and the obtained response rate. It then details the initial data screening and preliminary analysis, which includes addressing missing values, evaluating outliers, conducting normality tests, and exploring multicollinearity. Subsequently, the demographic profile of the respondents is presented, accompanied by the descriptive statistics for all constructs. The chapter continues by delineating the main findings in two primary sections: (1) the evaluation of the measurement model, covering aspects such as item reliability, internal consistency, convergent validity, and discriminant validity; and (2) the analysis of the structural model, which involves examining path coefficients, explained variance, effect size, and the model's predictive power. The chapter concludes with a discussion of the results of a supplementary PLS-SEM analysis that explores the moderating effects of digital marketing strategies within the structural model.

4.2 Response Rate

This study obtained data from SME managers in top and middle management roles within Pakistan's manufacturing sector. According to the Exportinfo directory (Exportinfo, 2020), the number of registered manufacturing SMEs is 6,561. The sample size was determined based on the guidelines provided by Hair et al. (2017), and adjusted to 789

SMEs to accommodate an anticipated response rate of approximately 46%, thereby ensuring sufficient statistical power.

The data collection process spanned three and a half months, beginning on November 18th, 2023. To ensure broader access and convenience for respondents, the survey was administered via Google Forms and shared through multiple professional channels. Specifically, the link was distributed using contact details sourced from the Chamber of Commerce database and further circulated through WhatsApp groups and LinkedIn InMail targeting SME executives. This multi-channel approach enhanced the reach and improved the overall response rate.

As summarized in Table 4.1, a total of 789 questionnaire sets were distributed, resulting in 368 completed responses. After excluding 19 incomplete submissions, 349 usable responses were retained for analysis—reflecting a usable response rate of 44.2%. This is consistent with response rates reported in prior SME studies (e.g., Hussain et al., 2020; Beh & Shafique, 2016).

Table 4.1
Response Rate

Description	**Number of Questionnaires**	**Response Rate %**
Total Distributed	789	
Total Returned	368	
Incomplete Responses	19	
Usable Responses	349	
Response rate percentage		46.6%
Usable response rate		44.2%
Total Distributed	789	

While the initial sampling strategy was intended as stratified random sampling based on SME sectoral distribution, practical constraints—particularly the lack of a complete and accessible SME population database—necessitated a shift to non-probability purposive and convenience sampling. Participants were accessed through professional networks and online platforms. Although this approach may limit statistical generalizability, it is aligned with widely accepted practices in emerging market SME research, where formal sampling frames are often unavailable (Creswell & Clark, 2017). As such, the findings aim for theoretical rather than statistical generalizability.

The diversity of response channels and alignment with contextual sampling norms helps mitigate concerns of bias and supports the representativeness of the data within the study's scope. All valid responses were analyzed using IBM SPSS (version 24) and SmartPLS (version 4).

4.2 Data Coding

In the categorization of data coding, Blair (2015) and Hurst (2023) pinpointed that the data coding rules have two categories. In the first part, assigning a code number to each construct creates ease of identification for analysis purposes. Second, items are assigned codes to identify the constructs in the study, ensuring that every variable is represented by its different aspects in the questions asked. Therefore, Table 4.2 shows the codes assigned to each construct in the present study.

Table 4.2
Variable Coding

Variables	Code
AI Adoption	AIA
Change Management Capability	CMC
Compatibility	C
Competitive Pressure	CP
Digital Marketing Strategy	DMS
Leadership Vision	LV
Relative Advantage	RA
SME Performance (FP)	FP
Technology Readiness	TR
Trading Partnerships	TP

4.3 Non-Response Bias Test

Non-response bias can notably affect the credibility of survey research, occurring when the opinions of respondents do not accurately mirror the views of the total sample population (Hendra & Hill, 2018). To mitigate this issue, an independent sample t-test was performed on all variables in the current study. This analysis encompassed the dependent, mediator, moderator, and independent variables, facilitating a comparison between early and late responses.

Early responses were those obtained within the first ten weeks, while late responses were collected after ten weeks. This time frame was considered appropriate, as top and middle-level managers, who were the primary respondents, often have busy schedules and additional administrative responsibilities (Baczyńska & Rowiński, 2020). SPSS version 25 was used to analyze the disparity between early and late responses. The findings showed no substantial variance between early and late responses, as indicated in Table 4.3.

Table 4.3
Descriptive Statistics for Early and Late Respondents

Variables	Responses	N	Mean	Std. Deviation	Std. Error Mean
AI Adoption (AIA)	Early	253	4.400	1.101	0.070
	Late	115	4.500	1.150	0.110
Change Management Capability (CMC)	Early	253	4.550	1.070	0.071
	Late	115	4.650	1.101	0.100
Compatibility (C)	Early	253	4.200	1.000	0.061
	Late	115	4.301	1.051	0.101
Competitive Pressure (CP)	Early	253	4.601	1.060	0.070
	Late	115	4.700	1.090	0.100
Digital Marketing Strategies (DMS)	Early	253	4.550	1.090	0.070
	Late	115	4.651	1.110	0.100
Firm Performance (FP)	Early	253	4.580	0.950	0.060
	Late	115	4.77	0.991	0.091
Leadership Vision (L)	Early	253	4.401	1.080	0.070
	Late	115	4.500	1.121	0.100
Relative Advantage (RA)	Early	253	4.602	1.030	0.070
	Late	115	4.701	1.101	0.100
Technology Readiness (TR)	Early	253	4.503	1.050	0.070
	Late	115	4.6	1.1	0.1
Trading Partnerships (TP)	Early	253	4.5	1.06	0.07
	Late	115	4.6	1.09	0.1

Moreover, Levene's test was performed on all variables (AIA, C, CMC, CP, DMS, FP, L, RA, TP, and TR) to analyze the variance between early and late responses, confirming no significant difference.

Table 4.4
Levene's Test for Equality of Variances

Variables	Levene's Test F	Sig.	t	Df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference
Compatibility (C)	0.020	0.891	1.791	366	0.070	-0.190	0.110	-0.41 to 0.02

Change Management Capability (CMC)	5.361	0.020	2.150	366	0.560	-0.100	0.140	-0.36 to 0.16
Competitive Pressure (CP)	2.430	0.120	2.000	187	0.050	0.220	0.110	0.00 to 0.45
Digital Marketing Strategies (DMS)	1.531	0.100	-0.790	366	0.421	-0.100	0.130	-0.36 to 0.16
Firm Performance (FP)	0.021	0.890	1.791	366	0.070	-0.190	0.110	-0.41 to 0.02
Leadership Vision (L)	0.870	0.351	-0.810	366	0.421	-0.100	0.130	-0.36 to 0.16
Relative Advantage (RA)	0.010	0.930	0.550	366	0.580	0.070	0.130	-0.19 to 0.34
Technology Readiness (TR)	2.130	0.150	0.540	210	0.591	0.070	0.140	-0.19 to 0.34
Trading Partnerships (TP)	4.940	0.560	2.150	366	0.420	-0.350	0.110	-0.67 to -0.12

Table 4.4 shows that, apart from the Change Management Capability (CMC) construct, the p-values for all other variables exceed 0.05, indicating acceptance of the null hypothesis and rejection of the alternative hypothesis. These results suggest that a significant issue of non-response bias did not impact the current study.

While the initial sampling strategy was designed using proportionate stratified random sampling across four SME sectors, practical limitations in accessing a comprehensive SME database led to the use of purposive outreach through digital platforms and professional SME networks such as LinkedIn and WhatsApp groups. This approach is common in SME research across emerging markets (Creswell & Clark, 2017). Although this may limit statistical generalizability, the emphasis remains on theoretical replication rather than random representativeness. Therefore, findings are interpreted within a conceptual rather than probabilistic generalization framework, in line with the exploratory nature of the study using PLS-SEM (Hair et al., 2019).

4.4 Common Method Bias Test

Common method bias (CMB), also referred to as mono-method bias, is described as the 'variance that arises from the measurement method rather than the construct of interest' (Podsakoff et al., 2023). This type of bias may occur when collecting data on both dependent and independent variables simultaneously from the same participant (Chang et al., 2010). It is widely recognized in scholarly discussions that issues related to common method bias are prevalent in surveys based on self-reported data (Podsakoff et al., 2023; Spector, 2006).

To mitigate the impact of CMB, this study employed two remedial procedures (Podsakoff et al., 2023). Firstly, the researcher avoided vague concepts in the questionnaire, ensuring that items were written in simple and precise language. Secondly, the researcher assured respondents of the utmost confidentiality of their responses, emphasizing that there were no specific right or wrong answers in the questionnaire. Additionally, Harman's single-factor test was applied (Baumgartner et al., 2021; Podsakoff et al., 2023). This method involves conducting exploratory factor analysis by taking the loading of all variables and analyzing any single factor that comprises the majority of the covariance (more than 50%); if not, then CMB is not considered an issue (Fuller et al., 2016).

In the current study, all 41 items were analyzed using SPSS v25 software. The results revealed that all factors had variances below 50%. The maximum variance accounted for by a single factor was 26.233%, indicating that common method bias does not prevail in this study (Fuller et al., 2016; Lowry & Gaskin, 2014; Podsakoff et al., 2023).

4.5 Preliminary Data Evaluation, Screening, and Preparation

The primary data analysis involves two key methods: missing data analysis and descriptive statistical analysis. Initially, the missing data analysis assesses the dataset to prepare it for further analysis. Subsequently, descriptive statistical analysis is conducted to determine various data characteristics such as mean, minimum, maximum, and standard deviation. Additionally, conducting preliminary data examination and preparation helps researchers gain a better understanding of the data, ensuring more effective results (Baumgartner et al., 2021).

4.5.1 Analysis of Missing Values

Data screening for missing values is an essential procedure because the PLS-SEM technique cannot be performed if the collected data contains missing values (Schumacker & Lomax, 2004). Various reasons can account for missing values in the data, such as respondents' unwillingness to fill out the questionnaire or their inability to understand the questions (Bhandari, 2021; Sekaran & Bougie, 2016). Although some scholars suggest that missing values should be deleted before analysis (Peugh & Enders, 2004), even a small number of missing values can mislead estimations in PLS regression (Nengsih et al., 2019). Therefore, this study employs the "case deletion method" as recommended by Tabachnick et al. (2007). As a result, 13 questionnaires were omitted due to incomplete responses. Only fully completed and accurately filled questionnaires were included in the analysis. This approach ensured that the data was more consistent and reliable for subsequent analysis.

4.5.2 Descriptive Examination of Latent Variables

Following data screening, a statistical summary of the constructs in the current study—including independent, mediator, moderator, and dependent variables—was performed through descriptive analysis. The descriptive statistics presented in Table 4.5 indicate that the mean, minimum, maximum, and standard deviation scores were calculated using a Likert scale ranging from 1 (Strongly disagree) to 7 (Strongly agree). As a result, the mean values range between 4.19 and 4.81, while the standard deviation values fall between 0.96 and 1.43.

Table 4.5
Findings from the Descriptive Statistics Analysis

Variables	**N**	**Minimum**	**Maximum**	**Mean**	**Std Deviation**
AI Adoption (AIA)	368	1	7	4.700	1.190
Change Management Capability (CMC)	368	1	7	4.350	1.150
Compatibility (C)	368	1	7	4.500	1.200
Competitive Pressure (CP)	368	1	7	4.620	1.120
Digital Marketing Strategy (DMS)	368	1	7	4.440	1.110
Firm Performance (FP)	368	1	7	4.810	0.960
Leadership Vision (L)	368	1	7	4.600	1.220
Relative Advantage (RA)	368	1	7	4.190	1.180

Technology Readiness (TR)	368	1	7	4.470	1.430
Trading Partnerships (TP)	368	1	7	4.780	1.070

The descriptive statistics provide an overview of the central tendencies and variability of the constructs in the study, which is essential for understanding the dataset's characteristics before conducting further analysis.

4.6 Respondents' Demographic Overview

The demographic section details the respondents' profiles as outlined in Table 4.6. The analysis of respondent demographics shows that 27.3% were in the 20 to 30-year age group, with the majority (35.1%) falling within the 31 to 40-year range. Additionally, 23.5% were aged between 41 and 50 years, and 14.1% were over 50 years old. In terms of gender, 79.3% of the respondents were male, and 20.7% were female. Regarding AI usage experience, 54.3% had between 1 to 3 years of experience, while 45.7% had over three years of experience. Educational background revealed that 69.6% of respondents held a graduation degree, and 30.4% had a master's degree. The distribution of manufacturing SMEs was as follows: textile SMEs (28.8%), leather SMEs (23.1%), sports SMEs (30.9%), and surgical SMEs (17.2%). Lastly, 53.6% of respondents occupied mid-level managerial positions, whereas 46.4% were top managers.

