AIDING STRATEGIC DECISION-MAKING TO IMPROVE PROFITABILITY USING ARTIFICIAL INTELLIGENCE IN INDIAN SMALL AND MEDIUM ENTERPRISES

by

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Dedication

This thesis is dedicated to my loving wife Vaidehi, whose continous support, encouragement, and love has been the foundation of my academic journey. Your support and encouragement throughout the ups and downs of this journey made me keep my focus on the goal all the time.

This thesis is equally dedicated to my late mother Mrs A. K. Annapurani and my father K V Chandran. Amma, you always were there for me no matter what and Appa, you continue to silently encourage me on in this journey and in life too.

I equally dedicate this thesis to my lovely children Ashwin and Nandini, who have been the pillars of encouragement contributing in their own unique way throughout the journey of this thesis.

Lastly, I want to dedicate this dissertation to Sebastian Sir and Mrs Chatellier, very special teachers from my school days without whom I would not be what I am today.

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ABSTRACT

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This dissertation focusses on the role of artificial intelligence (AI) to improve strategic decision making to improve profitability in the SMEs in India. With the Government of India envisioning doubling the Indian economy by 2025, the SME sector is vital to India's economy, serving as a key employer generator while contributing significantly to innovation.

With stiff competition amongst the SMEs in India for growth and sustainability, SMEs also deal with resource constraints, financial constraints & the need to make quick and efficient decisions to make their organizations profitable. The study employed quantitative based and qualitative based techniques, while the literature review enabled the establishment whether there were any theoretical framework focusing on strategic decision-making, AI, and their intersection with industry standard performance frameworks like Balanced Score Card.

The literature review identified the absence of a framework that brought about the use of AI in the Indian SME for strategic decisioning and improving profitability. The survey conducted among the participants from the Indian SMEs gathered data on their current AI adoption levels, perceived benefits of integrating AI for strategic decision making. Various statistical techniques-based evaluation of the data determined factors that played a key role in the use of Artificial Intelligence, Balanced Score Card for strategic decision making and their impact on improving profitability in Indian SMEs.

The key findings indicate that AI has the potential to contribute significantly to improve decision-making and thereby leading to improved financial performance. However, the research also identified several barriers to AI adoption, including lack of awareness, lack of talent and skills, limited access to skilled personnel and the need for quality data and a robust data infrastructure. Thus, in order to stay ahead of their competition, the SMEs must carefully consider the integration of AI into their organization for strategic decisions and improve profitability. This integration must be done in a planned and focused manner as AI integration also comes with a higher cost around technology, skills and good quality data.

The thesis recommends that SMEs should consider integrating AI, improving their data infrastructure to enable a better profitability, optimized resource allocation, and gain a competitive advantage over their competition

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CHAPTER I:

INTRODUCTION

1.1 Introduction

Small and medium-sized enterprises (SMEs) in any country and around the globe serve as the backbone of economies contributing significantly to employment, innovation, and economic growth. In India, this sector plays a particularly vital role, in driving entrepreneurship and fostering growth. However, navigating the complex and often unpredictable business landscape is no small feat for SMEs. To thrive in this fiercely competitive environment, agility in strategic decision-making stands out as a key need for SMEs and their management.

Unlike larger corporations with abundant resources and established market positions, SMEs often operate in resource-constrained environments, which makes their decisions even more critical. Each choice, whether related to market entry, product development, or resource allocation, can significantly impact the SME's ability to grow, innovate, and remain sustainable.

The past decade has witnessed transformative changes in India's economic landscape. The country, one of the world's fastest-growing economies, has navigated through a series of challenges and opportunities that have significantly shaped its growth trajectory. Central to this transformation has been the Small and Medium-sized Enterprises (SME) sector, which has played a pivotal role in fueling economic growth while simultaneously being impacted by the dynamic forces at play.

In recent years Artificial Intelligence (AI) has rapidly evolved into a technology of choice when it comes to solving business problems across industries.

The National Association of Software and Service Companies (NASSCOM) published a report NASSCOM AI Adoption Index(*NASSCOM AI ADOPTION INDEX Tracking India's Sectoral Progress on AI Adoption* 2022) where Artificial Intelligence has been viewed increasingly as an innovation and growth tool.

Figure 1 AI a tool for Innovation and growth

Source: NASSCOM AI ADOPTION INDEX REPORT 2022

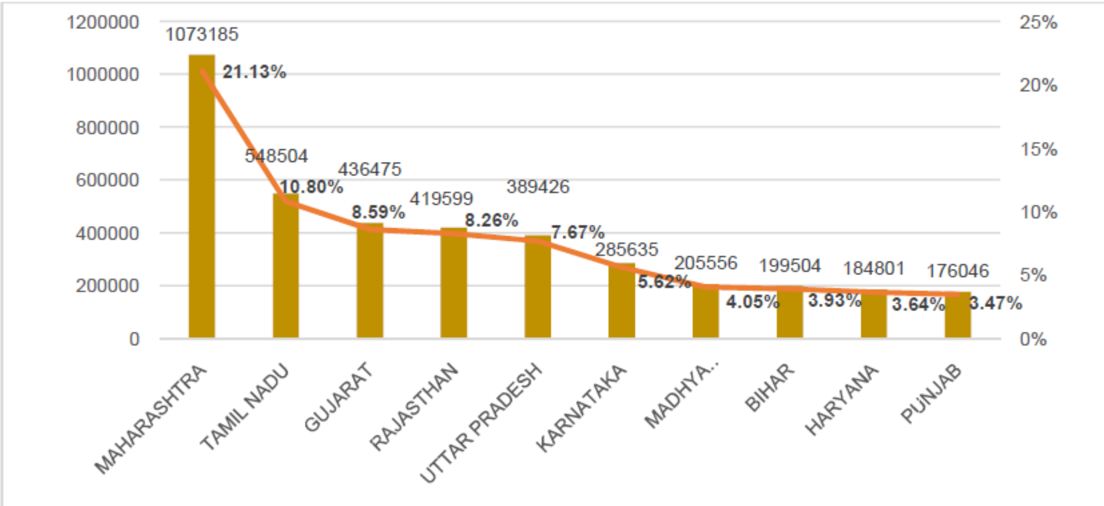
The NASSCOM report had participation across startup Multinational Companies (MNCs) (Global and Local) and public sector units. However, the report did not specifically mention Small and Medium Businesses in India.

According to the data (July 2024) from the Ministry of Micro, Small & Medium Enterprises (MSME) of India, the Udyam[1] Registration portal registered approx.

[1] It is the Government Portal for the registration of MSMEs. It was launched by the Union MSME Ministry in 2020. It provides free-of-cost and paperless MSME registration.

46,786,457 MSME. Of these 96.87 % were registered micro-enterprises that stood at 45,951,044 (96.87%), and the other small and mid-size enterprises comprised of the remainder 3.13 %.

Figure 2 State-wise MSMEs registered as per published data from Oct 2021



Source: udayamregistration.gov.in Portal

According to an article published in the Hindu[2], India is likely to double its economy to US$5 trillion by the year 2025. The International Monetary Fund (IMF) has projected that India would be the 3rd largest GDP by 2027-2028. Thus, to achieve this goal, there is a need to generate more employment and MSMEs have the potential to serve as a key employment generator. Therefore, the government has taken up the promotion of MSMEs to create new jobs in the sector. Further, the government aims to enhance MSME's share in exports and its contribution to GDP.

[2] https://www.thehindu.com/news/national/india-to-be-5-trillion-economy-by-end-of-2025-amit-shah/article67621285.ece

1.2 Research Problem

The use of technology in businesses is not new, and machines have been aiding humans in multiple industries for centuries. Using something as simple as an abacus, used by early shopkeepers to computers from modern times that aided with decision making to users, and especially to decision makers. All decisions, be it small, big, or strategic, rely on the availability of data and the ability to analyze the data and interpret the same. With the advent of Big Data [3] and cloud computing, availability of data, its computations and interpretation of the meaning of data has become easier. Strategic organizational decision-making in today's complex world is a dynamic process characterized by uncertainty(Trunk, Birkel & Hartmann 2020). Thus the process of decision making requires a more digital approach and outlook to ensure decisions are more nimble, agile. These processes are required to take into consideration the uncertainty in the decision making be it due to world politics, or changes in the local city where the organization is headquartered in.

The field of computer science focuses on developing machines and algorithms capable of performing tasks typically requiring human intelligence, such as problem-solving, learning, and decision-making (Russell Stuart & Norvig Peter 2020).

With such a dynamic changing business landscape and the volume of data being generated increasing regularly, decision-making becomes a lot more difficult for the

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[3] Big data is a field that treats ways to analyze, systematically extract information from, or otherwise deal with data sets that are too large or complex to be dealt with by traditional data-processing application software

human mind. That is where the Artificial intelligence-based decision-making process can contribute a lot to organizations especially the small and medium organizations which rely on an individual or a small group of individuals for strategic decision(Jarrahi 2018) Technology-related research in AI focused mainly on solving business problems, development of expert systems, robotic process automation (RPA), natural language processing (NLP), and image processing (Purdy & Daugherty 2016).

Due to challenges like regulatory concerns, the complexity of technology, and the availability of a skilled workforce, AI was not the primary focus of the SME sector. There is a literature gap as there are few research papers available about AI adoption in the SME sector in India. Therefore, there are very minimal or almost no research papers that study the impact of Artificial intelligence on strategic decision-making in Indian SMEs and how Artificial Intelligence could improve the quality of strategic decision-making and therefore the profitability of SME businesses in India.

Therefore, it is important to conduct a correlational analysis to understand strategic decisions, AI adoption its challenges and the impact of Artificial Intelligence-based strategic decisioning making in the SME sector in India. The general problem is that strategic decision-making in SMEs in India using Artificial intelligence is unexplored and thereby factors that enable and limit such an adoption and implementation and its use in India is unknown.

1.3 Purpose of Research

With the focus of the Government of India to encourage MSME sectors, it is of paramount importance for the MSME to think critically about using technology like Artificial Intelligence (AI)/ Machine Learning (ML) that would enable them to generate more revenue opportunities, shorten decision-making capabilities and improve their profitability.

There are studies and research by various scholars who have researched the following topics:

1. Design and implementation of AI technology solutions to address business challenges.
2. Impact of using artificial intelligence on industries and society where the focus was more on understanding the good and bad impacts of AI.
3. An in-depth analysis of how AI based solutions helped to solve business problems in a particular industry.
4. There is research which focusses on understanding the impact of the use of Artificial intelligence in the MSME sectors.

While all the above research contributes to strengthening the fact that artificial intelligence enables and optimizes growth and operations(Soni et al. 2020) , there is very little available research that establishes how Artificial intelligence can be of help to the MSME industry leaders to make strategic decisions that will improve their business's profitability.

Thus, with the massive opportunity for MSME industry growth backed by the Government of India and the size of the MSME industry in India, there is a significant research opportunity to study the relationship between Artificial Intelligence, strategic decision making and how it can be used by MSME industry leaders to improve the profitability of their businesses.

Having spent almost two decades working for global customers across the financial, retail, telecom and insurance industries delivering IT solutions and then moving to work in the MSME IT industry, made the author to come face to face with challenges that are faced by medium-sized industries, especially with financial constraints, competition, limited resources, and the continual need to improve profits for their businesses.

1.4 Significance of the Study

The SME sector has proved to be crucial for the growth of any economy, whether developed economy like the EU or, the USA or a developing economy such as India. According to the Ministry of Micro, Small and Medium Enterprises of India (MSME,2023)[4] MSME Gross Value Added (GVA) in India's Gross Domestic Product (GDP) during the year 2019-20, 2020-21 and 2021-22 was 30.5%, 27.2% and 29.2% respectively.

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[4]https://pib.gov.in/PressReleaseIframePage.aspx?PRID=1946375#:~:text=As%20per%20the%20latest%20information,27.2%25%20and%2029.2%25%20respectively.

As per the information received from the Directorate General of Commercial Intelligence and Statistics (DGCIS), the share of export of MSME specified products in all India exports during the year 2020-21, 2021-22 and 2022-23 was 49.4%, 45.0% and 43.6% respectively.

Significant contributions to GDP and exports demonstrate the high importance of MSMEs for the Indian economy,making the use of AI becomes a very significant topic to be researched in the Indian SME landscape.

While a lot of the SMEs have the general characteristics of limited size, scale, and being family-owned, it is also to be noted that most of them lag in technology adoption and face challenges in accessing finances. In addition to the above, some of the challenges are regional, ranging from high operating costs to fierce competition, and infrastructure. Talent retention, real estate costs, startup competition traffic congestion, living costs and keeping up pace with technology advancements are some of the other challenges faced by SMEs in India.

According to Drydakis (Drydakis 2022) use of AI applications in marketing and sales, cash flow forecasting, and HR activities were associated with reduced business risks for both small and medium enterprises. This indicated that AI enabled SMEs to boost their dynamic capabilities by leveraging technology to meet new types of demand, move at speed to pivot business operations, boost efficiency and thus, reduce their business risks. The study recommended and encouraged the SME decision-makers to utilize AI for their businesses. Mandapuram (Mandapuram 2017) suggested that AI can promote intelligent production methods to reduce loss and increase returns.

Thus this study may help India's SME sector to understand the use of Artificial Intelligence to aid strategic decisions and consequently improve the profitability of their businesses.

1.5 Significance to Theory

Balanced Scorecard (BSC) has been proven to be a very useful tool for more than three decades and is widely used by enterprises globally.

According to Malagueno and others,(Malagueño, Lopez-Valeiras & Gomez-Conde 2018) those who used BSC for their financial and innovation outcomes were able to strongly indicate the positive use of BSC in terms of financial performance and innovation outcomes.

The Strategic Decision Management process in SMEs is less complex than theoretical models and broadly follows a five-step process, which involves decision identification, information search , analysis, internal factor consideration (particularly technical expertise and financial resources), and decision making (considering financial analysis, assessment and the final commitment). While these steps may not be strictly sequential a lot of the decision-making is observed to be influenced by a closed group of decision makers. The quality with which these steps were undertaken is influenced by both organizational factors (the firm’s ownership and size) and individual factors (the owner/manager's educational qualification and experience) (Huang, X 2009).

The SME owners/managers rely heavily on their personal and professional networks for identifying opportunities in the business environment and for information search and advice in making their strategic decisions.   These relationships include those with government officials, university academics, and personal friends particularly those working together (Huang, X 2009).

The firm's ownership significantly influences the degree of participation in the strategic decision-making process. These decision makers generally are directors, founders' owners of the organization. The length of time for making a strategic decision is generally shorter in the private SMEs than their state-owned counterparts. The highly centralized management model, coupled with low level of participation, in the private-owned SMEs can lead to people dependent decisions resulting into longer times for decision making, conflict of interests, loss of opportunities.

TAM (Technology Acceptance Model)[5] is a widely used model that is useful in studying new technology adoption in industries. Qin and others (Qin et al. 2020) in their research wrote extensively about how TAM could be used for BIM (Building Information Modelling). Qin compared the various models of TAM from the time it was introduced in 1998 to its current version of TAM3.

After preliminary literature based research, it was difficult to find some extensive study that involved the SME sector where AI adoption, implementation, and use were evaluated for strategic decision-making and improving profitability; there by making it one of the primary reasons to research the combined effect of Balanced Score Card (BSC) and Artificial Intelligence using TAM related constructs to determine whether the three

[5] https://en.wikipedia.org/wiki/Technology_acceptance_model

constructs have a positive impact on the profitability of SMEs in India. Thus, this research was significant to the theory.

1.6 Significance to Practice

Through this research, it is intended to study the combined effect of BSC and TAM related constructs on strategic decisions that have a positive impact on the profitability of SMEs in India. Thus the research is significant to the practice as it will add to the new knowledge where industry sector leaders may gain more insights about essential factors that determine whether AI can be used in their organization. Leaders in the SME sector in India may be better equipped to make better decisions using an integrated process that combines BSC and AI to improve the profitability of their businesses.

1.7 Significance to Social Change

The SME sector is one of the most crucial sectors for any country that contributes to generating employment and thus helps in solving issues such as food, education and poverty (ScholarWorks & Sadashiv Jadhav 2021). Disruptive technologies such as AI can have a significant impact on the SME sector. It enables industries to create technology-based services and products to solve several societal challenges. In this thesis, the focus is to study factors which influence profitability and strategic decision making in India’s SME sector the most. Through this study, the aim is to bring positive social change so that the management of small organizations in India can make informed decisions about AI technology adoption, implementation, and use and make their work environments a better place for employees and local population.

1.8 Research Purpose and Questions

The study is based on two theoretical foundations, namely BSC and TAM. Research questions are formalized in such a way that they were useful in terms of understanding correlations between different independent variables and the dependent variable. Information about dependent and independent variables was captured using an online survey questionnaire. Most variables were measured using answers provided by survey participants using a 5-point Likert Scale.

The research questions are as below

RQ1 Can Strategic decision-making processes, guided by Artificial intelligence, impact financial performance metrics such as (EBITDA or Operating Margin) within the context of the Balanced Scorecard framework in Indian Small and Medium Enterprises?

RQ2 What are the key challenges faced by Indian Small and Medium Enterprises (SMEs) in implementing Artificial Intelligence (AI) in their decision-making processes, and their influence on the successful adoption and integration of AI technologies?

RQ1 is the primary research question being investigated and researched as part of this study. ***RQ2*** lays the way forward in view of the key challenges faced by the Indian SMEs towards the adoption of AI technologies for strategic decision making and improving profitability of Indian SMEs.

Each of the primary research questions has a set of secondary questions that requires validation before the main research questions hypothesis was validated. The subsequent chapters, especially chapter 3,4 elaborate the primary research questions, the secondary research questions and its contributions to the research hypothesis in detail.

1.9 Summary and Transition

This chapter started with the introduction to the economy, the status of the SMEs in India. Analysis of the few of the literature available indicated that there was very little research available where the use of Balanced Score card, its co relation with the use of Artificial Intelligence for improving profitability in the context of the Indian SMEs, making the study significant in the context of the SMEs in India.

The significance of the study is strengthened in the context of the SMEs in India given the focus of the Government of India to grow India's internet economy by almost 6X time in the next 8[6] years. This cannot be done without the use of efficient and emerging technologies such as AI, that needs adoption in the SMEs in India to accelerate their growth multifold making the research problem and question relevant to be analyzed further; to enable SME leads and executives in their journey to improve decision making and profitability of their organizations. Chapter 2 will focus on the literature review for the research problem at hand.

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[6] https://www.businesstoday.in/latest/economy/story/indias-digital-economy-to-register-6x-growth-reach-1-trillion-by-2030-384445-2023-06-06

CHAPTER II:

REVIEW OF LITERATURE

2.1 Introduction

The research problem discussed in Chapter 1 indicated the use of AI to enable profitability improvement in SMEs in India was unexplored. The co relation between the use of Balanced Score cards and AI in Indian SMEs as tools to improve profitability was unexplored. To understand the current state, literature review was conducted to understand the state of AI adoption, strategic decisioning approaches and profitability measurements methods used across various industries globally, contributing factors impacting AI adoption, and the relevance of technology adoption theories and its relation to AI based strategic decision-making to improve profitability across the SME sector in India. The research problem further becomes more relevant given India's large-scale initiatives as single digital identity (AADHAR), which is a 12-digit unique number for every citizen in India, the launch of Unified Payments Interface (UPI) which deals with almost 10 billion transactions per month. With the government's focus towards digitization and to add to it a working population whose average age is approximately 28 years, SMEs in India are in a unique position to contribute to the economy and AI in SMEs can play a significant role in the same (Nilekani Nandan & Bhojwani Tanuj 2023). The further sections of the chapter start with a description of the approach adopted to conduct the literature review, followed by a brief of the sources of information, the key terms used for the search and the methodology used for selecting the reviewed article.

The section beyond the brief contains the justification and relevant explanations regarding the theoretical foundations and relevant explanations regarding the theoretical foundation and theories used in recent studies.

A discussion about AI technology context, its adoption status across industries follows along with the discussion of the use of Balanced Score Card framework and its adoption across the industries. Discussion about theories specific to AI technology adoption in the context of profitability improvement in different industrial sectors and regions in India, followed by an in-depth analysis of adoption of AI technology in India, factors impacting profitability of SMEs sector in India forms the remainder of the chapter

2.2 Information Sources

The focus of the study was to help decision-makers within the SME sector in India to understand whether AI could be integrated with strategic decision-making processes of their organizations and there by improve the profitability of their organizations. One of the main sources for scholarly articles and peer reviewed research papers was Google Scholar and Research Gate. Literature published from the year 2010 to 2024 was primarily considered for this study with a few valid exceptions. Other sources included articles from the internet and newspapers and the Walden Dissertation and Doctoral Studies collection at Scholarworks.

Search keywords were: Strategic decision making, Strategic decision in SME, artificial intelligence, SME sector in India, Balanced Score Cards, technology acceptance model, AI in the SME sector, AI in the SME sector in India, AI in India, Balanced Score card in

India, and TAM, factors impacting profitability, AI and economy. All the search terms were used judiciously independently and in various permutations and combinations. Papers from technical, consulting firm such as Gartner and Mckinsey that contained essential and relevant information worth considering for this study was also referred to wherever necessary.

The first task was to shortlist relevant peer-reviewed research articles for this study using a structured approach. After careful consideration, there were around 156 research articles and books that were useful for this study. In total, the 70 articles were related to AI, some 30 articles contained Balanced Score cards related literature, and 20 articles were related to adoption of AI in Indian SMEs.

From all the resources referred, not more than 5 to 10 research papers contained information about BSC, TAM theories or AI adoption and factors impacting profitability of SMEs.

2.3 Theoretical Framework

One of the key objectives of any research is to contribute to the existing knowledge base. To contribute to any existing knowledge base research must be carried out using existing and established theories so the contributions are relevant, significant and trustworthy. Theoretical frameworks are like a research blueprint that researchers refer and use, to adopt and develop his or her theories (Grant & Osanloo 2014).

Theoretical frameworks are useful to study relationships between various constructs. Also, theoretical frameworks help define the researcher's scope and boundaries.

Theoretical framework connects relevant elements of the theories found during literature review to the specific formulation of the research problem(s). It helps the researcher see clearly the main theory or theories, and how they relate to the phenomenon of interest both (quantitative and qualitative) (Hughes 2019).

During the research, there could be frameworks that are developed by the researcher from a variety of theories, or parts of theories, or evolve during the literature review and even during the research. The framework developed by the researcher helps the researcher to link their research from the theories in the literature review to the field data and eventually analysis (Hughes 2019). Theoretical frameworks primarily used in this study were Technology Adoption Model (TAM) and Balanced Score Card (BSC).

The TAM, BSC theories formed the theoretical foundation to determine relations between various constructs that influenced AI technology adoption for strategic decision making and profitability improvements in SMEs. The next few sections elaborate on the theoretical foundations.

2.4 Strategic Decision Making

Strategic decision making is a critical part of the progress of any organization. Before, we understand strategic decision making, it is important to understand what an organization is. According to Janczak “An organization is a coalition in a business organization the coalition members include managers, workers, shareholders, customers, lawyers, and regulatory agencies” (Janczak 2005). Every organization exists and must learn to co-exist with uncertainty; they strive to act rationally in the face of technological and environmental uncertainities (Janczak 2005). Thus, organization is a set of people, human minds with different education, different experiences, different perspectives that all contribute in their way towards the betterment of the organization (Gibbons 2020). Strategic decisions are always multifaceted and tend to have an impact on the future of the organization. Thus, with this lens to view the challenges faced with strategic decisioning is not finding the right answer, but the right question. (Janczak 2005); and to do this role of the top managers is of high importance where they play a critical role to shape the objectives of their departments and in turn the organization and the strategy of the organization. Thus, strategy and strategic decisions act as an important determinant of organizations' performance outcomes. (Janczak 2005), which also aligns the study carried out by Wilden and others. (Wilden et al. 2013).

Strategic decision making in smaller firms resides with a single individual or a smaller group of individuals, whereas in larger organizations the decisions are undertaken by the strategic planning team or by the members of the executive management (Jansen et al., 2013).

According to Janczak (Janczak 2005) ,it is impossible to ignore the decision-making approach, however it is required to understand the decision-making process and in complex organizational decisions to determine which decision is the best or to determine if the outcome approach is the best is primarily due to skill or chance.

A growing body of literature explored the role of human and social capital in entrepreneurial strategic decision-making. Levels of expertise and education were key factors closely connected to the volume of information engaged in the decision process, and thus, are relevant inputs for the strategic decision process. (Jansen et al., 2013). Human capital refers to individuals or teams with the right skills, experience that possess the ability to analyze the information presented to them, make the right decision to help with the firm's performance, thus more the knowledgeable the decision makers are, more empowered they feel to accept greater risks.

Another key pillar that helps with strategic decision making is the experience of the decision makers or decision-making team. If the team or individual, especially in the SME environment has encountered a similar scenario/situation they are likely to deal with it with greater confidence from their repertoire of experience of similar situations. Thus, acceptance of risk levels will be higher if decision makers know what could occur and thereby are able to work out a plan to achieve higher levels of decision effectiveness.

2.5 Artificial Intelligence (AI)

Literature review showed that past studies were primarily focused on understanding and exploring the potential of AI to become a support in organizational decision making under uncertainty. Limited progress has been made on classifying various approaches to involve AI simulators and AI applications in the use of strategic decision making. In the past researchers like Spangler have attempted to seek answers for questions like "Does the user of AI based systems make better decisions using the AI systems? " (Spangler, 1991). Expert systems have been used for military and space programs for a long time, however there is not much evidence of using AI systems and their likes for strategic planning and organization decision making.

Similarly, Distributed Artificial Intelligence (DAI), a relatively new area which has been growing significantly in the body of research in the last few years. Research in distributed AI has been in several domains including social and organizational modelling. The relevance of Distributed AI to strategic decision making is further supported by the similarities to collective strategic decision-making definitions offered by Dutton (Spangler, 1991).

The use of AI based distributed models to support strategic decision making was seen with the ICS (Integrated Consulting Systems) developed at Stanford Research Institute (SRI). ICS integrates the knowledge of technology, firms, market adjustments, consumers inputs, to support competitive analysis and strategic planning (Spangler, 1991).

Given the predictive capabilities of Artificial Intelligence programs and software, such programs and capabilities are already being explored in decision intelligence making in marketing campaigns, enhanced customer experiences leading to multiple research areas around customer behavior, purchases by customers, product development, forecasting and other areas. (Davenport et al., 2020)

Norvig and Stuart in their paper added that computer science focused on algorithm development, backed by equivalent hardware, to enable machines to perform intelligent tasks. “The field of computer science focused on developing machines and algorithms capable of performing tasks typically requiring human intelligence, such as problem-solving, learning, and decision-making”(Norvig Peter & Russel Stuart 2020).

With a dynamic changing business landscape , adoption of digital technologies, increasing data volumes, decision making has become a lot difficult for the human mind. AI based decision making process can contribute a lot to organization especially the small and medium organizations, where strategic decision making is reliant on an individual or a small group of individuals for strategic decision (Jarrahi 2018)

2.6 Strategic Decisioning – Humans and AI relationship

According to Jarrahi (Jarrahi 2018), there is a symbiotic relationship between Human and AI in the organizational decision making. There are 3 key factors that make decision making quite hard resulting in large ambiguity in the decision making.

Intuition[7], in a decision-making context, is defined as the ability to understand and arrive at a decision without the need for conscious reasoning. In the business context, intuition can be understood as a 'gut feeling' or 'instinct' about the outcome of and decision that involves an investment or the development and marketing of a new product.

Uncertainty could be defined as a state where it is impossible to describe an existing state, predict a future outcome. This state occurs due to lack of knowledge about the alternatives or their results.

Equivocality is defined as something that is not clear, having multiple meanings or even opposite meanings. In the business context Jarrahi defines Equivocality as "Equivocality refers to the presence of several simultaneous but divergent interpretations of a decision.

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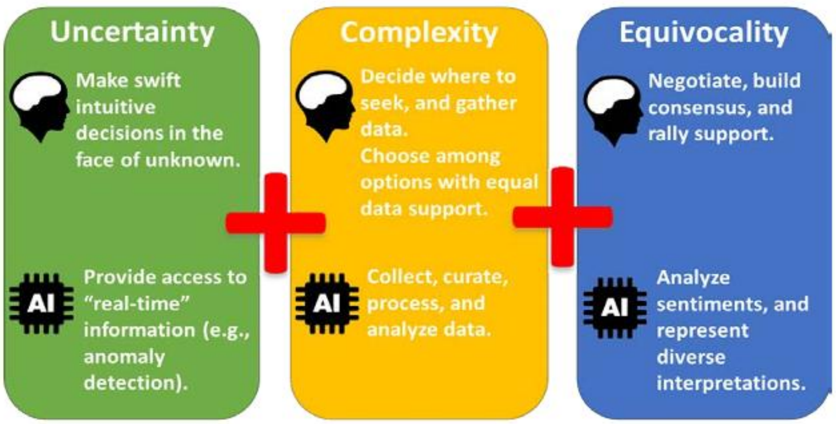
[7] Definition from Webster Dictionary online

Equivocality[8] often occurs due to the conflicting interests of stakeholders, customers, and policy makers" Jarrahi, 2018). Thus according to Jarahi, the presence of equivocality transforms decision making from an analytical rational approach to a highly subjective and perhaps political process that tries to meet the conflicting needs and objectives of multiple parties(Jarrahi 2018).

