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Understanding Artificial Intelligence Adoption, Implementation, and Use in Small and Medium Enterprises in India

Dipak Sadashiv Jadhav
Walden University

Walden University

College of Management and Technology

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Dipak Jadhav

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Review Committee
Dr. Paul Frankenhauser, Committee Chairperson, Management Faculty
Dr. Nikunja Swain, Committee Member, Management Faculty
Dr. Karina Kasztelnik, University Reviewer, Management Faculty

Chief Academic Officer and Provost
Sue Subocz, Ph.D.

Walden University
2021

Abstract

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MBA, Educatis University, 2012

BE, Pune University, 2010

Dissertation Submitted in Partial Fulfillment

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Doctor of Philosophy

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Abstract

This quantitative cross-sectional correlational study involves understanding the impact of various factors on Artificial Intelligence (AI) adoption, implementation, and use in the small and medium enterprises (SME) sector in India. Increased AI use across industry sectors including SMEs makes it essential to analyze decisions involving AI adoption. The main research question and secondary research questions were used to help understand correlations between diffusion of innovation (DOI), the technology, organization, and environment (TOE) framework, and technology adoption model (TAM) and decisions involving AI adoption. I used prevalidated survey instruments and online surveys via the Survey Monkey platform as part of data collection using social media to solicit participation. The correlational analysis of survey data from 152 participants indicated that out of 10 selected constructs from DOI, TOE, and TAM theories. Nine constructs when analyzed individually, showed low to moderate positive statistically significant correlations with decisions involving AI adoption. Compatibility did not show any statistically significant correlation with decisions to adopt AI. Implications for positive social change include improved management support, enhanced IT sophistication, and better handling of mimetic and normative pressure for SME leaders in terms of effective AI adoption. This quantitative correlational cross-sectional study may improve SMEs’ ability to channel organizational resources to create the most desirable AI-related products and services through effective use of innovative technology.

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Dedication

I dedicate this dissertation to my loving wife Priyanka and daughter Gautami. You have been an inspiration and force behind all my achievements. You nurtured my will and showed me the true meaning of the dedication and hard-work. You both were there beside me throughout this journey that was full of ups and downs. Your support and sacrifices during financial crises or challenges due to this journey has been commendable.

I wish to remember and equally dedicate my dissertation to my late mother Pramila and also to my father Sadashiv. Dad, you have been a silent partner in this long journey and you were always there to support throughout my life. I also want to dedicate this dissertation to all my friends who helped me in crystalizing my thoughts and helped me to maintain the motivation level. Thank you all for all your help and support.

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I thank all my colleagues of PhD program, for supporting me in every aspect of the entire program. I thank all the authors of all the blogs that I have referred, during the tenure of my dissertation. It also has helped me all the times to clarify my doubts.

I wish to thank my friends Avadhut Kharmale, Shirish Shivarkar, and Parikshit Pranesh for all the discussions, all the encouragement, and being with me in this journey. Last but not the least, I would like to thank my family for understanding my needs, covering me during many precious moments, and supporting me in fulfilling the dream that we saw together as a family.

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Chapter 1: Introduction to the Study

Artificial intelligence (AI) has become the technology of choice to solve complex business problems in various industrial sectors where small and medium enterprises (SMEs) are present. Many researchers worked on building technology-oriented solutions for solving business-critical issues. However, as AI adoption, implementation, and use have increased, other management aspects need attention.

There is a need to analyze what influences AI adoption, how AI is implemented in different scenarios, and how different types of users try to use AI technology. This will help in resolving clashes between humans and machines. The scope for management research is massive in the case of AI. In this study, aspects related to diffusion of innovation (DOI), the technology, organization and environment (TOE) framework, and the technology adoption model (TAM) and their impact on AI adoption, implementation, and use in India's SME sector was analyzed.

There are three types of research done in the field of AI. The first type is technical research to design and implement technological solutions to address business challenges. The second type of research is related to social studies, where the impact of AI adoption on society is studied. The primary focus in this category is to understand the good or bad impact of AI adoption such as loss of employment. The third category of research is an in-depth analyses of a particular industry and how solutions implemented for resolving business problems impact organizations.

In this study, I used the DOI, TOE, and TAM frameworks together and analyzed 10 different constructs from these theories. In this chapter, the background of the study was provided, along with the problem statement. Then I included a discussion about the purpose, followed by research questions and hypotheses. In the later sections, I provided details about the theoretical foundation, conceptual framework, and nature of the study, including definitions, assumptions, scope, delimitations, and limitations. Before summarizing and providing a connection to the next chapter, I discussed the study’s significance to theory, practice, and social change.

Background of the Study

I conducted searches using the Walden Library database and Google Scholar to understand the status of AI adoption across industries, focusing on India’s SMEs. The search revealed that most of the research was technological research, with some exceptions focusing on social implications of AI adoption, management studies, and business environment-related impacts of AI adoption. AI technology-related research was predominantly sponsored and funded by multinational technology leaders, AI consultants, and AI-related product development firms to meet their business targets.