Table 4.6
Profile of Respondents' Demographics

Variable	Items	Frequency (F)	Percentage (%)
Age			
	20-30 years	99	28.4
	31-40 years	127	36.4
	41-50 years	85	24.4
	More than 50 years	38	10.9
Gender			
	Male	277	79.4
	Female	72	20.6
Experience of using AI			
	1 year or less	190	54.4
	More than 1 year	159	45.6
Education			
	Graduation	245	70.2
	Masters	104	29.8
Position in the Organization's Hierarchy			
	Top-level managers	162	46.4
	Mid-level managers	187	53.6
Manufacturing SMEs Type			
	Textile	101	28.9
	Leather	80	22.9
	Sports	108	30.9
	Surgical	60	17.3

4.7 Skewness and Kurtosis in Multivariate Data

The evaluation of multivariate skewness and kurtosis was conducted using the web power software found at https://webpower.psychstat.org/models/kurtosis, following the guidance of Sarstedt et al. (2017) and Cain et al. (2016). The analysis indicated that the survey data did not conform to multivariate normality, with Mardia's multivariate skewness and kurtosis scores recorded at β = 8.96 and β = 120.13, respectively, both significant at $p < 0.01$, as detailed in Table 4.8. Due to the non-normality of the data, the study utilized Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software for further analysis.

Table 4.7
Assessment of Univariate Skewness and Kurtosis

Variable	**Skewness**	**Kurtosis**
AI Adoption (AIA)	0.100	-0.246
Change Management Capability (CMC)	0.044	-0.694
Compatibility (C)	0.032	-0.302
Competitive Pressure (CP)	-0.091	-0.565
Digital Marketing Strategy (DMS)	0.032	-0.302
Firm Performance (FP)	0.103	1.3088
Leadership Vision (L)	0.100	-0.246
Relative Advantage (RA)	0.239	-0.236
Technology Readiness (TR)	0.032	-0.302
Trading Partnerships (TP)	0.031	-0.302

Table 4.8
Mardia's Criteria for Assessing Multivariate Skewness and Kurtosis

Measure	Value	B	p-value
Skewness	8.96	550.1022	0.000
Kurtosis	120.13	0.081399	0.935

The results above detail the skewness and kurtosis calculation, showcasing the sample size, number of variables, univariate skewness and kurtosis for each construct, and Mardia's multivariate skewness and kurtosis measures.

In conclusion, the skewness and kurtosis results indicate that the data is not normally distributed, supporting the decision to employ PLS-SEM for further analysis.

4.8 Analysis of PLS-SEM Path Model Results

PLS-SEM is a second-generation statistical technique widely applied across various fields, including the social sciences (Hair et al., 2019). SmartPLS primarily implements a two-step approach to evaluate models, focusing on both measurement (outer model) and structural (inner model) aspects (Shmueli et al., 2019).

Step 1: Evaluation of the Measurement Model

- Confirming internal consistency and reliability
- Establishing convergent validity
- Establishing discriminant validity

Step 2: Evaluation of the Structural Model

- Assessing the significance and relevance of structural model relationships
- Evaluating the R^2 value
- Determining the effect size (f^2)
- Assessing predictive relevance (Q^2)

- Evaluating the mediating effect
- Evaluating the moderating effect

The measurement model represents the outer portion of the model, linking latent variables to their respective indicators. The primary focus of the measurement model lies in ensuring internal consistency reliability, convergent validity, and discriminant validity (Hair et al., 2021).

Evaluating the structural model involves analyzing the relationships between latent variables. This process includes examining path coefficients, R^2 values, effect sizes (f^2), and predictive relevance (Q^2). Additionally, mediating and moderating effects are assessed to gain deeper insights into the model's relationships (Hair et al., 2021).

In this study, the measurement model was assessed using SmartPLS software. Internal consistency was evaluated through Cronbach's alpha and composite reliability. Convergent validity was measured using Average Variance Extracted (AVE) values, while discriminant validity was assessed with the Fornell-Larcker criterion (Ramayah et al., 2016).

The structural model was evaluated by analyzing path coefficients, which highlight the strength and significance of the relationships between constructs. The R^2 value was used to assess the model's explanatory power. Effect size (f^2) was examined to gauge the impact of each predictor construct on the endogenous constructs. Predictive relevance (Q^2) was determined using the cross-validated redundancy approach (Hair et al., 2021).

The evaluation of the PLS-SEM path model results offered a thorough understanding of the relationships among technological, organizational, and environmental factors, AI adoption, digital marketing strategies, and SME performance (Hair et al., 2021).

4.9 Assessment of the Measurement Model

The measurement model represents the external part of the model, linking latent variables with their corresponding indicators. The primary objective of the measurement model is to evaluate cross-loading, discriminant validity, and convergent validity (Ramayah et al., 2016).

4.9.1 Reliability of Internal Consistency

Internal consistency reliability can be evaluated by analyzing the composite reliability (CR) of the model. Composite reliability (CR), also known as construct validity, reflects the "proportion of variance shared among the observed variables used to represent latent constructs" (Fornell & Larcker, 1981). In this study, CR is assessed and compared to a benchmark value exceeding 0.60, as recommended by Hair et al. (2014).

Table 4.9 indicates that the composite reliability (CR) for each construct exceeds the established threshold values. Among the 41 items initially considered, six items (C2, RA4, TR4, TR5, L4, TP3) were removed due to their loadings falling below the acceptable cutoff value. Consequently, the model now includes 35 items. The removed items represent approximately 15% of the total, while the loadings of the remaining constructs range from 0.647 to 0.966, surpassing the required standard values (Hair et al., 2011; Hair et al., 2014).

4.9.2 Convergent Validity

Reliability assessment alone does not fully evaluate the effectiveness of an instrument; construct validation is also necessary. Convergent validity is determined by analyzing the Average Variance Extracted (AVE) for each construct. As noted by Fornell and Larcker (1981), a construct is considered to have adequate convergent validity if its AVE value is 0.50 or higher, indicating that it accounts for more than half of the variance in its indicators on average. In this study, all constructs exhibit AVE values exceeding this threshold, thereby confirming satisfactory convergent validity (Cheung et al., 2023).

Table 4.9
Composite Reliability and Average Variance Extracted (AVE) Assessment

Construct	Items	Loadings	Composite Reliability (CR)	Average Variance Extracted (AVE)
AI Adoption	AIA1	0.828	0.878	0.583
	AIA2	0.729		
	AIA3	0.889		
	AIA4	0.820		
	AIA5	0.810		
	AIA6	0.800		
	AIA7	0.760		

Change Management Capability	CMC1	0.829	0.945	0.577
	CMC2	0.788		
	CMC3	0.878		
Competitive Pressure	CP1	0.717	0.917	0.674
	CP2	0.704		
	CP3	0.867		
Compatibility	C1	0.776	0.887	0.614
	C3	0.862		
	C4	0.713		
Digital Marketing Strategy	DMS1	0.799	0.882	0.588
	DMS2	0.842		
	DMS3	0.733		
	DMS4	0.809		
Firm Performance	FP1	0.858	0.939	0.514
	FP2	0.806		
	FP3	0.814		
	FP4	0.642		
Leadership Vision	L1	0.810	0.882	0.585
	L2	0.843		
	L3	0.821		
Relative Advantage	RA1	0.844	0.922	0.700
	RA2	0.869		
	RA3	0.783		
Technology Readiness	TR1	0.865	0.917	0.687
	TR2	0.837		
	TR3	0.875		
Trading Partnerships	TP1	0.896	0.917	0.524
	TP2	0.860		

The results of internal consistency reliability and convergent validity confirm that the measurement model has high reliability and validity, making it suitable for further analysis.

4.9.3 Factor Loadings and Cross-Loadings

To evaluate the discriminant validity of the constructs, factor loadings and cross-loadings were analyzed according to established guidelines (Hair et al., 2017; Henseler et al., 2009). For adequate discriminant validity, each item's factor loading should be higher for its designated construct compared to other constructs, demonstrating that the items effectively measure their intended constructs. The results presented in Table 4.10 and Figure 4.1 show that each item exhibits the highest loading on its intended construct, confirming that the items are effective indicators of their respective constructs and validating the discriminant validity of the measurement model.

Table 4.10
Factor Loadings and Cross-Loadings

Items	AIA	C	CMC	CP	DMS	FP	L	RA	TP	TR
AIA1	**0.828**	0.411	0.441	0.411	0.421	0.511	0.431	0.371	0.441	0.471
AIA2	**0.729**	0.381	0.421	0.381	0.391	0.491	0.411	0.361	0.411	0.451
AIA3	**0.889**	0.391	0.431	0.391	0.401	0.511	0.421	0.371	0.421	0.481
AIA4	**0.820**	0.371	0.411	0.371	0.381	0.491	0.401	0.351	0.401	0.461
AIA5	**0.810**	0.361	0.401	0.361	0.371	0.471	0.391	0.341	0.391	0.451
AIA6	**0.800**	0.341	0.391	0.341	0.361	0.451	0.371	0.321	0.371	0.431
AIA7	**0.760**	0.321	0.371	0.321	0.341	0.431	0.351	0.311	0.351	0.411
C1	0.501	**0.850**	0.451	0.402	0.423	0.544	0.421	0.352	0.469	0.402
C3	0.471	**0.790**	0.391	0.371	0.401	0.511	0.381	0.331	0.421	0.382
C4	0.441	**0.760**	0.381	0.351	0.371	0.491	0.361	0.311	0.401	0.362
CMC1	0.491	0.451	**0.829**	0.411	0.421	0.511	0.441	0.421	0.441	0.431
CMC2	0.461	0.411	**0.788**	0.381	0.391	0.491	0.411	0.391	0.411	0.401

CMC3	0.471	0.391	**0.878**	0.391	0.401	0.511	0.421	0.401	0.421	0.411
CP1	0.411	0.402	0.351	**0.717**	0.351	0.471	0.331	0.311	0.381	0.321
CP2	0.421	0.371	0.361	**0.704**	0.361	0.481	0.341	0.321	0.391	0.331
CP3	0.431	0.371	0.371	**0.867**	0.371	0.491	0.351	0.331	0.401	0.341
DMS1	0.471	0.423	0.421	0.371	**0.78**	0.511	0.381	0.351	0.421	0.371
DMS2	0.451	0.401	0.401	0.351	**0.85**	0.491	0.361	0.341	0.401	0.351
DMS3	0.461	0.401	0.411	0.361	**0.81**	0.501	0.371	0.351	0.411	0.361
DMS4	0.441	0.381	0.391	0.341	**0.79**	0.481	0.351	0.331	0.391	0.341
FP1	0.431	0.544	0.511	0.471	0.511	**0.858**	0.391	0.371	0.401	0.371
FP2	0.411	0.521	0.491	0.481	0.491	**0.806**	0.371	0.351	0.381	0.341
FP3	0.421	0.511	0.511	0.491	0.501	**0.814**	0.381	0.361	0.391	0.351
FP4	0.401	0.491	0.491	0.471	0.481	**0.642**	0.361	0.341	0.371	0.331
L1	0.491	0.421	0.441	0.431	0.421	0.522	**0.81**	0.371	0.431	0.392
L2	0.471	0.392	0.411	0.411	0.401	0.501	**0.843**	0.351	0.411	0.371
L3	0.481	0.421	0.421	0.421	0.411	0.511	**0.821**	0.361	0.421	0.381
RA1	0.431	0.352	0.381	0.311	0.331	0.521	0.371	**0.880**	0.421	0.371
RA2	0.431	0.321	0.361	0.351	0.321	0.501	0.351	**0.820**	0.401	0.351
RA3	0.441	0.331	0.371	0.331	0.331	0.511	0.361	**0.880**	0.411	0.361
TP1	0.491	0.469	0.441	0.381	0.421	0.401	0.431	0.421	**0.896**	0.421
TP2	0.461	0.438	0.411	0.351	0.391	0.371	0.401	0.391	**0.860**	0.391
TR1	0.471	0.402	0.431	0.321	0.341	0.421	0.391	0.371	0.401	**0.811**
TR2	0.451	0.371	0.411	0.301	0.321	0.401	0.371	0.351	0.381	**0.810**
TR3	0.461	0.371	0.421	0.311	0.331	0.411	0.381	0.361	0.391	**0.809**