Figure 3 Humans and AI in decision making situations.



Source: Business Horizons (2018) Jarrahi M

Strategic decision-making is the process through which organizations make long-term decisions that shape their direction and future, considering their goals, resources, and the external environment(Jarrahi, 2018). Strategic decision making in smaller firms resides with a single individual or a smaller group of individuals, whereas in larger organizations the decisions are undertaken by the strategic planning team or by the members of the executive management (Jansen et al., 2013).

2.7 Artificial Intelligence and its evolution in decision making

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[8] Definition from the Cambridge Dictionary online

As technology progressed, researchers were able to create advanced and more powerful machines. This advancement enabled AI to perform more complex tasks that required more human like abilities like sensing emotions, making tactical judgements in a particular scenario (Jarrahi 2018).

In an early published paper in International Journal of Information Management (IJIM), Seeger (Seeger, 1983) voiced a concern that is still current "complex programs of the kind developed in the field of artificial intelligence may lead to information system designs where the intellectual procedures of information work will be performed by machines. This could make a significant part of human information input obsolete."

In the era of AI and Big Data Miller (Miller 2018) argued the imperative of a new human-machine symbiosis and calls for the rethink of "how humans and machines need to work symbiotically to augment and enhance each other's capabilities.".

There has been an increased interest in examining the role of AI in recent years, i.e., automation or augmentation. Some AI practitioners and researchers argue that AI should be used to augment the human judgement rather than automation(Wilson & Daugherty 2018) and "AI systems should be designed with the intention of augmenting, not replacing, human contributions" (Jarrahi, 2018).

The authors Wilson and Daugherty (Wilson & Daugherty 2018) argue that companies that deploy AI mainly to displace employees will see only short-term productivity gains thereby highlighting the need to look at integrating AI long term into organization structures. Wilson and Daugherty (Wilson & Daugherty 2018) also claim that companies can benefit from optimizing “collaboration between humans and artificial intelligence” and develop employees’ “fusion skills” that enable them to work effectively at the human-machine interface.

Recent developments in the cloud, the availability of technical resources have enabled the rise of AI making it more explainable. Practitioners and researchers are also working towards making AI and its various algorithms easier to understand and explainable (Miller 2018).

With a lot of researchers having established the relationships between strategic decision making, the complexity of decision making and use of Artificial Intelligence systems to aid some of them, there is scope for research in the direction of using AI techniques, big data, especially in the context of SME where the availability of good quality data could be obstacle towards the embracing of AI technologies.

The rise of artificial intelligence has prompted extensive academic research on its potential implications for various aspects of organizational management, including strategic decision-making (Davenport et al. 2020).

The integration of AI into strategic management has been the subject of numerous studies, with researchers examining its potential benefits and drawbacks, as well as its impact on organizational performance and competitiveness. Furthermore, scholars have explored ethical and regulatory considerations that arise from the increasing reliance on AI in decision-making processes (Bughin et al. n.d.).

In an opinion paper published by Stork , it was concluded that “As AI has become more popular today due to Big Data, advanced algorithms, and improved computing power and storage, AI systems are becoming an embedded element of digital systems, and more specifically, are making a profound impact on human decision making" (Stork 2019).

2.8 Adoption of Artificial Intelligence in SMEs

In an article on the internet, Meredith Schmidt, executive vice president and general manager of small business and essentials at Salesforce, "AI will help small businesses offer more personalized experiences to their customers by maximizing their time and automating manual tasks," Schmidt said. "If you are spending almost a quarter of your day on manual tasks like inputting data, as our research showed, AI and automation can be a huge asset."(Cummins 2024). Numerous articles on the internet point to artificial intelligence and machine learning are two critical technologies that will help SMEs to improve their businesses through data and analytics.

In a literature review conducted by Bhalerao Kuldeep and other authors (Bhalerao, Kumar & Pujari 2022) it was concluded that there were many factors such as awareness about AI benefits, information technology skill level of employees, weak financial position, organization's size, entrepreneurial orientation, and quality of data available which formed significant reasons of barriers in the adoption of AI in SMEs.

In a research conducted by Dipak Jadhav , the author pointed out that "AI is a prominent technology that not only the SME sector in India is trying to embrace, but it is one of the most promising technologies for many large organizations and governments". His research concluded that AI is essential to be adopted SMEs in India to create services through effective use of AI as an innovative technology(ScholarWorks & Sadashiv Jadhav 2021).

Most of the SMEs in any country operate under financial, operational constraints and SMEs in India are no exception. Typically, SMEs are always challenged with the following issues when it comes to AI implementations and adoption

1. Lack of knowledge of the benefits of AI and in some cases lack of understanding as a technology emanating from lack of skilled human resources.
2. Lack of understanding and knowledge leads to difficulties in forming a strategy for AI implementation and adoption. Even if there is a strategy available for AI, non-availability of a mechanism to identify KPIs, to measure and track return of investment and business performance poses a challenge for the adoption and usage of AI in SMEs.
3. Data in SMEs is not always of the highest quality. It is available in chunks and not very usable and relevant leading to a lower adoption of AI technologies.

Thus, skill level of employees, understanding level of the benefits of of AI and lack of quality data are the key challenges to AI adoption in SMEs (Bhalerao, Kumar & Pujari 2022)).

According to Singh (Singh, Garg & Deshmukh 2008) Indian SMEs face challenges in terms of cost, quality, delivery, flexibility, and human resource development. Potluri and other authors (Potluri et al. 2012) found that small businesses in India face challenges in finance, marketing, and ot(Lehtomaa & Mattsson n.d.) found that Swedish Multinational Corporations (SMNCs) in India face challenges due to limited experience and knowledge of the Indian culture and market, strict control by corporate offices in Europe, and reliance on inappropriate Western values.

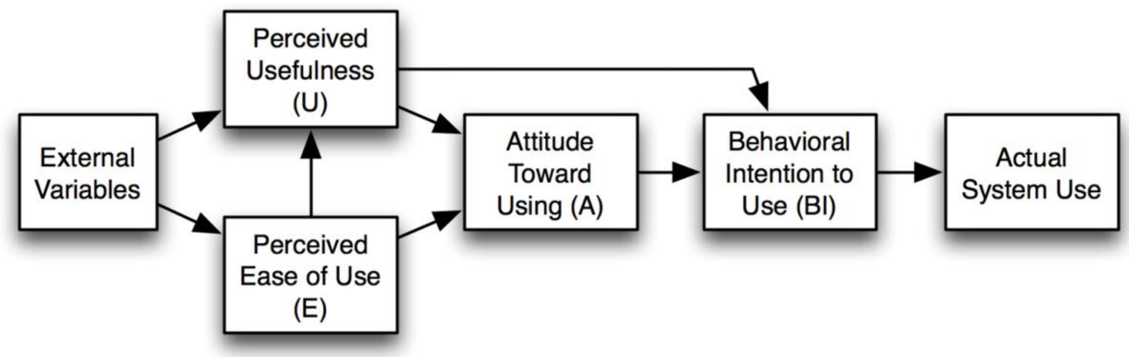
Rajagopal and others (Rajagopal et al. 2022) proposed a theoretical model that incorporates AI and marketing philosophy to enhance entrepreneurial strategic decisions. The research showed that involving internal stakeholders was helpful in managing the correlation among AI technologies and improve decision-making efficiency. Additionally, customer preferences and industry norms could moderate the link between AI systems and superior entrepreneurial judgment. The study provided entrepreneurs with technological means for enhancing decision-making and illustrates the limitless possibilities given by AI systems.

Basis the review of the research papers, it can be concluded that small and medium-sized enterprises (SMEs) in India face several challenges when implementing AI-based decision-making processes. These challenges include poor data quality, lack of understanding of cognitive technologies, data privacy, problems in integrating cognitive projects, expensive technologies, costs, and technical requirements and the lack of skilled resources with AI skills in the organization. Thus exploring AI based decision making in Indian SMEs makes the research topic more relevant.

2.9 Technology Adoption Model

Davis, Bagozzi, and Warshaw in 1989 developed the TAM theory that signified PEU, and PU in the view of an innovation adopter as focal points of consideration. TAM was considered as a logical extension of Ajzen and Fishbein's Theory of Reasoned Action (TRA) (Lule, Omwansa & Waema 2012) (Venkatesh & Bala 2008)

Figure 4 TAM Model



Source: Wikipedia

The actual system used is the endpoint where people use the technology. Behavioral intention is a factor that leads people to use technology. The behavioral intention (BI) is influenced by the attitude (A) which is the general impression of the technology.

The model suggests that when users are presented with a new technology, several factors influence their decision about how and when they will use it, notably:

Table 1 Key TAM model related definitions

Parameter Name	Definition

Perceived usefulness (PU)	The degree to which a person believes that using a particular system would enhance their job performance
Perceived ease-of-use (PEU)	The degree to which a person believes that using a particular system would be free from effort

Source: Wikipedia, (Venkatesh & Davis 2000a)

External variables such as social influence are an important factor in determining the attitude. In general, people will have the attitude and intention to use the technology. However, the perception may change depending on age and gender because not everyone is the same. TAM has been continuously studied and expanded—the two major upgrades being the TAM 2 and the unified theory of acceptance and use of technology (or UTAUT) (Marikyan & Papagiannidis 2023).

Wang and others (Wang et al. 2023) spoke about how AI has enabled the change in how to do online shopping. The research paper used the Technology Acceptance Model (TAM) as a theoretical framework, to examine how examines how AI can be made more effective and profitable in e-commerce and how entrepreneurs can make AI technology to assist in achieving their business goals.

Qin and others (Qin et al. 2020) used TAM as the basic model for studying the acceptance of Building Information Modelling (BIM) technology within organizations or companies. This study constructed a model that was based on TAM constructs.

According to Sebjan (Šebjan, Bobek & Tominc 2014), the possibility of innovation acceptance increased if adopters could envision advantages such as effort reduction and quality enhancement while performing the task. The adopter must think that the innovation is easy to use along with the PU, and it should not require a particular skill to be developed

TAM theory contained the primary assumption that the system could regulate its intended users' behavioral response and thus could impact user's discernment about the usefulness of the system. The PU was positively challenged mostly by the organization's innovativeness and then followed by process orientation within the organization, and it was least challenged positively by the organization's strategic orientation (Šebjan, Bobek & Tominc 2014).

While the organizational and Management Support (MS) were critical factors when it came to the technological adoption in an organizational context, the leader's knowledge and capabilities played a role with promoting a novel technology in their organization. Thus, organizations where there was management support to adopting novel technologies AI adoption was generally high (ScholarWorks & Sadashiv Jadhav 2021).

While the MS and CP as factors are important in TAM there are other determinants that are equally important in the TAM framework and contribute equally to the technology adoption. The TAM based studies section elaborates the usage of the determinants and TAM across geographies and industries.

2.10 TAM-Based Studies

TAM is one of the most important theories used as is or in combination with other innovation adoption models and framework. As PU and PEU were focus points on TAM, researchers used this model in usability studies related to information system deployments in an organizational setting. Below are some of the examples of TAM usage across industries and geographies.

According to the Sachez-Prieto and other authors (Sánchez-Prieto et al. 2019), to adequately accept and use AI-driven assessment tools by teachers, there was a need to enhance the AI knowledge base. The researchers used four TAM-based constructs: PU, PEU, attitude (AU), and behavioral intention (BI). Apart from this, the other four parameters, such as AI anxiety (AN), RA, subjective norm (SN), and trust (TR), were derived from Technology Innovation Theory. Out of four TAM-based attributes, PU and PEU contributed positively to change the prospective user's attitude and helped to improve behavioral intention towards AI adoption in SMEs in Australia , (Sánchez-Prieto et al. 2019; ScholarWorks & Sadashiv Jadhav 2021).

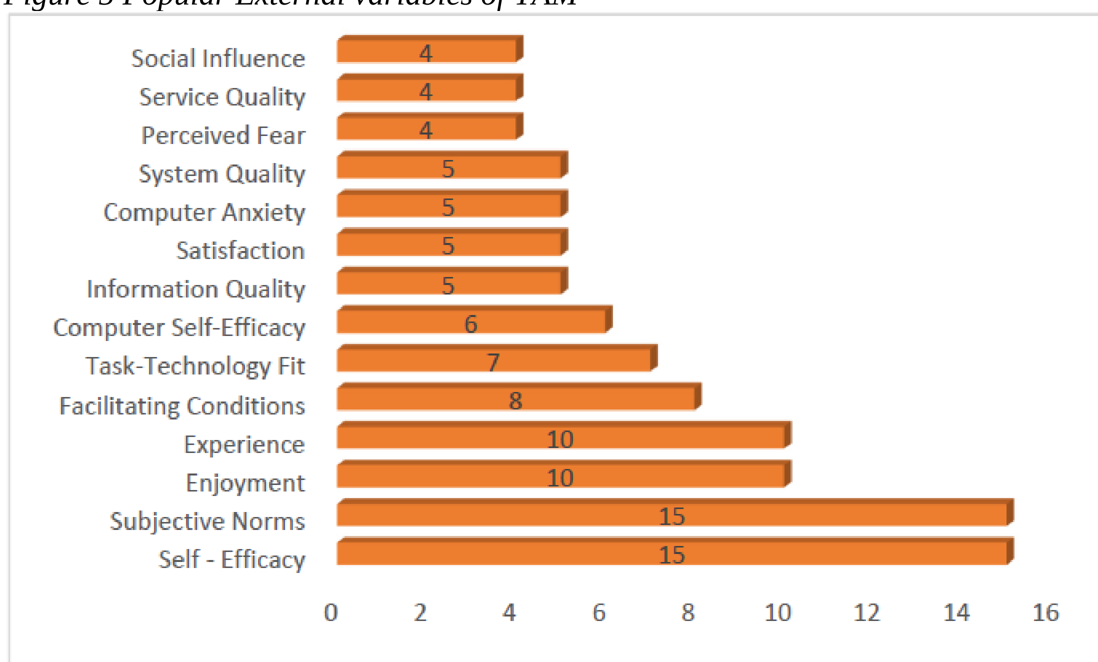
In another TAM based study about the adoption of smart mobility solutions in Malaysia, the researcher used four core constructs from TAM to determine the preference of RFID solution in mass parking spaces over roadside parking According to Ahmed and others (Ahmed et al. 2020), PU and PEU had a considerable impact on improving attitude towards smart mobility solutions.

In an empirical study conducted that was based on the TAM model to find factors influencing electronic income tax returns filing in India, a composite model using TAM and Diffusion of Innovation (DOI) was developed Kumar and others in the study (Kumar, Bhattacharyya & Krishnamoorthy 2023).

The use of Information and Communication Technology (ICT) by Small and Medium Scale businesses in Indonesia was studied using the TAM model and it involved the survey of 131 small firms. According to Suhartano and Leo, (Suhartanto & Leo 2018) PEU and PU PEU and PU formed the most critical parameters that were used in the study as part of the TAM model-based study.

In a systematic literature review exercise that was conducted by researchers in Malaysia for the sustainability of higher education during COVID -19 pandemic there were 14 external TAM variables that were the most popular ones

Figure 5 Popular External variables of TAM



Source: Google Scholar ‘A Systematic Review of the Technology Acceptance Model for the Sustainability of Higher Education during the COVID-19 Pandemic’.

The table below explains the definition of the popular external variables

The below TAM constructs will be incorporated into the study to determine the use of AI in strategic decision-making.

Table 2 Determinants of the perceived usefulness

Determinants	Definitions
Subject Norm (SN)	A person's perception that most people who are important to him/her think he/she should or should not perform the behavior in question
Job Relevance (JR)	An individual’s perception regarding the degree to which the use of AI or its equivalent is relevant to his or her job.
Output Quality (OQ)	The degree to which an individual believes that AI will help perform his or her job tasks well.
Result in Demonstrability (RD)	Tangibility of the results of using the innovation. that has been developed and whether the innovation demonstrated the objective that was set
Computer Self-Efficacy (CS)	The CS is the degree to which an individual believes that he or she can perform specific tasks/jobs using AI.
Perceptions of External Control (PEC)	The PECT is the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of AI.

Source: (Venkatesh & Bala 2008)

2.11 Balanced Score Card

The Balanced Score Card (BSC) is a measure that was developed by Robert Kaplan and David Norton that allows business executives an all-around view of their business. It is also a measure of the actions already taken (Kaplan & Norton 1991).

Balanced Scorecard allows managers and executive leaders to look at the business from 4 different perspectives.

1. Financial perspective – how do shareholders view the business?
2. Internal perspective – What must the business excel at?
3. Customer perspective – how do customers see the business?
4. Learning and innovation – What must the business improve on and learn new as well?

a) Financial perspective

Financial performance measures indicate whether the company's strategy, implementation, and execution are contributing to bottom-line improvement. Typical financial goals have to do with profitability and value. and shareholder value (Kaplan & Norton 1991).

b) Internal Perspective

Customer-based measures are important, but they must be translated into measures of what the company must do internally to meet its customers' expectations(Kaplan & Norton 1991)

c) Customer Perspective

Dealing with the most important aspects of what the customer thinks of the organization’s products and services, this perspective can have a larger impact to the revenue of the organization there by impacting the operating margin of any organization (Kaplan & Norton 1991).

d) Learning and Innovation Perspective

The ability of an organization to innovate, learn is tied to the employees and thereby to the value of the company(Kaplan & Norton 1991).

2.12 BSC Related Studies

Huang (Huang, HC 2009) in his research highlighted how BSC is a powerful tool for setting objectives and appropriate measures to facilitate objective achievements. It was presented how a BSC-based knowledge management system could help the management in strategic decision-making with the focus on the development of a rules-based knowledge management system that facilitated decision-making,

Empirical studies conducted in the Malaysian SMEs showed that BSC had a positive influence on the firm’s performance especially in the context of internationalization and innovations. However, this study did not focus on the co-related study of the firm's performance, BSC, strategic decision making and Artificial Intelligence, thereby allowing for an exploration of the co relation in this area.

Creamer and Freund (Creamer & Freund 2010) explained and reasoned the use of Adaboost a machine learning boosting algorithm that could be employed to improve corporate performance for a data-based Balanced Scorecard performance. This brings an interesting point of discussion that Artificial Intelligence can be employed in conjunction with the BSC framework and thereby contribute to improving business performance. This paper being very technical focused on a single algorithm to improve performance, however, did not explore the correlation between Strategic decision-making, artificial intelligence, and its impact on profitability.

Sterling (Sterling 2023) in his article wrote about how AI when incorporated within a proven framework as BSC can improve data analysis, resource allocation and performance monitoring of organizations.

2.13 Financial performance management parameters

As per the 5paisarearch team (5paisaReseach Team 2023) a critical financial metric that is used by organizations that provided insights into the company’s profitability and efficiency is Operating Margin. Operating margin enables organizations to decide on strategic initiatives, carry out benchmarking and other comparison with peer industry etc. Operating margin and EBITDA (Earnings Before Interest, Taxes, Depreciation, and Amortization) are both financial metrics used to evaluate a company's profitability, but they differ in their focus. Operating margin measures the profitability of a company's core operations, while EBITDA is a more comprehensive measure that includes non-operating income and expenses.

EBITDA provides a clearer picture of a company's overall financial performance, in terms of amount, while the operating margin is rather based on percentage which helps to compare the profitability with our companies. However, the operating margin is a more reliable measure of a company's operational efficiency, focusing also on finance activities.

Bouwens (Bouwens 2018) in his working paper concluded that EBITDA is a popular financial metric often disclosed to report on company performance. “EBITDA serves as a hybrid financial concept that combines elements of both earnings and cash flows. However, EBITDA conveys both cash flow and accrual information imperfectly, leaving the financial statement user with the question of what incremental information EBITDA conveys about the fundamental value of a company”.

Narayanaswamy (Narayanaswamy 2021) pointed out how established Indian companies use EBITDA as a measure of the financial performance of their organizations. However, there is minimal research on whether EBITDA is used as a measure of company performance and strategic decision-making in Indian SMEs.

2.14 Summary and Transition

Review of the available literature indicated that there was no extensive study that involved the SME sector where AI implementation and use were evaluated for using strategic decision-making and improving profitability. Though there was some study that indicates the use of EBIDTA and other financial metrics to determine the performance of the organization, there is no extensive study that explored the intersection between the financial performance parameters (EBDITA, Operating Margin) the Balance Score card framework (BSC) and AI in Indian SMEs that would help executives in SMEs with strategic decision making. Some of the research papers were helpful with identifying some of the challenges that are faced by the SMEs in AI adoption. Literature review highlighted the high dependence on human intelligence is high in SMEs, especially with decisioning resting in the hands of a select few in SME organizations. Use of BSC framework was also fragmented and, in some cases, nonexistent in SMEs.

Researchers and scholars used the Technology Acceptance model (TAM) to determine the acceptance of new technology for business problems. Thus, based on the literature review and the direction for the research, TAM is a suitable framework that could be used to study the intention of use and the possibility of actual use of AI, and BSC to enable strategic decision-making in SMEs.

Therefore, our aim to study the combined effect of Balanced Scorecard (BSC) constructs alongside Technology Acceptance Model (TAM) related constructs in the context of Artificial Intelligence as the technology and determine the positive impact on the profitability parameters (EBDITA, Operating Margins) of the SME in India forms a novelty in the research from a technology and process perspective. This research will look to contribute positively to the adoption factors of some of the latest technologies like Generative AI, and AI tools in profitability enhancements for SMEs.

The next chapter provides details of how the research would progress, focusing on the research objectives, the research questions while working withing the boundaries of the ethical practices, identification and working within the limitation of the research that would emanate as part of the research.

CHAPTER III:

METHODOLOGY

3.1 Overview of the Research Problem

As seen in the previous chapter (literature review) the novelty in the research is the opportunity to co relate Artificial Intelligence, Balanced Score card to improve profitability and strategic decision making for SMEs in India. The further chapters of the thesis explore and try to delve deeper to address some of the gaps identified and the research questions that were introduced in the chapter 1.

The research aims to explore the effects of integrating Artificial Intelligence (AI) into the strategic decision-making processes of Indian Small and Medium Enterprises (SMEs). By the assessment of current levels of AI adoption and its influence on various financial and non-financial performance indicators, the study sought to develop actionable recommendations for SME leaders. To achieve this, it was essential to understand the challenges that contributed the most to the reluctance of SME decision-makers to integrate AI into their decision-making processes. Identifying some of the barriers, complexities, and key factors provided a good understanding of the current state of AI adoption and laid the foundation for better recommendations. Furthermore, the study aimed to ensure that the proposed AI solutions aligned with the Indian SMEs scenario. By identifying the factors, best practices, and models that proved effective at reducing costs or increasing revenues, measured by metrics such as EBITDA or profit margins, the research sought to offer practical guidance for SMEs to leverage AI for enhancing profitability and maximizing company value.

3.2 Research Purpose

With the integration of Artificial Intelligence (AI) into business becoming increasingly important across industries including SMEs, this research sought to address the challenges and opportunities associated with implementing AI in decision-making processes. The primary focus of the research objectives was to identify opportunities and area to enhance strategic decision-making and thereby make a positive impact on the profitability of the SME industry in India.

Table 3 Research Objectives and Rationale

Objective#	**Research Objective**	**Rationale**
RO1	Evaluate, and propose practical recommendations for the optimal integration of AI in strategic decision-making to enhance financial performance outcomes in Indian SMEs	The integration of Artificial Intelligence (AI) into strategic decision-making processes has the potential to impact the performance outcomes of Indian Small and Medium Enterprises (SMEs). By evaluating the current state of AI adoption and its impact on financial and non-financial

Objective#	Research Objective	Rationale
		metrics, practical recommendations can be developed to guide SME executives in better integration of AI, ensuring enhanced overall organizational performance and sustainability of SME enterprises.
RO2	Identify, analyze, and understand the challenges faced by Indian SMEs in the implementation of AI in decision-making processes, with a focus on exploring the barriers, and key factors affecting the successful adoption and integration of AI technologies.	To understand the landscape of AI adoption in Indian SMEs, it is required to understand the challenges that increase the reluctance of SME decision makers to integrate AI into their decision-making process. Uncovering the barriers, complexities, and key factors will provide a good understanding of the current state and lay the foundation for better recommendations

By acknowledging the challenges, identifying effective models, and possibly exploring innovative solutions, this research endeavored to contribute valuable knowledge that could empower executives of Indian SMEs to explore the use of AI to integrate with strategic decision making (improving profitability) for their businesses.

Research objective #1 formed the primary research objective that aimed to explore the various factors related to the integration of Artificial Intelligence (AI) into strategic decision-making processes to enable business executives in SMEs in India to improve the revenue and/or the margins (financial perspectives) for their organizations.

3.3 Conceptual Framework

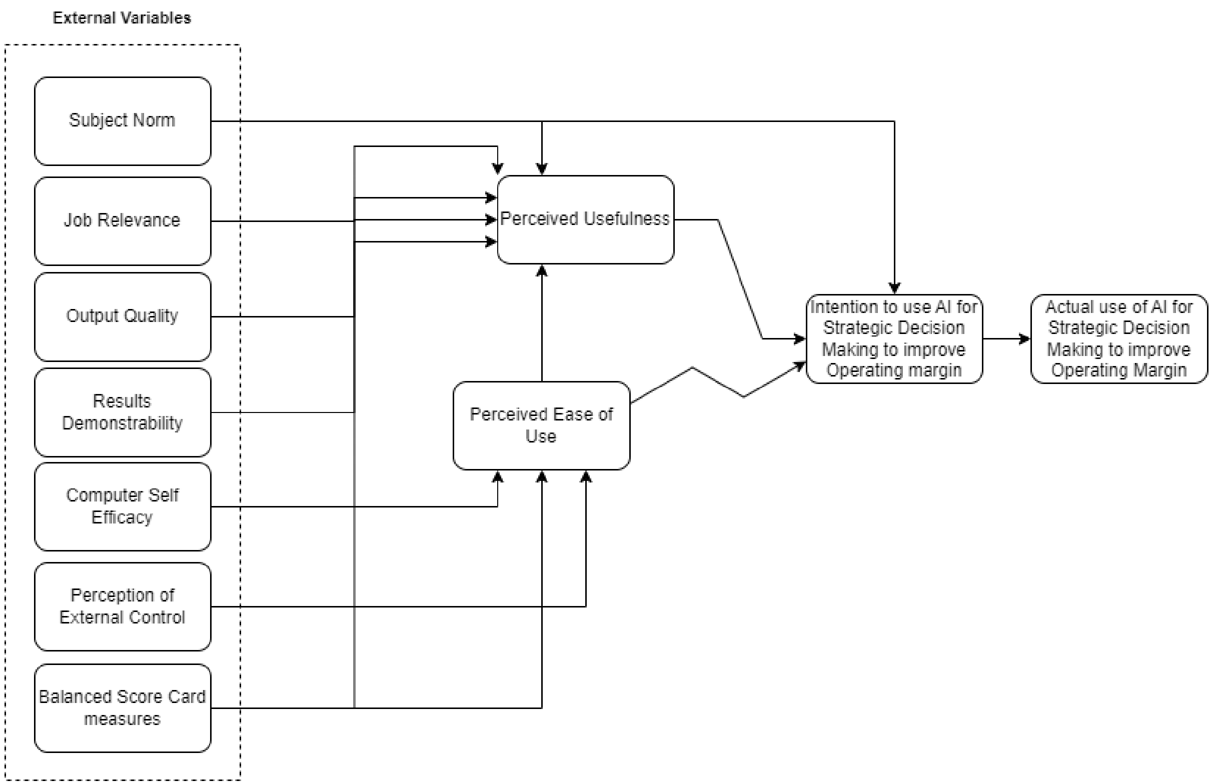
This study used an empirical model[9] approach to study the relationship between AI strategic decision-making factors, financial performance metrics that impact the profitability of the Indian SME.

The framework was built and conceptualized by the author based on the Technology Acceptance model. The influence of AI on strategic decision making and improved profitability was determined by the two key factors from TAM model, Perceived Usefulness (PU) and the Perceived Ease of Use (PEU). These two factors determined the intent of the end users to apply AI for their use for their profitability improvements within their organizations.