The SME sector is a contributing factor to the world economy. According to the European Commission (2018), 99.8% of business organizations are SMEs, and they provide jobs to 66.6% of the workforce within the European Union (EU). Challenges faced during AI adoption involved societal implications, leadership influence, decision-making methodology, and policy paralysis (Alsheibani et al., 2018). According to Walczak (2016), some of the critical challenges involving AI adoption were lack of persistent efforts, lack of prioritization, and shortage of skilled resources.

When I studied the AI adoption status in the SME sector across various countries, a similar pattern was found. As stated by Savola et al. (2018) different technological aspects, organizational factors, and environmental constructs influence AI adoption in the SME sector. AI adoption by SME sector in Finland and Sweden received attention by customers and media and thus accelerated the process of AI use (Savola et al., 2018). SMEs compared to larger organizations struggle while adopting AI technology due to lack of standardized business practices, structured approaches towards innovation, and lack of sufficient experience in management (Brynjolfsson & McAfee, 2018).

New technology adoption at an individual level was primarily described by leveraging DOI theory and TOE framework helped in understanding organizational level new technology adoption. However, there were few studies available which focused on adoption, implementation, and use of AI among SMEs in India. This was a specific literature gap which I intended to address as part of this study. This study was important as it may help business leaders in the Indian SME sector to effectively adopt AI technology and use it to bring positive social change.

Problem Statement

Allen Newell and Herbert Simon at a Dartmouth conference in 1956 introduced transformational change using AI for the first time. It was evident that AI and its applications were not recent innovations in the market. Enhanced computing capabilities and cheap data storage and processing advancements have broken limitations and restrictions on AI research areas. AI was not just a useful technology solution, but also started impacting business strategies. 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).

There were concerns involving strategic fitment issues, lack of organizational capabilities, and stringent regulatory requirements (Aboelmaged, 2014). AI adoption in SMEs was fragmented in terms of customer service, fraud detection, and the development of credit distribution algorithms (Bahrammirzaee, 2010). Due to challenges like regulatory concerns, complexity of technology, and availability of a skilled workforce, AI adoption was not the primary focus of the SME sector. There was a significant literature gap as there were very few research papers available about AI adoption in the SME sector in India. Therefore, it was important to conduct a cross-sectional correlational study to understand AI adoption in the SME sector in India. The general problem was that there was slow and fragmented AI adoption in various industries. The specific problem was that those factors which enable and limit the impact on AI adoption, implementation, and use in India's SME sector were unknown.

Purpose of the Study

The purpose of this quantitative cross-sectional correlational study was to study the impact of technological, organizational, and environmental factors on the adoption, implementation, and use of AI technology in the SME sector in India. India is a strategic location for many multinational companies (MNCs), SME and skilled workforce help these companies achieve their outsourcing targets. AI technology provided an opportunity to enhance the contribution of the SME sector in India due to engineering talent available.

During this cross-sectional correlational study, correlations between the dependent variable decision of AI adoption, implementation, and use (DOA) and independent variables IT sophistication (ITS), relative advantage (RA), complexity (CP), management support (MS), compatibility (CL), mimetic pressure (MP), normative pressure (NP), regulatory concerns (RC), perceived usefulness (PU), and perceived ease of use (PEU) were studied. These parameters were researched using theoretical models such as the DOI, TOE, and TAM.

Research Questions and Hypotheses

The study was based on three theoretical foundations: DOI, TOE, and TAM. Research questions were formalized in such a way that they were useful in terms of understanding correlations between 10 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 seven-point Likert Scale.

The primary research question for this study was:

RQ: What are the various factors that enable and limit DOA, implementation, and use in the SME sector in India?

The following secondary research questions were used related to technology help in terms of understanding the DOI and TOE contexts of AI adoption in the SME sector in India.

SQ1: Does ITS have any statistically significant correlation with DOA in the SME sector in India?

$H_0$1: ITS does not have a statistically significant correlation with DOA in the SME sector in India.

H_a1: ITS does have a statistically significant correlation with DOA in the SME sector in India.

SQ2: Does RA have any statistically significant correlation with DOA in the SME sector in India?

$H_0$2: RA does not have a statistically significant correlation with DOA in the SME sector in India.

H_a2: RA does have a statistically significant correlation with DOA in the SME sector in India.

SQ3: Does CP have any statistically significant correlation with DOA in the SME sector in India?

$H_0$3: CP does not have a statistically significant correlation with DOA in the SME sector in India.

H_a3: CP does have a statistically significant correlation with DOA in the SME sector in India.

The following secondary research questions related to organizational context were used to understand the DOI and TOE frameworks related to AI adoption in the SME sector in India.