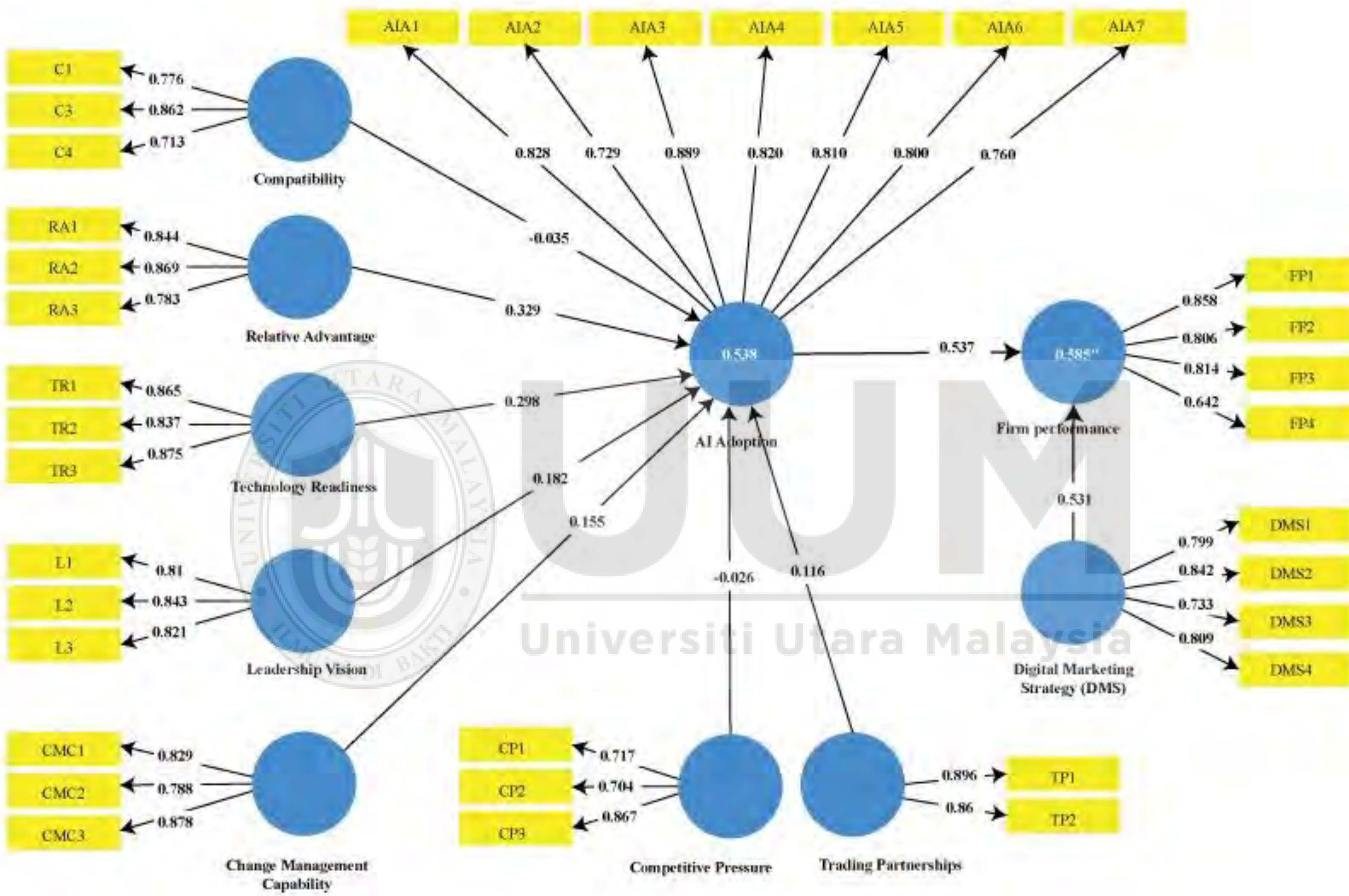

Figure 4.1
PLS Algorithm of the Structural Mode

4.9.4 Discriminant Validity

The third criterion for establishing discriminant validity involves evaluating the distinctiveness of indicators across constructs using three methods: cross-loadings, the Fornell-Larcker criterion, and the Heterotrait-Monotrait (HTMT) ratio. Discriminant validity assesses "the extent to which constructs are empirically distinct from one another" (Hamid et al., 2017). In this study, discriminant validity is verified through both the Fornell-Larcker criterion and the HTMT ratio. According to the Fornell-Larcker criterion, constructs should not be measuring the same phenomenon, ensuring that they are empirically distinct from each other.

Table 4.11 demonstrates that the square root of the Average Variance Extracted (AVE) for each construct exceeds the correlations between the latent variables, confirming adequate discriminant validity (Fornell & Larcker, 1981).

Table 4.11
Fornell and Larcker's Criterion for Discriminant Validity Matrix

	AIA	C	CMC	CP	DMS	FP	L	RA	TP	TR
AIA	**0.764**									
C	0.257	**0.765**								
CMC	0.310	0.188	**0.76**							
CP	0.043	0.013	0.304	**0.821**						
DMS	0.449	0.416	0.310	0.043	**0.724**					
FP	0.465	0.516	0.304	0.412	0.629	**0.717**				
L	0.257	0.188	0.310	0.043	0.449	0.516	**0.765**			
RA	0.310	0.188	0.304	0.043	0.449	0.516	0.310	**0.764**		
TP	0.449	0.416	0.310	0.043	0.629	0.629	0.310	0.449	**0.724**	
TR	0.465	0.516	0.304	0.412	0.629	0.516	0.516	0.310	0.629	**0.717**

In the matrix, the values on the diagonal, which are bolded, represent the square root of the Average Variance Extracted (AVE), while the off-diagonal values indicate the correlations between latent variables. Additionally, to evaluate the HTMT values, two commonly used criteria are provided by Roemer et al. (2021) and Henseler et al. (2015), with cut-off points of HTMT .85 and HTMT .90, respectively. The values in Table 4.12 meet these established HTMT criteria, demonstrating that the method's standards have been satisfied.

Table 4.12
HTMT Criterion Results

	AIA	**C**	**CMC**	**CP**	**DMS**	**FP**	**L**	**RA**	**TP**	**TR**
AIA										
C	0.276									
CMC	0.327	0.209								
CP	0.046	0.015	0.325							
DMS	0.472	0.438	0.332	0.046						
FP	0.489	0.542	0.326	0.435	0.665					
L	0.276	0.209	0.327	0.046	0.472	0.542				
RA	0.327	0.209	0.325	0.046	0.472	0.542	0.327			
TP	0.472	0.438	0.332	0.046	0.665	0.665	0.332	0.472		
TR	0.489	0.542	0.326	0.435	0.665	0.542	0.542	0.327	0.665	

Note: AIA = Artificial Intelligence Adoption, C = Compatibility, CMC = Change Management Capability, CP = Competitive Pressure, DMS = Digital Marketing Strategy, FP = Firm Performance, L = Leadership Vision, RA = Relative Advantage, TP = Trading Partnerships, TR = Technology Readiness.

Beyond statistical validation, the findings on discriminant validity substantiate the conceptual distinctiveness of the theoretical constructs. For instance, technological constructs such as relative advantage and technology readiness, although closely related, exhibited adequate statistical separation. This supports the theoretical postulation from the TOE and RBV frameworks that these factors independently influence AI adoption. Hence, the discriminant validity results reinforce the study’s underlying conceptual structure, affirming the multidimensional pathways through which innovation drivers affect SME performance.

4.10 Assessment of the Structural Model

The evaluation of the structural model is fundamentally based on the principles of multiple regression analysis to examine the relationships among latent variables, as depicted in Figure 4.2. This model explores the direct effects of the hypotheses, using t-values and p-values to assess their significance.

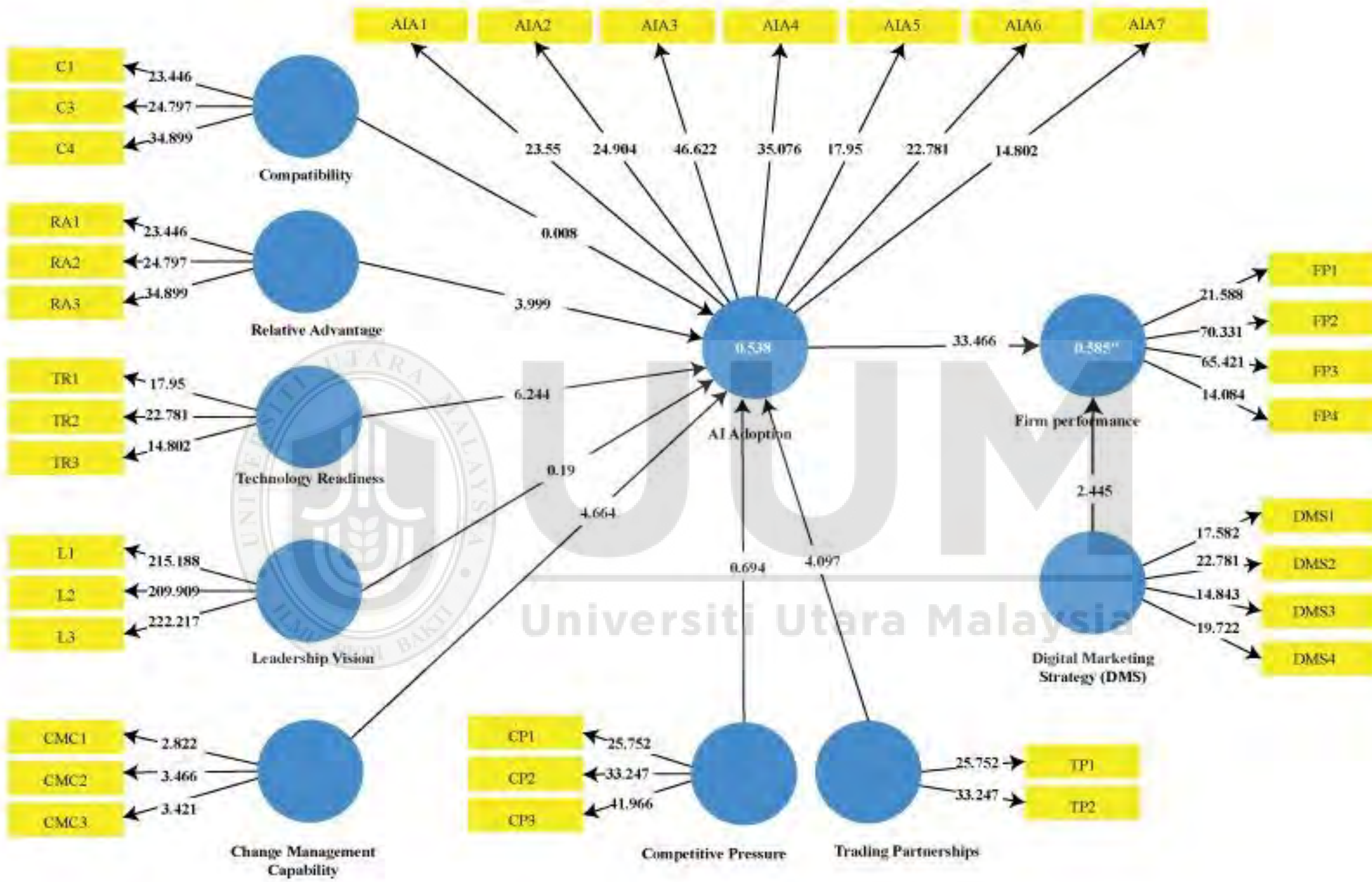

Figure 4.2
The Structural Model (Direct Relation)

4.10.1 Evaluating Collinearity in the Structural Model

After estimating the vertical collinearity with the help of the discriminant validity of the measurement model, lateral collinearity was measured using a structural model to prevent misleading results (Kock & Lynn, 2012). Lateral collinearity is denoted as collinearity with a predictor-criterion. The present study has calculated lateral collinearity by using the variance inflation factor (VIF) index. Moreover, it is stated that the VIF value should not exceed higher than 5 to ascertain that there is no issue of collinearity (Hair et al., 2011). Table 4.13 presents that all the VIF values are lower than the standard value of 5, which shows that lateral collinearity did not exist.