[9] https://en.wikipedia.org/wiki/Empirical_modelling

As with any framework the impact on the outcome factors was determined by the inputs external variables that were provided to the framework / model. In the study there were several external variables that were incorporated from the TAM and the BSC framework. Together with the input and the output variables, the conceptualized framework was created to proceed with the analysis of the research objectives. The figure below provides a visual representation of the AI – Enabled Strategic Decision framework for profitability improvement.

Figure 6 AI Enabled Strategic Decision framework for profitability improvement



Source: Conceptualized and conceived by the author, 2023

To test the above framework a logistic regression-based model was adopted to determine the co relation between external variables and the two key variables of perceived ease of use and perceived usefulness. In addition, to determine the relationship of PU and PEU, analysis alongside key dimensions along the financial perspective such the impact to Operating margin using Artificial Intelligence also was carried out; multi-dimensional analysis thus contributed to a well-rounded result which will be discussed in the results chapter (Chapter 4) of the study.

The table below provides a description of the various variables that were used in the model to determine their influence on the study and the research objectives.

Table 4 TAM variables and its importance

Variable	Description	Importance	sub variables
Output Quality (OQ)	The degree to which an individual believes that AI will help perform his or her job tasks well.	Perceived Outcome Quality (OQ) in TAM is critical as it measures users' perceptions of the effectiveness and performance of a technology, influencing their acceptance and continued usage decisions.	2

Perceptions of External Control (PEC)	The PECT is the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of AI.	Perception of External Control (PEC) in TAM is crucial as it evaluates users' beliefs about the influence of external factors (such as luck or others' actions) on their ability to use technology effectively, impacting their adoption decisions and behavior.	3
Result in Demonstrability (RD)	Tangibility of the results of using the innovation that has been developed and whether the innovation demonstrated the objective that was set	Results Demonstrability (DE) in TAM is significant as it measures users' perceptions of how tangible and observable the benefits and outcomes of a technology are, which affects their willingness to adopt it.	0
Subject Norm (SN)	A person's perception that most people who are important to him/her think he/she should or should not perform the behaviour in question	Subject Norms (SN) play a crucial role in the Technology Acceptance Model (TAM), influencing individuals' perceptions and behaviors towards adopting new	3

		technologies, thereby shaping their acceptance decisions based on societal expectations and peer influence.	
Computer Self-Efficacy (CS)	The CS is the degree to which an individual believes that he or she can perform specific tasks/jobs using AI.	Computer Self-Efficacy (CSE) in TAM is crucial as it evaluates users' confidence in their ability to use technology effectively, influencing their attitudes and intentions towards adopting and using new technologies.	0
Job Relevance (JR)	An individual's perception regarding the degree to which the use of AI or its equivalent is relevant to his or her job.	Perceived Job Relevance (JR) in TAM is pivotal as it assesses how users perceive the utility and applicability of a technology in their work context, directly impacting their motivation and intention to adopt it.	3

Source: (Venkatesh & Bala 2008; Venkatesh & Davis 2000b) and as conceived by the author

Table 5 BSC variables and its importance

Variable	Description	Importance	Sub variables
Operating Margin, EBIDTA	Monitor the finance perspective of any organization and enable keeping a tight control on the operating margins/revenue growth of any organization. The financial perspective plays a crucial role in strategic decision making for any SMEs	The financial perspective of the Balanced Scorecard (BSC) is vital as it tracks key metrics like EBITDA and operating margin, which reflect a company's profitability and operational efficiency. These metrics guide strategic decisions to ensure long-term financial health and stability.	6
Employee Satisfaction and Engagement (ESE)	Assess employee satisfaction and engagement levels through surveys and feedback mechanisms.	SMEs rely on and flourish when their employees are engaged and productive, resulting in lower attrition. Longer loyal	3

Variable	Description	Importance	Sub variables
	Engaged employees are more likely to contribute to innovation and organizational success.	employees would mean better productivity and better sustenance	
Innovation and New Product Development (INPD)	Evaluate the SME's ability to innovate and develop new products or services. Metrics can include the number of new product launches, time-to-market for new products, and the percentage of revenue derived from new offerings.	Innovation is key for SMEs to stay competitive and meet evolving customer needs. Developing new products or services helps SMEs expand their offerings and enter new markets, contributing to long-term sustainability.	0
Knowledge Management (KM)	Measure the effectiveness of knowledge-sharing mechanisms within the organization. This may include metrics on the use of internal knowledge	For improved productivity, innovation in SME organizations are required to have knowledge-sharing mechanisms within the	0

Variable	Description	Importance	Sub variables
	repositories, collaboration tools, and the successful application of shared knowledge in decision-making.	organization to improve the productivity of the employees and organizations	
Operational Efficiency (OE)	Measure the efficiency of key operational processes, such as production, delivery, and service provision. Key performance indicators (KPIs) might include cycle time, lead time, and resource utilization.	Operational efficiency is vital for SMEs to manage costs, improve productivity, and deliver products or services effectively. Efficient internal processes contribute to better profitability and competitiveness.	0

Source:(Kaplan & Norton 1991) and as conceived by the author (2023)

3.3.1 Dependent Variable

Measuring the impact of various financials perspectives as EBITDA and or Operating margin[10] of the organization will help to determine the effectiveness of the organization's strategic decision making when using AI. Though both financial performance parameters are used in the context of organization profitability measurement, for this study impact of the use of AI on Operating Margin (OM) was analyzed; as OM is a financial indicator and a direct measure of whether the core business is profitable or not. Operating margin formed the primary financial parameter dependent variable that was analyzed for the various other independent variables used in the study.

Operating margin is calculated as below

Operating margin (OM) = Operating Income (OI) /Revenue (R)

Operating Income (OI) will be defined as EBITDA.

Revenue (R) is defined as the total amount of income that a company or organization generates from sale of goods and services. It is also referred to as top line of the organization or company.

3.3.2 Independent Variables

The independent variables used in the study were a combination of the variables from both the theoretical models of Balanced Score card (BSC) and Technology Adoption Model (TAM). Table 4 depicts the definitions of the variables and its importance in the study

[10] https://en.wikipedia.org/wiki/Operating_margin

3.4 Operationalization of Theoretical Constructs and framework

The study was based on the theoretical foundations of the Technology Acceptance Model (TAM), Balanced Score Card (BSC). The study focused on the impact of financial perspectives, mainly operating margin and EBIDTA with AI. While the study formed the core research question and objective, the study also explored the relation of the use of AI and its influence on employee satisfaction, knowledge management, learning and innovation. Though not directly related, employee satisfaction, knowledge management, learning and innovation all can contribute to improved productivity there by improving the Operating margins, EBIDTA of organizations.

In this study, there were 11 main variables related to BSC and TAM theory. However, as part of the study some of the main variables had sub variables associated with them as part of the questions that were put to the participants. The table below shows the relation between the model category, the variables and the question that was related to the variables from the survey.

Table 6 Operationalization of the constructs

Sr#	Theoretical Model	Variables	Question
1	BSC – Financial perspective	resp_bcspm3	AI can be used a innovative tool that can help in the improvement of revenue and / or operating margin for my organization

Sr#	Theoretical Model	Variables	Question
2	BSC -Financial Perspective	resp_bscpm1	We use EBIT to measure the organization performance (EBIT is Earnings before Interest and Taxes)
3	BSC- Financial Perspective	resp_bscpm2	We use Operating Margin as our primary measure to measure organization and various departments performance
4	BSC-Financial Perspective	resp_bscpm4	We are seeing improvements in our bottom line (profits and margins) using AI
5	BSC-Financial Perspective	resp_bscpm5	We are exploring AI for revenue growth initiatives (Marketing, Campaigns, Leads, sales etc) to improve our top line (revenues)
6	BSC-Financial Perspective	resp_bscpm6	We are seeing improvements in our revenue using AI
7	Organizational Context	resp_bscpm7	In your opinion, what is an approx. improvement in your bottom line expected from the AI Initiatives?
8	Organizational Context	resp_bscpm8	In your opinion, what is an approx. improvement in your top line expected from the AI Initiatives?

Sr#	Theoretical Model	Variables	Question
9	TAM	resp_cs	We have AI initiatives already in progress to improve profitability and I am actively involved for the same
11	Technology	resp_di1	There are measures in place to measure organization performance but the data required is not in a single place
12	Technology	resp_di2	The effort required to bring the appropriate data , cleanse it and make it presentable to measure organization performance is significantly large
13	Technology	resp_di3	There are appropriate data and reports in place to measure organization performance with minimal human intervention
14	BSC -Learning Perspective	resp_ese1	My organization encourages enablement (training, learning etc) to help develop the necessary skills for AI initiatives
15	BSC -Learning Perspective	resp_ese2	We could benefit from AI driven insights that could help to improve Employee satisfaction and engagement thereby help improve employee retention

Sr#	Theoretical Model	Variables	Question
16	BSC- Learning Perspective	resp_ese3	Improved Employee retention could improve efficiency and there by positively impact profitability of the organization
17	BSC - Internal Perspective	resp_inpd	AI is a disruptive development, and my organization is exploring AI for innovative ways to improve the business
18	TAM	resp_jr1	Does your role involve day to day decision making or strategic decision making?
19	TAM	resp_jr2	Are you familiar using Artificial Intelligence or implementing Artificial Intelligence in your organization?
20	TAM	resp_jr3	In your current job role, to what extent do you believe that AI could help with strategic decision making or day to day decision making?
21	BSC- Learning Perspective	resp_km	We could benefit from Knowledge initiatives related to AI that would improve our understanding of how to use AI for strategic decisioning and day to day decisioning

Sr#	Theoretical Model	Variables	Question
22	BSC- Internal Perspective	resp_oe	We are exploring AI for operational efficiencies (Automation, process efficiencies etc) initiatives to improve the bottom line (margins)
23	TAM	resp_oq1	AI can positively impact financial performance parameters (E.g.: Revenue, Operating margin, EBIT etc.) if used in the right manner?
24	TAM	resp_oq2	AI can help impact non-financial performance parameters (E.g.: Customer Service Index, Customer Retention, Employee retention index etc.) positively
25	TAM	resp_pec1	We have the necessary skills, plans and structure in place to support AI initiatives to integrate decision making into the process
26	TAM	resp_pec2	We have the necessary Infrastructure to support decisioning making initiatives using AI
27	TAM	resp_pec3	We have the support at all levels in the organization to enable and integrate AI for decision making

Sr#	Theoretical Model	Variables	Question
31	TAM	resp_rd	We are already exploring AI for decisioning wherever possible
32	TAM	resp_sn1	My organization has a vision, direction to use AI to improve the workings of business functions
33	TAM	resp_sn2	We think that using AI will have a positive impact on individuals and team productivity
34	TAM	resp_sn3	We think using AI will improve operational efficiency and positively impact the profitability of our organization

3.5 Research questions

In the earlier sections, the research objectives highlighted the importance of what the research is looking to achieve. As with every research, there were a set of research questions that required answering to prove the validity of the research. For this study a primary question that formed the core of this research. The primary research question was

RQ1 Can Strategic decision-making processes, guided by Artificial intelligence, impact financial performance metrics such as (EBITDA or Operating Margin) within the context of the Balanced Scorecard framework in Indian Small and Medium Enterprises?

Null Hypothesis ($H_0$1): “Strategic decisioning process especially financial performance metrics (EBITDA or Operating Margin) is impacted positively when guided by Artificial Intelligence in the context of the Balanced Scorecard framework”

Alternate Hypothesis ($H_1$1): “Strategic decisioning process especially financial performance metrics (EBITDA or Operating Margin) has no impact when guided by Artificial Intelligence in the context of the Balanced Scorecard framework”

To determine the hypothesis of the primary research question, there were 8 secondary questions that were hypothesized to determine the hypothesis for the primary research question.

SQ1 Is EBIDTA impacted positively when guided by Artificial Intelligence for decision making?

Null Hypothesis ($H_0$1): “EBIDTA is positively impacted by the use of Artificial Intelligence in the decision-making process in SMEs.”

Alternate Hypothesis ($H_1$1): “Artificial Intelligence when integrated into the decision-making process has no significant impact on EBDITA in SMEs.”

SQ2 Is Operating Margin impacted positively when guided by Artificial Intelligence for decision making?

Null Hypothesis ($H_0$2): “Operating Margin is positively impacted by the use of Artificial Intelligence in the decision-making process in SMEs.”

Alternate Hypothesis ($H_1$2): "Artificial Intelligence when integrated into the decision-making process has no significant impact on Operating Margin in SMEs."

SQ3 Does the use of artificial intelligence have a co relation with the improvement of operating margins in SMEs?

Null Hypothesis ($H_0$3): "Operating Margin is improved by the use of Artificial Intelligence when integrated in the decisioning making processes in SMEs."

Alternate Hypothesis ($H_1$3): "Artificial Intelligence when integrated into the decision-making process has no significant impact on Operating Margin in SMEs."

SQ4 Does the use of artificial intelligence have a co relation with the improvement of revenues in SMEs?

Null Hypothesis ($H_0$4): "Revenues are improved by the use of Artificial Intelligence when integrated in the decisioning making processes in SMEs."

Alternate Hypothesis ($H_1$4): "Artificial Intelligence when integrated into the decision-making process has no significant impact on revenues in SMEs."

SQ5 Is Artificial Intelligence an innovative tool that enables SMEs to significantly impact their revenues and operating margins ?

Null Hypothesis ($H_0$5): "Artificial Intelligence is an innovative tool that has the ability to influence revenues and operating margins of SME organizations positively."

Alternate Hypothesis (H_15): "Artificial Intelligence is an innovative tool that has no significant impact on the ability to of SME organizations to influence revenues and operating margins."

SQ6 Is Artificial Intelligence an innovative tool that can be integrated into the decision-making process for SMEs?

Null Hypothesis (H_06): "Artificial Intelligence is an innovative tool that can be integrated into the decision-making process for SMEs for a significant impact."

Alternate Hypothesis (H_16): "Artificial Intelligence is an innovative tool that has no significant impact when integrated into the decision-making process for SMEs."

SQ7 Is there an association of exploring AI for revenue growth initiatives (Marketing, Campaigns, Leads, sales etc) to improve top line (revenues) in Indian SMEs?

Null Hypothesis (H_07): "There is no significant association between exploring AI for revenue growth initiatives and improvements in the top-line revenues in Indian SMEs."

Alternate Hypothesis (H_17): ""There is significant association between exploring AI for revenue growth initiatives and improvements in the top-line revenues in Indian SMEs."

SQ8 Does AI positively impact financial performance parameters (E.g.: Revenue, Operating margin, EBIT etc.) if used in the right manner in Indian SMEs?

Null Hypothesis (H_08): "AI does not positively impact financial performance parameters (e.g., Revenue, Operating margin, EBIT) when used in the right manner in Indian SMEs"

Alternate Hypothesis ($H_1$8): "AI positively impacts financial performance parameters (e.g., Revenue, Operating margin, EBIT) when used in the right manner in Indian SMEs."

In addition to the primary research question, there was another research question conceptualized to determine whether there were any additional barriers in implementing AI based strategic decisioning for profitability improvement and if there were any further co relation from the literature review done on this subject by earlier scholars.

RQ2 What are the key challenges faced by Indian Small and Medium Enterprises (SMEs) in implementing Artificial Intelligence (AI) in their decision-making processes, and their influence on the successful adoption and integration of AI technologies?

To answer the above research question, the following secondary questions were postulated to determine the correlation between the key challenges faced by the Indian SMEs, with the emphasis being on the availability of data that would be used by Artificial Intelligence, the availability of the skills in their organization and the availability of infrastructure required to implement the AI for supporting the strategic decision making.

SQ9 How does the availability of the right skill set influence an AI aided strategic decision-making processes in SMEs?

Null Hypothesis ($H_0$10): “Availability of the right skills in the SME organization significantly impacts the organization’s ability to implement AI aided strategic decision making.”

Alternate Hypothesis ($H_1$10): “Availability of the right skills in the SME organization has no impact in the organization’s ability to implement AI aided strategic decision making.”

SQ10 How significant is the need for an infrastructure for SMEs to enable their ability to implement AI aided strategic decision making?

Null Hypothesis ($H_0$11): “The presence of a robust infrastructure significantly enhances the ability of SMEs to implement AI-aided strategic decision-making processes.”

Alternate Hypothesis ($H_1$11): “The presence of a robust infrastructure has no significant impact on the ability of SMEs to implement AI-aided strategic decision-making processes.”

3.6 Research Design

The research design and methodology were proposed to be focused as a cross-sectional study that could examine the relationship between the BSC and TAM theoretical models, the extent to which they influenced AI implementation, and its potential use to improve profitability for the SME sector in India and in turn aiding strategic decision making amongst the executive team of the SMEs. The approach was to create a survey where the participants were employees from the SME sectors who used BSC or something similar[11], key decision makers who were responsible for the direction of the companies and technical team who were data aware i.e. they understood the value of data and were aware of potential use of AI.

We proposed the use of a survey tool like Google Forms to design and host the survey.

There are three (3) known methods of research primarily quantitative, qualitative, and mixed methods.

Qualitative methods of research are generally applied when one studies a single phenomenon over a longer period or multiple phenomena(UNIT 8 QUALITATIVE RESEA. (IGNOU 2018)

Quantitative methods are used when there is statistical and numerical analysis and inferences to be drawn(Gupta Smita 2017). (IGNOU & Gupta Smita 2017)

Mixed methods are used when both qualitative and quantitative data together can provide a better understanding of the research problem(Fischler Abhraham n.d.)

For this research, a quantitative method to study the correlation between the factors that influenced strategic decisions and impact the profitability of SMEs in India was applied. As the idea was to study the factors that aided strategic decision-making to improve profitability using Artificial Intelligence, it was important to design the survey so that it covered a decent cross-section of the population.

[11] A similar framework could be the use of GAAP and Non-GAAP practices within SMEs, with the use of Operating Margin and EBITDA

To ensure the validity and effectiveness of the survey, previously validated surveys was searched for. Given the novelty of the research and the limited literature available, the survey question had to be designed from scratch.

To understand the use of AI in strategic decisions and improve profitability in India's SME sector, a cross-sectional survey[12] was adopted. Cross-sectional surveys were chosen because they are inexpensive and fast. For a point in time, the cross-sectional survey also could act as a catalyst for future surveys and research. A cross-sectional survey design helped to reach the participant group with less effort and met the minimum sample size essential for the analysis.

3.7 Population and Sample

The target population were decision-makers at various levels involved in strategic decision-making and day to day decision making, and technologists involved in the adoption, implementation, or use of AI technology within their organization or in a personal capacity.

In a LinkedIn[13] article, Ankush Jain (2023) estimated that there were approximately 42 million MSMEs in India registered and unregistered in 2023. In 2023, the MSME sector contributed to 6.11 % of the manufacturing GDP and 24.63 % of the Service sector producing approximately 6000 products and employing about 106 million people.

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12 https://www.surveylegend.com/survey-examples/cross-sectional-surveys/

13 https://www.linkedin.com/pulse/sme-sector-india-statistics-trends-challenges-ankush-jain-cfa

As per data from the Ministry of Micro, Small & Medium Enterprises, the Udyam[14] Registration portal registered approx. 20,061,407 MSMEs in 2023. The registered micro-enterprises stood at 19,430,788 (96.87%), followed by small enterprises at 576,752 (2.87%) and midsized enterprises at 53,867 (0.26%).

Micro enterprises are small businesses or household businesses that are likely to run into financial constraints with the use of technology as niche as Artificial intelligence, hence for this research, the micro enterprises were not included in the sample population for the research data.

3.8 Participant Selection

Participation in this research was entirely voluntary and emphasized the participant's right to choose whether they would like to take part in the study. Participants received the appropriate information about the research goal. There was no monetary benefit paid for the participation in the research survey, nor conflict of interest or undue influence to coerce the influence or outcome in the research environment. There were three questions added in the survey to help identify the role of the participants and determine whether the participants were involved in AI initiatives in their organization and whether they were involved with decision making.

3.9 Instrumentation

[14] It is the Government Portal for the registration of MSMEs. It was launched by the Union MSME Ministry in 2020. It provides free-of-cost and paperless MSME registration.

The online survey instrument allowed participants to participate in the survey without disclosing their personal information, avoiding any bias while deriving the survey's conclusion. The online surveying method provided the participants' flexibility to attempt the survey at a convenient time and place. Email was the preferred option to respond to surveys where organizations had a restricted environment to access the unofficial websites within their premises. However, during this study social media was used and there was no need to send the questionnaire via email to participants.

The survey instrument used for this study was created to make it more suitable for gathering data related to AI, its implementation in SME, its relevance for TAM, BSC theoretical constructs. The questions were designed such that the participants were not required to understand the underlying theoretical constructs (ScholarWorks & Sadashiv Jadhav 2021).

Questions related to demographic information about the participants about participant’s title, industry sector, gender, age group, education level, and experience in using AI technology were also added(ScholarWorks & Sadashiv Jadhav 2021). The form had a facility to accept the facility of accepting free flow text from survey participants.

The next survey instrument used were questions around BSC (Balanced Score Card). Questions from this survey helped to collect information around the usage of Balanced Score Card and how it is being used by end users and implementors in the SME section in India.

3.10 Data Collection Procedures

According to Statista[15] as of Feb 2023, it is estimated that there are more than 90,000,000 employees in the MSME sector in India. However, there was no information available on how many employees work in 53,867 SMEs[8]. There was no authentic information regarding how many of India's SME sector use AI-related initiatives or how many are directly or indirectly involved in AI technology for strategic decision-making. A question regarding this was added to the survey to understand whether participants had some experience using AI technology, whether they were involved in activities using AI technology and whether they saw the use of AI in strategic decision making. The requisite number of participants were solicited by engaging the participants using social media. The online survey was rolled out to the participants using Google forms platform. To conduct a study in the required time, meet the quality requirements, and possibly within the possible efforts, selecting a relevant sample size was very important

The study collected data through a survey, and it represented quantitative data. Data was collected through a Google forms questionnaire. There was a provision to set up an interview with the participants if needed. For the research to produce a realistic outcome, the data was distributed over a decent size of the population. There were 46 questions covering gender educational background, different positions, use of AI in the organization, willingness to use AI for strategic decision-making, impact of using AI for profitability, factors impacting the use of AI in their organization(s) and the use of Balanced score card parameters or similar. The questions used a Likert[16] scale (scale from

[15] https://www.statista.com/statistics/1384916/india-number-of-employees-of-registered-msmes/

[16] https://en.wikipedia.org/wiki/Likert_scale

0 -5) and some free text responses. The free text responses were limited to 3 questions and were optional. The responses of these questions were also limited to 200 words per question. The qualitative nature of this response was also considered to allow for participants to express their thoughts in a concise manner.

Given the number of enterprises and the number of employees in SMEs in India, it was not humanly possible to reach out to each one of them. Given the limited time available and the cross-section nature of the study, social media sites such as LinkedIn, and Facebook were used to publish the survey in groups that the researcher was part of ,to collect data to be used for the analysis.

Online survey method was used to collect the required data about AI, strategic decision using AI and its influence on improving profitability in Indian SMEs. Some of the survey questions were influenced by the survey instruments used to determine the factors influencing the acceptance of cloud computing environments (Amron et al. 2019). Post the setup of the Google forms survey, the survey was put up on LinkedIn for participation. The survey link was also shared on WhatsApp with a close professional network of friends and family. During the timeframe the survery was open, there were 75 responses that were received which formed the basis for the data preparation and further data analysis.

3.11 Data Management, data protection and storage

In adherence to ethical standards and with a paramount commitment to safeguarding participants' rights, this research upheld the principles of confidentiality and anonymity throughout all phases of the study. All collected data was treated with the utmost sensitivity and stored securely with restricted access. No personal information related to the organization, or the participants such as name was collected during the research. All the information collected during the research was stored using appropriate protocols as defined by SSBM, Geneva respecting GDPR.

Due to the feature of the survey tool, it was required to have the email of the participant recorded in the form and thereby in the data set. However, for all the analysis the email address of the participants was eliminated from the raw response file that was used for the data analysis. This approach ensured that the analysis file did not contain any personal information of the participant that could be used to trace it back to the participant at any time. The data collected by the questionnaire was tored on a password-protected spreadsheet on my laptop and in a secure cloud storage on the author's personal drive until the dissertation/research process is complete. After the dissertation, the data will be stored in a password-protected folder on secure cloud drive for the prescribed timeframe as per SSBM and GDPR standards.

3.12 Ethics, Confidentiality & Anonymity

The study adhered to established ethical guidelines, prioritizing informed consent, confidentiality, and voluntary participation. Measures were put in place to protect the rights and privacy of participants throughout the research process.

While conducting the research, primarily during the data collection, and rolling out the survey to all the participants, the following practices were considered. All the necessary information such as the purpose of the research and its outline was readily provided to all the participants before they participated in the data collection.

3.13 Informed Consent

All the necessary information such as the purpose of the research and its outline was made available to the participants before they participated in the survey. It was intended that the participants were aware and provided their content before the survey is attempted. The consent was part of the online survey tool provided. **(Appendix A, Appendix B)**. The participants were allowed to withdraw from the participance of the survey at any time during the survey. The consent process was conducted in a language and format accessible to participants, ensuring their comprehension.

3.14 Threats to Validity

Threats to validity are indispensable aspects of quantitative research studies involving the survey instruments, as an ineffective discussion of the research validity creates hindrances in understanding the research (Steckler & McLeroy 2008) To be precise, the discussions about the threats to validity is critical in quantitative research especially while using statistical methods to find answers to questions or validate the researcher's claim (Cruzes & Ben Othmane n.d.). It is essential to discuss threats to the validity to sufficient depth, as it can become difficult to prove the applicability of research in one setting to another, or the results' generalization becomes a task of significant effort otherwise ((Steckler & McLeroy 2008), There were four types of research validities that the researcher considered viz measurement (construct), conclusion, internal, and external validity threat (Steckler & McLeroy 2008)..

3.14.1 External Validity

According to Cruzes and others, (Cruzes & Ben Othmane n.d.), external validity proves the generalization of the results, and external validity threats limit this generalization. The survey was rolled out to all participants simultaneously, and no participant was subjected to repetitive surveys and thus addressing and reducing the threat to external validity.
The participant selection criteria were that the participant must be directly or indirectly involved in AI-related project or initiative-related decision-making and working in the SME sector. To address the threat of the setting's representation, the survey was rolled out to participants simultaneously. To minimize the impact of time and location threat, the survey was rolled out simultaneously to all the participants and allocated a similar timeframe to respond (ScholarWorks & Sadashiv Jadhav 2021).

3.14.2 Internal Validity

When the researcher addresses the threat to internal validity, the environmental conditions or settings should not alter the results and support the researcher's claim through appropriate and sufficient evidence. To increase the results' reliability while using the survey questionnaire during the research, the researcher must work on multiple threats such as history, mutation, imitation of treatment, and motivation (Cruzes & Ben Othmane n.d.).

As part of this research, a point in time study was conducted instead of an elongated study. there by nullifying the history related internal validity threat. Threats related to mutation were applicable if studies conducted at different times to deliver quite similar results. Given this research was a point in time study so the mutation related threat to internal validity was not applicable. As the survey completion time for an individual respondent was moderate, all participants were able to complete the survey in a single sitting. Each participant was encouraged to take the survey once though they were not restricted from changing the responses. Also, a participant did not require to answer similar questions multiple times in the survey; thus, it adequately addressed the testing threats (ScholarWorks & Sadashiv Jadhav 2021).

The study was used to understand factors impacting the decision of using AI for strategic decisioning in SME sector of India for improving profitability and the quality of strategic decision making. The participant population in the study were the employees directly or indirectly involved in the decision making about the AI project or initiative; and strategic decision making thus, there was no significant difference across survey participants working for different SME in India (ScholarWorks & Sadashiv Jadhav 2021).

The participant selection threat criteria addressed subject selection related threats to internal validity. The researcher rolled out the survey to all the participants around the same timeframe. The confidentiality agreement and survey conducting rules ensured that no undue influence or the possibility of one participant influencing other participants' responses to the survey. This precautionary measure helped to overcome the limitation of treatment appropriately.

The survey did not require the participant to use any other references; the participant answered all the questions using their experience working on AI-related projects. Completing the survey was not expected to be a time-consuming activity; all the participants completed the survey in a single sitting. These factors mitigated the challenge of a lack of motivation as a threat to internal validity(ScholarWorks & Sadashiv Jadhav 2021).

3.14.3 Construct Validity

According to Cruzes and others (Cruzes & Ben Othmane n.d.), construct validity is about the dependent and independent variables represented the theoretical concept used as the primary driver of the research.

The researcher ensured that questions in the survey were clear enough and did not have overlap within themselves to ensure that one section in the survey did not influence the answer in another section.All the participants took the survey during a similar timeframe and did not have prior knowledge or hints from other participants to address the threat of treatment testing.