SQ4: Does MS have any statistically significant correlation with DOA SME sector in India?

$H_0$4: MS does not have any statistically significant correlation with DOA in the SME sector in India.

H_a4: MS does have a statistically significant correlation with DOA in the SME sector in India.

SQ5: Does CP have any statistically significant correlation with DOA in the SME sector in India?

$H_0$5: CP does not have any statistically significant correlation with DOA in the SME sector in India.

H_a5: CP does have a statistically significant correlation with DOA in the SME sector in India.

The following secondary research questions related to environmental context were used to understand the TOE framework related to AI adoption in the SME sector in India.

SQ6: Does MP have any statistically significant correlation with DOA in the SME sector in India?

$H_0$6: MP does not have any statistically significant correlation with DOA in the SME sector in India.

H_a6: MP does have a statistically significant correlation with DOA in the SME sector in India.

SQ7: Does NP have any statistically significant correlation with DOA in the SME sector in India?

$H_0$7: NP does not have any statistically significant correlation with DOA in the SME sector in India.

H_a7: NP does have a statistically significant correlation with DOA in the SME sector in India.

SQ8: Does RC have any statistically significant correlation with DOA in the SME sector in India?

$H_0$8: RC does not have any statistically significant correlation with DOA in the SME sector in India.

H_a8: RC does have a statistically significant correlation with DOA in the SME sector in India.

The following secondary research questions were related to the TAM theory and understanding AI adoption in the SME sector in India.

SQ9: Does PU have any statistically significant correlation with DOA in the SME sector in India?

$H_0$9: PU does not have any statistically significant correlation with DOA in the SME sector in India.

H_a9: PU does have a statistically significant correlation with DOA in the SME sector in India.

SQ10: Does PEU have any statistically significant correlation with DOA in the SME sector in India?

$H_0$10: PEU does not have any statistically significant correlation with DOA in the SME sector in India.

H_a10: PEU does have a statistically significant correlation with DOA in the SME sector in India.

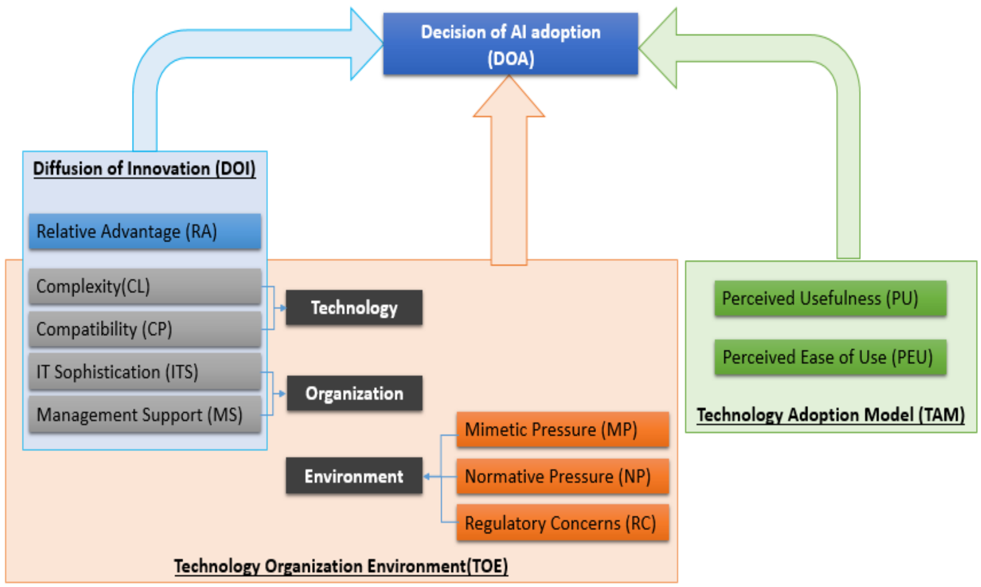
Theoretical Foundation

This quantitative cross-sectional correlational study involved a survey investigating correlations between various factors related to the decision of AI adoption in India's SME sector. The theoretical frameworks for the study were DOI, TOE framework, and TAM. DOI theory helped in understanding how diffusion of any innovation happens across the time. TOE framework provided an organizational perspective of innovation adoption by categorizing factors in technological, organizational, and environmental constructs. The TOE framework helped in terms of understanding successful innovation, adoption, and implementation of the new technology in an organization. TAM theory helped to understand perspectives involving novel technology according to end-users.

Figure 1 includes 10 independent variables and their alignment with theoretical frameworks (DOI, TOE, and TAM). CP, CL, ITS, and MS were common constructs between the DOI and TOE frameworks. CP and CL were part of the technology context, and ITS and MS were part of organizational context within the TOE framework. These frameworks were further discussed in detail in the literature review, where I explained the alignment of theoretical models to the research. I also provided details about how other researchers leveraged these models in their study related to new technology adoption in various industries.