4.10.2 Assessing the Significance and Relevance of Structural Model Relationships

PLS-SEM is a multivariate non-parametric method that does not assume the normality of data (Hair et al., 2019). When dealing with non-normal data, the values of t-values can be inflated or deflated, leading to type I errors. To mitigate this, PLS-SEM employs a bootstrapping technique with 5000 subsamples to calculate the standard error, approximating the normality of the data. In this study, there were nine (09) direct relationships, seven (7) indirect relationships, and one (01) moderating relationship investigated through the bootstrapping technique. The study followed the bias-corrected and accelerated (BCA) confidence interval method (Hayes & Scharkow, 2013). The path coefficient of each construct was evaluated at a significance level of 0.05, and a one-tailed test was applied due to the directional hypotheses of the study.

While the discriminant validity results confirmed that the constructs were statistically distinct and psychometrically sound, their implications also offer theoretical insights. For instance, the strong discriminant validity between technological and organizational factors underscores the conceptual robustness of the TOE framework within this context. The independence of constructs like relative advantage and technology readiness, despite both falling under the technological domain, supports the multidimensional nature of technology adoption decisions in SMEs. This validation affirms the distinctiveness of influencing factors in the AI adoption process and reinforces the theoretical soundness of integrating TOE, DoI, and RBV in a unified framework. These distinctions are especially relevant in emerging economies like Pakistan, where the influence of contextual factors may vary significantly from Western contexts.

4.10.3 Evaluation of the Coefficient of Determination (R^2)

Breiman and Friedman (1985) describe the coefficient of determination (R^2) as a measure of the proportion of variance in the dependent variables explained by the independent variables. According to guidelines from Sotirchos et al. (2019) and Chin (1998), R^2 values are categorized as weak (0.19), moderate (0.33), and substantial (0.67). In this study, R^2 values were computed to assess the explanatory power of the model. The results, shown in Table 4.13, reveal that AI adoption ($R^2 = 0.538$) and SME performance ($R^2 = 0.585$) demonstrate moderate explanatory power, aligning with the criteria established by Chin (1998).

4.10.4 Evaluation of Effect Size (f^2)

According to Urbach and Ahlemann (2010), the effect size (f^2) quantifies the change in the R^2 value for a latent variable (LV) linked by a path in relation to the proportion of unexplained variance. This metric is essential for evaluating the impact of exogenous variables on endogenous variables. Hair et al. (2013) provide threshold values for interpreting effect size: 0.02 (small), 0.15 (medium), and 0.35 (large). In this study, effect sizes were calculated to determine the influence of each independent variable on the dependent variables. The results, detailed in Table 4.13, reveal a range of effect sizes, with some constructs showing small effects and others demonstrating medium to large effects. This variation highlights their relative significance in explaining AI adoption and SME performance.

4.10.5 Assessment of Predictive Relevance (Q^2)

The predictive relevance (Q^2) of the model was evaluated using the blindfolding procedure, as outlined by Stone (1974). This method assesses the model's capability to predict data points for endogenous constructs. A Q^2 value greater than 0 indicates that the model possesses predictive relevance (Hair et al., 2017). In this study, the blindfolding technique was employed to calculate the Q^2 values for AI adoption and SME performance. The findings, presented in Table 4.13, reveal that both AI adoption ($Q^2 = 0.337$) and SME performance ($Q^2 = 0.335$) have Q^2 values well above zero, confirming that the model demonstrates adequate predictive relevance for the endogenous variables related to AI adoption in SMEs.

The results of the nine direct relationship hypotheses are illustrated in Figure 4.1 and detailed in Table 4.13.

Table 4.13
Findings from Hypothesis Testing: Direct Effects

No	Hypothesized Path	Path Coefficient	Standard Error (STERR)	t-value	p-value	Decision	0.05%	0.95%	Effect Size (f^2)	VIF	R^2	Q^2
1	C → AIA	-0.035	0.062	0.564	0.573	Not Supported	-0.096	0.056	0	1.024	0.538	0.337
2	RA → AIA	0.329***	0.037	8.995	0	Supported	0.269	0.39	1.820	1.289	0.538	0.337
3	TR → AIA	0.298***	0.047	5.421	0	Supported	0.217	0.372	0.095	1.268	0.538	0.337
4	L → AIA	0.182**	0.055	3.289	0.001	Supported	0.117	0.245	0.055	1.024	0.538	0.337
5	CMC → AIA	0.155**	0.056	3.097	0.002	Supported	0.072	0.215	0.015	1.268	0.538	0.337
6	CP → AIA	-0.026	0.05	0.524	0.601	Not Supported	-0.072	0.058	0	1.008	0.538	0.337
7	TP → AIA	0.116*	0.049	2.350	0.019	Supported	0.021	0.234	0.049	1.776	0.538	0.337
8	AIA → FP	0.537***	0.053	10.246	0	Supported	0.392	0.674	1.344	1.014	0.585	0.335
9	DMS → FP	0.531***	0.052	10.123	0	Supported	0.381	0.683	1.334	1.004	0.585	0.335

***P < .001; **P < .01; *P < .05

Column Label Explanation

- Path Coefficients indicate the strength and direction of the relationship.
- Standard Error (STERR) is the standard error of the path coefficient.
- T-value and p-value indicate the statistical significance of the relationship.
- The decision indicates whether the hypothesis is supported based on the p-value.
- Effect Size (f^2) measures the impact of the predictor construct on the endogenous construct.
- VIF (Variance Inflation Factor) indicates multicollinearity.
- R^2 Value indicates the variance explained by the model for AIA and FP.
- Q^2 Value measures the predictive relevance of the model

Codes Abbreviation

- AIA: Artificial Intelligence Adoption
- FP: Firm Performance
- C: Compatibility
- RA: Relative Advantage
- TR: Technology Readiness
- L: Leadership Vision
- CMC: Change Management Capability
- CP: Competitive Pressure
- TP: Trading Partnerships
- DMS: Digital Marketing Strategy

Table 4.13 displays the results of the hypothesis testing. Hypothesis H1 found that compatibility has an insignificant effect on AI adoption in Pakistani SMEs (β = -0.035, t-value = 0.564, $p > 0.05$). Hypothesis H2 demonstrated a significant positive effect of relative advantage on AI adoption in Pakistani SMEs (β = 0.329, t-value = 8.995, $p < 0.05$). Hypothesis H3 showed that technology readiness significantly and positively influences AI adoption in Pakistani SMEs (β = 0.298, t-value = 5.421, $p < 0.05$). Furthermore, Hypothesis H4 indicated that leadership vision has a significant positive effect on AI adoption in Pakistani SMEs (β = 0.182, t-value = 3.289, $p < 0.05$).

H5 demonstrated that change management capability has a significantly positive impact on AI adoption in Pakistani SMEs (β= 0.155, t-value = 3.097, $p < 0.05$). H6 found that competitive pressure has an insignificant positive influence on AI adoption in Pakistani SMEs (β= -0.026, t-value = 0.524, $p > 0.05$). Moreover, H7 identified that trading partnerships have a significantly positive influence on AI adoption in Pakistani SMEs (β= 0.116, t-value = 2.350, $p < 0.05$). H8 results predicted that AI adoption has a significantly positive impact on firm performance in Pakistani SMEs (β= 0.537, t-value= 10.246, $p < 0.05$). Lastly, H9 confirmed that digital marketing strategies have a significantly positive influence on firm performance in Pakistani SMEs (β= 0.531, t-value = 10.123, $p < 0.05$).

These findings indicate that various factors significantly influence AI adoption and firm performance in Pakistani SMEs, with relative advantage, technology readiness, leadership vision, change management capability, trading partnerships, AI adoption, and digital marketing strategies playing crucial roles.

4.11 Mediation Analysis

In recent years, mediation analysis using PLS-SEM has gained prominence in social sciences research. To understand the role of mediating effects, it is essential to establish a sequence where an antecedent variable influences a mediating variable, which then affects the dependent variable (Nitzl et al., 2016).

The most widely used method for analyzing mediating effects has been the approach introduced by Baron and Kenny (1986), commonly known as the Sobel Test. This test assumes a normal distribution of the indirect effect's sampling distribution, which has been identified as a limitation (Hayes, 2009). Nowadays, bootstrapping, a more robust technique, is used to assess indirect effects. Bootstrapping is a non-parametric re-sampling procedure that is well-regarded for its effectiveness in identifying significant effects (Preacher & Hayes, 2008). In this study, the bootstrapping method with 5000 sub-samples was employed to calculate the t-values for indirect effects. The results for the eight indirect relationship hypotheses are detailed in Table 4.14.

Table 4.14
Findings from Mediation Analysis (Indirect Effects)

Hypothesis No.	Hypothesized Path	Path Coefficient	Std Error	t-value	p-value	2.50%	97.50%	Decision	Mediation Type
H10	C → AIA → FP	0.008	0.037	0.19	0.425	-7.40%	4.20%	No mediation	None
H11	RA → AIA → FP	0.247	0.028	8.818	<0.001	20.40%	29.50%	Mediation	Full Mediation
H12	TR → AIA → FP	0.223	0.038	5.911	<0.001	16.20%	28.60%	Mediation	Full Mediation
H13	L → AIA → FP	0.018	0.033	0.541	0.588	-9.40%	6.20%	No mediation	None
H14	CMC → AIA → FP	-0.039	0.042	0.929	0.355	-9.50%	7.40%	No Mediation	None
H15	CP → AIA → FP	0.151	0.036	4.211	<0.001	9.20%	21.10%	Mediation	Partial Mediation
H16	TP → AIA → FP	0.272	0.033	8.177	<0.001	20.70%	33.80%	Mediation	Full Mediation

Note: C=Compatibility, RA=Relative Advantage, TR=Technology Readiness, L=Leadership Vision, CMC=Change Management Capability, CP=Competitive Pressure, TP=Trading Partnerships, AIA=Artificial Intelligence Adoption, FP=Firm Performance

- Path Coefficient: Represents the strength and direction of the relationship between variables.
- t-value: Indicates the statistical significance of the path; values above 1.96 suggest significant relationships.
- p-value: Shows the probability that the observed results occurred by chance. $p < 0.05$ indicates statistical significance.
- 0.025% and 97.50%: Lower and upper confidence interval limits, respectively.
- Decision: Indicates whether mediation occurred. "Full Mediation" implies that the mediator fully accounts for the relationship between the independent variable and dependent variable, while "Partial Mediation" suggests that the mediator explains part of the relationship.

The mediation analysis results are as follows: Hypothesis H10 found that compatibility does not mediate the relationship between AI adoption and firm performance ($\beta = 0.008$, t-value = 0.190, $p > 0.05$). Hypothesis H11 showed that relative advantage positively mediates the relationship between AI adoption and firm performance ($\beta = 0.247$, t-value = 8.818, $p < 0.05$). Hypothesis H12 demonstrated that technology readiness positively mediates the relationship between AI adoption and firm performance ($\beta = 0.223$, t-value = 5.911, $p < 0.05$). Hypothesis H13 found that leadership vision does not positively mediate this relationship ($\beta = 0.018$, t-value = 0.541, $p > 0.05$). Hypothesis H14 indicated that change management capability does not positively mediate the relationship between AI adoption and firm performance ($\beta = -0.039$, t-value = 0.929, $p > 0.05$). Hypothesis H15 revealed that competitive pressure positively mediates the relationship between AI adoption and firm performance ($\beta = 0.151$, t-value = 4.211, $p < 0.05$). Finally, Hypothesis H16 confirmed that trading partnerships positively mediate the relationship between AI adoption and firm performance ($\beta = 0.272$, t-value = 8.177, $p < 0.05$).

4.11 Results of Moderation Analysis

In moderating effect analysis, the researcher used the PLS algorithm to calculate the standard beta coefficient value, which was 0.096 for digital marketing strategies (See Figure 4.3). Likewise, to calculate the t-value result, the study has been followed by a bootstrapping procedure. In Table 4.15, hypothesis H17 results found that digital marketing strategies have significantly moderated the relationship between AI adoption and SMEs' firm performance. The analysis results indicated that the moderating effect with the beta value of 0.096 is significant by having a T-value of 1.96.