A brief introduction was added at the beginning of the survey questionnaire to increase awareness about the research subject. Though the participants received the brief information about the research, they were not to be made aware of the the actual hypothesis unless and until the research was complete and the research report was published. This process ensured that the hypothesis testing did not unduly influence the responses of the participants. Though the number of employees in the Small and Medium Industries in India is a huge, given the voluntary nature of the survey was impossible to reach a such a huge population. Thus, the participation sample size arrived at in the range of 120 participants in the region where the author resides i.e. SMEs in and around Pune. The 120 participants numbers were sought to take care of situations related to incomplete responses, participants dropping of the survey mid-way, participants not responding to the survey. The expected population for the analysis was pegged around 80 responses. However, the response collected the response from 75 survey participants. All the participants completed the survey in a single sitting, reducing the impact to construct validity.

3.15 Data Analysis

The aim of the data analysis was to explore the interactions and correlations between various sub-variables related to the Technology Acceptance Model (TAM), the Balanced Scorecard (BSC), and the decision to use AI for profitability improvements and strategic decision-making in Indian SMEs. The data collected through the cross-sectional survey was analyzed using IBM SPSS software version 29 to evaluate the relationships between the various dependent and independent variables.

3.15.1 Methodological Approach

A methodical approach to analyze the data was applied to enable the documentation of the results in chapter 4.

3.15.1.2 Tool evaluation

Even before the data analysis was carried out, the tool to be used for the analysis was required to be determined. There were 3 software that were evaluated for a brief period before IBM Statistical Package for The Social Sciences (SSPS) software version 29 was chosen as the tool for the analysis. The 3 software that were evaluated were

- IBM Statistical Package For The Social Sciences (SSPS) version 29
- Minitab
- Jamovi

IBM Statistical Package for The Social Sciences (SSPS) version 29 was chosen are the tool of choice due to the richer set of features such as weight application, more statistical models, better graphical representation of the which enabled a quicker and smoother analysis of the dataset.

The data analysis was carried out in two stages namely

a) Initial data analysis which was carried out at the whole data set level including

    1. Initial descriptive analysis
    2. Outlier detection and elimination
    3. Data normalization using Z-scores
    4. Variable reduction of composite variables by average the respective sub variable per case

b) For every research question or secondary research question there was a logistics regression analysis carried out to determine the hypothesis and the results of the research question analysis.

    1. Logistic regression analysis
    2. Dimension reduction using PCA

The analysis included comprehensive descriptive statistics to profile demographic variables and characterize the data distribution. This included calculating measures such as minimum, maximum, mean, median, mode, standard deviation, and determination of the normality of the data whether the data is skewed to the right or left (Case and Ambrosius, 2007, pp. 33–52).

Outliers were identified and appropriately managed to ensure accuracy of the data. Normalization techniques, specifically Z-scores, were employed to standardize data across different scales, to ensure facilitation of meaningful comparisons (Case and Ambrosius, 2007, pp. 33–52).

Composite variables were created by aggregating sub-variables within constructs such as Subject Norm (SN), Employee Satisfaction and Engagement (ESE), Perception of External Control (PEC), Job Relevance (JR), Data and Infrastructure (DI), and Balanced Scorecard Performance Measurement (BSCPM) financial parameters. This reduction enhanced the clarity and simplicity of subsequent analysis.

Logistic regression analysis was pivotal in examining the impact of identified factors on AI adoption and its implications for organizational profitability. Key statistical measures such as -2 Log likelihood, Cox & Snell R^2, and Nagelkerke R^2 were employed to assess the goodness of fit and the explanatory power of the logistic regression model.

Each of the above measures in combination were useful to determine the hypothesis out comes. The table below lists a brief explanation of the measure, its use and limitations

Measure Name	Description	Interpretation	Limitation
Cox and Snell R2	The measure that is used to explain the variation in the model i.e. how well the model aligns to the observed data	Higher the number is better.	The measure itself can't go to 100 % , so it is difficult to judge how well the model aligns to the observed data, with lower data indicating a closer alignment
Nagelkerke R2	An improved version of the Cox and Snell R2 which can go upto 100 %. Thus, this measure is a better predictor of the observed data's alignment with the model.	Higher the better	Though the measure is easy to understand it is not very straightforward to interpret as R2 in simple linear regression.

-2 Log likelihood	The measure that allows the determination of how poorly the model predicts the pass/fail outcomes	Lower the number better. Higher number indicates the model is not predicting well	The measure itself is sensitive to very large datasets. It lacks a intuitive intepretibility and is sensitive to outliers

Thus 3 above measures were used in conjunction to determine the hypothesis results and the interpretation of the hypothesis based on how well the model aligned to the observed data, how well the model was able to explain the variation in model and the observed data and finally the overall quality and strength of the model.

The Hosmer-Lemeshow test assessed how accurately the regression model reflected the actual data by comparing the observed and expected frequencies of the outcomes in smaller subgroups. The Hosmer Lemeshow test further used Chi square tests and p values to ensure the observed data is not by chance and p value. Hosmer- Lemeshow test is sensitive to small sample sizes and very large sample sizes.

However, in this thesis, all the above measures were used in combination to interpret the results of the hypothesis.

Given that there was a composite variable approach applied to simplify the approach and analysis, there was a need identified to determine if there were any key groups of predictors being formed that could determine any hidden patterns and there by elucidate critical factors influencing AI-driven decision-making and profitability improvements in the Indian SME context. Thus, there was a dimension reduction technique using PCA that was applied to the original response variable responses. This approach enabled the identification of any statistical relation between the original variables and identify any patterns within the data, that significantly influenced AI-driven decision-making and profitability improvements (Nguyen & Holmes 2019).

3.16 Summary and Transition

This study was conducted to explore how AI adoption influenced decision-making and enhances profitability in Indian SMEs, leveraging the theoretical frameworks of the Technology Acceptance Model (TAM) and Balanced Scorecard (BSC). The research methodology employed a cross-sectional survey, analyzed using IBM SPSS version 29. The study also addressed potential validity threats, including conclusion, construct, external, and internal validity, with strategies outlined to mitigate these threats. Ethical standards were strictly adhered to, ensuring the protection of participants and enhancing the reliability and trustworthiness of the results.

In conclusion, the methodological framework provided a rigorous approach to explore the complex dynamics of AI adoption for strategic decisioning in Indian SMEs and also explained the usage and the limitations of the models also. The subsequent chapter will delve into detailed insights from data collection processes, statistical analyses, and conclusive findings, advancing our understanding of AI's strategic integration for enhancing SME profitability and decision-making efficiency.

CHAPTER IV:

RESULTS

4.1 Introduction

The purpose of this thesis was to study the existence and extent of the relationship between use of AI technologies and the financial perspective (BSC) and their influence to adopt, implement, and use AI technology for strategic decision making and improve profitability of the SME sector in India. The TAM and BSC were the framework that was used to measure the influence of AI for decision making and profitability improvement for the SME sections in India. The key predictors that were used in this study were Subject Norm (SN), Job Relevancy (JR), Perception of External Control (PEC), Employee Satisfaction and Engagement (ESE), Balanced Score Card Parameters (BSCPM), Results Demonstrability (RD), Computer Self Efficacy (CS), Knowledge Management (KM),The main research question and sub questions guided this study. The focus of the leading research question was to understand whether there is any statistically significant relationship between the variables.

The previous chapter dealt with research addressing the purpose of the research, the research objective, identifying the research questions, detailing the methodology of the research. This chapter will elaborate the data analysis including the descriptive and inferential statistics for each of the research questions including the main research questions.

4.2 Data Preparation

The survey responses were downloaded to the local laptop into MS Excel. Once the responses were downloaded the email addresses from all the responses were eliminated and saved as a fresh Excel dataset. This updated data set was used for all analysis. In preparation for the analysis each of the columns were renamed to meaningful columns to help with further analysis.

The Vlookup function of Excel was utilized judiciously to help with converting the string values to numeric values. The figure below lists the lookup conversion tables that were used.

Figure 7 Lookup values for data preparation

part_age	
>50 years	4
20 to 30 years	1
31 to 40 years	2
40 to 50 years	3

Gender	
Female	2
Male	1
Prefer not	3

Part Role	
CXO	5
Founder	6
Middle Management	3
Others	1
Senior Management	4
Technical	2

Academics	
Diploma	1
Graduate	2
Others	4
Post Graduate	3

Org Age	
>30 years	4
0-10 years	1
11 to 20 years	2
20 to 30 years	3

Leichert Scale	
Agree	4
Disagree	2
Not Sure	3
Strongly Agree	5
Strongly Disagree	1

org type	
Limited Liability Partnership (LLP)	3
One Person Company	2
Proprietorship Firm	1
Public Limited Company	5
Pvt Limited Company	4

Percentage map	
> 10 %	4
0 to 3 %	1
3 to 10 %	2
Not sure	3

Source: Conceptualized by the author

The responses values for all the associated variables from question no 9 to 36 were recorded in the scale unit such as one (strongly disagree), two (disagree), three (not sure /neither agree nor disagree) four (agree), five (strongly agree) in IBM SPSS V29 dataset. Initial analysis of the data set indicated that there was not one single dependent variable that could be used for the inferential analysis for the research questions. Thus, there was a need to identify the dependent variable to determine the inferential statistics for the research questions. In all there were 8 dependent variables identified to help with the inferential statistics and analysis of the main research question.

The table below lists the dependent variables and the associated questions from the survey, which formed the basis for the testing of the hypothesis of the sub questions

Table 7 Hypothesis to Survey question to dependent variable map

Variable	**Survey Question**
resp_bcspm3	AI can be used as an innovative tool that can help in the improvement of revenue and / or operating margin for my organization
resp_bscpm1	We use EBIT to measure the organization performance (EBIT is Earnings before Interest and Taxes)
resp_bscpm2	We use Operating Margin as our primary measure to measure organization and various departments performance
resp_bscpm4	We are seeing improvements in our bottom line (profits and margins) using AI
resp_bscpm5	We are exploring AI for revenue growth initiatives (Marketing, Campaigns, Leads, sales etc) to improve our top line (revenues)
resp_bscpm6	We are seeing improvements in our revenue using AI
resp_oq1	AI can positively impact financial performance parameters (E.g.: Revenue, Operating margin, EBIT etc) if used in the right manner?
resp_rd	We are already exploring AI for decisioning wherever possible

Source: As conceived by the author 2024

Post the identification of the sub research questions and its variables, there were composite variables that were created and aligned to the 11 independent variables. The composite variables were constructed by averaging the independent predictor variables. The table below lists the final composite variables and how they were constructed.

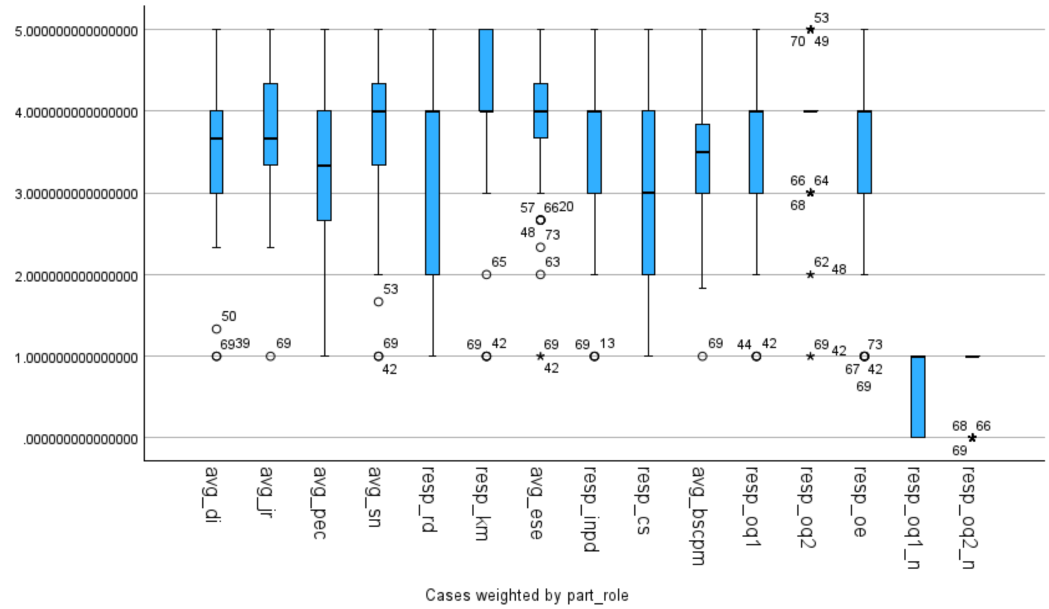
Table 8 Final independent variable map

Variable Name in data set	Survey question	Independent Variable name	Function used to create the composite variable
avg_di	9,10,11	di1,di2,di3	Average (di1,di2,di3)
avg_jr	12,13,17	jr1, jr3, jr3	Average(jr1,jr2,j3)
avg_pec	14,16,26	pec1, pec2, pec3	Average(pec1,pec2,pec3)
avg_sn	15,19,20	sn1, sn2, sn3	Average(sn1,sn2,sn3)
resp_km	22	resp_km	none
avg_ese	21,23,24	ese1, ese2,ese3	Average(ese1,ese2,ese3)
resp_inpd	25	resp_inpd	None
resp_cs	27	resp_cs	None
avg_bscpm	28,29,32,34,35,36	bscpm1, bscpm2, bscpm3,bscpm4,bscpm5,bscpm6	Average(bscpm1, bscpm2,bscpm3,bscpm4,bscpm5,bscpm6)
resp_oe	33	resp_oe	None
resp_rd		resp_od	None

Source: As conceived by the author

Once the variables set was created, the data was passed through box plots to identify any outliers. As depicted in the figure below the variables were measured by using the Likert scale. The responses were within the Likert scale of 1 -Strongly disagree to 5 – Strongly agree.

Figure 8 Box plot for the independent and dependent variables



Source: As generated by the IBM Statistical Package for the Social Sciences (SSPS) version 29 software

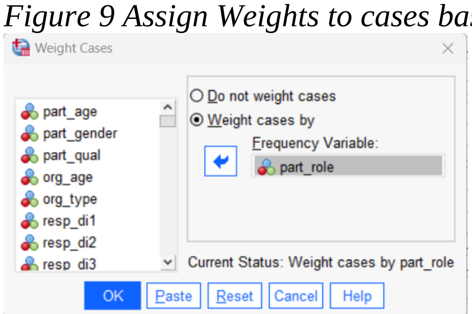
The box plot identified 10 cases as extreme outliers and 11 cases as outliers. It was decided to remove the extreme outliers from the dataset (row numbers – 68,69,70,66,64,62,53,48,49,42). This resulted in the total number of valid cases being reduced from 75 to 65. These 65 cases formed the basis for the further statistical analysis using IBM Statistical Package for the Social Sciences (SSPS) version 29.

Applying weights to the dataset

Weighting is a statistical technique in which datasets are manipulated through calculations to bring them more in line with the population being studied. The key difference between the initial sample composition and weighting is that weights are applied after data is collected and allow researchers to correct for issues that occurred during data collection(Roxana 2020). There were only 65 cases that were valid for the further analysis, weights in IBM Statistical Package for the Social Sciences (SSPS) was applied to enable the measurement of the population by bringing it to a desired representation of the population.

The choice of the variable to be used for the weights was critical. Normally researchers apply weights on demographic variables such as gender, region, education etc. In this research data case, the use of part_role for weights enabled to bring the population cases to the desired population (238 cases) that was used for the analysis. Part role represented the role that the participant performed in their organization. Use of the weights in this case ensured that the hard-to-reach demographic groups were still considered in an equal proportion to the final data. This also ensured the data set is more correct enabling the results to be more accurate of the population being represented(Mercer, Lau & Kennedy 2018).

Figure 9 Assign Weights to cases based on role



Source: IBM Statistical Package for the Social Sciences (SSPS) version 29

Once the weights were assigned, the IBM STATISTICAL PACKAGE FOR THE SOCIAL SCIENCES (SSPS) data set was further enhanced to filter the outliers in the final data set. This was done by adding a column outlier in the dataset and the cases to be eliminated were marked with a ‘Y’. Using the filter functionality of SSPM the outliers were eliminated from the dataset making it ready for analysis.

Figure 10 Outlier Elimination

```
USE ALL.
COMPUTE filter_$=(Outlier<>"Y").
VARIABLE LABELS filter_$ 'Outlier<>"Y" (FILTER)'.
VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.
FORMATS filter_$ (f1.0).
FILTER BY filter_$.
EXECUTE.
```

Source: IBM Statistical Package for the Social Sciences (SSPS) version 29 code used by the author

4.3 Reliability Statistics

With the dataset ready for in-depth analysis, the first set of statistical tests applied was reliability statistics. Reliability statistics are crucial to validate the quality of the data there by making them an important statistic measure in research to ensure accurate and reliable inferences in research.

One of the most popular reliability statistic measures is Cronbach’s Alpha. Cronbach Alpha assesses how well the items in the questionnaire are related to each other and whether they measure a similar concept. Cronback Alpha value varies from 0 to 1. A higher value typically greater than 0.7 indicates that the items are highly related and measure the same concept well(Mohsen & Reg 2011) .

The purpose of Cronbach's Alpha analysis was to check the reliability of the 5-point Likert Scale and whether any of the independent variables measured using this scale had any undue influence. The reliability statistics conducted on the data set indicated that the Cronbach Alpha was .892 making the data and the scale reliable as in table below.

Table 9 Cronbach Alpha summary

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.892	.900	19

Source IBM Statistical Package for the Social Sciences (SSPS) version 29

The impact of Cronbach Alpha, if each of the independent variables were eliminated was also tested for. The results are depicted below

Table 10 Cronbach Analysis – Item wise statistics

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
avg_di	66.360028860	81.968	.075	.	.899
avg_jr	66.026695527	77.368	.607	.	.885
avg_pec	66.472582973	74.695	.578	.	.884
avg_sn	65.970418470	75.234	.725	.	.882
resp_rd	66.398989899	73.329	.531	.	.886
resp_km	65.727994228	79.632	.282	.	.893
avg_ese	65.931457431	76.225	.647	.	.884
resp_inpd	66.212842713	73.185	.642	.	.882
resp_cs	66.702020202	71.288	.613	.	.883
resp_bscpm1	66.247474747	76.979	.368	.	.891
resp_bscpm2	66.152236652	77.416	.334	.	.893
resp_bcspm3	65.857864358	76.719	.542	.	.886
resp_bscpm4	66.684704185	73.690	.544	.	.886
resp_bscpm5	66.264790765	71.969	.603	.	.883
resp_bscpm6	66.740981241	73.940	.610	.	.883
avg_bscpm	66.324675325	74.636	.884	.	.879
resp_oq1	66.039682540	75.319	.533	.	.886
resp_oq2	65.805916306	78.964	.410	.	.889
resp_oe	66.299422799	71.738	.639	.	.882

Source IBM Statistical Package for the Social Sciences (SSPS) version 29

All the independent variables and the dependent variables had a similar impact

4.4 Descriptive Statistics

The central tendency of the variables was measured using means and standard deviation skewness and kurtosis. The paragraph below defines and explains the measures primarily mean, standard deviation, kurtosis, skewness and its significance in the statistics-based inferencing.

Mean is defined as the average of the values of an item in a dataset.

Standard deviation is defined as a measure that shows the deviation of values in a data set from the mean of that item. A lower value for standard deviation means that the values are closer to the mean so lower risk while a higher standard deviation indicates that the value is spread over a wider range so higher risk.

Table 11 Descriptive statistics independent variables

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
part_age	216	1	3	2.19	.855	-.375	.166	-1.533	.330
part_gender	231	1	3	1.13	.389	3.007	.160	8.915	.319
part_role	231	1	6	4.31	1.542	-.311	.160	-1.165	.319
part_qual	231	1	4	2.50	.691	.072	.160	-.210	.319
org_age	231	1	4	1.99	1.000	.781	.160	-.433	.319
org_type	228	1	5	3.39	1.367	-.796	.161	-.787	.321
avg_di	231	1.0000000000	5.0000000000	3.5411255411	.76903659105	-.803	.160	1.588	.319
avg_jr	231	2.3333333333	5.0000000000	3.8744588745	.55527064656	.101	.160	-.052	.319
avg_pec	231	1.6666666667	5.0000000000	3.4285714286	.82448720914	-.292	.160	-.724	.319
avg_sn	231	2.6666666667	5.0000000000	3.9307359307	.63399125782	.014	.160	-.769	.319
resp_rd	231	2	5	3.50	1.017	-.231	.160	-1.098	.319
resp_km	231	1	5	4.17	.695	-1.031	.160	3.093	.319
avg_ese	231	2.0000000000	5.0000000000	3.9696969697	.61975954083	-.382	.160	.304	.319
resp_inpd	231	1	5	3.69	.879	-.511	.160	-.015	.319
resp_cs	231	1	5	3.20	1.077	-.004	.160	-1.099	.319
avg_bscpm	231	1.8333333333	5.0000000000	3.5764790765	.56608658580	.259	.160	.622	.319
resp_oe	231	1	5	3.60	1.003	-.491	.160	-.578	.319
Valid N (listwise)	213								

Source: IBM Statistical Package for the Social Sciences (SSPS) version 29

The table depicts the average of all the independent variables varied between 3.54 and 4.17. This indicated that the responses had a tendency to be more right tailed and more positive (hovering around 4 – Agree on the Likert scale). With most of the items having a relatively low standard deviation, indicated that most of the values fell within the mean range which is good indicating the spread of the data closer to the mean. However, for a few values the standard deviation indicated the data was more spread across. Two noticeable predictor variables which had a high standard deviation were resp_rd (Results Demonstrability) and resp_cs (Computer Self efficacy). Most of the variables had negative skew statistics indicating a lighter tail, There were two values for kurtosis statistic that exceed beyond the range of +/-1 which were resp_km (Knowledge Management) and avg_di (Data Infrastructure). This indicated a small deviation or violation from the normal bell curve distribution.

4.5 Demographic variables - Statistics

This section provides descriptive analysis for the demographic variables that were collected during the survey. This research was targeted at the Indian SMEs. 20 % of the respondents indicated that they were part of public limited organizations. However, none of the data that matched the above was eliminated from the research with the assumption that the respondents had knowledge of the Indian SMEs.

Table 12 Demographic statistics - participants

CATEGORY	VALUES	FREQUENCY	PERCENTAGE
EDUCATION	Diploma	5	6.67%
	Graduate	36	48.00%
	Others	3	4.00%
	Postgraduate	31	41.33%
GENDER	Female	15	20.00%
	Male	59	78.67%
	Prefer not to say	1	1.33%
ORGANIZATION TYPE	Limited Liability Partnership (LLP)	5	6.67%
	One Person Company	4	5.33%
	Proprietorship Firm	12	16.00%
	Public Limited Company	15	20.00%
	Pvt Limited Company	35	46.67%

	(blank)	4	5.33%
ORGANIZATION ROLE	CXO	5	6.67%
	Founder	14	18.67%
	Middle Management	17	22.67%
	Others	7	9.33%
	Senior Management	15	20.00%
	Technical	17	22.67%
PARTICIPANT GENDER	Male	59	78.67%
	Female	15	20.00%
	Prefer not to say	1	1.33
ORGANIZATION AGE	0-10 years	24	32.00%
	11 to 20 years	30	40.00%
	20 to 30 years	9	12.00%
	>30 years	12	16.00%
INDUSTRY	Information Technology	27	36.00%
	Manufacturing	4	5.33%
	Others	44	58.66%

Source: Statistics from the author's research data set

The above table highlights the demo graphics of the participants and their organization which also provides an insight into the SME industry in India. 72 % of the respondents were part of organizations which were less than equal to 20 years from the organization's inception. Most of the respondents indicated that they were part of the Information technology industry which meant they likely were software organizations providing services including AI Services to their customers making that population's responses significant to the research. The remainder of the respondents indicated that they worked with multiple industries and hence it was difficult to decipher which industry was their primary industry and they were all classified as 'Others'.

75 % of the respondents indicated they were part of the SME industry, making their responses again significant to the research. 78% of the respondents indicated they were male perhaps indicating a skew from the gender data though this may not have a significant impact on the overall analysis and research. Further research direction in this area should look to harmonize the respondents across the genders.

The organization role variable has a good spread of respondents across levels in the organization ranging from CXOs to respondents in technical and middle management.

4.6 Change of response scale of the dependent variables

The survey responses related to the independent and the dependent variables were gathered on a 5-point Likert scale from 1 – Strongly Disagree to 5 – Strongly agree. Switching from a Likert scale to a dichotomous scale simplified the analysis and allowed for the use of simpler statistical methods such as logistic regression analysis.

Likert scales tend to introduce imprecision due to subjective interpretations of each point on the scale (Barzizza et al. 2023). Converting to a binomial scale (0,1) simplifies responses to clear-cut categories, reducing subjectivity. Binomial scale effectively captures and models uncertainty providing a better picture of the analysis.(Merkey & Bubeliene 2019).

Thus, to simplify the research and use of simpler statistical methods the following variables responses were converted from a Likert scale to a binomial scale. The variables primarily were dependent variables the resp_bscpm1 to resp_bscpm_6, resp_rd, resp_oq1. These variables formed the basis of the 8 secondary questions which in turn helped to form the interpretation of the main research questions mentioned in the earlier sections of the thesis

The further sections of this chapter detail the individual research questions, its hypothesis, the sub hypothesis questions and the results of each of the analysis of the hypothesis.

Inferential statistics were used to determine the relationships between the dependent variables and the independent variables. Logistic regression analysis helped to determine the probability of the outcome based on the predictor variables and determined in identifying the most influential variables that influenced the outcome of the logistic regression analysis. Principal Component Analysis (PCA) was applied to the set of original variables to determine if there were any patterns that could be identified within the original variables that played a significant role in the determination of additional results and potential recommendations.

4.7 Logistic regression model - brief explanation

Before each of the research questions and their results are interpreted, it is required to provide guidelines of how the research questions and their results would be interpreted. Though chapter 3 (Methodology) provided the explanation of the models, and the various statistical measures used, this section provides a quick reference of the models, the statistical measures used along with reference range and purpose. This brief explanation enabled a better understanding of the results and the interpretation of the results and therefore the hypothesis.

The inferential statistical analysis was carried out using a binomial logistics regression analysis module in IBM SSPS tool. The section below explains in brief the various inference parameters that were used to determine the inference of the hypothesis.

The Nagelkerke R^2 value is a measure of the goodness of fit for logistic regression models, which are used for binary or categorical dependent variables.

i) Understanding Nagelkerke R^2

Purpose: The Nagelkerke R^2 value is an adjusted version of the Cox and Snell R^2 value. It adjusts the Cox and Snell R^2 so that the maximum value it can achieve is 1.

This makes the Nagelkerke R^2 easier to interpret, like the R^2 in linear regression.

Range:

The Nagelkerke R^2 value ranges from 0 to 1, where:

0 indicates that the model does not explain any of the variance in the dependent variable.

1 indicates that the model perfectly explains all the variance in the dependent variable.

Interpretation of a Nagelkerke R^2:

A Nagelkerke R^2 value greater than 0.7 is considered a strong relationship between the predictors (independent variables) and the outcome (dependent variable).

ii) Understanding the Hosmer-Lemeshow Test

The Hosmer-Lemeshow Test is a statistical test used to evaluate the goodness of fit for logistic regression models. The test is particularly useful for assessing how well a logistic regression model predicts a binary (two-outcome) dependent variable.

Purpose: The primary purpose of the Hosmer-Lemeshow test is to determine if the observed event rates match the expected event rates in subgroups of the model population. In other words, it tests whether the predictions made by a logistic regression model are consistent with the actual outcomes observed in the data.

Working of Hosmer-Lemeshow Test

The test divides the data into smaller groups most groups of ten basis the probabilities from the logistic regression model in an ascending order. For reach group the observed and the expected frequencies are then calculated. Post this calculation a Chi-square statistic is calculated to complare the expected to the observed frequencies across the groups. Once the Chi-square is computed, the P-value is computed. If the p -value is above 0.05, we accept the null hypothesis indicating the observed data matches the model predicted data. If the value is less than 0.05 the null hypothesis is rejected.

Thus if the model is considered a good fit if there is no difference between the observed and expected frequencies indicating that the model is a good fit.

iii) **Logistic Regression Table Analysis**

The logistic regression table analysis output is a key statistic table that is of significance in the interpretation of the result. The key terms of the table that are of significance in the interpretation of the results for this research are as below

a) **Wald:** A test statistic used to determine the significance of individual predictors in the model. The higher the value, the more significant is the variable.
b) **Sig. (p-value):** Indicates the statistical significance of the predictor. A p-value less than 0.05 generally means the predictor is statistically significant.
c) **S.E. (Standard Error)**: Measures the accuracy of the coefficient estimates. Smaller values indicate more precise estimates.
d) **B (Coefficient)**: Indicates the direction and magnitude of the relationship between the predictor variable (Zscore) and the outcome variable. Positive values suggest a positive relationship, while negative values suggest a negative relationship.
e) **Exp(B) (Odds Ratio)**: Represents the change in odds of the outcome occurring for a one-unit change in the predictor variable. Values greater than 1 indicate increased odds, while values less than 1 indicate decreased odds.