Figure 1

Proposed Model



Nature of the Study

I was interested in understanding whether there were any statistical correlations between various constructs present in the DOI, TOE, and TAM theories and DOA in the SME sector in India. This quantitative cross-sectional correlational study provided an opportunity to study correlations between dependent and independent variables in a natural setting by conducting a point in time study. The cross-sectional design enabled me to focus on a specific industry sector: in this case, the SME sector in India.

The survey questionnaire used for this research contained 39 questions with a seven-point Likert Scale (with range from one for strongly disagree and seven for strongly agree) for most non demographic questions. There were 10 independent variables out of which seven independent variables ITS, CP, CL, MS, MP, NP, and RC were common to the DOI and TOE frameworks. Remaining two variables PEU and PU were part of the TAM theory. To build the questionnaire for this research, I used three different pretested and prevalidated survey instruments ('Organizational Adoption of Virtual Worlds Survey', 'Cloud Adoption by IT Manager', and 'User Acceptance of Information Technology').

The first survey instrument ‘Organizational Adoption of Virtual Worlds Survey’ was developed by Dr. Tom Yoon. I used the most of the questions from this survey instrument as is survey instrument as it covered many constructs ITS, RA, CP, CL, MS, MP, NP, and RC from DOI and TOE theory I was interested in analyzing.

I used some questions from two other survey instruments. I chose to include demographic questions from 'Cloud Adoption by IT Manager' survey instrument developed by Opala (2012). I used some questions about PU and PEU from ‘User Acceptance of Information Technology’ survey instrument designed by Venkatesh et al. (2003). I applied minor alterations for survey questions to align these questions with the research topic related to AI adoption in the SME sector in India.

In this study, I understood perspectives of employees about AI and how they foresee the implementation and use of AI technology in the SME sector in India to meet the business goals. Data were collected using an online survey hosted on Survey Monkey. Participants in the survey were employees in the SME sector in India who were involved in AI-related projects or initiatives at their organization or in a personal capacity. I did not collect information about specific organizations but rather observations of participants about their industry sector specific to AI adoption, implementation, and use. Once the data collection was complete, I conducted various statistical tests and performed hypothesis testing by checking if there were any statistically significant correlations between each of the independent variables and the dependent variable.

Definitions

Artificial Intelligence (AI): Technology or a computer system that can perform tasks that typically require human intelligence. According to Kok et al. (2009), a generalized way of defining AI was to consider if these systems could think and act rationally in a similar way as human beings.

Complexity (CL): The number of steps and the difficulty level of each step that must be performed in order to adopt new technology is called as complexity (Rogers, 2003). In the survey questionnaire, question number 27 and 28 were used to determine two sub variables CL1 and CL2 which formed the independent variable CL. These two sub variables CL1 and CL2 were measured using a Likert scale with seven levels (values ranging from one strongly disagree to seven for strongly agree).*Computational Intelligence:* Computer Intelligence can be termed as a combination of intelligent tools and computational methods capable of processing raw data input to produce periodic responses to make intelligent decision (Raj, 2019).

Compatibility (CP): The degree to which the adopter of the new technology perceives innovation to be consistent with existing technology, processes, user experiences, and suitability in terms of sociocultural values is called as compatibility (Rogers, 2003). In the survey questionnaire, questions from 15 to 18 were used to determine four sub variables CP1, CP2, CP3, and CP4 which formed the independent variable CP. These four sub variables CP1, CP2, CP3, and CP4 were measured using a Likert scale with seven levels (values ranging from one strongly disagree to seven for strongly agree).

Deep Learning: When a computer program includes multiple layers of neural networks and can learn on its own similar to the human brain by developing neural networks and using this knowledge for learning new tasks, performing regression analysis, classifying data, decluttering raw data, and encoding and decoding the data for solving decision tree problems (Hatcher & Yu, 2018).

Emotional Intelligence (EI): EI is the various emotional and social skills used by individuals to express themselves and maintain social relationships in different ways (Hickman & Jureia, 2017).

Intelligent Agent: An autonomous machine that can receive and process information dynamically from the surrounding environment using various sensors and perform goal-specific tasks by making intelligent decisions through data processing (Sánchez-López & Cerezo, 2019).

IT sophistication (ITS): IT sophistication is referred as the nature, complexity, and interdependence of the management and use of IT within an organization (Raymond et al., 2011). In the survey questionnaire, question no. seven, eight, and nine were used to determine three sub variables ITS1, ITS2, and ITS3 that formed an independent variable ITS. These three sub variables ITS1, ITS2, and ITS3 were measured using Likert scale with seven levels (values ranging from one strongly disagree to seven for strongly agree).

Machine Learning (ML): Computers that can perform tasks by learning from data analysis via data fed to the machine. According to Shanthamallu et al. (2017), ML is a computer programming field that involves computer programs learning using data analysis.