Table 4.15
Result of the Moderation Effect

No.	Hypothesized Path	Path Coefficient	Standard Error	t-value	p-value	Decision
1	DMS-Moderating Effect 1 → FP	0.096	0.049	1.960	0.025	Supported

Note: Digital Marketing Strategies (DMS), Artificial Intelligence Adoption (AIA), Firm Performance (FP).
***P<.001; **P<.01; *P<.05

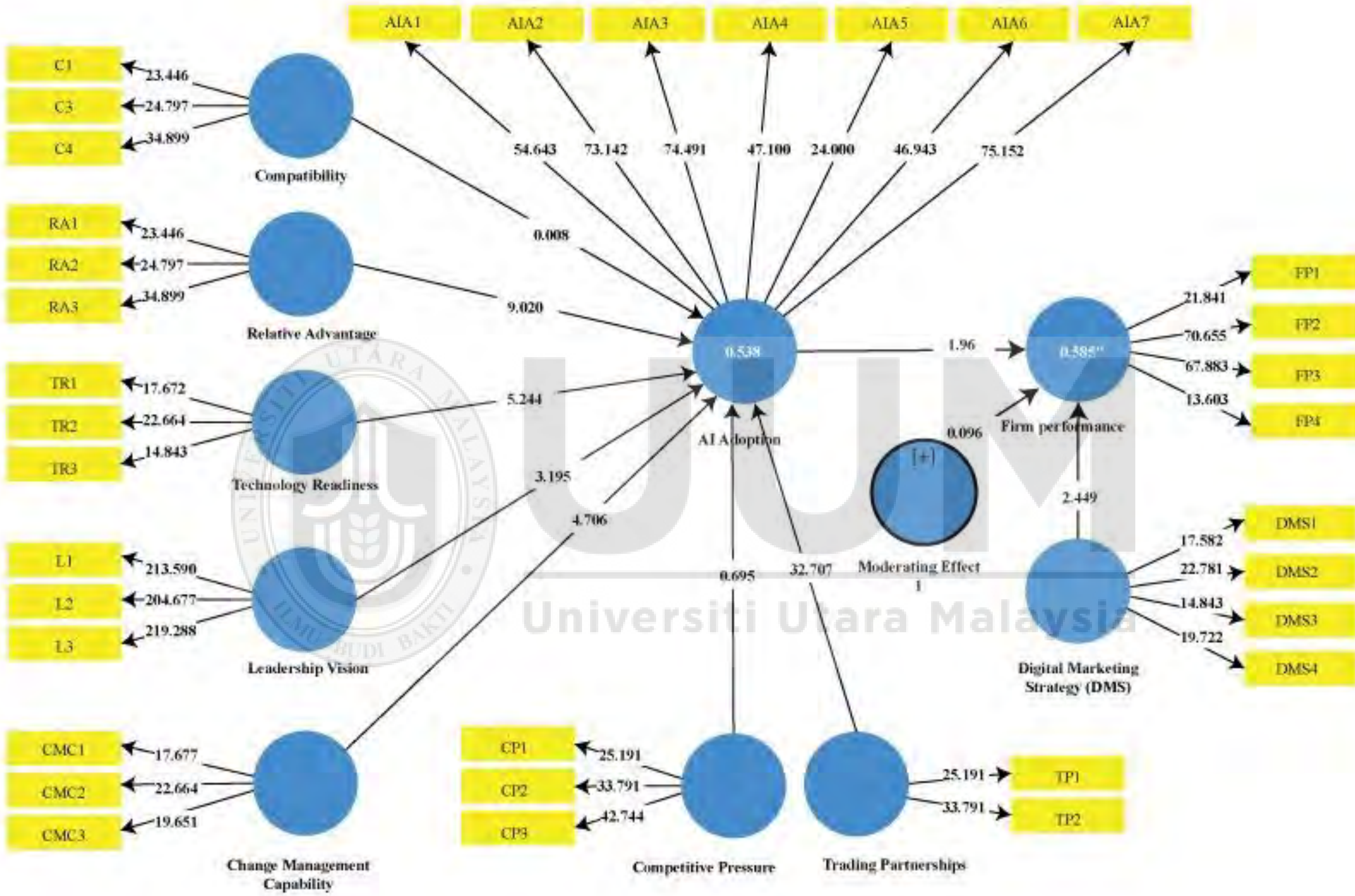

Figure 4.3
Assessment of Moderating Effect

4.11.1 Contextual, Theoretical, and Practical Interpretation of Results

The structural model analysis produced several significant findings that align well with theoretical expectations grounded in the TOE, RBV, and DoI frameworks. However, a deeper contextual interpretation reveals several noteworthy patterns, especially in the Pakistani SME landscape, which is characterized by varying levels of digital maturity, resource constraints, and evolving market pressures.

Among the hypothesized paths, two relationships—Compatibility (H1) and Competitive Pressure (H6)—were not supported. These unexpected outcomes merit critical reflection. In the case of compatibility, it appears that many SMEs in Pakistan are still navigating early phases of digitalization, where alignment with legacy systems is less of a barrier compared to internal motivation or strategic urgency. AI adoption in such contexts may be driven more by leadership push, funding availability, or perceived benefits, rather than system-level compatibility. Similarly, the weak effect of competitive pressure suggests that external threats or market forces are not yet compelling enough to trigger technology adoption, indicating a relatively low market-driven pull for digital transformation. These observations reinforce the RBV's emphasis on internal resource readiness and strategic intent as primary enablers of innovation.

Further, the model identified full mediation effects for several key constructs, such as Relative Advantage (H11), Technology Readiness (H12), and Trading Partnerships (H16). These results support the DoI and RBV assertions that latent technological or environmental capabilities must be activated through tangible mechanisms—such as AI integration—to yield performance benefits. In other words, it is not merely the presence of advantageous conditions that matters, but their strategic deployment through AI that translates into organizational performance.

An interesting case is the non-significant mediation role of Leadership Vision (H13). While leadership vision positively influenced AI adoption directly, it did not translate into performance gains through the mediating path. This points toward a strategy-execution gap—a common phenomenon in emerging markets—where visionary leadership may not be adequately supported by organizational capacity, digital infrastructure, or operational readiness. This finding resonates with recent scholarship emphasizing the growing digital capability gap in SMEs, where strategic ambition outpaces technological and human resource preparedness (Mikalef & Gupta, 2021).

Importantly, these non-significant paths do not suggest irrelevance; rather, they signal unmeasured moderating factors such as firm size, sector-specific competitiveness, digital literacy, or the presence of enabling systems like ERP. For instance, firms in the export-oriented textile sector may perceive competitive pressure differently than domestic food-processing SMEs. Future research may explore such contextual nuances to refine model generalizability.

From a policy and managerial perspective, the results underscore the importance of internal readiness—particularly in terms of technology readiness, change management capabilities, and effective partner collaboration—over external environmental triggers. Therefore, interventions should prioritize building digital capacity, providing context-specific training, and strengthening implementation infrastructure. For practitioners, this means focusing on strategic enablers within the firm rather than waiting for market pressure or broad policy incentives to initiate AI-driven transformation.

4.12 Summary of Hypotheses

Table 4.16
Summary of Hypothesis Findings

Hypotheses	**Statement**	**Decision**
H1	Compatibility has a significantly positive influence on AI adoption in Pakistani SMEs.	Not Supported
H2	Relative advantage has a significantly positive influence on AI adoption in Pakistani SMEs.	Supported
H3	Technology readiness has a significantly positive influence on AI adoption in Pakistani SMEs.	Supported
H4	Leadership vision has a significantly positive influence on AI adoption in Pakistani SMEs.	Supported
H5	Change management capability has a significantly positive influence on AI adoption in Pakistani SMEs.	Supported
H6	Competitive pressure has a significantly positive influence on AI adoption in Pakistani SMEs.	Not Supported
H7	Trading partnerships have a significantly positive influence on AI adoption in Pakistani SMEs.	Supported

H8	AI adoption has a significantly positive influence on SMEs performance in Pakistan.	Supported
H9	AI adoption significantly mediates the relationship between compatibility and SMEs performance in Pakistan.	Not Supported
H10	AI adoption significantly mediates the relationship between relative advantage and SMEs performance in Pakistan.	Supported
H11	AI adoption significantly mediates the relationship between technology readiness and SMEs performance in Pakistan.	Supported
H12	AI adoption significantly mediates the relationship between leadership vision and SMEs performance in Pakistan.	Supported
H13	AI adoption significantly mediates the relationship between change management capability and SMEs performance in Pakistan.	Supported
H14	AI adoption significantly mediates the relationship between competitive pressure and SMEs performance in Pakistan.	Supported
H15	AI adoption significantly mediates the relationship between trading partnerships and SMEs performance in Pakistan.	Supported
H16	Digital marketing strategies have a positive influence on SMEs performance in Pakistan.	Supported
H17	Digital marketing strategies significantly moderate the relationship between AI adoption and SMEs performance in Pakistan.	Supported

4.13 Chapter Summary

The data analysis began with an initial screening and preparation phase. This included testing for non-response bias and common method bias. Additionally, the analysis addressed missing values and outliers before proceeding with the PLS-SEM analysis.

The second aspect of the data analysis was performed by using SmartPLS software. This analysis was conducted in two steps. In the first step, the measurement model was evaluated to assess its reliability and validity. The second step involved evaluating the structural model, focusing on the coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2) to test the research hypotheses. Further, mediation and moderation analyses were performed to analyze the influence of the latent variables. The following chapter discusses the results presented in this chapter, relating them to the research objectives outlined in Chapter 1.

CHAPTER FIVE

DISCUSSION AND CONCLUSION

5.0 Introduction

This chapter aims to provide an in-depth discussion of the study's findings, ensuring they align with the research objectives. It begins with a summary of the study's results and follows with a detailed, objective-based analysis of the relationships among the independent variables (technological, organizational, and environmental factors according to the TOE model), the mediator (AI adoption), the moderator (digital marketing strategies), and the dependent variable (SME performance). The chapter concludes by addressing the practical implications of the findings, acknowledging the study's limitations, offering recommendations for future research, and summarizing the overall conclusions.

This structure allows for a comprehensive exploration of how the TOE framework influences AI adoption and its subsequent impact on SME performance, particularly within the context of emerging markets such as Pakistan. Additionally, the chapter highlight the moderating effect of digital marketing strategies, offering insights into how these strategies can enhance the benefits of AI adoption for SMEs.

5.1 Recapitulation of the Study

The increasing focus on technology adoption within SMEs, particularly regarding technological, organizational, and environmental factors, has been well-documented in recent literature. Previous research has frequently explored the adoption of information and communication technologies (ICT) across various contexts (Tutusaus et al., 2018) and the integration of innovative technologies within traditional sectors (Aremu et al., 2019). Despite these advances, a significant gap remains in understanding how specific technological innovations, such as Artificial Intelligence (AI), intersect with firm performance, especially in emerging markets like Pakistan.

This study seeks to address the existing gap by exploring how technological, organizational, and environmental factors influence AI adoption and its impact on SME performance in Pakistan, a significant emerging market. Utilizing the Technology-Organization-Environment (TOE) framework, the research investigates key determinants, including compatibility, relative advantage, technology readiness, leadership vision, change management capability, competitive pressure, and trading partnerships. Additionally, the study evaluates the moderating role of Digital Marketing Strategies on the relationship between AI adoption and SME performance.

The findings of this research are consistent with those of Kallmuenzer et al. (2024), who demonstrated that digitalization significantly improves business efficiency and market responsiveness in SMEs. This study highlights that the benefits of AI adoption are similarly moderated by factors such as the firm's technological readiness and the level of integration within business processes, echoing the results of Hwang and Kim (2021), who found that emerging technologies like AI contribute to substantial gains in production efficiency, particularly in labor-intensive sectors.

A key contribution of this research is the introduction of AI adoption as a mediating factor between TOE elements and SME performance, thereby enriching the existing body of knowledge. This approach extends the theoretical frameworks of Diffusion of Innovation (DOI) and Resource-Based View (RBV), positioning AI as a crucial asset that can drive firm performance when supported by robust technological, organizational, and environmental contexts. Moreover, the study aligns with Mishrif and Khan (2023), who emphasized the importance of technology adoption as a survival strategy during crises such as the COVID-19 pandemic. The resilience provided by AI and other digital tools highlights the necessity of these technologies for maintaining operational continuity and customer engagement.