4.8 Research Question 1

The primary research question was to determine whether Artificial intelligence has an impact on the financial performance metrics performance measures and whether the use of standard performance management models such as the Balanced Scorecard framework improved strategic decision in Indian SMEs.

RQ1 Can Strategic decision-making processes, guided by Artificial intelligence, impact financial performance metrics such as (EBITDA or Operating Margin) within the context of the Balanced Scorecard framework in Indian Small and Medium Enterprises?

Null Hypothesis ($H_0$1): "Strategic decisioning process especially financial performance metrics (EBITDA or Operating Margin) is impacted positively when guided by Artificial Intelligence in the context of the Balanced Scorecard framework in Indian Small and Medium Enterprises"

Alternate Hypothesis ($H_1$1): "Strategic decisioning process especially financial performance metrics (EBITDA or Operating Margin) has no impact when guided by Artificial Intelligence in the context of the Balanced Scorecard framework in Indian Small and Medium Enterprises"

The research question was answered by completing the hypothesis of the secondary research questions.

4.8.1 SQ1 Impact of AI on EBIDTA and Org. Performance

SQ1 Is EBIDTA impacted positively when guided by Artificial Intelligence for decision making in Indian SMEs?

Null Hypothesis ($H_0$1): "EBDITA is positively impacted by the use of Artificial Intelligence in the decision-making process in Indian SMEs."

Alternate Hypothesis ($H_1$1): "Artificial Intelligence when integrated into the decision-making process has no significant impact on EBDITA in Indian SMEs."

Table 13 SQ1 Impact of EBDITA on organization performance, AI - bscpm1

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	161.730[a]	0.433	0.602

Hosmer and Lemeshow Test

Step	Chi-square	Df	Sig.
1	16.072	8	0.041

Classification Table[a]

		Predicted		
		resp_bscpm1_n		
		0	1	%Correct
resp_bscpm1_n	0	55	21	72.4
	1	21	134	86.5
Overall %				81.8

Source – IBM Statistical Package for the Social Sciences (SSPS)

Model Summary - Results Interpretation for bscpm1

a) Interpretation of a Nagelkerke R^2

A Nagelkerke R^2 value greater than 0.7 is considered a strong relationship between the variables. The Nagelkerke R^2 value of 0.602 indicates that the model explains approximately 60.2% of the variance which suggests there is moderately strong relationship between predictors (independent variables) and the outcome (dependent variable).

b) Hosmer and Lemeshow Test

Given the p value is <0.05 statistically it can be concluded the model does not fit the data well, and there is a difference between the observed and predicted values. In this event, the p-value (0.041) though closer to the threshold of .05 is still less than the threshold.

c) Logistic Regression Table Output

Table 14 SQ1 Logistic Regression Table output for bscpm1

bscpm1 – EBIDTA as the dependent variable

	B	S.E.	Wald	Df	Sig.	Exp(B)
Zscore(avg_bscpm)	4.104	0.67	37.6	1	<.001	60.552
Constant	1.804	0.32	32.53	1	<.001	6.074
Zscore(resp_oe)	-2.01	0.44	20.96	1	<.001	0.134

Zscore(resp_inpd)	0.859	0.28	9.114	1	0.003	2.361
Zscore(resp_km)	-0.59	0.27	4.742	1	0.029	0.552
Zscore(resp_rd)	-0.55	0.46	1.429	1	0.232	0.575
Zscore(avg_pec)	-0.49	0.41	1.42	1	0.233	0.613
Zscore(resp_cs)	0.357	0.33	1.166	1	0.28	1.428
Zscore(avg_di)	-0.13	0.24	0.292	1	0.589	0.876
Zscore(avg_jr)	0.176	0.33	0.291	1	0.589	1.192
Zscore(avg_sn)	-0.12	0.51	0.052	1	0.82	0.891
Zscore(avg_ese)	-0.04	0.44	0.009	1	0.926	0.96

Source: IBM Statistical Package for the Social Sciences (SSPS)

d) Classification Table

The overall percentage correct prediction of 81.8% indicates that the model has good predictive accuracy. The model was more accurate predicting that EBIDTA was a measure of organization financial performance. The model predicted approximately 86.6 % correctly that EBDITA was impacted positively using AI.

e) Interpretation

The p value of 0.041 from the Hosmer Lemeshow test indicated there is a difference between the observed data and the predicted data. The Nagelkerke value of 0.62 (62%) indicated that there is a moderate relationship between the predictors (independent variables) and the outcome (dependent variable). Of the 11 predictors the regression output analysis indicated that there were 4 predictor variables BSCPM (Balanced Score Card Parameters (BSCPM), Operating Efficiency (OE), Innovation and New Product Development (INPD), Knowledge Management (KM) that were statistically significant with the BSCPM financial parameters having an exponential positive significance thereby making it the most significant predictor model whose single unit change can influence the outcome variable almost single handedly.

f) Conclusion

Although the p value was < 0.05, the value was very close to the threshold of 0.05. The model predicted 86.6% times correctly that EDBITA was positively impacted by AI. The bscpm-financial parameters variable single handedly influenced the outcome variable related to EBDITA. Thereby it can be concluded that the null hypothesis ($H_0 1$): "EBDITA is positively impacted by the use of Artificial Intelligence in the decision-making process in Indian SMEs" **can be accepted.**

4.8.2 SQ2 Impact of AI on OM and Org. strategic decision making

SQ2 Is Operating Margin impacted positively when guided by Artificial Intelligence for decision making in Indian SMEs?

Null Hypothesis ($H_0 2$): "Operating Margin is positively impacted by the use of Artificial Intelligence in the decision-making process in Indian SMEs."

Alternate Hypothesis ($H_1 2$): "Artificial Intelligence when integrated into the decision-making process has no significant impact on Operating Margin in Indian SMEs."

Following is the logistic regression results carried out

Table 15 SQ2 Impact of OM on organization financial performance, AI -bscpm2

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	132.955	0.444	0.646

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	16.74	8	0.033

Classification Table[a]

		Predicted		
		resp_bscpm2_n		
		0	1	%Correct
resp_bscpm2_n	0	46	16	74.2

1	15	154	91.1
Overall %			86.6

Model Summary - Results Interpretation for bscpm2

a) Interpretation of a Nagelkerke R^2

A Nagelkerke R^2 value greater than 0.7 is considered a strong relationship between the variables. The Nagelkerke R^2 value of 0.646 indicates that the model explains approximately 64.6% of the variance which suggests there is moderately relationship between predictors (independent variables) and the outcome (dependent variable).

b) Hosmer and Lemeshow Test

Given the p value is <0.033 statistically it can be concluded the model does not fit the data well.In other words the model is a poor fit with difference between the observed and predicted values.

c) Logistic Regression Table Output

Table 16 SQ2 Logistic Regression Table output for bscpm2

Variables in the Equation(bscpm2)

	B	S.E.	Wald	df	Sig.	Exp(B)
Constant	2.562	0.41	38.74	1	<.001	12.956
Zscore(avg_bscpm)	3.258	0.61	28.16	1	<.001	25.986
Zscore(resp_inpd)	1.464	0.32	20.5	1	<.001	4.323
Zscore(resp_oe)	-1.39	0.41	11.65	1	<.001	0.25
Zscore(avg_pec)	-1.6	0.48	11.09	1	<.001	0.202
Zscore(resp_cs)	1.112	0.44	6.525	1	0.011	3.039
Zscore(resp_rd)	-1.22	0.59	4.258	1	0.039	0.294
Zscore(avg_di)	-0.57	0.3	3.648	1	0.056	0.567
Zscore(avg_jr)	0.314	0.37	0.703	1	0.402	1.368
Zscore(avg_sn)	0.292	0.58	0.253	1	0.615	1.339
Zscore(resp_km)	0.12	0.27	0.199	1	0.656	1.127
Zscore(avg_ese)	0.027	0.48	0.003	1	0.955	1.027

Source: IBM Statistical Package for the Social Sciences (SSPS)

d) Classification Table

The overall percentage correct prediction of 86.6% indicates that the model has good predictive accuracy. The model was more accurate predicting that Operating margin was a measure of organization financial performance.

e) Interpretation

The p value of 0.033 from the Hosmer Lemeshow test indicated a poor fit of the data. The Nagelkerke value of 0.646(64.6%) indicated that there is a moderate relationship between the predictors (independent variables) and the outcome (dependent variable). Of the 11 predictors the regression output analysis indicated that there were 6 predictor variables BSCPM (Balanced Score Card Parameters (BSCPM), Innovation and New Product Development (INPD), Operating Efficiency (OE), Perception of External Control (PEC), Computer Self Efficacy (CS), Results Demonstrability (RD), Knowledge Management (KM) that were statistically significant with the BSCPM financial parameters having an exponential positive significance

f) Conclusion

The p value (0.033) was < 0.05 from the Hosmer and Lemeshow test. This value is significantly low indicating a variance in the observation and prediction, although the classification table predicted with greater accuracy. The bscpm-financial parameters variable single handedly influenced the outcome variable related to Operating Margin. Thus, basis p value it can be concluded that the null hypothesis (H12): “Operating Margin is positively impacted by the use of Artificial Intelligence in the decision-making process in Indian SMEs” **be rejected and the alternate hypothesis be accepted.**

4.8.3 SQ3 Co relation between AI and profitability

SQ3 Does the use of artificial intelligence have a co relation with the improvement of profitability in Indian SMEs?

Null Hypothesis ($H_0$3): "Profit margin is improved by the use of Artificial Intelligence when integrated in the decisioning making processes in Indian SMEs."

Alternate Hypothesis ($H_1$3): "Artificial Intelligence when integrated into the decision-making process has no significant impact on profit margin in Indian SMEs."

Table 17 SQ3 Impact of AI, decision on profit margins - bscpm4

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	60.796	0.642	0.886

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	4.36	8	0.806

Classification Table[a]

		Predicted		
		resp_bscpm4_n		
		0	1	%Correct
resp_bscpm4_n	0	151	0	100.0
	1	5	75	93.8
Overall %				97.8

Model Summary - Results Interpretation for bscpm4

a) Interpretation of a Nagelkerke R^2

A Nagelkerke R^2 value greater than 0.7 is considered a strong relationship between the variables. The Nagelkerke R^2 value of 0.886 indicates that the model explains approximately 88.6% of the variance which suggests there is a very strong relationship between predictors (independent variables) and the outcome (dependent variable).

b) Hosmer and Lemeshow Test

Given the p value of 0.806 statistically it can be concluded the model fits the data very well making the model a very good fit for the data.

c) Logistic Regression Table Output

Table 18 SQ3 Logistic Regression Table output for bscpm4

Variables in the Equation (bscpm4)

	B	S.E.	Wald	df	Sig.	Exp(B)
Constant	-9.684	3.51	7.63	1	0.01	0
Zscore(avg_bscpm)	13.35	5.16	6.69	1	0.01	627889.796
Zscore(avg_pec)	15.979	6.23	6.58	1	0.01	8703133.92
Zscore(resp_inpd)	-13.31	5.61	5.64	1	0.02	0
Zscore(avg_jr)	-2.629	1.13	5.41	1	0.02	0.072
Zscore(resp_rd)	7.097	3.08	5.32	1	0.02	1207.913
Zscore(avg_sn)	-6.769	3.26	4.32	1	0.04	0.001
Zscore(resp_cs)	-3.887	1.88	4.26	1	0.04	0.021
Zscore(resp_km)	-3.251	1.68	3.77	1	0.05	0.039
Zscore(avg_ese)	2.291	1.33	2.97	1	0.09	9.884
Zscore(resp_oe)	2.6	1.71	2.32	1	0.13	13.47
Zscore(avg_di)	-0.898	0.66	1.88	1	0.17	0.408

Source: IBM Statistical Package for the Social Sciences (SSPS)

d) Classification Table

The overall percentage correct prediction of 97.8% indicates that the model has good predictive accuracy. The model was more accurate predicting the use of AI for improvements to the profitability and bottom line of the organization.

e) Interpretation

The p value of 0.806 from the Hosmer Lemeshow test indicated there the model fit the data very well. The Nagelkerke value of 0.886(88.6%) indicated that there was a very strong relationship between the predictors (independent variables) and the outcome (dependent variable). Of the 11 predictors the regression output analysis indicated that there were 5 predictor variables BSCPM (Balanced Score Card Parameters (BSCPM), Perception of External Control (PEC), Innovation and New Product Development (INPD), Job Relevance (JR), Results Demonstrability (RD) that were statistically significant. BSCPM financial parameters and Perception of External Control (PEC) had an exponential positive significance.

f) Conclusion

Basis the above interpretation with a p value of 0.806 it can be concluded that the null hypothesis ($H_0 3$): "Profit margin is improved by the use of Artificial Intelligence when integrated in the decisioning making processes in Indian SMEs." **can be accepted.**

4.8.4 SQ4 Co relation of AI and revenue

SQ4 Does the use of artificial intelligence have a co relation with the improvement of revenues in SMEs in India when integrated with initiatives for revenue improvement?

Null Hypothesis ($H_0 4$): "Artificial Intelligence when integrated into the decision-making process for revenue improvement has significant impact on revenues in SMEs in India."

Alternate Hypothesis ($H_1 4$): "Artificial Intelligence when integrated into the decision-making process for revenue improvement has no significant impact on revenues in SMEs in India."

Table 19 SQ4 revenue improvement analysis – bscpm5

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	107.648	0.572	0.782

Hosmer and Lemeshow Test

Step	Chi-square	Df	Sig.
1	12.42	8	0.133

Classification Table[a]

		Predicted		
		resp_bscpm5_n		
		0	1	%Correct
resp_bscpm5_n	0	76	9	89.4

1	10	136	93.2
Overall %			91.8

Model Summary - Results Interpretation for bscpm5

a) Interpretation of a Nagelkerke R^2

A Nagelkerke R^2 value greater than 0.7 is considered a strong relationship between the variables. The Nagelkerke R^2 value of 0.782 indicates that the model explains approximately 78.2% of the variance which suggests there is a very strong relationship between predictors (independent variables) and the outcome (dependent variable).

b) Hosmer and Lemeshow Test

Given the p value of 0.133 is greater than the threshold of .05 statistically it can be concluded the model fits the data very well.

c) Logistic Regression Table Output

Table 20 SQ4 Logistic Regression Table output for bscpm5

Variables in the Equation (bscpm5)

	B	S.E.	Wald	df	Sig.	Exp(B)
Zscore(avg_bscpm)	4.283	0.83	26.44	1	<.001	72.431
Zscore(resp_oe)	3.239	0.75	18.9	1	<.001	25.503
Zscore(resp_inpd)	2.564	0.64	16.09	1	<.001	12.994
Zscore(avg_ese)	-2.48	0.68	13.25	1	<.001	0.084
Constant	1.184	0.33	13.08	1	<.001	3.269
Zscore(resp_cs)	-1.52	0.6	6.348	1	0.012	0.22
Zscore(avg_jr)	1.197	0.53	5.029	1	0.025	3.309
Zscore(avg_pec)	-1.07	0.57	3.572	1	0.059	0.343
Zscore(avg_sn)	-0.99	0.74	1.826	1	0.177	0.371
Zscore(avg_di)	0.472	0.4	1.366	1	0.242	1.603
Zscore(resp_rd)	0.655	0.64	1.063	1	0.303	1.925
Zscore(resp_km)	0.292	0.36	0.645	1	0.422	1.339

Source: IBM Statistical Package for the Social Sciences (SSPS)

d) Classification Table

The overall percentage correct prediction of 91.8 % indicates that the model has good predictive accuracy.

e) Interpretation

The p value of 0.133 from the Hosmer Lemeshow test indicated there the model fit the data very well. The Nagelkerke value of 0.782(78.2%) indicated a very strong relationship between the predictors (independent variables) and the outcome (dependent variable). Of the 11 predictors the regression output analysis indicated that there were 6 predictor variables BSCPM (Balanced Score Card Parameters (BSCPM), Operating Efficiency (OE), Innovation and New Product Development (INPD), Employee Satisfaction and Engagement (ESE), Computer Self Efficacy (CS), Job Relevance (JR), that were statistically significant with the BSCPM financial parameters and Operating Efficiency (OE) having an exponential positive significance.

f) Conclusion

Basis the above interpretation and given that the p value is greater than 0.05 indicating the model is a good fit, it can be concluded that the null hypothesis ($H_0$4): "Artificial Intelligence when integrated into the decision-making process has significant impact on revenues in SMEs in India. **can be accepted**

4.8.5 SQ5 AI an innovation tool to influence revenue & profit

SQ5 Is Artificial Intelligence an innovative tool that enables SMEs in India to significantly impact their revenues and operating margins?

Null Hypothesis ($H_0$5): "Artificial Intelligence is an innovative tool that has the ability to influence revenues and operating margins in SME organizations in India."

Alternate Hypothesis ($H_1$5): "Artificial Intelligence is an innovative tool that has no impact on the ability to influence revenues and operating margins of SME organizations in India."

Table 21 SQ5 Ability of AI to influence Revenues and margins - bscpm3

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	90.015	0.428	0.699

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	13.338	8	0.101

Classification Table[a]

		Predicted		
		resp_bscpm3_n		
		0	1	%Correct
resp_bscpm3_n	0	32	10	76.2
	1	10	179	94.7
Overall %				91.3

Source: IBM Statistical Package for the Social Sciences (SSPS)

Model Summary - Results Interpretation for bscpm3

a) Interpretation of a Nagelkerke R^2

A Nagelkerke R^2 value greater than 0.7 is considered a strong relationship between the variables. The Nagelkerke R^2 value of .699 indicates that the model explains approximately 69.9% of the variance which suggests there is a moderately strong relationship between predictors (independent variables) and the outcome (dependent variable).

b) Hosmer and Lemeshow Test

Given the p value of 0.101 statistically it can be concluded the model fits the data well or in other words it is a good fit.

c) Logistic Regression Table Output

Table 22 SQ5 Logistic Regression Table output for bscpm3

Variables in the Equation (bscpm3)

	B	S.E.	Wald	df	Sig.	Exp(B)
Constant	3.676	0.61	36.78	1	<.001	39.508
Zscore(resp_km)	1.973	0.47	17.88	1	<.001	7.192
Zscore(resp_rd)	-3.65	0.92	15.59	1	<.001	0.026
Zscore(avg_sn)	2.48	0.85	8.594	1	0.003	11.937
Zscore(avg_di)	-1.57	0.59	7.202	1	0.007	0.208
Zscore(avg_bscpm)	1.781	0.68	6.937	1	0.008	5.939
Zscore(resp_oe)	1.089	0.56	3.818	1	0.051	2.971
Zscore(resp_cs)	1.08	0.72	2.261	1	0.133	2.944
Zscore(avg_jr)	-0.53	0.54	0.937	1	0.333	0.591
Zscore(resp_inpd)	-0.37	0.41	0.831	1	0.362	0.69
Zscore(avg_ese)	0.386	0.63	0.37	1	0.543	1.47
Zscore(avg_pec)	-0.29	0.47	0.367	1	0.545	0.751

Source: IBM Statistical Package for the Social Sciences (SSPS)

d) Classification Table

The overall percentage correct prediction of 91.3% indicates that the model has good predictive accuracy. The model was accurate predicting positively that AI is an innovative tool that influenced revenues and profitability positively.

e) Interpretation

The p value of 0.101 from the Hosmer Lemeshow test indicated there the model fit the data very well. The Nagelkerke value of 0.699(69.9%) indicated that there was a strong relationship between the predictors (independent variables) and the outcome (dependent variable). Of the 11 predictors the regression output analysis indicated that there were 5 predictor variables Knowledge Management (KM), Results Demonstrability (RD), Subject Norm (SN), Data Infrastructure (DI), Balanced Scorecard Parameters (BSCPM). Subject Norm (SN) showed significant contributions to the model. There was no single independent variable that significantly influenced the model.

f) Conclusion

Basis the above interpretation and with with p value > 0.05, it can be concluded that the null hypothesis (H_05): "Artificial Intelligence is an innovative tool that has the ability to influence revenues and operating margins in SME organizations in India." **can be accepted.**

4.7.6 SQ6 AI, Innovation and decision making

SQ6 Is Artificial Intelligence an innovative tool that can be integrated into the decision-making process for Indian SMEs?

Null Hypothesis (H_06): "Artificial Intelligence is an innovative tool that can be integrated into the decision-making process for SMEs in India for a significant impact."

Alternate Hypothesis (H_16): "Artificial Intelligence is an innovative tool that has no significant impact when integrated into the decision-making process for SMEs.in India"

Table 23 SQ6 Impact of AI on decision making - rd

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	141.552	0.527	0.708

Hosmer and Lemeshow Test

Step	Chi-square	Df	Sig.
1	26.886	0	0.001

Classification Table[a]

		Predicted		
		resp_rd		
		0	1	%Correct
resp_rd	0	87	10	89.7
	1	15	119	88.8
Overall %				91.8

Source: IBM Statistical Package for the Social Sciences (SSPS)

Model Summary - Results Interpretation for rd

a) Interpretation of a Nagelkerke R^2

A Nagelkerke R^2 value greater than 0.7 is considered a strong relationship between the variables. The Nagelkerke R^2 value of .708 indicates that the model explains approximately 70.8% of the variance which suggests there is a strong relationship between predictors (independent variables) and the outcome (dependent variable).

b) Hosmer and Lemeshow Test

Given the p value of 0.001 statistically it can be concluded the model is a very poor fit or in other words there is a large variance between the observed data and the predicted data.

c) Logistic Regression Table Output

Table 24 SQ6 Logistic Regression Table output for rd

	B	S.E.	Wald	df	Sig.	Exp(B)
Zscore(avg_sn)	2.759	0.47	33.89	1	<.001	15.781
Constant	1.058	0.29	13.43	1	<.001	2.881
Zscore(avg_ese)	-1.51	0.41	13.37	1	<.001	0.221
Zscore(resp_oe)	1.186	0.33	13.15	1	<.001	3.275
Zscore(avg_di)	0.91	0.28	10.37	1	0.001	2.484
Zscore(resp_cs)	1.485	0.46	10.28	1	0.001	4.416
Zscore(avg_bscpm)	-1.08	0.38	8.109	1	0.004	0.339
Zscore(resp_inpd)	0.887	0.39	5.087	1	0.024	2.427
Zscore(avg_jr)	0.695	0.34	4.105	1	0.043	2.004
Zscore(avg_pec)	-0.65	0.4	2.706	1	0.1	0.522
Zscore(resp_km)	0.227	0.28	0.643	1	0.423	1.255

Source: IBM Statistical Package for the Social Sciences (SSPS)

d) Classification Table

The overall percentage correct prediction of 91.8% indicates that the model has good predictive accuracy.

e) Interpretation

The p value of 0.001 from the Hosmer Lemeshow test indicated there the model did not fit the data well. The Nagelkerke value of 0.708(70.8%) indicated that there was a strong relationship between the predictors (independent variables) and the outcome (dependent variable). Of the 11 predictors the regression output analysis indicated that there were 6 predictor variables Subject Norm (SM), Employee Staffing and Satisfaction (ESE), Operating Efficiency (OE), Data Infrastructure (DI), Computer Self Efficacy (CS), showed significant contributions to the model. In the model BSCPM financial parameters show a negative coefficient which indicated that financial predictor variable negatively influenced from integrating AI in decision making. This could be because integrating AI for decisioning making came with higher costs of operation, technical infrastructure, higher salaries and employee-based costs too.

f) Conclusion

Basis the above interpretation, p value <0.05, it can be concluded that the null hypothesis ($H_0$6): "Artificial Intelligence is an innovative tool that can be integrated into the decision-making process for SMEs in India for a significant impact." **be rejected and the alternative hypothesis be accepted.**

4.8.7 SQ7 AI role in revenue growth

SQ7 Does the use of artificial intelligence have a co relation with the improvement of revenues in Indian SMEs?

Null Hypothesis ($H_0$7): "Revenue is improved by the use of Artificial Intelligence in Indian SMEs."

Alternate Hypothesis (H_17): "Artificial Intelligence has no significant impact on revenue in Indian SMEs."

Table 25 SQ7 AI versus revenue growth - bscpm6

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	123.731	0.492	0.7

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	14.872	8	0.062

Classification Table[a]

		Predicted		
		resp_bscpm6		
		0	1	%Correct
resp_bscpm6	0	151	12	92.6
	1	12	56	82.4
Overall %				89.6

Model Summary - Results Interpretation for bscpm6

a) Interpretation of a Nagelkerke R^2

A Nagelkerke R^2 value greater than 0.7 is considered a strong relationship between the variables. The Nagelkerke R^2 value of .7 indicates that the model explains approximately 70% of the variance which suggests there is a strong relationship between predictors (independent variables) and the outcome (dependent variable).

b) Hosmer and Lemeshow Test

Given the p value of 0.062 statistically it can be concluded the model is a good data fit or in other words the observed data and the predicted data almost match.

c) Logistic Regression Table Output

Table 26 SQ7 Logistic Regression Table output for bscpm6

Variables in the Equation(bscpm6)

	B	S.E.	Wald	df	Sig.	Exp(B)
Constant	-2.98	0.53	31.28	1	<.001	0.051
Zscore(avg_pec)	4.007	0.86	21.63	1	<.001	55.002
Zscore(avg_bscpm)	1.676	0.51	10.65	1	0.001	5.347
Zscore(avg_sn)	-2.03	0.66	9.588	1	0.002	0.131
Zscore(avg_jr)	1.2	0.43	7.761	1	0.005	3.319
Zscore(resp_oe)	1.605	0.59	7.451	1	0.006	4.975
Zscore(resp_inpd)	-1.1	0.43	6.633	1	0.01	0.334

Zscore(resp_km)	-0.64	0.26	5.886	1	0.015	0.528
Zscore(resp_rd)	-1.08	0.55	3.888	1	0.049	0.338
Zscore(avg_ese)	-0.64	0.43	2.278	1	0.131	0.525
Zscore(resp_cs)	-0.35	0.37	0.939	1	0.333	0.702
Zscore(avg_di)	0.09	0.28	0.1	1	0.751	1.094

Source: IBM Statistical Package for the Social Sciences (SSPS)

d) Classification Table

The overall percentage correct prediction of 89.6% indicates that the model has good predictive accuracy.

e) Interpretation

The p value of 0.062 from the Hosmer Lemeshow test indicated there was a good model fit. The Nagelkerke value of 0.708(70.8%) indicated that there was a strong relationship between the predictors (independent variables) and the outcome (dependent variable). Of the 11 predictors the regression output analysis indicated that there were 5 predictor variables that contributed to the model. Of these PEC, BSCPM, SN contributed significantly to determining improvement in revenue when using AI in Indian SMEs.

f) Conclusion

Basis the above interpretation of the p value it can be concluded that the null hypothesis ($H_0$7): “Revenue is improved by the use of Artificial Intelligence in Indian SMEs.” **can be accepted.**

4.8.8 SQ8 AI’s impact on financial performance parameters

SQ8 Does AI positively impact financial performance parameters (E.g.: Revenue, Operating margin, EBIT etc.) if used in the right manner in Indian SMEs?

Null Hypothesis ($H_0$8): “AI positively impact financial performance parameters (e.g., Revenue, Operating margin, EBITDA) when used in the right manner in Indian SMEs”

Alternate Hypothesis ($H_1$8): “AI does not positively impact financial performance parameters (e.g., Revenue, Operating margin, EBITDA) when used in the right manner in Indian SMEs.”