Management Support (MS): MS is support provided by executive management of a firm in terms of adopting a technology innovation by allocating organizational resources which include financial and nonfinancial resources (Cruz-Jesus et al., 2019). In the survey questionnaire, question number 19, 20, and 21 were used to determine three sub variables MS1, MS2, and MS3 which formed the independent variable MS. These three sub variables MS1, MS2, and MS3 were measured using a Likert scale with seven levels (values ranging from one strongly disagree to seven for strongly agree).

Mimetic Pressure (MP): Often, organizations in an industry sector mimic the behavior of their successful peers or competitors or even adopt new technology or processes that their counterparts have adopted, which is a result of mimetic pressure (Shahzad et al., 2021). In the survey questionnaire, question number 22 and 23 were used to determine sub variables MP1 and MP2 which formed the independent variable MP.

These two sub variables MP1 and MP2 were measured using a Likert scale with seven levels (values ranging from one strongly disagree to seven for strongly agree).

Normative Pressure (NP): Expectations from customers or similarly structured organizations in markets (Di & Xia, 2017). In the survey questionnaire, question number 24, 25, and 26 were used to determine three sub variables NP1, NP2, and NP3 which formed the independent variable NP. These three sub variables NP1, NP2, and NP3 were measured using a Likert scale with seven levels (values ranging from one strongly disagree to seven for strongly agree).

Perceived ease-of-use (PEU): The degree to which an individual or an organization believes that minimal effort is required to use or deploy the new technology or process (Venkatesh et al., 2003). In the survey questionnaire, question number 34, 35, and 36 were used to determine three sub variables PEU1, PEU2, and PEU3 which formed the independent variable PEU. These three sub variables PEU1, PEU2, and PEU3 were measured using a Likert scale with seven levels (values ranging from one strongly disagree to seven for strongly agree).

Perceived usefulness (PU): The degree to which an individual or organization believes that new technology or processes may enhance their work effort (Venkatesh et al., 2003). In the survey questionnaire, question number 31, 32 and 33 were used to determine sub variables PU1, PU2, and PU3 which formed the independent variable PU.

These thee sub variables PU1, PU2, and PU3 were measured using a Likert scale with seven levels (values ranging from one strongly disagree to seven for strongly agree).

Regulatory Concerns (RC): Concerns involving law and regulations in order to successfully continue to operate as well as awareness about changes in laws and regulations impacting businesses (Almubarak, 2017). In the survey questionnaire, question number 29 and 30 were used to determine sub variables RC1 and RC2 which formed the independent variable RC. These two sub variables RC1 and RC2 were measured using a Likert scale with seven levels (values ranging from one strongly disagree to seven for strongly agree).

Relative advantage (RA): The degree to which new technology or innovation is perceived to be better compared to the technology or processes it replaced is called as relative advantage (Rogers, 2003). In the survey questionnaire, question number 10 to 14 were used to determine five sub variables RA1, RA2, RA3, RA4, and RA5 which formed the independent variable RA. All five sub variables RA1 to RA5 were measured using Likert scale with seven levels (values ranging from one strongly disagree to seven for strongly agree).

Robotic Process Automation (RPA): RPA is an application of technology that helps in automating business processes using a well-defined rule engine. It helps in terms of automating routine tasks involving consuming structured data and rule or data-based decision trees (Aguirre & Rodriguez, 2017).

Small and Medium Enterprise (SME): According to the Ministry of Micro, Small, Medium Enterprise (MSME, 2020), a SME is one where investment is more than 10,000,000 Indian Rupees (INR) and up to 500,000,000 INR, and turnover is between 50,000,000 and 2,500,000,000 INR.

Assumptions

I outlined assumptions in this study to reveal facts which were unproven to be true. The primary assumption assumed that AI benefits outweigh its disadvantages and thus the reason for its adoption. The SME sector in India would be able to increase its competitiveness and take advantage of novel technologies to offer better solutions to their customers at affordable prices.

The second assumption was that competition, thirst to create and provide innovative solutions, products, and services to customers were the main inhibiters of the SME sector in India that encourages them to adopt new technology and innovate. Growing computing power and enhanced data analytics capabilities within systems helps the SME sector to innovate in a cost effective way and adopt new technology (Shanthamallu et al., 2017).

The third assumption was that executives, IT managers, and IT professionals working in the SME sector in India were responsible for technology adoption related decisions. Thus they possessed the required understanding of AI technology for efficient decision making. The fourth assumption was that all survey participants had access to internet and can access online survey on Survey Monkey website. This ensured that all the participants can answer questions in the web based survey using their laptop, desktop, or smart phone.

The fourth assumption was that all participants had access to the Internet to participate in online surveys. They had access to the online survey questionnaire and could answer all questions after due consideration.