Furthermore, this research aids in boosting business performance in challenging markets, aligning with Sustainable Development Goal (SDG) 9—Industry, Innovation, and Infrastructure. By promoting the adoption of innovative technologies like AI, SMEs can enhance their competitiveness, contribute to industrial innovation, and build resilient infrastructures, all of which are vital for sustainable development in emerging economies.

In total, 17 hypotheses were formulated based on these theoretical underpinnings. The statistical analysis, conducted using SPSS v25 and SmartPLS 3.3.2, revealed that 13 of these hypotheses were supported, while 4 did not exhibit a significant influence on AI adoption or its mediating role. These findings emphasize the complex and nuanced relationships between the TOE factors, AI adoption, and SME performance.

Data for this study were collected from export-oriented manufacturing SMEs in Pakistan, with a specific focus on firms actively engaging with or exploring the adoption of AI technologies. Participants were carefully selected using a judgmental (purposive) sampling technique, targeting upper and middle management personnel who possess strategic insight into technological decision-making within their organizations. To ensure data relevance and credibility, structured questionnaires were distributed to 789 selected SMEs across four major industrial sectors (textiles, leather, sports goods, and surgical instruments). Contact information was sourced from the Pakistan Export Directory and cross-verified with sector-specific networks such as LinkedIn and industry associations. The study achieved a valid response rate of approximately 46%, which aligns with empirical benchmarks established in prior research on Pakistani SMEs, thereby ensuring sufficient robustness for PLS-SEM analysis.

This research significantly advances the understanding of how SMEs in emerging markets can leverage AI and digital marketing strategies to improve their competitiveness and performance. By comprehensively examining the factors influencing AI adoption and its impact on firm performance, the study offers valuable insights for both academic researchers and industry practitioners. These findings provide a strategic roadmap for SMEs aiming to capitalize on AI-driven opportunities in the digital era, reinforcing the critical role of digitalization, as highlighted by Kallmuenzer et al. (2024) and others in the broader literature.

5.2 Discussion of Findings

The subsequent section provides a comprehensive discussion of hypothesis testing related to the study.

5.2.1 Objective 1: Examining the Influence of Technological, Organizational, and Environmental Factors on AI Adoption in Pakistani SMEs

The first objective of this study was to investigate how technological, organizational, and environmental factors affect AI adoption in Pakistani SMEs, guided by the TOE, DoI, and RBV frameworks. The results reveal several patterns, contradictions, and context-specific insights that deepen our understanding of AI adoption dynamics in an emerging economy.

5.2.2 Technological Factors

- **Compatibility and AI Adoption (H1):** Contrary to theoretical expectations, compatibility was not found to significantly influence AI adoption. While prior models emphasized the importance of compatibility (e.g., TAM, early TOE studies), this finding aligns with more recent literature (Shahzad, 2023; Lee et al., 2022), suggesting that in emerging markets, firms may prioritize perceived value or urgency over seamless integration. One plausible explanation is that Pakistani SMEs, constrained by outdated systems, may be willing to endure compatibility issues if AI promises a competitive edge. This divergence prompts further inquiry into whether compatibility becomes more influential at later adoption stages or in firms with higher digital maturity.
- **Relative Advantage and AI Adoption (H2):** Relative advantage demonstrated a strong and significant influence on AI adoption. This reaffirms DoI's assertion that innovation diffusion is largely shaped by perceived benefits. Consistent with Mathani et al. (2024) and Sharma et al. (2022), SMEs in Pakistan appear to adopt AI primarily for its operational and strategic gains—such as enhanced customer engagement and cost-efficiency. This insight directly addresses the research problem by validating that SMEs in resource-constrained contexts remain benefit-driven in their adoption decisions.
- **Technology Readiness and AI Adoption (H3):** The significant effect of technology readiness underscores the critical role of internal infrastructure and human capital in enabling AI adoption. As echoed by Saleem et al. (2024) and Abaddi (2024), firms with higher levels of technological preparedness are better

positioned to adopt and integrate advanced tools. This supports the RBV perspective that firms' internal capabilities, not just environmental triggers, are central to innovation uptake.

5.2.3 Organizational Factors

- **Leadership Vision and AI Adoption (H4)**: Leadership vision had a significant impact on AI adoption, validating earlier studies (Smith et al., 2024). Strategic direction and top management support appear vital in shaping organizational readiness. However, later analysis (see Section 5.2.6) revealed that this leadership-driven adoption does not always translate into performance gains—suggesting a possible execution gap. This invites reflection on whether leadership intent must be coupled with mid-level operational buy-in and reskilling efforts to realize AI's full potential.
- **Change Management Capability and AI Adoption (H5)**: Change management capability also showed a significant positive relationship with AI adoption. This aligns with the literature emphasizing that adoption is not just technical but organizational (Lemos et al., 2022). Effective communication, employee involvement, and adaptive workflows appear to play key roles in navigating AI-driven transformations. This finding reinforces the need for SMEs to build absorptive capacity—not merely awareness—before embracing AI.

5.2.4 Environmental Factors

- **Competitive Pressure and AI Adoption (H6)**: Unexpectedly, competitive pressure did not significantly affect AI adoption. This contradicts some prior assumptions but is consistent with recent empirical work (Santosa & Surgawati, 2024). One explanation may be that many Pakistani SMEs operate in semi-monopolistic or informal markets, where peer pressure or consumer sophistication is insufficient to drive tech adoption. This highlights a contextual nuance where market dynamics in emerging economies may dilute the influence of external pressure unless accompanied by digital policy shifts or regulatory compulsion.
- **Trading Partnerships and AI Adoption (H7)**: Conversely, trading partnerships significantly influenced AI adoption. Strong external collaborations, including with suppliers and technology vendors, can serve as enablers of innovation by providing technical resources, insights, and shared platforms. This aligns with the environmental construct of TOE and supports the idea that SMEs are more likely to adopt AI when embedded in ecosystems that facilitate learning and reduce adoption risks.

The findings for Objective 1 reveal a nuanced picture. Internal capabilities (technology readiness, leadership, change management) and perceived benefits are stronger drivers of AI adoption than environmental pressures. This supports the RBV claim that firm-specific assets matter more than external triggers in capability-constrained contexts. The non-significance of compatibility and competitive pressure introduces tension within TOE, suggesting that some constructs may require adaptation for emerging economies or early-stage digital adopters.

These insights directly contribute to addressing the research problem by revealing which mechanisms support or hinder AI uptake in Pakistani SMEs. They also inform policymakers and practitioners on where to focus efforts—namely, capacity building, leadership alignment, and external ecosystem support.

The findings further reinforce alignment with SDG 9 (Industry, Innovation, and Infrastructure), showcasing that strategic AI deployment, when supported by readiness and partnerships, can lead to inclusive and sustainable industrial growth.

5.2.5 Objective 2: The Influence of AI Adoption on SMEs' Performance in Pakistan

The second objective of this study was to investigate how AI adoption influences SME performance in Pakistan. The findings strongly support H8, affirming a significant positive relationship between AI adoption and firm performance. Importantly, this relationship spans across operational, financial, marketing, and innovation-related domains—revealing that the impact of AI is both multidimensional and context-sensitive.

- H8: Artificial Intelligence Adoption → SME Performance (Supported)

AI adoption emerged as a catalyst for operational excellence. Consistent with Hwang and Kim (2021) and Lu et al. (2022), AI has enabled Pakistani SMEs to streamline workflows, reduce process redundancies, and unlock new efficiencies—especially in sectors undergoing post-pandemic recovery. The operational advantage is not merely in automation, but in how AI supports decision-making and responsiveness in dynamic market conditions.

Financial performance gains were similarly evident, aligning with literature such as Mikalef and Gupta (2021a) and Badghish and Soomro (2024). Firms deploying AI for cost control, sales forecasting, or inventory optimization experienced better margins and revenue growth. These financial improvements suggest that AI's value extends beyond experimentation—it plays a strategic role in enabling SMEs to achieve profitability and scalability.

Marketing capabilities were another key area of improvement. AI-facilitated segmentation, personalization, and real-time analytics were identified as enablers of customer satisfaction and loyalty. These outcomes, supported by Riikkinen et al. (2018), illustrate AI's potential to elevate SME market responsiveness in an increasingly digital consumer environment. Such improvements reflect the broader theme of digital transformation—a critical concern for SMEs seeking relevance in fast-evolving ecosystems.

In addition to economic gains, AI adoption fostered sustainable business model innovation. Environmental and ethical dimensions of AI were recognized as part of a shift toward sustainability-aligned entrepreneurship. As per Toniolo et al. (2020), AI-driven improvements in energy use, safety, and resource management can promote both efficiency and corporate responsibility. This aligns with SDG 9, supporting innovation-led industrialization in developing economies like Pakistan.

Despite these encouraging results, the discussion would be incomplete without addressing potential challenges. The transformative power of AI comes with ethical and operational risks—such as bias in decision systems, lack of explainability, and overreliance on opaque algorithms. These concerns, highlighted by Yudkowsky (2008), necessitate robust governance mechanisms. For SMEs with limited regulatory oversight and technical expertise, this represents a critical gap.

Another subtle tension lies in the strategic alignment of AI with firm vision. While AI may enhance performance metrics, its long-term value depends on whether adoption is driven by reactive mimicry or deliberate strategy. This concern echoes across SME digitalization literature and was observed in cases where short-term gains did not necessarily translate into competitive transformation.

These findings collectively suggest that AI adoption, when effectively aligned with organizational goals and supported by readiness and marketing strategies, can serve as a strategic enabler of SME competitiveness. However, its benefits are not automatic. SMEs must move beyond superficial adoption to develop integrated AI capabilities that address both short-term operational needs and long-term strategic resilience.

From a policy standpoint, the findings underscore the need for public-private partnerships that build SME capacity in AI deployment, digital literacy, and risk management. Academically, the results contribute to extending the TOE-RBV-DoI integration by showing how innovation potential becomes performance impact through execution, digital complementarity, and contextual alignment.

In conclusion, AI adoption has a transformative effect on SME performance, but its strategic value depends on how well it is embedded into the organizational fabric. This study advances the discourse by presenting an empirically grounded, context-specific view of AI's multifaceted impact—providing a roadmap for future research and practical guidance for SME leaders navigating digital disruption.

5.2.6 Objective 3: The Mediating Role of AI Adoption Between Technological, Organizational, and Environmental Factors and SMEs' Performance in Pakistan

The third objective of this study was to assess whether AI adoption mediates the relationship between technological, organizational, and environmental factors and SME performance in Pakistan. The results revealed a nuanced pattern: some factors influence performance only through AI adoption, while others appear disconnected from performance despite being conceptually important.

AI adoption significantly mediated the relationship between relative advantage, technology readiness, competitive pressure, and trading partnerships with SME performance. These findings confirm the conceptual proposition—rooted in the Diffusion of Innovations (DoI) and Resource-Based View (RBV)—that innovation potential translates into performance gains only when actual adoption occurs.

For instance, relative advantage (H11) reflects the perceived benefits of AI, and its strong mediation pathway indicates that these benefits materialize only when AI is actively implemented. Similarly, technology readiness (H12) enables firms to operationalize AI, reinforcing the RBV's emphasis on resource availability and absorptive capacity. The significance of competitive pressure (H15) and trading partnerships (H16) as mediated paths highlights the strategic importance of external collaboration and market responsiveness in mobilizing AI effectively.

These results align with prior studies (e.g., Sharma et al., 2022; Saleem et al., 2024) and extend the TOE framework by showing how external and internal conditions interact through AI adoption to shape performance outcomes.

Conversely, compatibility, leadership vision, and change management capability did not exhibit significant mediation effects. These findings, while initially counterintuitive, suggest important contextual realities in the Pakistani SME ecosystem.

For compatibility (H10), the non-significant mediation path may reflect the fact that SMEs prioritize AI's perceived benefits over how well it integrates with existing systems. This finding is echoed by Shahzad (2023) and Udeogu et al. (2024), who observed that early-stage AI adopters often overlook integration issues in favor of innovation gains.

The non-significant mediation of leadership vision (H13) points to a possible gap between strategic ambition and execution. While leaders may advocate for AI, their vision may not be sufficiently supported by operational capabilities or technical investments to convert that vision into performance outcomes. This resonates with Soni (2023), who emphasized that visionary leadership alone is insufficient in resource-constrained environments.