Table 27 SQ8 Financial parameters impact – oq_1

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	83.244	0.517	0.779

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	14.886	8	0.061

Classification Table[a]

		Predicted		
		Resp_oq_!		
		0	1	%Correct
resp_oq!	0	44	10	81.5
	1	3	174	98.3
Overall %				94.4

Model Summary - Results Interpretation for oq1

a) Interpretation of a Nagelkerke R²

A Nagelkerke R² value greater than 0.7 is considered a strong relationship between the variables. The Nagelkerke R² value of .779 indicates that the model explains approximately 77.9% of the variance which suggests there is a strong relationship between predictors (independent variables) and the outcome (dependent variable).

b) Hosmer and Lemeshow Test

Given the p value of 0.061 statistically it can be concluded the model is a good data fit or in other words the observed data and the predicted data almost match.

c) Logistic Regression Table Output

Table 28 SQ8 Logistic Regression Table output for oq_1

Variables in the Equation (oq1)

	B	S.E.	Wald	df	Sig.	Exp(B)
Constant	5.158	1.03	25.27	1	<.001	173.835
Zscore(resp_km)	2.519	0.62	16.76	1	<.001	12.412
Zscore(avg_sn)	10.07	2.47	16.66	1	<.001	23589.11
Zscore(resp_oe)	4.37	1.08	16.49	1	<.001	79.035
Zscore(resp_rd)	-6.497	1.69	14.79	1	<.001	0.002
Zscore(avg_pec)	-2.166	0.74	8.468	1	0.004	0.115
Zscore(avg_ese)	-2.51	0.99	6.456	1	0.011	0.081
Zscore(resp_inpd)	1.45	0.57	6.393	1	0.011	4.262
Zscore(avg_di)	2.044	0.81	6.353	1	0.012	7.72
Zscore(avg_bscpm)	-1.957	0.9	4.76	1	0.029	0.141
Zscore(resp_cs)	1.117	0.68	2.679	1	0.102	3.055
Zscore(avg_jr)	0.275	0.51	0.29	1	0.59	1.317

Source: IBM Statistical Package for the Social Sciences (SSPS)

d) Classification Table

The overall percentage correct prediction of 94.4% indicates that the model has good predictive accuracy.

e) Interpretation

The p value of 0.061 from the Hosmer Lemeshow test indicated that the model fits the data well. The Nagelkerke value of 0.779(77.9%) indicated that there was a strong relationship between the predictors (independent variables) and the outcome (dependent variable). Of the 11 predictor variables, Subject Norm was significant in driving the outcome of the hypothesis indicating that SMEs in India were likely to follow suit to adopt AI for decisioning making and improvement of profitability if others in the SME industry lead the way for them.

f) Conclusion

Basis the above interpretation and the p value of 0.062, it can be concluded that the null hypothesis (H_08): “AI positively impact financial performance parameters (e.g., Revenue, Operating margin, EBITDA) when used in the right manner in Indian SMEs.” **can be accepted.**

4.8.9 RQ1 Key Findings and interpretation

In Chapter 3 the author set out with a key research objective “Evaluate and propose practical recommendations for the optimal integration of AI in strategic decision making to enhance financial performance outcomes in SMEs in India.”

Against the research objective and the primary research question, there were 8 secondary questions that were analyzed to determine the primary hypothesis and the determination of what was achieved against the research objective that was set.

The secondary research questions were designed to get the participants responses for the below dimensions

- AI and its influence on Financial Performance Metrics
- Use of AI and its impact to improve top line (revenues) and bottom lines (profitability)
- AI and innovation
- Integration of AI in the organization’s strategic decision-making framework

The further sections explain the findings in a more detailed and lucid manner.

4.8.9.1 AI as an innovation tool and its role in the strategic decision making

The research questionnaire contributed to asking the participants to share their responses around the use of AI as an innovative tool. The hypothesis concluded that Artificial Intelligence was an innovative tool that had the ability to influence revenues and operating margins in SME organizations in India. The research hypothesis also concluded that Artificial Intelligence when looked to be used as an innovative tool to be integrated for decision making did not have a significant impact. Further investigation into the logistics regression analysis table lead to the below key findings

1) AI as an innovative tool to be used in SMEs in India that impacted revenues, and profitability was dependent on the acceptance of AI from the participants peers in the organization and SME industry. This finding also emphasized the fact that AI adoption and initiatives in SMEs were always a top-down approach i.e. Such initiatives must have the support of the executive management and key stakeholders in the organization. With more support at the organization level in the form of robust technology infrastructure, appropriate knowledge initiatives as training, skilling could lead to more innovative use of Artificial Intelligence.
2) Though the participants' believed AI is an innovative tool, their acceptance of AI as a tool that contributed to strategic decision-making when integrated in the organization largely depended on the acceptance of their industry peers. The presence of a strong technology infrastructure that provided data of a better quality also played a large role in viewing AI as a tool for strategic decision making.

3) It is also very critical to ensure employee engagement is constantly emphasized at all levels to alleviate any apprehensions that employees might have, once the use of AI is more prevalent in the organization. These types of apprehensions could be alleviated by the creation of a better skilled work force through better AI skilling initiatives and better monetary benefits to such skilled work forces.
4) Investing in employees could improve employee satisfaction and engagement, however, organizations need to invest in such initiatives thereby resulting in an increase in costs for the organization. Increase of costs will results in lowering of profitability and there by having a negative impact on EBIDTA.While this impact could be temporary, and a gradual improvement noted as AI adoption increases, such initiatives are still required to be monitored and tracked and measured.

4.8.9.2 AI and its influence on Financial Performance Metrics

There were two dimensions along which the secondary questions were analyzed, and the hypothesis carried out. The first set of questions analyzed the influence of AI on financial performance metrics. The financial performance metrics that were evaluated were EBDITA and Operating Margin**.**

Key Findings for Financial Performance Metrics:

- AI influences financial performance parameters such as Operating Margin and EBITDA in Indian SMEs when used appropriately, thereby strengthening the idea that AI, can be used as an innovative tool, to enhance decision-making processes.
- EBIDTA emerged as the key metric that was positively influenced by Artificial Intelligence. Participants responses showed that AI as an innovative tool

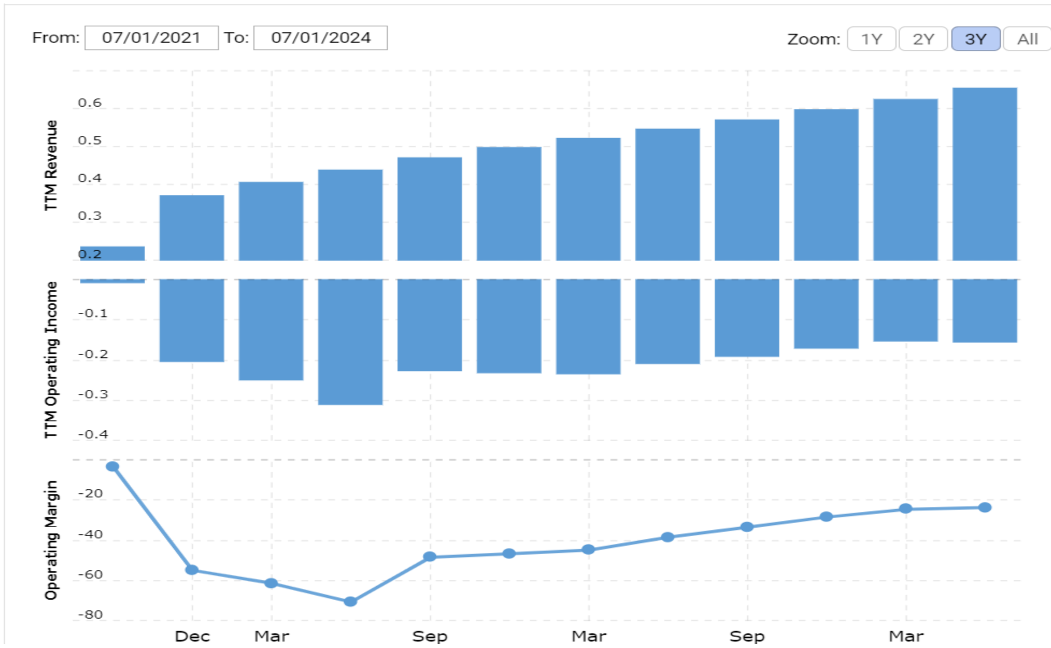
influenced EBITDA as well. Though EBITDA was influenced positively by AI, factors such as knowledge management, results demonstrability, operating efficiency indicated a negative trend in the logistic regression analysis. Operating efficiency being a negative trend using Artificial intelligence could be due to excessive focus on measurement of operating efficiency being achieved using AI for the initiatives that involved AI. Excessive focus on measurement of efficiencies for all AI based initiatives could be counterproductive for SMEs. SME organizations need to establish a balance of their efficiency measurement criteria for their AI initiatives, by narrowing down on the key objctives of using AI in their organization and creating a road map and execution plan for the same.

- Being influenced by external market factors or waiting for market acceptance of AI could also mean missed opportunities or the organization being overly cautious to commit to AI investments or take bold decisions could also negatively impact EBITDA.
- Thus, the above findings indicate that the above factors negatively impacted EBITDA, even though AI and financial metrics were working in the organization’s favour.
- The second interesting finding was that though EBITDA was positively influenced Artificial Intelligence, Operating Margin was not significantly influenced using Artificial Intelligence. EBITDA primarily helps in understanding the organization’s ability to generate earnings from its primary business activities,

whereas Operating Margin determines the profit organizations retain after all the operating costs are covered.

- SMEs always operate within financial constraints and always look for ways to generate revenue quickly and this could be the reason AI positively influenced EBITDA. The initial investment and implementation costs to implement AI often require significant investment in technology, training and even process changes and can act as temporary brakes to the operating margin. However, over time once these costs are absorbed, there will be improvement to the operating margin. Example – Fresh works a Chennai based SME that is headquartered in California. Fresh works is known for AI driven CRM and ITSM SAAS solutions. Freshworks invested in AI technologies to provide customized customer support and predictive analytics. Over a period as their product matured, there was a lowering of their operating expenses, offsetting their initial investment and there by leading the path to a sustained financial growth with solutions being offered across IT service management, marketing automation, sales automation and more.

Figure 11 Fresh works Operating margin trend



Source: https://www.macrotrends.net/stocks/charts/FRSH/freshworks/operating-margin

Even though Freshworks has not reached a positive operating margin yet as their focus is on growth, capturing markets and reaching out to more customers, their adoption of AI technologies for their customers via AI enabled products has led to a rapid increase in the operating margins thereby reducing their losses as they grow into a sustainable and profitable business

Key findings for revenue and profitability

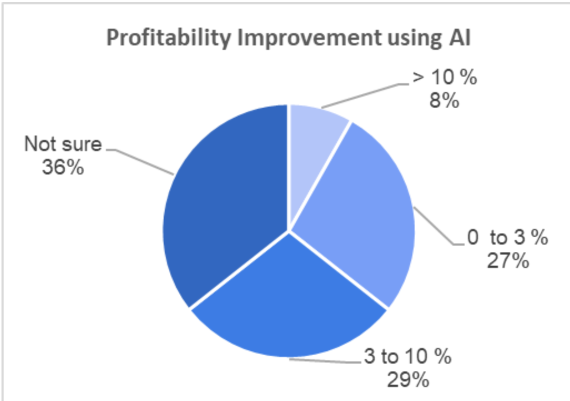
Hypothesis results around revenue and profitability related secondary questions indicated the following that top lines and bottom lines were impacted using AI in the Indian SMEs.

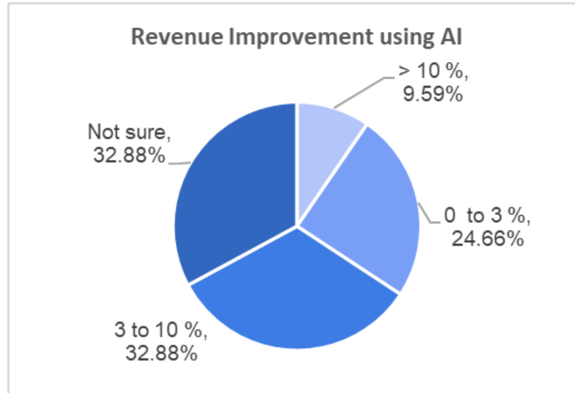
1) Other than the financial performance indicators as EBDITA and Operating Margin, adoption of AI to improve revenue and profitability by the SME peers

played a significant role in the use of AI for revenue and profitability improvement.

2) At the same time, though the adoption of AI was driven by market forces where organizations appeared to take their time to evaluate whether AI was useful for their business before they could adopt and integrate it within their environment. A negative Subject Norm and a positive PEC appears to be counter intuitive at the outset. Further investigation into the responses across the participants indicated that although the participants felt strongly that AI would play a significant part in improving profitability 36% of the respondents were unsure of whether AI would really contribute to improvement of revenue and profitability in their organization's context. A larger pecentage of the respondents almost close to 60 % indicated that AI could improve their revenues or profitability marginally between 0 and 3 % . Thus in conjunction with a negative Subjective norm and positive PEC, it can be interpreted as SMEs are looking to adopt AI for growth and profitability however on their own terms and pace and not being pressurized by the influence of their peer organization and other external pressures. In other words, SMEs are evaluating AI for their organization's context and looking to adapt to AI for their growth and profitability rather than being driven by the adoption of the AI by their peers.

Figure 12 Participants response AI based profitability and revenue improvements





Source: Authors Dataset and graph-based analysis using Excel

4.8.10 Conclusion

The primary research question demonstrated that "Strategic decisioning process especially financial performance metrics (EBITDA or Operating Margin) is impacted positively when guided by Artificial Intelligence in the context of the Balanced Scorecard framework in Indian Small and Medium Enterprises". SMEs in India are adopting AI for strategic decisioning process especially around revenue improvement and in turn EBITDA. Though the improvement in the operating margin did not appear to be positively impacted by AI, adoption of AI in the Indian SMEs is improving. The impact on the operating margin would have a positive impact, once the adoption of AI to measure the key financial indicators in the context of a framework as BSC matures and receives a larger community of adoption.

4.9 Research Question 2

RQ2 What are the key challenges faced by Indian Small and Medium Enterprises (SMEs) in implementing Artificial Intelligence (AI) in their decision-making processes, and their influence on the successful adoption and integration of AI technologies?

As part of the research, the following secondary questions were postulated to determine the correlation between the key challenges faced by the Indian SMEs, with the emphasis being on the availability of data that would be used by Artificial Intelligence, the availability of the skills in their organization and the availability of infrastructure required to implement the AI for supporting the strategic decision making.

4.9.1 SQ9 Factors for AI based decision making

SQ9 How does the availability of the right skill set influence an AI aided strategic decision-making processes in SMEs?

Null Hypothesis ($H_0$9): "Availability of the right skills in the SME organization has no impact on the organization's ability to implement AI aided strategic decision making."

Alternate Hypothesis ($H_1$9): "Availability of the right skills in the Indian SME organization has a significant impact in the organization's ability to implement AI aided strategic decision making."

Table 29 SQ9 Factors impacting AI based strategic decisioning

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	238.564	0.279	0.376

Hosmer and Lemeshow Test

Step	Chi-square	Df	Sig.
1	27.288	8	<.001

Classification Table[a]

Predicted		
resp_rd		
0	1	%Correct

resp_rd	0	72	25	74.2
	1	28	106	79.1
Overall %				77.1

Model Summary - Results Interpretation for rd

a) Interpretation of a Nagelkerke R^2

A Nagelkerke R^2 value greater than 0.7 is considered a strong relationship between the The Nagelkerke R^2 value of .376 indicates that the model explains only 37.6% of the variance which suggests there is a not a very strong relationship between predictors (independent variables) and the outcome (dependent variable).

b) Hosmer and Lemeshow Test

Given the p value <0.001 statistically it can be concluded the model is statistically insignificant and the model does not explain the data or in other words the observed data and the predicted data does not match.

c) Logistic Regression Table Output

Table 30 SQ9 Logistic Regression Table output for rd

Variables in the Equation (resp_rd)

	B	S.E.	Wald	df	Sig.	Exp(B)
Zresp_pec1	0.933	0.19	24.99	1	<.001	2.543
Constant	0.474	0.16	8.314	1	0.004	1.606
Zresp_ese1	0.504	0.2	6.318	1	0.012	1.656
Zresp_jr2	0.296	0.2	2.282	1	0.131	1.345
Zresp_km	0.229	0.19	1.477	1	0.224	1.257
Zresp_jr1	-0.16	0.17	0.872	1	0.35	0.851
Zresp_ese2	0.163	0.2	0.643	1	0.423	1.177

Source: IBM Statistical Package for the Social Sciences (SSPS)

d) Classification Table

The overall percentage correct prediction of 77.1% indicates that the model has decent predictive accuracy.

e) Interpretation

The p value of <0.001 from the Hosmer Lemeshow test indicated there the model did not fit the data well. The Nagelkerke value of 0.376(37.6%) indicated that there was a very weak relationship between the predictors (independent variables) and the outcome (dependent variable). Of the 6 predictor variables, two variables PEC and ESE were significant in driving the outcome of the hypothesis

f) Conclusion

Basis the above interpretation and the p value <0.001 and basis the Hosmer Lemeshow test, it can be concluded that the alternate hypothesis ($H_0$9): "Availability of the right skills in the Indian SME organization has a significant impact in the organization's ability to implement AI aided strategic decision making." **can be accepted.**

4.9.2 SQ10 AI based decisioning and Infrastructure

S10 How significant is the need for an infrastructure for SMEs to enable their ability to implement AI aided strategic decision making?

Null Hypothesis ($H_0$10): "The presence of a robust infrastructure has no impact on the ability of SMEs to implement AI-aided strategic decision-making processes."

Alternate Hypothesis ($H_1$11): "The presence of a robust infrastructure has a significant impact on the ability of SMEs to implement AI-aided strategic decision-making processes."

Table 31 SQ10 Impact of infrastructure on AI based strategic decisions

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	238.564	0.279	0.376

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	27.288	8	<.001

Classification Table[a]

		Predicted		
		resp_rd		
		0	1	%Correct
resp_rd	0	48	49	49.5
	1	28	106	79.1
Overall %				66.7

Model Summary - Results Interpretation for rd

a) Interpretation of a Nagelkerke R^2

A Nagelkerke R^2 value greater than 0.7 is considered a strong relationship between the The Nagelkerke R^2 value of .376 indicates that the model explains only 37.6% of the variance which suggests there is a not a very strong relationship between predictors (independent variables) and the outcome (dependent variable).

b) Hosmer and Lemeshow Test

Given the p value <0.001 statistically it can be concluded the model is statistically insignificant and the model does not explain the data or in other words the observed data and the predicted data does not match.

c) Logistic Regression Table Output

Table 32 SQ10 Logistic Regression Table output for rd

Variables in the Equation(respn_rd)

	B	S.E.	Wald	df	Sig.	Exp(B)
Zresp_pec3	0.595	0.16	13.57	1	<.001	1.813

Constant	0.368	0.15	6.35	1	0.012	1.445
Zresp_pec2	0.406	0.17	6.008	1	0.014	1.501
Zresp_di3)	0.182	0.15	1.432	1	0.232	1.2
Zresp_di1	-0.12	0.2	0.334	1	0.563	0.889
Zresp_di2)	0.029	0.19	0.022	1	0.882	1.029

Source: IBM Statistical Package for the Social Sciences (SSPS)

d) Classification Table

The overall percentage correct prediction of 66.7% indicates that the model has moderate predictive accuracy.

e) Interpretation

The p value of <0.001 from the Hosmer Lemeshow test indicated there the model did not fit the data well. The Nagelkerke value of 0.376(37.6%) indicated that there was a very weak relationship between the predictors (independent variables) and the outcome (dependent variable). Of the 5 predictor variables, two variables PEC2 and PEC3 were significant in driving the outcome of the hypothesis with PEC2 being statistically very significant.

f) Conclusion

Basis the above interpretation and the p value <0.001 and basis the Hosmer Lemeshow test, it can be concluded that the alternate hypothesis ($H_0$10): “The presence of a robust infrastructure has a significant impact on the ability of SMEs to implement AI-aided strategic decision-making processes.” **can be accepted.**

4.9.3 RQ2 Key Findings and interpretation

The secondary questions hypothesis concluded that a robust infrastructure and the availability of the right skills in the Indian SME organization were the key to the adoption of AI in the Indian SMEs.

The right skills, a structured approach to the adoption of AI initiatives was highlighted and indicated as of paramount importance. While the AI initiatives in Indian SMEs is of focus, adoption of AI is driven by organizations encouraging the enablement to develop the right skills to integrate AI within their ecosystems.

AI initiatives are successful if such initiatives receive the support at all levels in the organizations i.e. from the CXO level who provide the direction for the adoption to AI to the business teams that implement AI to improve their own efficiencies and productivity.

The secondary questions highlighted two challenges in relation to the research question

a) **Infrastructure:** The presence of a strong infrastructure is a key success factor for a successful AI implementation. Without adequate technical and organizational infrastructure, SMEs in India are likely to face significant hurdles in the adoption of AI technologies. Adoption of technology can be expensive, and SMEs in India need to think and keep the costs of adoption of technology as well in mind. When it comes to technology infrastructure, organizations are required to consider the following at a minimum.

b) **Data Collection, processing, Storage**: All AI based initiatives rely on data to identify patterns, train the models and provide inferences. Thus, for all SMEs or any organization, collection , transformation storage of data is critical. . Without a robust data pipeline to perform the collection, transformation and storage, AI implementation becomes almost impossible. Artificial Intelligence based modelling; predictions also need high end computing power which use Graphic Processing Units (GPUs) than Central Processing Units (CPU). More processing power, better predictions need more data, thereby resulting into more storage. SMEs with their financial constraints would not be inclined to invest into larger data centres and larger computing power.

c) **Data protection and security**: Since AI could deal with sensitive data as customer information, the data is required to be secure and protected to ensure that the data is secure. SMEs would be required to have an established security infrastructure to ensure that their application and data are safe guarded against data breaches and cyber-attacks.

d) **Skill Set:** As with any other technology or process the availability of people with the right knowledge and understanding of AI is essential for AI integration. The lack of such skilled personnel in AI and data analytics can have a significant impact on the implementation of AI aided decision-making processes**.**

AI systems need professionals with expertise in data science, Machine learning to develop, train and maintain models. Some of these professionals are expensive resources with high salaries, possibly having SME leaders evaluate the need for such high-cost resources.

In such instances, SME leaders could look to invest in platforms that are already AI enabled, look for government backed initiatives, work on a Talent enablement initiative to build the AI talent pool within the organization or even partner with universities and other education institutes to develop their AI initiatives and talent pool

4.9.4 Conclusion

The key challenges encountered within Indian SMEs to implement AI for their decision-making processes are primarily related to the need for a robust infrastructure and the availability of a skilled workforce with key issues related to data collection, storage, quality of data and the technology related to processing of such data in large volumes. SMEs organizations in India could adopt a Software as a Service (SAAS) approach where they could invest in a platform that already employs Artificial Intelligence and can be integrated into the Organization’s ecosystem. Alternatively, they could invest in the right skills to develop the AI based platform in house, investing in the right infrastructure talented workforce to use AI for profitability improvements. Whichever approach the SMEs adopt, it is very evident that SMEs will need to adopt AI within their business ecosystems so they could work towards improving their profitability of their business and use AI to help with strategic decisioning.

Listed below are some examples where organizations have implemented AI for improving efficiencies and introducing a culture of innovation

1) Magic Bus a nonprofit organization in India in 2024 adopted the use of cloud computing and AI to create a training platform that enabled them to increase the efficiency of their sessions and improve the learning outcomes and employable skills for their students. Because of its digital platform, educators were able to

tangibly identify the results of their students and enhance their monitoring and evaluation of their programs (Microsoft 2024b).

2) Tatva care A healthcare startup in India that provides support for chronic patients, in 2024 created an application that helped to automate the doctors practice, with focus on Outpatient Procedures Departments (OPD) procedures and support in 16 regional languages. (Microsoft, 2024).

c) In its pursuit to transform the business operations of its customers, Genpact was constrained by its dependence on manual tasks. These tasks consumed excessive time and effort, while also increasing the risk of errors and rework thereby impacting productivity and profitability. Genpact looked to leverage the potential of AI to help boost employee productivity and streamline operations as well. Genpact developed a scalable application using Azure Open AI, Microsoft SQL Server, Azure Blob Storage, Microsoft Bing, and other Azure products. This application enabled the fostering of an innovation culture and knowledge sharing across Genpact's global workforce. This platform been used globally across Genpact's user base of 125,000 users facilitating 2 million transactions and use in 120 unique cases(Microsoft 2024a).

d) **Udaan** is a B2B e-commerce platform serving SMEs in India, that facilitates matchmaking between buyers and suppliers, boosting Udaan's growth in a highly competitive market. With a large b2b platform bases, Udaan likely uses AI for price optimization, inventory management, and customer behavior analysis.

e) **Fresh works**, a Chennai-based SME offering AI-driven CRM solutions, emphasizes the importance of secure cloud infrastructure. Fresh works caters to other organizations across the world and provides an innovative platform that is AI driven providing IT services, CRM and even customer services.

4.10 Principal Components Analysis (PCA) based findings

The logistic regression analysis-based findings addressed the two primary research questions (RQ1, RQ2). The approach adopted to model the analysis for the various secondary questions was to determine an outcome variable that would determine the outcome of hypothesis of the secondary questions. As part of the approach there were close to 36 independent variables around which there were responses collected by the participants. To simplify the model and analysis some of the independent variables were converted to composite variables and the outcome variables were changed to a binomial scale. To identify any more patterns, relationships that may contribute to this research at the individual response level, the author looked to analyze the independent responses and their relationships, if any. Principal Component Analysis (PCA) was adopted as the analysis tool to carry out this analysis.

PCA was chosen as the tool to enable the author to help author identify any additional patterns amongst the original non composite variables (original responses from the participants responses) to identify any groups which could identify any additional observations to determine the influence of AI for strategic decisioning in the Indian SMEs to improve business outcomes, revenue and profitability.

Table 33 PCA Table matrix

Structure Matrix

	Component					
	Group1	Group2	Group3	Group4	Group5	Group6
Perception of External Control_1	0.778			0.404		
Results Demonstrability	0.737	0.353		0.374		-0.354
Subject Norm_1	0.737			0.595		-0.452
Computer Self Efficacy	0.736			0.465		
Operating Efficiency	0.724			0.710		
Perception of External Control 3	0.674					
Job Relevancy 2	0.663					
Innovation and Product Development	0.658	0.334	0.473	0.346	-0.363	
Perception of External Control 2	0.617			0.453		
Employee and Staff Engagement 1	0.605	0.514			-0.358	
Subject Norm 2		0.832				
Employee and Staff Engagement 2		0.824	0.330			
Job Relevancy 3		0.781		0.307		
Subject Norm 3	0.384	0.719		0.313		-0.436
Employee and Staff Engagement 3		0.605	0.449			
Balanced score card performance measure 2			0.847			
Balanced score card performance measure 1			0.790			
Data infrastructure 2	-0.396		0.595		0.382	0.428
Data infrastructure 1	-0.357		0.586		0.403	0.486
Knowledge Management		0.535	0.577			
Balanced score card performance measure 5	0.524			0.797		
Balanced score card performance measure 4	0.495			0.781	0.401	
Balanced score card performance 4		0.508		0.767		
Balanced score card performance 6	0.568			0.662	0.403	
Data infrastructure 3					0.787	
Job Relevancy 1						0.675

Refer to table for the definition of the variables.

Source: IBM Statistical Package for the Social Sciences (SSPS)

The Principal Component Analysis identified 6 groups of the variables that explained 68.4 % of the variance in the data with an eigen value of > 1.

For each of the groups, identified variables that had an eigen value of >0.3 were significant for the analysis. The sections below detail the findings per group basis the variables values loading and the simple phrases to determine if there any additional dimension or finding that may not have been uncovered as part of the logistic regression analysis.

4.10.1 Group 1 AI Readiness and Strategic Integration

4.10.1.1 Key Variables and Loadings

resp_pec1 (0.778): Are there necessary skills, plans, and structure for AI initiatives.

resp_rd (0.737): Are you exploring AI for decision-making.

resp_sn1 (0.737): Is there org level vision and direction for AI in business functions.

resp_cs (0.736): Are you exploring AI initiatives for improving profitability.

resp_oe (0.724): Is AI being used for operational efficiencies.

resp_pec3 (0.674): Is there support for AI at all organizational levels.

resp_jr2 (0.663): What is the familiarity with AI.

resp_inpd (0.658): Is AI a disruptive innovation.

resp_pec2 (0.617): Is there the requisite infrastructure for AI decision-making.

resp_ese1 (0.605): How is the encouragement for skill development.

resp_bscpm6 (0.568): Is there revenue improvements from AI.

resp_bscpm5 (0.524): Is AI being used for revenue growth.

resp_bscpm4 (0.495): Can profit improvements from AI.

resp_sn3 (0.384): is there AI's impact on operational efficiency.

resp_di1 (-0.357): Are there Data availability issues.

resp_di2 (-0.396): are larger effort required for data management.

4.10.1.2 Key findings

The questions in this group assessed the readiness for AI to evaluate strategic vision, organizational support, infrastructure, skills, and the potential impact AI could have on business performance.

A key finding was that AI's success is deeply tied to having the right mix of strategic planning, skilled people, and proper infrastructure. At the same time, data management and employee familiarity with AI also play critical roles in ensuring the long-term success of AI initiatives.

A strong foundation in skills, infrastructure, and strategic vision for AI played a huge part in integration of AI successfully and realize benefits such as improved profitability and operational efficiencies.