Scope and Delimitations

This study was conducted to understand correlations between constructs from DOI, TOE, and TAM theories and AI adoption, implementation, and use in India's SME sector. Only ten constructs were selected (ITS, RA, CP, CL, MS, MP, NP, REC, PU, and PEU). One construct RA was specific to DOI theory. There were four constructs (CL, CP, ITS, and MS) those were common to DOI and TOE theory. CL and CP were related to technology group within TOE. ITS and MS were related to organization within TOE. MP, NP, and RC were related to environment within TOE. There were two constructs (PU and PEU) related to TAM.

Though there were other innovation theories available and used such as theory of reasoned action, social cognitive theory, and activity theory, I focused only on DOI, TOE, and TAM theory. Aspect of diffusion of innovation over a time period was analyzed using DOI. Organizational level technology adoption was analyzed using TOE. Ease of use and usability of the new technology from the perspective of end user was analyzed using TAM theory. This study helped me to analyze these three different perspectives together. I aimed to generate an understanding about factors which influence

AI adoption in the SME sector that could be leveraged across industry types and sizes within India and other countries.

Limitations

There were primarily two limitations in this study which might had a potential impact on outcomes. The first limitation was that very little or no external validity is available for convenience sampling as easy accessibility of participants makes them eligible to participate in the research study. In order to address this limitation I selected participants from the SME sector in India who has prior experience or exposure to AI related projects or initiatives.

The second limitation was the focus on ITS, RA, CP, CL, MS, MP, NP, RC, PU, and PEU factors related to AI adoption, implementation, and use in the SME sector in India. The DOI, TOE, and TAM theories consisted various constructs associated with technology, organization, and environment. To address this limitation, I adopted survey instruments ('Organizational Adoption of Virtual Worlds Survey', 'Cloud Adoption by IT Manager', and 'User Acceptance of Information Technology') those were adjusted, tested, and contained similar constructs or variables.

Significance of the Study

The SME sector has proved to be crucial for the growth of any economy, whether developed economies like the EU or a developing economy such as India. According to the Federation of Indian Chamber of Commerce and Industry (FICCI, 2016), the SME sector in India provided 80% of total jobs in the industry with just 20% of investment, and was the largest employment provider after the agricultural sector. From 2015 to

2016, the SME sector contributed 28% of the Indian GDP and had a 34% share of total exports (FICCI, 2016). However, the SME sector faced challenges involving availability of required financial resources, training of human resources, ability to acquire and access latest technologies, and operating cash flow (Watad et al., 2018).

AI technology can enable the SME sector in India to take advantage of the latest technological capabilities to innovate faster and participate in a growing digital ecosystem (Kumar et al., 2017). This study may help India's SME sector to understand critical enablers to adopt AI technology in their organizations and increase their product innovativeness to meet business goals. This study may also help the SME sector in terms of faster innovation, creating novel services, and reducing operating costs by leveraging technological advancements.

Significance to Theory

DOI and TOE theories were found useful to study new technology adoption in industry sectors such as Telecom, Insurance, and High Tech manufacturing (Aljindi, 2015; Jakšič & Marinč, 2019). AI based product adoption related empirical studies were also based on DOI and TOE theories where new technology adoption rates and related challenges were analysed (Purdy & Daugherty, 2016; Walczak, 2016). The decision making process for selecting AI based products to address business challenges were part of the studies using TOE and TAM theories (Li et al., 2017). DOI, TOE, and TAM based research models helped to understand the impact of AI on management functions (Alsheibani et al., 2018; Chen, 2019; Duchessi et al., 1993).

I did not find an extensive study that involved the SME sector operating in India where AI adoption, implementation, and use was evaluated using DOI, TOE, and TAM theories together. Through this study, I studied the combined effect of DOI, TOE, and TAM related constructs on AI adoption, implementation, and SME use in India. Thus this study is significant to the theory.

Significance to Practice

Through this study, I attempted to create new knowledge to help understand the combined effect of DOI, TOE, and TAM related constructs to AI technology adoption, implementation, and use in India’s SME sector. I studied the impact of factors such as ITS, RA, CP, CL, RC, MS, MP, NS, PU, and PEU related to AI in the SME sector. This study is significant to the practice as it adds to the new knowledge where industry sector leaders may gain more insights about essential factors involving AI technology used in their organization. The leaders in the SME sector in India may be better equipped to enhance organizational resource allocation to meet their strategic goals.

Significance to Social Change

The SME sector is one of the most crucial industrial sector for any country as it creates employment opportunities and thus helps in solving societal issues such as hunger, poverty, lack of healthcare services, and education to under privileged. Disruptive technologies such as AI have a significant impact on the SME sector. It enables the industry to create technology-based services and products to solve many societal challenges. In this cross-sectional study, the focus was to study factors which influence AI adoption in India’s SME sector. Through this study, I intended to bring positive social change so that management of small organizations in India can make informed decision about AI technology adoption, implementation, and use.