Similarly, change management capability (H14) did not lead to performance gains through AI, possibly because procedural readiness does not always translate into successful technology implementation. It may reflect a deeper misalignment between managerial intentions and technological execution—an area warranting further qualitative exploration.

Overall, the findings reinforce the idea that AI adoption is a critical conduit through which both internal capabilities and external pressures translate into firm performance. It is not the presence of resources or drivers alone, but their activation through digital transformation, that leads to tangible outcomes.

From a policy perspective, these results stress the need to support AI implementation capability—not just promote awareness or strategic intent. For SMEs, this means investing in tangible enablers like digital tools, training, and collaborative ecosystems. For governments, it points to the value of subsidizing AI infrastructure, facilitating knowledge-sharing networks, and incentivizing collaborative innovation.

For scholars, these mediation patterns offer empirical support for multi-theory integration (TOE, RBV, DoI), while also exposing theoretical tensions—such as when leadership vision fails to translate into outcomes. These gaps represent important avenues for future research, particularly in developing economy contexts.

In summary, the mediating role of AI adoption underscores its centrality in translating firm-level drivers and environmental stimuli into improved performance. It also highlights that digital transformation is not a linear or guaranteed process—some pathways require deeper structural or contextual support to yield results. These insights offer practical guidance for SME leaders and policymakers seeking to maximize the performance impact of AI adoption.

5.2.7 Objective 4: The Moderating Role of Digital Marketing Strategies in the Relationship Between AI Adoption and SME Performance

The fourth objective of this study was to evaluate whether digital marketing strategies (DMS) moderate the relationship between AI adoption and SME performance in the context of Pakistan. The results provided strong empirical support for this moderating effect (H17), highlighting DMS as a critical amplifier of AI's impact on firm performance.

This finding contributes meaningfully to the Resource-Based View (RBV) by positioning digital marketing not just as a standalone capability, but as a strategic complement to AI. While AI adoption can streamline operations, enhance decision-making, and optimize resource use, its transformative potential is magnified when embedded within effective digital marketing systems.

Digital marketing strategies—characterized by the use of data analytics, automation tools, and customer engagement platforms—enable SMEs to better exploit AI-driven insights. This synergy allows firms to shift from reactive to proactive market behavior, improving agility and customer-centricity. The RBV framework suggests that such integrated capabilities are difficult to imitate, thus yielding sustainable competitive advantage (Barney, 1991; Huang & Rust, 2021).

The moderation effect also reveals an important strategic tension: AI adoption alone is not enough to yield superior performance outcomes. Without a supportive marketing infrastructure, the benefits of AI may remain underleveraged. This highlights a broader challenge in digital transformation journeys—technology implementation must be paired with capability development to produce firm-level gains.

This is particularly salient for SMEs in developing economies like Pakistan, where resource constraints often limit holistic technology integration. In such contexts, DMS act as both a catalyst and conduit—helping translate AI capabilities into market-facing outcomes such as improved customer engagement, lead generation, brand positioning, and sales growth (Kumar et al., 2023; Enshassi et al., 2024).

From a managerial perspective, these findings emphasize that AI adoption should not be pursued in isolation. SMEs must concurrently invest in developing or accessing digital marketing competencies to fully realize the performance potential of AI. This includes building internal talent, leveraging automation platforms, and enhancing digital outreach strategies.

Policymakers and support organizations can also play a role by offering training programs, subsidized access to digital tools, and mentoring initiatives that help SMEs align their marketing and technological capabilities.

Overall, the moderating effect of DMS in the AI-performance relationship underscores a broader insight from this research: digital transformation in SMEs is multi-dimensional. It requires not only adopting advanced technologies but also strategically embedding them into key functional areas like marketing to drive meaningful performance improvements.

This finding extends both the TOE and RBV frameworks by illustrating that the real value of technological and organizational resources is realized through strategic alignment and integration. It also adds a practical lens to ongoing scholarly and policy debates around how best to enable digital transformation in resource-constrained firms.

5.3 Implications of the Study

The integration of Artificial Intelligence (AI) into the operations of Small and Medium-sized Enterprises (SMEs) is transformative, particularly in emerging markets like Pakistan. This study empirically examines how AI adoption influences SME performance, with AI acting as a mediating variable, and how digital marketing strategies moderate this relationship. It incorporates constructs from the Technology-Organization-Environment (TOE) framework, the Diffusion of Innovations (DoI) theory, and the Resource-Based View (RBV), addressing conceptual, methodological, and practical gaps. The implications are distinctly organized into theoretical, methodological, and practical contributions to enhance clarity and demonstrate the uniqueness of this research.

5.3.1 Theoretical Implications

This study makes several important theoretical contributions. It uniquely integrates the TOE, DoI, and RBV frameworks—chosen over others such as TAM or Dynamic Capabilities Theory—to offer a comprehensive and multi-level understanding of AI adoption and performance in SMEs. These three frameworks together allow the study to consider external triggers (TOE), innovation attributes (DoI), and internal resources (RBV) in a single coherent model.

A novel contribution of this study lies in its conceptualization of AI adoption as a mediating mechanism through which various technological, organizational, and environmental factors influence SME performance. The mediation findings provide empirical support for the transformative role of AI—it is not merely a standalone resource or process but a conduit through which contextual enablers translate into improved outcomes.

Moreover:

- TOE is extended by incorporating AI- and digital marketing–specific constructs, demonstrating the framework's adaptability in dynamic, digitally evolving SME environments.
- DoI is applied to explain AI as a disruptive innovation whose benefits materialize only when appropriately adopted.
- RBV is reinforced by illustrating how firm-level capabilities (e.g., leadership vision, change management) must be mobilized via AI to create competitive advantage.

The inclusion of digital marketing strategies as a moderating variable introduces a cross-functional perspective rarely integrated with AI adoption models, offering a richer understanding of SME competitiveness in the digital age.

5.3.2 Methodological Contributions

The study also contributes methodologically through its use of PLS-SEM on a large, cross-sectoral sample. A total of 789 surveys were distributed, yielding 368 valid responses, of which 349 were usable for analysis—exceeding minimum thresholds for structural equation modeling.

While stratified random sampling was initially proposed, limited access to SME databases necessitated a shift to purposive sampling, using professional networks and online channels. This adaptation—common in research on SMEs in emerging economies (Creswell & Clark, 2017)—allowed for targeted data collection from SME decision-makers. Although this limits statistical generalizability, it enhances theoretical and contextual validity, especially when addressing complex adoption phenomena.

The study also applies rigorous measurement model validation, including AVE, CR, HTMT, and discriminant validity procedures, reinforcing the credibility of its latent constructs. Furthermore, the mediation and moderation testing enhances the explanatory depth of the model.

5.3.3 Practical and Managerial Contributions

This study provides actionable guidance for various stakeholders:

For SMEs and Entrepreneurs:

- The results emphasize the importance of AI adoption as a transformational enabler. Performance gains from factors like technology readiness or environmental support only manifest when AI is effectively adopted—highlighting the centrality of the mediating process.
- SMEs are encouraged to invest in AI not as a standalone technology but as an embedded system, linked with marketing strategies, innovation efforts, and operational planning.
- Organizational capabilities—such as change management, leadership support, and external partnerships—emerge as more influential than competitive pressure, guiding entrepreneurs to prioritize internal development over external reactions.

This study identifies structural, financial, and skill-related constraints that impede AI adoption. Suggested policy actions include:

- Establishing AI incubators or local innovation hubs
- Offering targeted tax relief or innovation grants
- Launching national digital upskilling initiatives for SMEs
- Enabling cross-sectoral collaboration between SMEs and tech providers

These interventions would support not only adoption but sustained integration of AI into SME ecosystems—unlocking long-term productivity and competitiveness.

For Technology Vendors:

- Vendors can use these insights to design affordable, modular AI tools that integrate with SMEs' marketing and operational systems.

- Solutions should be tailored to varying levels of digital maturity, and bundled with training and onboarding support, especially for firms with limited digital literacy or technical infrastructure.
- Emphasis should be placed on solutions that enable performance transformation through adoption—not just access to tools.

5.3.4 Transferability to Other Developing Economies

Though focused on Pakistan, this study's conceptual model and findings are transferable to other developing economies undergoing similar digital transformations. Countries in South Asia, Sub-Saharan Africa, and the Middle East, where SMEs form the economic backbone but face digitalization hurdles, may adapt this framework with minor contextual modifications.

The AI mediation mechanism and the moderating influence of digital marketing strategies offer a replicable analytical model for scholars and policymakers aiming to accelerate SME innovation ecosystems in comparable settings.

By distinctly articulating its theoretical, methodological, and practical contributions, this research positions itself as a novel, robust, and policy-relevant examination of AI adoption and SME performance. Specifically, it:

- Extends TOE, DoI, and RBV through integration and contextual adaptation
- Introduces the mediating role of AI and the moderating role of digital marketing as dual-layer mechanisms driving SME performance
- Demonstrates methodological rigor with valid construct measurement and robust structural analysis
- Offers concrete, scalable recommendations for entrepreneurs, government actors, and tech providers
- Provides a generalizable framework for other developing countries facing similar digital capability gaps

This study contributes to both scholarly discourse and real-world practice, serving as a foundation for future interdisciplinary research and policy design in digitally evolving SME sectors.

5.4 Limitations of Study

While this research provides valuable insights into the adoption of Artificial Intelligence (AI) by SMEs in Pakistan, it does acknowledge certain limitations. Firstly, the study's focus is limited to specific geographic and sectoral contexts, primarily within the manufacturing sector of Pakistani SMEs. This narrow sector-specific focus may limit the generalizability of the findings to other industries or regions. The study's conclusions, while significant for manufacturing SMEs in Pakistan, might not fully represent the broader SME landscape across different sectors, such as services or retail, or in other developing or developed countries.

Secondly, this study employs a cross-sectional design, capturing data at a single point in time. While this method offers a useful snapshot of the current state of AI adoption, it does not allow for the observation of changes and developments over time. Consequently, this limits the ability to explore the evolving nature of AI adoption and its long-term impact on SME performance.

Another limitation is the reliance on self-reported data from top and middle-level managers of SMEs. While these respondents provide crucial insights into AI adoption within their organizations, there is an inherent risk of bias. The study might have benefited from a more diversified data collection approach, incorporating inputs from lower-level employees, customers, or suppliers. Including perspectives from external stakeholders could have provided a more balanced and comprehensive view of AI's impact on SME performance.

Although this study employed a cross-sectional design using a robust sample from four SME sectors, the reliance on purposive sampling through professional networks may limit statistical generalizability. However, this limitation is counterbalanced by theoretical replication, aligning with recommendations for contextual research in emerging economies. Additionally, the study primarily relied on quantitative data; thus, it could not capture nuanced organizational processes or leadership behaviors. Future qualitative or mixed-method approaches could unpack these underlying dynamics in more depth.

5.5 Directions for Future Research

In light of the findings and limitations of this study, several avenues for future research are proposed to deepen understanding of AI adoption and its impact on SMEs, particularly in emerging markets.

Future research should extend beyond the manufacturing and service SMEs included in this study to encompass other high-impact sectors such as retail, agriculture, logistics, and healthcare. Additionally, replicating this model across diverse regions—such as Southeast Asia, Sub-Saharan Africa, and the Middle East—can validate the framework in contexts with similar infrastructural and regulatory constraints. Comparative cross-cultural studies could reveal how institutional support, digital maturity, and socio-cultural norms influence AI adoption patterns.

This study employed a cross-sectional design, limiting the ability to capture dynamic changes over time. Future studies should adopt longitudinal or multi-wave research designs to examine how AI adoption matures and evolves within SMEs. This approach would allow researchers to explore the temporal dimensions of adoption—tracking shifts in performance, capability development, and digital maturity.

While this study offers robust quantitative evidence, qualitative insights could provide deeper context. Future researchers are encouraged to adopt mixed-methods approaches, integrating in-depth interviews, ethnographic case studies, or focus groups. This would allow exploration of nuanced themes such as employee resistance, trust in automation, leadership communication styles, or digital literacy barriers. Including perspectives from a wider range of stakeholders—e.g., operational staff, IT teams, external consultants—would offer a fuller picture of the organizational and human aspects of AI integration.