Larger social acceptance of AI as a technology was also critical for the acceptance of AI as a technology in SMEs. This factor also emphasized the need for organization level buy in for AI based initiatives, with equal emphasis for skill development for AI adoption.

4.10.2 Group 2 AI Decision Making Productivity & Employee

4.10.2.1 Key Variables and Loadings

resp_sn2 (0.832): Does AI have a positive impact on productivity.

resp_ese2 (0.824): AI-driven insights for employee satisfaction.

resp_jr3 (0.781): AI's role in strategic decision-making.

resp_sn3 (0.719): Operational efficiency through AI.

resp_ese3 (0.605): Improved retention through AI.

resp_km (0.535): Knowledge initiatives related to AI.

resp_ese1 (0.514): Skill development for AI.

resp_bscpm3 (0.508): Use of operating margin for performance measurement.

resp_rd (0.353): Exploring AI for decision-making.

resp_inpd (0.334): AI as a disruptive innovation.

4.10.2.2 Key Findings

This group highlights how AI could help with transforming multiple dimensions of an organization, from improving productivity to enhancing employee satisfaction and supporting strategic decision-making.

AI’s ability to streamline operations and provide valuable insights for performance measurement and retention makes it a critical tool for modern business success. Developing learning plans and road maps to improve employee skills on AI and its related skills could improve employee’s satisfaction for further adoption of AI-driven insights, leading to potentially higher productivity and retention.

4.10.3 Group 3 AI, financial performance & org. readiness

4.10.3.1 Key Variables and Loadings

resp_bscpm2 (0.847): Use of operating margin for performance measurement.

resp_bscpm1 (0.790): Use of EBIT for performance measurement.

resp_di2 (0.595): Effort required for data management.

resp_di1 (0.586): Data availability issues.

resp_km (0.577): Knowledge initiatives related to AI.

resp_inpd (0.473): AI as a disruptive innovation.

resp_ese3 (0.449): Impact of retention on profitability.

resp_ese2 (0.330): AI-driven insights for employee satisfaction.

4.10.3.2 Key Findings

This group appears to focus on financial performance tracking, data challenges, and how AI affects the workforce. This group primarily revolves around financial performance measurement, data challenges, AI innovation, and its impact on employees.

Financial metrics as EBDITA, Operating margin are impacted by the use of AI. However, challenges related to data management and availability are identified as key blockers to the implementation of AI.

There is also a growing emphasis on building AI-related knowledge and looking at AI as a tool for transformation and innovation.

Effective performance measurement and data management systems are essential for leveraging AI in strategic decision-making. Knowledge initiatives play a crucial role in improving understanding and use of AI thereby emphasizing the need for performance systems like Balanced Score cards, employees with the right skills and knowledge who could experiment and integrate AI initiatives in SME organizations Through this finding it can be concluded that if data in the SME organizations is of acceptable quality, knowledge management initiatives and skill programs for employees are in place, innovations and the use of AI can play a large role for EBIDTA and operating margin improvement for Indian SMEs.

4.10.4 Group 4 AI for Business growth and efficiency

4.10.4.1 Key Variables and Loadings

resp_bscpm5 (0.797): AI for revenue growth initiatives.

resp_bscpm4 (0.781): Profit improvements from AI.

resp_bscpm3 (0.767): Use of operating margin for performance measurement.

resp_oe (0.710): AI for operational efficiencies.

resp_bscpm6 (0.662): Revenue improvements from AI.

resp_sn1 (0.595): Vision for AI in business functions.

resp_cs (0.465): AI initiatives for improving profitability.

resp_pec2 (0.453): Infrastructure for AI decision-making.

resp_pec1 (0.404): Necessary skills, plans, and structure for AI.

resp_rd (0.374): Exploring AI for decision-making.

resp_inpd (0.346): AI as a disruptive innovation.

resp_sn3 (0.313): AI's impact on operational efficiency.

resp_jr3 (0.307): AI's role in strategic decision-making.

4.10.4.2 Key Findings

This group possibly highlights the impact of AI on revenue growth and operational efficiencies making it a critical factor for further exploration in the context of AI, SMEs in India. AI projects that have a strategic focus towards revenue growth via existing customer improvement initiatives , new customer acqusitions and a focus on operational efficiency improvement initiatives using AI to automate daily operations etc, have the ability to impact business positively. Organizations that have the blessings of the executive leaderships to define and implement a AI strategy and initiatives, were more likely to realise the benefits of AI in strategic decisioning to improve profitability more quicker.

4.10.5 Group 5 Data Management & AI driven growth

4.10.5.1 Key Variables and Loadings

resp_di3 (0.787): Availability of data and reports.

resp_di1 (0.403): Data availability issues.

resp_bscpm6 (0.403): Revenue improvements from AI.

resp_bscpm4 (0.401): Profit improvements from AI.

resp_di2 (0.382): Effort required for data management.

resp_ese1 (-0.358): Skill development for AI.

resp_inpd (-0.363): AI as a disruptive innovation.

4.10.5.2 Findings

The findings of this group suggest that the ability of using AI as a disruptive innovation is more likely to increase as the data management and infrastructure to use AI in the organization improved. With an established data infrastructure and the availability of the right data in the organization , the probability of better revenue and thereby profitability is higher. However the challenges related to having the right skills in the organization is likely to have negative impact on the use of AI to improve the profiability in the organization and its use as disruption technology.Strong data management systems and practices are amongst the key pre requisites to realise AI's potential. Effective data management practices allows organizations to establish the foundational data platform to leverage AI for performance measurement and strategic decision-making.

4.10.6 Group 6 AI and Decision influences

4.10.6.1 Key Variables and Loadings

resp_jr1 (0.675): Role in decision-making.

resp_di1 (0.486): Data availability issues.

resp_di2 (0.428): Effort required for data management.

resp_rd (-0.354): Exploring AI for decision-making.

resp_sn3 (-0.436): AI's impact on operational efficiency.

resp_sn1 (-0.452): Vision for AI in business functions.

4.10.6.2 Findings

The group primarily revolved around the importance of decision-making. To enable the use of AI for strategic decision making, the group's finding emphasised the importance of having a strong AI vision and the use of AI in business functions. While a broad vision for AI is required for the business, it use for strategic decisioning should be started off as a vision with more narrow focus , determining its applicability for the organizaion and thereby assessing its complexity or challenges in the implementation for the organization. The findings of the group broadly implies that individuals with decisioning making authority are more likely to support AI initiatives with a focus on establishing the data management platform and workflow first while applying a cautious approach on using AI and relying solely on AI for decision making.

Broadly, organizations with well-defined AI goals, management buy in, strong data management practices are more likely to succeed in their AI initiatives.

4.11 Summary

The study explored the impact of AI on strategic decision-making in Indian SMEs, focusing on various factors like infrastructure, skills, profitability, decision making and revenue using Balanced score card. The analysis used logistic regression to test hypotheses related to these factors. There were two research questions to be analyzed.

RQ2: What are the key challenges faced by Indian SMEs in implementing AI in their decision-making processes, and their influence on the successful adoption and integration of AI technologies**?**

RQ1: Can Strategic decision-making processes, guided by Artificial intelligence, impact financial performance metrics such as (EBITDA or Operating Margin) and non-financial performance measures within the context of the Balanced Scorecard framework in Indian Small and Medium Enterprises?

4.11.1 Summary

4.11.1.1 Overall Impact of AI on Indian SMEs

The comprehensive analysis of the logistic regression results and hypothesis testing indicated that the integration of AI into strategic decision-making processes had a significant positive impact on Indian SMEs. The findings supported the importance of a robust infrastructure, the role of employee skills, and the use of performance measurement systems like the Balanced Scorecard in realizing the benefits of AI.

In addition, the results from PCA also highlighted several critical areas that influenced the successful integration of AI in Indian SMEs. Organizational readiness, including the presence of necessary skills, infrastructure, and a strategic vision for AI, is crucial for realizing the benefits of AI. Enhancing employee skills and satisfaction through AI-driven insights could lead to higher productivity and retention, positively impacting profitability. Effective performance measurement and data management systems were essential for leveraging AI in strategic decision-making.

The findings emphasized the importance of investing in skills development, infrastructure, and data management practices to realize the benefits of AI. Organizations should also develop a clear strategic vision for AI use to guide successful integration and maximize benefits.

4.11.1.2 Infrastructure

A robust infrastructure improves the ability of SMEs to implement AI in strategic decision-making. To achieve this, the SMEs should consider technical infrastructure development such as appropriate storage mechanisms, data integration mechanisms, AI platforms and technologies to ensure the smooth transfer of data from various sources and its effective integration within the organization before embarking on the AI based insights and strategic decisioning frameworks. The infrastructure could be on the cloud native technologies which are prevalent today or if the SMEs choose could be on premise infrastructure and technology until the time, they are not comfortable moving to the cloud. Establishing a robust data infrastructure for SMEs could be daunting task; ranging from choice of various computer hardware to store the data, to choices of hosting the data on premise versus storing the data in the cloud infrastrcture.The various technologies choices for data storage like the use of RDBMSs like Oracle, Postgres, data ingestion software like Informatica , reporting tools like Power BI , AI tools like R, Python, H20.ai is all of paramount importance for SMEs to consider to enable a robust infrastructure. Similarly a data infrastructure on the cloud like AWS, or GCP or Azure would help the SMEs to simplify their cloices of technologies for a robust infrasturcture by using the native technologies and services that the cloud providers provide and enable the SMEs to focus on delivering value from technologies for their business.

Example: AWS (Amazon Web services)[17] a leading cloud provider, provides a calculator where one with a decent understanding of the services of AWS can estimate the costs required for the services.

4.11.1.3 Employee Skills and Enablement:

Data management skills as data integration (Extract Transform and Load, (ETL)), data modelling, reporting & BI, Data science and machine learning along with enablement in AI for employees and the management alike are crucial for overcoming resistance and maximizing the benefits of AI integration. This highlights the need for continuous training and development programs to enhance AI-related skills among employees.

4.11.1.4 Innovation and Operational Efficiency:

AI-driven innovation and improvements play a crucial role in boosting revenues and profitability via operational efficiency. Thus, streamlining operations and driving innovations could help SMEs in India to achieve a better financial performance. AI could be leveraged to drive innovation and streamline operations and contribute significantly to improving profitability and financial performance.

4.11.1.5 Performance Measurement Systems:

The use of comprehensive performance measurement systems like the Balanced Scorecard plays an essential role for monitoring and enhancing the impact of AI on financial performance of companies. Adoption of such measurement systems would help Indian SMEs to make informed decisions based on AI and data-driven insights.

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[17] https://calculator.aws/#/

4.11.1.6 Financial Performance:

The findings indicate that AI integration impacts financial performance parameters like revenue improvement and profitability. Through this research the potential of AI to drive financial growth and sustainability in Indian SMEs is emphasized.

PCA analysis highlighted several critical areas that influence the successful integration of AI in Indian SMEs. Organizational readiness, including the presence of necessary skills, infrastructure, and a strategic vision for AI, are crucial for realizing the benefits of AI. Enhancing employee skills and satisfaction through AI-driven insights could lead to higher productivity and retention, positively impacting profitability. Effective performance measurement and data management systems are essential for leveraging AI in strategic decision-making.

The findings thus underscore the importance of investing in skills development, infrastructure, and data management practices such as ensuring the quality of data to be used in AI initiatives is of good quality, data is available for reporting and accessible to the right personnel in the organization to realize the benefits of AI. Organizations should also develop a clear strategic vision for AI use to guide successful integration and maximize benefits.

4.12 Conclusion

Discussion of the research questions and the PCA from the previous sections conclude that AI has a positive impact on the strategic decision-making processes of Indian SMEs, leading to possible improved revenues and profitability. The key to successful AI integration lies in robust infrastructure, enhanced employee skills, innovative ways of adoption of AI for improvement of revenue and operational efficiencies. This was driven using comprehensive performance measurement systems as Balanced Score Card Thus with appropriate strategy, focused planning, and adoption Indian SMEs can harness the full potential of AI to achieve sustainable growth and competitive advantage. The next chapters discuss the findings and their impact in detail followed by recommendations, implications and areas for future research on this subject.

CHAPTER V:

DISCUSSION

5.1 Introduction

With the recent advances in technologies, like the advent of cloud-based technologies, artificial intelligence has become more mainstream and more generally accessible to businesses of all sizes. With this positive leap in the world of technologies, SMEs in India are now in a better position to explore and adopt the use of Artificial intelligence for strategic decision making to improve their profitability. Evaluation of this hypothesis formed the primary research objective of this thesis. To support the research, there were two research objectives conceived, one to evaluate the integration of AI for strategic decision making in Indian SMEs to improve their financial outcomes (profitability); the other research focused on the primary challenges Indian SMEs encountered to enable strategic decision-making using AI for their businesses. To enable meeting of the research objectives, theorical models as Technology Acceptance Model (TAM) and Balanced Score Card (BSC) were used to determine the use of AI for strategic decision in the Indian SMEs. The co relational study of the framework in relation to AI for strategic decision making formed the core of this study.

By acknowledging the challenges, identifying effective models, and possibly exploring innovative solutions, this research endeavored to contribute valuable knowledge that could empower executives of Indian SMEs to navigate the use of AI for their businesses and strategic decision making (improving profitability) for their businesses.

The further sections of this chapter outline the discussions of the results of the research questions from the previous chapter.

5.2 Discussion of Research Question One

This section discusses the findings related to the primary research question 1. The primary research question was

RQ1 Can Strategic decision-making processes, guided by Artificial intelligence, impact financial performance metrics such as (EBITDA or Operating Margin) within the context of the Balanced Scorecard framework in Indian Small and Medium Enterprises?

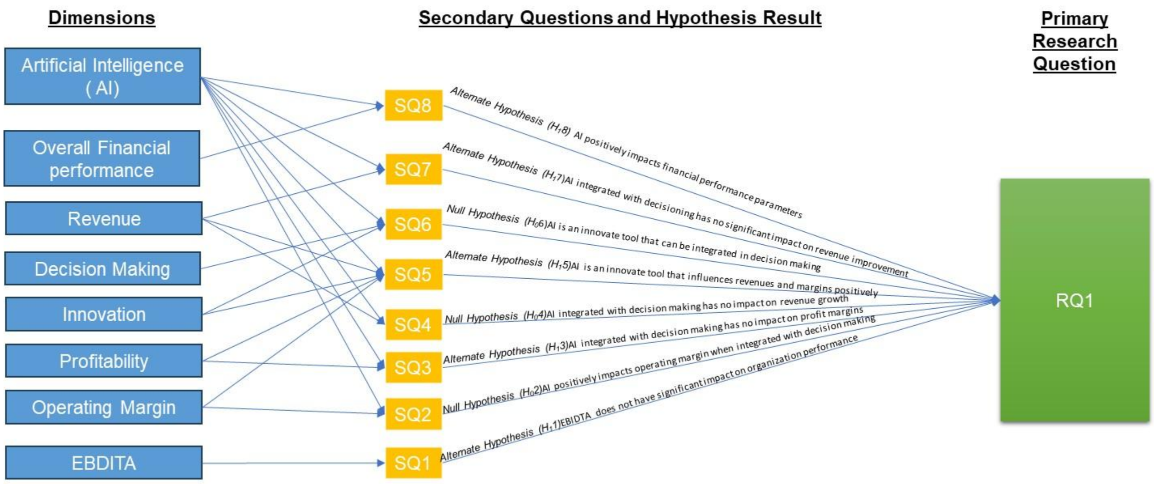
Null Hypothesis (H_{01}): "Strategic decisioning process especially financial performance metrics (EBITDA or Operating Margin) is impacted positively when guided by Artificial Intelligence in the context of the Balanced Scorecard framework in Indian Small and Medium Enterprises"

Alternate Hypothesis (H_{11}): "Strategic decisioning process especially financial performance metrics (EBITDA or Operating Margin) has no impact when guided by Artificial Intelligence in the context of the Balanced Scorecard framework in Indian Small and Medium Enterprises"

This research question focussed on determining whether financial performance metrics as EBIDTA or operating margin was impacted when AI was integrated along with the use of industry standard performance framework as Balanced Score card in Indian Small and Medium Enterprises. This discussion integrates the findings from the secondary research questions and hypothesis to provide a holistic view of AI's impact on financial performance.

The figure below depicts the dimensions, secondary research questions the hypothesis that contributed to the hypothesis of the primary research question

Figure 13 Primary research question map



Source : As conceived by the author

As from the diagram, the research question and the secondary research questions contributed to the analysis of the hypothesis. The analysis was conducted across several dimensions (Figure 13) to determine the influence of the dimensions to the research question and there by hypothesis.

5.2.1 Overview of Findings

This research question explored how Artificial Intelligence (AI), when integrated with the Balanced Scorecard (BSC) framework, could have an impact on financial performance metrics, particularly EBITDA and Operating Margin, in Indian SMEs. The secondary research questions inspected AI's influence on key business factors such as profitability, revenue growth, innovation, and strategic decision-making.

The results confirmed the hypotheses, particularly around the impact of AI on EBITDA and revenue growth. The findings also highlighted some limitations in AI's current ability to improve Operating Margin.

5.2.2 AI's Impact on Financial Performance Metrics

5.2.2.1 AI's Strong Impact on EBITDA

The results clearly showed a strong positive correlation between AI integration and EBITDA, confirming the null hypothesis (H01) that AI positively impacts EBITDA in Indian SMEs. This finding is of high significance, suggesting that AI has a strong potential to influence business functions in a positive way that directly enhance an organization's profitability.

I) How AI influences EBITDA?

- **Decision-Making**: AI enables data-driven insights that help SMEs make more informed, strategic decisions. For example, by using AI tools for demand forecasting, inventory management, and pricing strategies, SMEs can improve their waste reduction , thereby improving revenues without incurring significant additional costs. 32 % of the respondents where their organizations or they themselves already engaged in AI initiatives responded that on a average using

AI they are likely to see an improvement of their top line between 5-10 % once their AI initiatives are implemented.

- **Operational Efficiency**: Using AI to automate routine tasks, AI indirectly helps in streamlining operations, reduction in human error all leading to an improvement in operating efficiency. This is significant for SMEs in India which operate under tight financial controls and the focus is on cost control, these efficiencies can make a significant difference in profitability.

II) Comparison with Existing Literature

The positive impact of AI on EBITDA aligns with existing research where AI has been shown to optimize processes and boost profitability.

Example: A Chemical firm providing intelligent solutions for the mining industry was able to improve its EBDITA by 10-15 % by the use of AI and the use of digital twin technologies which enabled the combination of chemical and metalurgical process to define a new model that explained,predicted and controlled the resulting metal recovery (Grebe, Franke & Heinzl 2023).

In a study carried out by Ho and others (Ho et al. 2022) it was determined that AI and EBITDA have a positive relationship and that higher adoption of AI enabled a growth in the revenue , better monitoring and control of capital expenditure.

AI's ability to provide actionable insights to optimize their operations, reduce waste, and improve overall efficiency, thereby contributing to positively to improve EBITDA (Drydakis 2022). However, research in SMEs in India has been more limited, making this finding particularly important for SMEs in markets like India, where AI and technology adoption is higher than in recent years.

When AI is integrated with industry standard framework like Balanced Score Cards has the ability to significantly improve key financial metrics in Indian SMEs. Using AI to generate analytics can help SMEs in India to deeper insights into enable more precise forecasts, budgets, resource allocations , opportunities for revenue gneration , thereby improving EBDITA of organizations, agreeing with (Terry 2023) whose research suggested that Balanced Score Card is a good framework to measure organization measure and that AI can play a significant role in improving profitability in SMEs.

5.2.2.2 Operating Margin: Mixed Results

Unlike EBITDA, the impact of AI on Operating Margin was less pronounced, as the null hypothesis ($H_0$2) for Operating Margin was rejected. The lack of a significant positive impact suggests that although SMEs view AI as technology that is very helpful fo them, it has not been translated into improvements in operating margins for SMEs in India.

The Top 10 % of the respondents who were involved in AI initiatives in their organization (CXO, Founders or Senior Management personnel) were of the opinion that AI would impact their margins positively between 3 to 5 % and their revenues by a similar percentage. However they were unable to provide a true impact of AI on margins as the organizations had embarked on AI initiatives only recently i.e. Apr 2024.

I) What is the intepretation of the mixed results?

- **Initial Costs**: One potential reason for this finding is the upfront costs of implementing AI. The AI requires substantial investment in technology infrastructure, training, and integration into existing systems, training employees. Eventhough investment in AI would be considered as CAPEX other related costs such as training and skilling of employees process changes, cloud related expenses and similar costs would be recorded as operating expenses impacting negatively the P&L of the organization temporarily but on long term basis the profitability would be improved. This finding also aligns with the fact that AI adoption involves a learning curve for businesses. With learning involved returns are seen only after the technology is integrated and optimized.

- **Focus on Long-Term Gains**: Operating Margin, which measures the percentage of revenue left after covering operating expenses, may improve over time. SMEs often operate with tight margins, and while AI can improve efficiency, these gains might not be visible in the short term. In a study conducted by Yaiprasert and Hidayanto (Yaiprasert & Hidayanto 2024), concluded that "Applying AIML for cost optimization in logistics has far-reaching implications for practical implementation. AIML empowers logistics providers to significantly reduce costs through optimized cost of route planning, dynamic pricing, and demand forecasting, resulting in improved efficiency, reduced operating costs, and enhanced profitability"

Thus various studies have found that operational cost reductions and efficiency improvements from AI take time to manifest in financial metrics like Operating Margin .

5.2.2.3 Revenue Growth : Positive Correlation

The research showed that AI has a strong positive impact on revenue growth, supporting the null hypothesis ($H_0$4) that AI improves top-line metrics for SMEs. The results showed that AI is able to contribute to revenue improvements.

This is likely due to SMES being able to identify the right customer base to target , understand customer needs and feedback to improve their services or product(s) quality, be able to design better marketing strategies for better reach of products and improve forecasting of sales; all of which leads to better revenue growth.

I) AI-Driven Revenue Growth in SMEs

- Customer Insights: AI can faciliate SMEs to develop deeper and better insights into their client and customer behavior, preferences, and buying patterns, allowing for more personalized marketing and sales efforts. These AI generated insights could lead to higher conversion rates,increased revenue and better customer experiences.
- Optimized Operations: Using AI to determine supply & demand of products and manage the inventory, can enable the SMEs to ensure that the products are available when needed, boosting sales and simultanesouly helping to reduce the need to stock up .

II) Comparison with Other Studies

These findings are consistent with researches carried out by other researchers where they concluded that AI can not only can be used to effectively to drive sales and marketing initiatives but helps other functions as customer service, lead generation, inventory management and other functions (Bandari 2019). However, the adoption of AI for revenue growth in SMEs has been slower, largely due to limited resources and a lack of technical expertise and financial constraints as well (Bhalerao, Kumar & Pujari 2022) (Drydakis 2022) .

This research contributes to the growing body of evidence that AI contributes significantly improve sales and revenue generation in SMEs, particularly as SMEs become more familiar with the technology. This study also contributes to the growing body of research that education and training initiatives in the field of AI improves the revenue generation potential for SMEs. (Haleem et al. 2022).

5.2.3 The Role of AI in Strategic Decision-Making

5.2.3.1 AI's Contribution to Decision-Making

One of the key question evaluated in the research was whether AI could be effectively intergrated into strategic decision-making processes. The results showed that AI plays an important role in supporting decisions in SMEs related to financial performance. The null hypothesis ($H_0$5), that AI has a positive impact on strategic decision-making, was accepted.

5.2.3.2 AI as a Disruptive Innovation

The findings also support the idea that AI is a disruptive innovation in the SME space, transforming traditional business processes. However, SMEs are often cautious about adopting AI, as indicated by the Subject Norm (SN) results, where peer pressure and market trends influence adoption. This suggests that while AI is recognized as a valuable tool, SMEs may delay adoption until they see proven results from competitors.

5.2.3.3 AI and Better Decisions

- Data-Driven Insights: AI provides access to real-time data and predictive analytics, helping business leaders make informed decisions. For example, AI can analyze large datasets to identify market trends, customer preferences, and competitive landscapes, enabling more accurate strategic planning.
- Faster and More Accurate Decisions: AI reduces decision-making time by automating data analysis, allowing business leaders to respond more quickly to market changes.

5.2.3.4 Challenges to Adoption

Despite the benefits, the adoption of AI in strategic decision-making remains limited in some SMEs, partly due to organizational resistance and a lack of technical skills. The results highlighted the importance of top-down support and strong leadership in driving AI initiatives. Without executives key stakeholders in the organization, collectively agreeing that AI is critical to the organization and is a innovative tool that could help the organization, implementing AI in the organization would be a uphill task especially given that AI adoption is an investment for SMEs in India who operate in significant financial constraints.

5.3 Discussion of Research Question Two

This section discusses the findings related to the primary research question 2. The research question was

RQ2 What are the key challenges faced by Indian Small and Medium Enterprises (SMEs) in implementing Artificial Intelligence (AI) in their decision-making processes, and their influence on the successful adoption and integration of AI technologies?

This research question focussed on identifying challenges and obstacles faced by Indian SMEs in implementing AI in their decision making. The research focussed on availability of data and infrastructure primarily and its relation with the integration with AI for strategic decisioning purposes. This discussion integrates the findings from the secondary research questions and hypothesis to provide a holistic view of the challenges and impediments to implementing AI in the strategic decision making process.

SQ9 How does the availability of the right skill set influence an AI aided strategic decision-making processes in SMEs?

SQ10 How significant is the need for an infrastructure for SMEs to enable their ability to implement AI aided strategic decision making?

5.3.1 Overall Findings

The secondary research questions concluded that a strong infrastructure and the availability of the right skills within Indian SMEs were essential to successfully adopting AI. It was found that having the right skills and following a structured approach to AI initiatives were crucial for successful adoption and implementation.

While AI adoption remained the focus, it became evident that organizations encouraging skill development to integrate AI into their ecosystems were more likely to succeed with AI initiatives. The support of AI initiatives at all levels—from leadership at the CXO level, which provides the strategic direction, to business teams, which implement AI to improve efficiency and productivity—was key to the success of these initiatives.

Two main challenges were highlighted in relation to the research question (RQ2):

5.3.1.2 Infrastructure

A strong infrastructure was identified as a critical factor for successful AI implementation. Without adequate technical and organizational infrastructure, Indian SMEs faced significant barriers to AI adoption (Bhalerao Kuldeep, Kumar Arya & Pujari Purvi 2022).

Often significant, technology's cost calls for cautious thought for SMEs. When talking about infrastructure, some important parts came out as clear:

1) AI projects mostly depend on data to train models and offer insights; data collecting, processing, and storage are therefore rather important. SMEs would not benefit from the use of AI without a without a strong framework for data collection, converting, and storage. Moreover AI projects and usage requires a computational capability of a higher order; usually, Graphics Processing Units (GPUs) rather than conventional CPUs are involved. Constrainted by budgets, SMEs tread with caution,when it comes to investments in larger processing capability or investments in computational investments as higher capacity hardware or data centres.

2) Given that AI applications could handle private information, such as consumer data protection of such data is required to looked at by SME with utmost seriousness. SMEs would require to ensure that their data and infrastructure is safe from malicious intents ranging from data breaches to cyberattacks.

3) AI solutions must be scalable as SMEs' data ecosystems develop to manage the increasing volume of data.

Using the scalable computing resources and AI capabilities provided by cloud-based platforms such as AWS, Google Cloud, and Microsoft Azure SMEs could experiment the use of AI and their services within their budget. Once the experiment is a success SMEs could fast track the adoption of AI for decision-making and profitability enhancements. Highlighted below are some examples of how artificial intelligence has been helping Indian SMEs:

1. A nonprofit company MagicBus in 2024, in India used cloud computing and artificial intelligence to build a training tool enhancing session effectiveness and learning results for pupils. By means of its digital platform, teachers were able to improve their assessment of instructional initiatives (Microsoft 2024b).
2. A healthcare startup Tatva care in 2024 developed an AI-driven application to automate outpatient procedures in 16 regional languages, providing much-needed support for chronic patients (Microsoft 2024c).

3. Genpact, a global professional services firm,in 2023-24 turned to AI to improve employee productivity and streamline operations. Leveraging Azure OpenAI and other Microsoft products, Genpact created the "GenAI Playground," a scalable application fostering innovation across its workforce. With 125,000 users, the platform generated millions of interactions and language-processing units (tokens), revolutionizing business operations (Microsoft 2024a).

Usage of Software as a Service (SAAS) products and services could provide an alternate route to AI integration, to fast track the adoption of AI ,allowing SMEs to focus on their main business and increase profitability. This approach is a recommended approach for SMEs to encourage the use of AI-driven solutions to reduce reliance on expensive infrastructure.