Summary and Transition

This chapter started with the introduction to this quantitative cross-sectional correlational study. Then, I addressed the background of the study and defined the problem statement. This was followed by the purpose and research questions and hypotheses. I included details about management theories applicable and useful for this research along with definitions, assumptions, and the scope of the research. Lastly, I addressed the significance of this study in terms of theory, practice, and social change. I identified challenges previous researchers faced and limitations of research methodologies. I also analyzed whether the research problem of interest was already addressed. Chapter 2 contains a literature review.

Chapter 2: Literature Review

This chapter contains a detailed review of literature relevant to this quantitative cross-sectional correlational study. The specific problem was that factors that enable and limit AI adoption implementation and use in India's SME sector were unknown. A literature review was conducted to understand the state of AI adoption across various industries globally, contributing and prohibiting factors impacting AI adoption, and the relevance of innovation adoption theories and its relation to AI adoption across the SME sector in India. After evaluating multiple innovation theories, I selected the DOI, TOE, and TAM theories for this research.

In the first section, I included description about the literature review strategy, followed by brief about information collection sources, key search terms, and the methodology used for selecting a scholarly peer reviewed article. The second section contains justifications and relevant explanations regarding the theoretical foundation and theories used in recent studies. A discussion about AI technology context and adoption status across industries follows. Theoretical constructs relevant to hypotheses and research questions were addressed. This also included a detailed discussion about theories specific to AI technology adoption.

The next section contains an evaluation of AI technology adoption scenarios in different industrial sectors and the state of adoption across different locations. This is followed by an in-depth analysis of adoption of AI technology in India, focusing on the SME sector in India. The chapter concludes with a summary and transition to the next chapter.

Literature Review Strategy

The focus of the quantitative cross-sectional correlational study was to help decision-makers within the SME sector in India to understand factors impacting AI adoption, implementation, and use. The primary source for scholarly articles and peer-reviewed research papers was the Walden Library. Databases used were Business Source Complete, SAGE Journals, ProQuest, and EBSCOHost. Google Scholar was also extensively used for finding suitable research. Literature published from year 2016 to 2021 was primarily considered for this study with a few valid exceptions.

Search keywords were: *artificial intelligence*, *SME sector in India*, *diffusion of innovations*, *technology organization environment*, and *technology acceptance model*, *AI in the SME sector*, *AI in the SME sector in India*, *AI in India*, *DOI*, *TOE*, and *TAM*. I used these search terms judiciously as well as various permutations and combinations. Some technical or consulting firm such as Gartner and Mckinsey contained essential and relevant information worth considering for this study.

The first task was to shortlist relevant peer-reviewed research articles for this study using a structured approach. After careful consideration, I determined that around 172 research articles, books, and dissertations were useful for this study. Four books were related to AI, and two books were related to quantitative research methodologies. Most of the 172 selected research articles were from 20 industry publications or editorials covering topics related to AI technology adoption across the industries. From all the resources referred, 32 research papers contained information about the DOI, TOE, or TAM theories and AI adoption.

Theoretical Foundation

The purpose of any research is to contribute to the existing knowledge base. The research must be based on theories so that contributions become relevant, significant, and trustworthy. Osanloo and Grant (2014) said the theoretical framework is a blueprint for research that a researcher adopts from existing theories and develops. A conceptual framework is always based on the empirical knowledge or structure, it is often used to explore details about research problem or related phenomenon (Adom et al., 2018).

Theoretical frameworks are useful to study relationships between various constructs. Also, theoretical frameworks are used to help define the researcher’s scope and boundaries (Adom et al., 2018). In this study, the DOI, TOE, and TAM theories formed the theoretical foundation to determine correlations between various constructs that influence AI technology adoption. I elaborate on this phenomenon in the next few sections.

DOI

For this study the DOI theory formed the main theoretical foundation. I evaluated the applicability for AI technology adoption by understanding an impact of constructs ITS, RA, CP, CL, MS, MP, NP, RC, PU, and PEU within the SME sector of India. In the DOI context, innovation was a novel phenomenon, product, technology, idea, or behavior of an entity considered new by the adopter (Rogers, 2003). According to Rogers (2003), the DOI theory helps in explaining how the innovation adopted by communities with the help of spreading of awareness about the innovation through communication channels. The phenomenon of innovation adoption is called the innovation diffusion process. The

DOI theory is used to discuss reasons for innovation adoption, methods of adoption, and the pace of innovation adoption by individuals and organizations (Rogers, 2003). In this study, I focused on finding the factors those influence the AI adoption in the SME sector in India.