While this study drew upon the TOE, DOI, and RBV frameworks, future work could incorporate additional theoretical lenses to refine the understanding of AI-related transformations. Dynamic Capabilities Theory could be applied to explore how SMEs adapt and reconfigure resources over time to maintain competitiveness in volatile environments. Institutional Theory may help explain how regulatory, normative, and cognitive pressures shape technology adoption across regions. Future research might also test alternative mediation/moderation mechanisms—such as organizational agility, absorptive capacity, or innovation ambidexterity.

Several unexpected findings—such as the non-significant role of compatibility and leadership vision—highlight the need to examine context-specific barriers. Future studies could investigate whether these constructs are mediated by cultural, structural, or technological maturity factors not captured in this model. For instance, qualitative inquiry may reveal whether leadership support is symbolic rather than operational, or whether compatibility is deprioritized due to urgency-driven adoption decisions.

Another promising area is the examination of AI readiness—both technical and cultural—within SMEs. Future studies may assess how readiness levels impact successful implementation and scalability of AI tools. Additionally, emerging concerns around algorithmic bias, data privacy, and transparency deserve empirical attention. Researchers should explore how SMEs perceive and navigate ethical trade-offs associated with AI, especially in resource-constrained environments with limited regulatory guidance.

In sum, future research should adopt a more interdisciplinary, context-sensitive, and longitudinal lens to unpack the evolving role of AI in SMEs. These directions will not only strengthen the theoretical contributions of the field but also inform more practical, inclusive, and sustainable digital transformation strategies.

5.6 Conclusion

This study explored the complex interplay between technological, organizational, and environmental factors that influence AI adoption in Pakistani SMEs, and examined how such adoption impacts firm performance. Guided by the TOE framework and enriched by the Diffusion of Innovations (DoI) and Resource-Based View (RBV) theories, the research provided a multidimensional understanding of AI integration, focusing on both direct and indirect pathways—most notably through the mediating role of AI adoption and the moderating effect of digital marketing strategies.

By integrating three theoretical frameworks, this study addressed a notable research gap in the literature on AI adoption in SMEs, particularly within developing economies. The findings confirmed that core enablers such as technology readiness, relative advantage, and strategic partnerships significantly influence AI adoption, while environmental pressures like competitive intensity and compatibility concerns were less impactful—challenging assumptions prevalent in technology adoption literature. Notably, the non-significant mediation effect of leadership vision suggests that while strategic vision is necessary, it must be supported by executional capacity and technological readiness to generate performance benefits.

The moderating role of digital marketing strategies was found to be significant, reinforcing the idea that AI, when aligned with customer-centric outreach and data-driven marketing practices, can yield greater firm performance. This highlights a critical implication for practice: AI should not be deployed in isolation but as part of a broader, integrated digital transformation agenda.

These insights offer both theoretical and practical value. Theoretically, the study advances the TOE framework by embedding AI-specific constructs and contextual variables relevant to emerging markets. Methodologically, the research contributes by employing PLS-SEM on a substantial cross-sectoral sample in Pakistan—demonstrating rigorous validation procedures and strong explanatory power. Practically, it offers a roadmap for SME managers, policymakers, and technology providers to strategically invest in readiness, partnerships, and digital capabilities rather than respond reactively to market pressures.

In conclusion, this study contributes to ongoing scholarly debates on digital transformation by showing that AI adoption in SMEs is not only a function of resource availability but also of strategic alignment and ecosystem readiness. It encourages future research to explore longitudinal effects, context-specific barriers, and ethical considerations in AI adoption, particularly in under-researched regions. The central message is clear: for SMEs to unlock AI's full potential, a holistic, capability-driven approach must replace fragmented, trend-driven adoption. This shift is essential not only for firm-level performance but also for achieving broader goals of sustainable innovation and inclusive technological progress.

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Appendices

Appendix A - Study Questionnaire

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Title of the Study: LINKING TECHNOLOGICAL, ORGANISATIONAL, AND ENVIRONMENTAL FACTORS WITH ARTIFICIAL INTELLIGENCE (AI) ADOPTION AND SMES PERFORMANCE IN PAKISTAN

This doctoral inquiry seeks to dissect the effects of technological, organizational, and environmental variables on the adoption of Artificial Intelligence (AI) and its correlation with the performance metrics of SMEs in Pakistan. It is the researcher's hope that the insights gained from this study will contribute to elevating the operational capabilities within Pakistan's manufacturing sector for SMEs. Engaging in this questionnaire is deeply appreciated, as it is instrumental to ensuring the depth and validity of the research outcomes.

Your input is crucial to the fruition of this research. Rest assured, all information provided will be treated with strict confidentiality. For further information about this study or assistance with the survey, please feel free to get in touch.

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Organization: ....

Your willingness to participate is genuinely appreciated. Thank you for your valuable time and cooperation.

Section A: Demographic Profile of Respondents

This section collects demographic details to provide context for your responses.

1. **Gender:**
   - o Male
   - o Female
2. **Age Range:**
   - o 20-30 years
   - o 31-40 years
   - o 41-50 years
   - o Over 50 years
3. **Highest Educational Attainment:**
   - o Undergraduate Degree
   - o Graduate Degree
4. **Role in the Organization:**
   - o Executive Management
   - o Operational Management
5. **Industry Category of SME:**
   - o Textile Sector
   - o Leather Sector
   - o Sporting Goods Sector
   - o Surgical Equipment Sector
6. **Experience in AI and Digital Marketing:**
   - o 1-3 years
   - o Over 3 years

Section B: Perceptions on AI, Factors Affecting Adoption, Digital Marketing Strategies, and SME Performance

This section evaluates your perceptions of AI adoption within your organization, the factors influencing its integration (technological, organizational, and environmental), the role of digital marketing strategies in enhancing its impact, and the overall performance of your SME.

For each statement, please indicate the extent of your agreement using the following 7-point Likert scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Somewhat Disagree, 4 = Neutral, 5 = Somewhat Agree, 6 = Agree, 7 = Strongly Agree.

Please answer each item based on your experience and knowledge of your organization.

	AI Adoption and Impact:	1	2	3	4	5	6	7
AIA1.	The adoption of AI in our operations is more cost-effective compared to other technological investments.	1	2	3	4	5	6	7
AIA2.	Implementing AI in our processes has resulted in time and cost savings over other technologies.	1	2	3	4	5	6	7
AIA3.	AI has streamlined our operations, reducing the time, effort, and costs associated with achieving competitive advantages.	1	2	3	4	5	6	7
AIA4.	AI has enhanced the capabilities of our HR managers in selecting the best candidates.	1	2	3	4	5	6	7
AIA5.	Decision-making quality in recruitment and selection processes has improved due to AI adoption.	1	2	3	4	5	6	7
AIA6.	The overall effectiveness of our technology-related actions has increased since adopting AI.	1	2	3	4	5	6	7
AIA7.	AI has granted us greater control and expedited decision-making, particularly in security-related matters.	1	2	3	4	5	6	7

Part A: Technological Factors

This part examines how AI integrates into your organization's existing systems and infrastructure.

Compatibility (C)

Compatibility measures how well AI fits with your organization’s current systems and processes.

	Compatibility (C):	1	2	3	4	5	6	7
C1.	AI applications are well-aligned with our current communication and network environment.	1	2	3	4	5	6	7
C2.	AI applications fit seamlessly with our existing hardware.	1	2	3	4	5	6	7
C3.	AI applications are easily integrated into our existing infrastructure.	1	2	3	4	5	6	7
C4.	AI applications are consistent with our current computerized data resources.	1	2	3	4	5	6	7

Relative Advantage (RA)

Relative advantage assesses the benefits AI provides to your organization compared to other technologies.

	Relative Advantage (RA):	1	2	3	4	5	6	7
RA1.	AI applications have led to increased productivity among our employees.	1	2	3	4	5	6	7

RA2.	AI applications have significantly improved our customer service quality.	1	2	3	4	5	6	7
RA3.	AI applications have made better use of our IT resources.	1	2	3	4	5	6	7
RA4.	AI applications have enhanced our flexibility in operations and integration with other systems.	1	2	3	4	5	6	7

Technology Readiness (TR)

Technology readiness evaluates your organization's capacity to adopt and sustain AI technologies.

	Technology Readiness (TR):	1	2	3	4	5	6	7
TR1.	Our organization is well-equipped with the necessary resources to develop and implement AI applications.	1	2	3	4	5	6	7
TR2.	Our organization provides timely access to resources required for effective AI deployment.	1	2	3	4	5	6	7
TR3.	We have knowledgeable consultants who understand both AI and our industry's specific needs.	1	2	3	4	5	6	7
TR4.	We have the necessary resources for ongoing AI model monitoring and obtaining feedback.	1	2	3	4	5	6	7
TR5.	Our organization has a centrally managed practice for AI.	1	2	3	4	5	6	7

Part B: Organizational Factors

This section focuses on how internal organizational elements, such as leadership and change management, influence AI adoption.

Leadership Vision (L)

Leadership vision examines how leadership views AI and its role in driving organizational success.

	Leadership Vision (L):	1	2	3	4	5	6	7
L1.	Our leaders are open and willing to take on the risks associated with implementing AI.	1	2	3	4	5	6	7
L2.	Our leaders view IT capabilities as an essential strategic asset for the organization.	1	2	3	4	5	6	7
L3.	Our leaders are committed to integrating AI technologies into our business processes.	1	2	3	4	5	6	7
L4.	Our leadership believes that AI adoption is crucial for maintaining our competitive position in the market.	1	2	3	4	5	6	7

Change Management Capability (CMC)

Change management capability assesses your organization's ability to handle the transitions associated with AI adoption.

	Change Management Capability (CMC):	1	2	3	4	5	6	7
CMC1.	Our organization has experience with implementing significant changes in business processes.	1	2	3	4	5	6	7

CMC2.	Our organization has successfully transitioned to utilizing new technology products.	1	2	3	4	5	6	7
CMC3.	We have a proven track record of effectively managing and implementing change.	1	2	3	4	5	6	7

Part C: Environmental Factors

Environmental factors assess external influences like competition and partnerships that impact AI adoption.

Competitive Pressure (CP)

Competitive pressure evaluates how market competition influences your organization's AI strategies.

	Competitive Pressure (CP):	1	2	3	4	5	6	7
CP1.	The pace of innovation within our industry has prompted us to accelerate our adoption of new operating processes and products.	1	2	3	4	5	6	7
CP2.	The increasing adoption of AI technologies in our industry pressures us to do the same.	1	2	3	4	5	6	7
CP3.	We experience substantial price competition in our industry that influences our strategic decisions.	1	2	3	4	5	6	7

Trading Partnerships (TP)

Trading partnerships measure how relationships with partners impact AI adoption.

	Trading Partnerships (TP):	1	2	3	4	5	6	7
TP1.	We are aware of and utilize the outputs from AI applications employed by our trading partners.	1	2	3	4	5	6	7
TP2.	We have a good understanding of how to integrate inputs from trading partners into our AI systems.	1	2	3	4	5	6	7
TP3.	We recognize the importance of connecting our IT systems with those of our trading partners to optimize operations.	1	2	3	4	5	6	7

Part D: Digital Marketing Strategies (DMS)

Please evaluate the following statements regarding the use and effectiveness of Digital Marketing Strategies in your organization. Utilize the scale provided to indicate how much you agree with each statement.

	Digital Marketing Strategies Impact:	1	2	3	4	5	6	7
DMS1.	Our company effectively manages customer relationships through various digital media channels.	1	2	3	4	5	6	7
DMS2.	By using digital media analytics, our company is able to accurately predict customer preferences.	1	2	3	4	5	6	7
DMS3.	Digital media is a key tool for our company in managing relationships with channel members.	1	2	3	4	5	6	7

DMS4.	Our digital marketing strategies have been successful in attracting new customers.	1	2	3	4	5	6	7

Part E: SME Performance (FP)

Please indicate the extent to which you agree with the following statements about your firm's performance. Use the following scale for your responses

	Firm Performance (FP)	1	2	3	4	5	6	7
FP1.	Our firm sales growth is increasing rapidly.	1	2	3	4	5	6	7
FP2.	We are not experiencing financial difficulties currently.	1	2	3	4	5	6	7
FP3.	We are continuously introducing new products and services.	1	2	3	4	5	6	7
FP4.	The implementation of AI is enhancing our business performance.	1	2	3	4	5	6	7

Thank you for your participation.