For example

1. Udaan, a B2B e-commerce platform that caters to Indian SMEs, used artificial intelligence for inventory control, price optimization, and consumer behavior monitoring, thereby driving its usage and providing improved customer satisfaction even for its clients.
2. Freshworks, an artificial intelligence-powered CRM tool, gives its clients all around safe cloud infrastructure, IT services, CRM, and customer support solutions

5.3.1.3 Personnel skills

Apart from infrastructure, adoption of artificial intelligence depends critically on the availability of qualified experts in data analytics and AI. The lack of such experts makes it rather difficult to include artificial intelligence into decision-making procedures. SMEs still need specialists with knowledge in data science and machine learning to design, train, and maintain AI models even if they might choose SAAS platforms or cloud-based solutions.

Such expertise is expensive and could be difficult for SMEs to afford. Glassdoor[18] estimates that machine learning engineers' annual pay in 2024 falls between 600,000 and 4,700,000 INR (7000 to 57,000 USD). Data engineers and data scientists are even more expensive with their salaries between 700,000 and 4,000,000 INR (8,300 to 50,000 USD).

To overcome this challenges, SMEs must explore various possibilities ranging from government-backed initiatives, talent enablement programs, and university-based collaborations to grow their AI talent pool (Watney & Auer 2021) . In addition to these possibilities SMEs could also acquire the required skills for AI-driven decision-making by means of internal training or outside institution cooperation.

5.3.1.4 Conclusion

The primary challenges faced by Indian SMEs in implementing AI for decision-making revolved around the need for a robust infrastructure and a skilled workforce. Key issues related to data collection, storage, and processing technology emerged as critical factors.

[18] https://www.glassdoor.co.in/Salaries/machine-learning-engineer-salary-SRCH_KO0,25.htm

To overcome these hurdles, SMEs in India could either adopt a SAAS approach, integrating existing AI platforms into their ecosystems, or invest in building the necessary infrastructure and talent to develop AI solutions in-house. Regardless of the path chosen, it was clear that AI adoption was crucial for improving profitability and enabling more strategic decision-making within Indian SMEs.

5.4 AI Integration in SME – A broader discussion

The previous sections analyzed the research questions and their results in detail. In this section we will explore the overall impact of AI integration within Indian SMEs, drawing insights from a broader, more holistic perspective. We will explore how the Balanced Scorecard Performance Metric (BSCPM) parameters , Data Infrastructure (DI), and Employee Satisfaction and Engagement (ESE) variables and other variables interact to shape strategic decision-making.

5.4.1 BSCPM and AI Integration in Decision-Making

The BSCPM variables incorporated answers from the participants that centered on financial indicators from the Balanced Scorecard framework, and AI specific parameters related to increases in revenue and profitability.

Strongly favorable links between this composite score and the inclusion of artificial intelligence into strategic decision-making were revealed by the results. This emphasizes how, in Indian SMEs, artificial intelligence is becoming even more essential for financial success. The information points to artificial intelligence becoming more than simply a technical tool. Small businesses are looking at artificial intelligence as a main force behind improved financial results. SMEs may make more educated and data-oriented decisions using artificial intelligence, therefore improving their financial performance. For Indian SMEs, where financial resources are sometimes constrained, artificial intelligence offers a benefit by allowing better, data-driven decision-making directly affecting profitability.

5.4.2 Data Infrastructure (DI) and Its Role in AI Integration

Though not very significant, the DI variable which concentrated on the resilience of data infrastructure also demonstrated a positive correlation with the dependent variables. This suggests that a strong data infrastructure helps magnifies the financial advantages of artificial intelligence acceptance. Stated differently, a strong basis of quality data will increase the proabability to enhance the financial performance, decision making capacity, and AI capability of a business.

This result underlines for Indian SMEs the need of investing in data infrastructure. Strong data structures enable artificial intelligence to operate as it should, thereby guaranteeing the exact insights produced for next actions. Although SMEs with limited resources may find it difficult to give such investments top priority, the data revealed that doing so offers a necessary competitive edge, therefore enabling businesses to utilize the advantages of artificial intelligence and enhance general company performance.

5.4.3 ESE financial performance & impact to AI initiatives

Interestingly, the variables measuring employee happiness and engagement the Employee happiness and Engagement variable showed a negative link with the measures of financial success. Although this outcome seems unexpected and perhaps contradictory, it implies that better employee satisfaction may be connected to reduced short-term financial measures, including operating margins.

This may be the result of more money spent on projects such improved staff retention campaigns, greater compensation, or training courses many of which would be motivated by developments linked to artificial intelligence. Though long-term success depends on these investments, they could put strain on short-term profitability.

This brings a crucial issue for Indian SMEs for discussion: how can they strike a balance between preserving good financial measures and the necessity to invest in employee satisfaction? More research is required to investigate this relationship more thoroughly, but the evidence indicates that even if raising employee engagement might be costly, it is absolutely vital for long-term organizational survival. One participant indicated that they spend approximately 750000 INR(900 USD) on employee engagement mostly encompassing learning development training and incentives and recognition fees..

5.4.4 Broader Implications and Takeaways

Thus, looking at the financial parameters (BSCPM), Data Infrastructure (DI) and the Employee Satisfaction and Engagement (ESE) all together there are come critical conclusions that could be drawn of how Indian SMEs are investigating to use AI as a transformation tool that assists strategic decision-making in Indian SMEs.

Improving financial performance mostly depends on artificial intelligence and data infrastructure; nonetheless, the difficulty in controlling employee happiness adds even another level of difficulty. For Indian SMEs, this means that integration of artificial intelligence cannot occur in a vacuum.

Strong data infrastructures must be developed by companies if they are to fully benefit from artificial intelligence. They must also give much thought to the human effect to make sure that expenditures in staff members do not compromise financial objectives. SMEs hoping for sustained development must find the proper mix of data preparedness, artificial intelligence adoption, and staff happiness.

5.5 Conclusion and Transition Summary

The thorough debates over the main and secondary research issues came to the conclusion that artificial intelligence combined with decision making can assist increase profitability of SMEs in India. To reach the same SMEs in India, though, would mean making sure the data infrastructure is strong and offers a clean basis to guarantee seamless integration of artificial intelligence into Indian businesses.

Although the value of infrastructure cannot be underlined enough, including pertinent training and development initiatives to raise AI and BSC based measures promotes a culture of learning and innovation to maximize the advantage of AI integration.

A Data driven organization that moves to become a Data and AI driven organization leading to a more inventive and fast-growing firm starts with a solid data foundation and innovation culture employing thorough performance measuring tools.

CHAPTER VI:

SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS

6.1 Summary

The research set out to explore how strategic decisioning and financial performance metrics are impacted when enabled by artificial intelligence (AI) and metrics driven framework as Balanced Score card within the context of Indian Small and Medium Enterprises (SMEs). Through the application of both qualitative and quantitative methods, the thesis research examined aspects such as the adoption of AI, infrastructure requirements, and the effect of AI on performance metrics like revenue and profitability.

The introduction chapter framed the research by exploring the role of Artificial Intelligence (AI) in SMEs and its role in enabling strategic decisions. The chapter introduced and briefly discussed the research objectives, highlighting the novelty in the research where AI could be used to improve financial performance and overall competitiveness, using the Balanced Scorecard (BSC) framework. The key research questions focused on how AI impacts financial metrics like EBITDA and operating margins and the barriers Indian SMEs faced for AI adoption.

The literature review in chapter 2 examined the existing body of research on AI adoption, strategic decision-making, and the BSC framework in the SME sector and across other orgnizations. There were gaps ientified , especially in understanding how AI impacts Indian SMEs and their financial outcomes. The review also introduced critical concepts like Employee Satisfaction and Engagement (ESE) , Subject Norm (SN), Knowledge Management (KM) and others which were later analyzed to understand their influence on AI adoption in SMEs in India.

The literature review revealed a lack of comprehensive studies examining the impact of AI on strategic decision-making and profitability within Indian SMEs, particularly in relation to financial performance metrics (e.g., EBITDA, Operating Margin) and the Balanced Scorecard (BSC) framework. While some studies addresed AI adoption challenges, other indicated a reliance on human intelligence for decision-making and a fragmented use of the BSC framework among SMEs. The Technology Acceptance Model (TAM) was determined as a suitable approach for assessing AI adoption intentions, thus paving the way for the research to explore the integration of BSC and TAM frameworks to explore AI's potential for improving profitability in Indian SMEs.

Chapter 3 related to the Methdology explained the research design, the methods that were used to analyse AI's impact on SMEs in India. Surveys, statistical methods like logistic regression were used to measure the influence of AI on financial parameters and its co relation with operational performance in the Indian SMEs.

The results in chapter 4 presented empirical findings, showing that impact of AI adoption, and how it could significantly improve financial metrics such as EBITDA and operating margins when used rightly combined with performance frameworks as Balanced Score Card. The results also acknowledged the challenges associated, like the cost of AI implementation and the need for skilled talent. Moreover, the need for data infrastructure, employee satisfaction, and peer influence emerged as essential factors in determining the success of AI adoption in Indian SMEs.

The discussion in chapter 5 provided an interpretation of the results along side the existing literature. The chapter demonstrated how AI could improve financial outcomes while contributing to customer experiences, and internal processes. As with any coin that has two sides, the chapter also pointed out some of the challenges that Indian SMEs faced with adoption of AI in the SMEs. The discussion also drew attention to the importance of top-down leadership support in driving successful AI adoption, especially in SMEs where resources are always not in abundance.

6.2 Implications of the Research

6.2.1 Theoretical Implications

This research contributes to the growing body of literature on AI adoption in SMEs by providing insights into how AI influences BSC perspectives. The findings reinforce that not only is AI a technological innovation but also a strategic tool also that can be integrated into financial and operational frameworks to deliver growth and efficiency. This finding is important and key in developing economies where SMEs form a backbone of the economy.

The research used the TAM framework and integrated some of its key parameters like Subject Norm (SN) into the analysis enabling the study to examine the understanding and influence of social and peer pressure of AI adoption. Subject Norm (SN), or the pressure felt by SMEs to adopt AI due to peer or industry trends, was found to significantly impact the decision to implement AI technologies, particularly customer-facing processes. This aligns with diffusion of innovation theory, which posits that peer influence accelerates the adoption of new technologies. Inspite of peer pressure for AI adoption, the study also revealed that SMEs were adopting AI at their own pace and for their own needs rather than joining the bandwagon of AI.

The role of Employee Satisfaction and Engagement (ESE) is another important theoretical contribution. This research contributes to the literature by highlighting the connection between employee satisfaction and the successful implementation of AI initiatives. ESE emerged as both a driver and challenge for AI adoption, demonstrating that while employee satisfaction is necessary, it can also temporarily strain financial performance due to increased costs in training and retention. This temporary strain could cause a minor dip in the operating margin for SMEs, until the benefits of the training and retention are not visible.

6.2.2 Practical Implications

For SME leaders, policymakers, and AI service providers, the research offers practical takeaways:

Financial Performance: AI has demonstrated potential to drive substantial improvements in financial metrics, particularly EBITDA and profitability. Almost 60 % of the respondents responded that AI has the ability to drive substantial improvement in the financial metrics to the range of 3 to 10 %. However this improvement should occur as combination of disciplined processes, multiple revenue streams which are driven by AI in the BSC framework and cannot be solely driven by AI. Thus SMEs leaders should look towards AI-driven tools that enhance resource allocation, cost optimization, and decision-making.

Customer Satisfaction: AI, especially in CRM systems, enables SMEs to better understand and respond to customer needs. Personalization, powered by AI, can significantly improve customer satisfaction and retention, which are key for business growth.

Haptik[19] (Jio Haptik Technologies Limited) is an AI company that empowers conversational commerce experience. With support for over 130 languages, Haptik provides a platform to help brands including SME brands to acquire, convert,engage user with AI driven , personalized conversation. With such a platform SMEs in India and the customer base in India, SMEs and their customer base could get a localised shopping experience improving the user experience by 15-20 % .

Wellness Forever[20] is a retail pharmacy chain with more than 300 stores in the state of Maharashtra , Goa and Karnataka. Employing the use of Microsofts data and analytics stack, the brand has been able to improve customer experience by adding multiple channels for order including whatsapp order, improving the last mile to deliver for orders as well. With improved platform and AI algorithms employed, inventory status across 3 states now is updated in 30 mins against 5 days early which improves the customer experience multifold.

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[19]https://customers.microsoft.com/en-in/story/1544285355968909391-haptik-professional-services-azure-en-india

[20] https://customers.microsoft.com/en-in/story/1506509820366560791-wellness-forever-retailers-azure-en-india

Locobuzz[21] is a customer experience platform that has been developed for customer engagements and today serves an elite brand list across multiple countries.Founded in 2015 and based in Mumbai, Locobuzzis a SaaS platform focused on customer experience and digital engagement. The platform is powered through the use of AI and machine learning, it offers services that range from social media analytics to customer feedback and sentiment analysis, enabling brands to interact meaningfully with their audiences, thereby providing a good customer experience to Locobuzze's client base. Given the list of customers ranging from Top banks in India to top telecom customers from 2015 to 2024 , Loco buzz has been improving customer experience for its customers and their clients using AI. Ezample: Locobuzz was able to improve customer sentinment score for a large automative giant in India to 8,18 and improve first level response from 10 hrs to 3 hrs.

Subject Norm (SN) Influence: Subject Norm (SN), or peer influence, emerged as a key driver of AI adoption in sectors like e-commerce and healthcare. For example, Udaan, a B2B platform, implemented AI for price optimization and inventory management, which motivated other SMEs to follow suit. This demonstrates that SMEs often adopt AI when they see market leaders doing so, reinforcing the competitive pressure to innovate.

6.2.3 Broader Implications

[21] https://locobuzz.com/customer-stories/locobuzz-streamlines-response-management-for-an-automobile-stalwart/?utm_source=adwords&utm_medium=ppc&utm_term=loco

Beyond the immediate financial and operational impacts, the research suggests broader implications:

Sustainability: AI can be used to enhance sustainability practices in SMEs by optimizing energy usage, reducing waste, and improving resource allocation. Although this was not the focus of the study, it presents a promising area for future research.

Example[22]

ITC is one of India's foremost private sector companies with a Gross Revenue of ₹ 69,446 crores (8,227,684,296 USD) and Net Profit of ₹ 24,478 crores (2,900,055,528 USD) (as on 31.03.2024) with presence in FMCG, hotels, Packaging, Paperboards & Specialty Papers, Agri & IT Businesses. With an incredible focus on digital transformation for a future tech organization ITC leverages cutting edge technologies as AI/ML, Industry 4.0, Big Data, Addvanced analytics for business growth and innovation too.

As part of their innovation and growth strategy ITC has implemented an integrated planning and and supply management tool that is powered by AI/ML resulting into improved vehicle turnaround time, real time stock movements lesser wastage of fuel for transportation of goods.

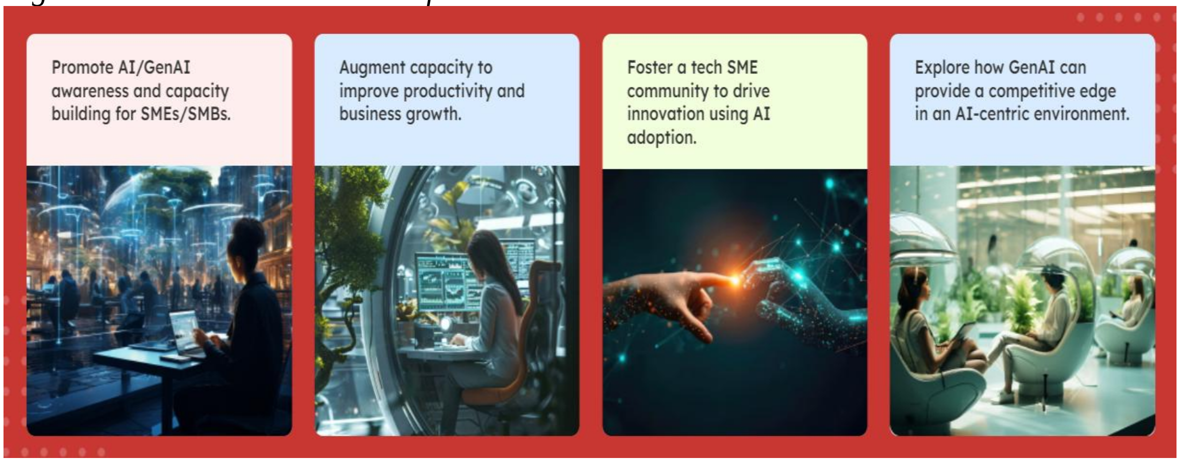
ITCMAARS (Metamarket for Advanced Agriculture and Rural Services) is a super app that emprovers local farmers with advisories, market linkages precision farming, online soil testing, and crop nutrition features leading the path to agri based sustainability.

[22] https://www.itcportal.com/digital-transformation-at-itc.aspx

Adopting Industry 4.0 practices and various AI/ML patterns, computer vision and IOT based crop monitoring, the paper boards and speciality paper business at ITC has paved the path to sustainability initiatives at ITC.

Government Support: Policymakers can play an essential role in helping SMEs overcome barriers to AI adoption by offering incentives, grants, or training programs designed specifically for SMEs. Government-backed AI training initiatives could help reduce the skills gap. For Example: NASSCOM has various initiatives launch that are helping SMEs in the adoption of AI. NASSCOM AI program is na initiative that collaborates with the Government of India, enterprises and start ups alike to develop skills, policies and develop solutions for social impacts. Under the Nasscom AI program, with a specific focus on the SME and SMB, NASSCOM offers the below programs

Figure 14 NASSCOM Initiatives for SME in India



Source https://nasscom.in/ai/ai-enablement/

6.3 Limitations of the Current Research

While this study makes valuable contributions, several limitations should be noted:

Short-term Focus: This study provides a snapshot of AI adoption, but a longitudinal study tracking AI's impact over time in Indian SMEs could provide a deeper understanding of its long-term benefits and challenges.

Scope of AI Applications: The study primarily focused on AI in decision-making and financial parameters improvement. Future research should explore how other emerging AI technologies, such as GenAI (Generative AI), impact SME operations. Future studies should also focus on understanding the impact of AI on other perspectives of BSC (Learning, Customer, Internal) in SMEs in India and globally.

Data Collection via Social Media: The primary data collection channels for this research were LinkedIn and Facebook, social platforms where engagement can be highly variable depending on the audience's familiarity with and interest in academic surveys. Additionally, participants who are more active on LinkedIn or Facebook may have certain shared characteristics, such as a greater openness to technology, compared to those in more traditional or less digitally engaged industries.

Sample Size: Although the research aimed to capture a broad spectrum of views from Indian SMEs. The study was based on a relatively small sample size due to a limited number of respondents. Despite efforts to broaden the reach through multiple rounds of follow-ups, reminders, and outreach on social media platforms like LinkedIn and Facebook, response rates remained low.The limited sample size may reduce the statistical power of the findings and could lead to a narrower understanding of AI adoption and its impact on SMEs. This smaller dataset could constrain the ability to capture a full range of experiences, challenges, and outcomes that might exist across a broader population of SMEs in India. The majority of respondents were located in the Pune region, a city with unique economic and business characteristics. Pune is known for its vibrant tech and manufacturing sectors, which may not fully reflect the diversity of SME ecosystems across India, such as those found in other major regions (e.g., Delhi NCR, Mumbai, Bengaluru, or Chennai). The regional concentration could introduce biases in the findings, as the challenges, resource availability, and digital adoption trends in Pune may differ from those in other parts of India. Thus, the results may not be entirely representative of the varied SME landscape across India's rural and urban settings.

Industry Representation: Although the study attempted to reach a diverse set of industries within the SME sector, the actual respondents may represent a limited range of business types and sizes. Certain sectors that are more prevalent in other regions, such as textile manufacturing in Tamil Nadu or agribusiness in Punjab, may have unique AI adoption needs and constraints that this study does not address.The concentration on specific industries within Pune may have inadvertently shaped the insights around AI adoption, financial constraints, and engagement practices.

Impact on Generalizability: Given these limitations, caution should be taken when attempting to generalize the findings to all Indian SMEs. A more extensive sample, covering a wider range of regions and industries in India, would likely yield more robust and generalizable results, providing a deeper understanding of AI adoption and its challenges across diverse business contexts. Future studies should consider a stratified sampling approach that includes SMEs from multiple regions and industries across India to better capture the heterogeneity of the SME landscape. Expanding beyond social media to include email surveys, phone interviews, and offline methods may also help reach a wider demographic and increase the sample size.

6.4 Conclusion

This thesis set out to explore how integrating Artificial Intelligence (AI) , Balanced Scorecard (BSC) framework can impact the strategic decision-making and financial performance of Indian SMEs. The study focused on answering two core questions: whether AI improves financial metrics such as EBITDA and operating margins, and what challenges and enablers exist for AI adoption in Indian SMEs. Through analysis, the study showed that AI could drive improvements in strategic decision-making, financial performance, operational efficiency for SMEs in India.

6.4.1 Summary of Key Findings and Hypotheses

Firstly, we proved that SME in India can improve their financial performances mainly EBITDA and sales margins, by including AI as part of their businesses. AI's integration positively impacted financial metrics like EBITDA (Chapter 4, Table 14, Table 27). The findings showed that AI-enabled decision-making optimizes resources, enhanced efficiency, and in turn aided in financial planning, which aligns with RQ 1, indicating that AI supports higher profitability and financial sustainability in SMEs. Being overly cautious, being influenced by external market factors or waiting for market acceptance of AI could also lead to missed opportunities to commit to AI investments and there by having a negative impact on the EBIDTA. Although AI is an investment part of CAPEX and may not have a direct impact on the P&L of the organization, given operating costs like training, skilling of employees, cloud and AI based infrastucture could impact the P&L there by setting back the operating margin temporarily. However these investments will translate to better effiencies over the period of time and have a positive impact on Operating margin.

An illustrative example which proves our findings is the company Freshworks. In fact, Freshworks has invested in AI to improve its CRM and ITSM offerings, as a consequence the company has been consistently reducing its losses and improving on operating margins.

The study also concluded that the use of Balanced Score card in conjuction with the use of artificial intelligence helped to provide a framework that could be of help for SMEs to have AI driven framework that would drive growth and improve profitability

Secondly, we have rasied different challenges of AI Adoption.Despite the benefits, high implementation costs, lack of a skilled workforce, and insufficient data infrastructure emerged as significant barriers (Chapter 4, Section 4.9). These findings supported research question 2, which anticipated these challenges in Indian SMEs. Additionally, Employee Satisfaction and Engagement (ESE) was shown to play a critical role in successful AI adoption; while essential for implementation, it can temporarily increase operating costs due to training and retention and infrastructure investments.

In this thesis we have highlighted the importance of the Role of Subject Norm (SN) and the Customer Experience, as strong drivers for AI adoption in SMEs in India,

Subject Norm, or peer influence, was found to be a important motivator for AI adoption. The analysis showed that SMEs are more likely to adopt AI technologies when they observe similar moves among competitors and industry leaders . This finding identified in Chapter 5 section 5.2.3.2 suggests that market forces, adoption and peer actions are strong drivers for AI adoption in SMEs.

Another important realization is the indirect benefit of higher customer satisfaction as artificial intelligence improves activities involving consumers as well as internal efficiency.

In essence, artificial intelligence not only marks a technological development but also a strategic need for Indian small businesses. AI adoption for organizations could not only help organizations to improve their consumer experiences, but also contribute to improvement of profitability and growth by streamlining the decisioning making process for SME using AI. Indian SMEs might place themselves at the forefront of innovation and competitiveness in the worldwide market by using artificial intelligence in a framework like BSC, investing in the appropriate infrastructure, upskilling the staff, and guaranteeing alignment between AI projects and long-term business objectives.

From financial performance to customer interaction and operational efficiency, the integration of newer artificial intelligence solutions as Generative AI (GenAI) has the ability to create improvements in a lot of corporate operations. Even with GenAI now becoming slowly mainstream in businesses, the road to complete artificial intelligence adoption still demands for overcoming obstacles such infrastructure limitations, talent shortages, and key expenses.

6.4.2 Future Recommendations

Extending the knowledge gained from this study, many further paths are advised. Future studies on the long-term consequences of artificial intelligence acceptance in SMEs should investigate

a) **Longitudinal research**: Longitudinal research might follow how artificial intelligence affects operational and financial measures throughout time, therefore offering a more whole view of its ongoing influence.

b) **Industry Wise Research**: Given that each of the industries have their own unique challenges, , future studies should research the impacts of AI the specific impacts of AI in sectors like manufacturing, retail, and healthcare.

c) **GenAI**: Adoption of Generative AI (GenAI) offers SMEs a great potential. GenAI products provide SMEs fresh means to save expenses and simplify processes: those for content generation, customer service automation, and process optimization. For instance, Genpact has used Azure OpenAI to build the GenAI Playground, therefore promoting operational effectiveness and creativity. This tool has helped lower manual duties, increase productivity, and create text-based solutions by means of over 125,000 users and 2 million interactions thereby displaying the power of adoption of GenAI.

d) **Sustainability and AI**: More study is required to investigate how SMEs could implement sustainable practices driven by artificial intelligence. This study could help not only with environmental objectives as lowering energy consumption, optimizing supply chains, and reducing waste but also help with associating sustainability initiatives with profitability improvement initiatives.

e) **Collaborative AI Models:** SMEs could work with other companies, government projects, and universities to create AI talent and promote innovation. With GenAI and AI needing a skilled and trained workforce, such partnerships could offer SMEs the tools they would need to implement these technologies.

Lastly this study concludes that the integration of AI in the Indian SMEs will ensure the continuous success and expansion of the organizations. With the correct assistance from government policies, industry partnerships, SMEs in India may use artificial intelligence to achieve not just short-term profitability but also long-term sustainability and competitive advantage in an increasingly technologically driven market.

APPENDIX A

SURVEY COVER LETTER

Research Questionnaire - Aiding Strategic Decision-making to improve profitability using Artificial Intelligence in Indian Small and Medium Enterprises

This questionnaire is for Academic Thesis/Research Project. This questionnaire is designed to gather insights and opinions of key decision makers including not restricted to Founders, CXOs, Executive Management personnel, senior management personnel and others who are willing to contribute to this questionnaire regarding whether AI can help with strategic decision that could improve profitability of small and medium size enterprises.Participants responding to the questionnaire will yield valuable insights not only enriching the academic exploration for solutions but also contributing to practical implementation of solutions that could contribute to improving profitability of SMEs in India.

Brief Introduction to the Topic of the research

With a transformative change in India's economic landscape and with the small and medium enterprises playing a pivotal role, the impact of Artificial Intelligence on the Indian SMEs as a tool for key decision makers, cannot be ignored. Combining the power of tools such as Balanced Score Card and the possibility of using Artificial Intelligence to determine better insights that can aid decision makers of small and medium enterprises, is what this research looks to co relate and explore. Through this research , industry sector leaders may gain more insights about essential factors involving AI technology being used or could be used in their organization . The research also aims to enable the leaders the SME sector in India to be better equipped to make better decisions using an integrated process that combines industry standard processes as balanced score cards and AI to improve the profitability of their businesses.

APPENDIX B

INFORMED CONSENT

Consent and Participation

Procedures:
The participant attempts the online survey. The researcher will close the survey when approximately 100 participants attempt the survey. The researcher will collect the data from the survey website and complete the analysis.
Voluntary Nature of the Study: Research should only be done with those who freely volunteer. So everyone involved will respect your decision to join or not. You will be treated the same whether you join the study or not. If you decide to join the study now, you can still change your mind later. You may stop at any time. The researcher seeks 100 volunteers for this study.
Risks and Benefits of Being in the Study: Being in this study does not involve any risks even of the minor discomforts that can be encountered in daily life, such as stress. This study offers no direct benefits to individual volunteers. This study aims to benefit society by enabling leaders in the SME sector to make an informed decision about using AI for Strategic decision-making.
Payment: No financial benefit is involved during this study to the participants.
Privacy: The researcher is required to protect your privacy. Your identity will be kept anonymous, within the limits of the law. The researcher will not ask for your name at any stage of the research. The researcher will not use personal information shared for any purposes outside of this research project. Also, the researcher will not include your name or anything else that could identify you in the study reports. If the researcher were to share this dataset with another researcher in the future, the researcher would be required to remove all names and identifying details before sharing; this would not involve another round of obtaining informed consent. Data will be kept secure by the researcher in a password-protected folder and file on a personal computer. Data will be kept for at least 5 years, as required by the university. You might wish to retain this consent form for your records. You may ask the researcher or SSBM Geneva for a copy at any time
Obtaining Your Consent If you wish to volunteer, please indicate your consent by proceeding to the first question in the survey

APPENDIX C

INTERVIEW GUIDE

Not applicable

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