A well-defined process of innovation adoption was one of the significant contributions of the DOI theory. Rogers (2003) defined innovation adoption decision making as a five-step process frequently used by a unit of adoption, either an individual or an organization. The first step in the process was gaining knowledge about the innovation to build an initial understanding of the novel phenomenon. During the second stage, which was called as persuasion, an innovation adoption unit builds an outlook towards the innovation to consider for the adoption. In the next stage, the adopter uses the information collected in the first stage and attitude created during the second stage to decide on innovation acceptance or rejection. The next two stages are dependent on the affirmative decision taken in the third stage. Implementation of the decision of innovation adoption is the fourth stage. The last stage is utilization of innovation by the adopter. In this study, the focus was on three aspects decision of adoption, implementation, and use of the innovation.

In DOI theory, organizational innovativeness is defined as the early adoption of innovation by an organization compared to its competitors or comparable peers (Rogers, 2003). According to Rogers (2003) there are three different distinguishable groups of predictors, such as leadership traits (leader's ability to embrace the change) and attributed integral to the organizational characteristics (size, formal organizational structure, communication channels, complexity, and centralization). Some of the factors mentioned above, such as management support, organizational structure, resource availability, and complexity, were of prime interest to this study.

Executive management's attitude towards innovation determines the innovation adoption culture nurtured within an organization. The organizational structure defines whether few top executives or several middle level managers can be the decision-makers about the new technology adoption (Rogers, 2003). When few executives take the decision it is called as centralization, when middle managers have the power of decision making, it is called as decentralization. The centralization often acts as a major limiting factor in organizational innovation adoption (Bergeron et al., 2017; Xu et al., 2017; Cruz-Jesus et al., 2019).

As executive leadership was involved in more strategic level thinking and running the business, they do not have an opportunity to become aware of operational problems and thus could not suggest innovative solutions. If the central leadership team is ineffective, then the systemic limitations built within the organization may prohibit or delay the innovation adoption process (Cruz-Jesus et al., 2019; Syamsuar, 2018; Bergeron et al., 2017).

During the study, I studied the organizational aspects used to understand if the size and organizational structure impacted AI technology adoption in India's SME sector. Complexity of technological innovation demands a higher degree of experience, expertise, awareness, and knowledge within the members of the organization. The expertise may enable these members to persuade the leadership to provide necessary approvals and commit organizational resources to the new technology adoption.

If organizational structure and decision-making process are too complicated it becomes counterproductive for the new technology adoption (Kim et al., 2018; Xu et al., 2017; Cruz-Jesus et al., 2019). However, large and complex organizations can put more organizational resources such as skilled staff and money and thus utilize innovations effectively (Almubarak, 2017; Nath et al., 2016; Awa & Ojiabo, 2016). As many small organizations have a less complicated organizational structure, I wanted to confirm if complexity impacted AI adoption.

Communication channels are referred as interconnectedness within the organization as per the DOI theory based previous research (Almubarak, 2017; Awa & Ojiabo, 2016). Organizational communication channels determine if the perspective about the new technology is built appropriately within the organization. Effective communication and sharing of all the required information builds the organization's knowledge culture and thus act as an enabling factor for new technology adoption. According to Rogers (2003), interconnectedness has a positive impact on new technology adoption. Research studies conducted by Yoon and Davis (2018), Nath et al. (2016) proved that efficient communication channels improves organizational innovativeness. In the study, ITS is considered as an enabler of better communication channels for dissipation of new technology adoption related information.

The organization's size was measured using different parameters such as the number of employees, the number of offices, its turnover, and the customer base. During the study size of the organization was assumed to be small or medium. As per the Ministry of Micro, Small, and Medium Enterprises (MSME) (2020), small and medium enterprise investment more than 10,000,000 Indian Rupees (INR) and up to 500,000,000 INR in the plant and machinery or equipment and have the turnover more than 50,000,000 INR and up to 2,500,000,000 INR. In the past research, though the researchers measured an organization's size differently, the size positively correlated with the new technology adoption (Nath et al., 2016; Almubarak, 2017; Awa & Ojiabo, 2016; Kim et al., 2018).

In the DOI based study, it was found that larger organizations can spend more funds and allocate required resources thus are more efficient in new technology adoption (Valdebenito & Quelopana, 2019; Almubarak, 2017). Some of the researcher's Cruz-Jesus et al. (2019); Alkhalil et al. (2017); Tripopsakul (2018) claimed that many firms found innovation to be mandatory to remain competitive. The amount of committed resources available for the innovation adoption team determines its success; Rogers (2003) referred to resource availability as organizational slack. These resources could be financial resources and non-financial resources such as human resources, physical resources, and other resources such as political support within the organization. Slack is referred as resources readily available within the organization to allocate for new initiatives.

According to Alkhalil et al. (2017), the availability of the organization’s resources provides the flexibility needed for experimentation and helps to mitigate the risk involved in the adoption of novel technology. Sayginer and Ercan (2020) and Yap and Chen

(2017) found that organizational slack is an essential influencing factor that positively impacts the successful innovation adoption. In this study, the organizational slack or resource availability was of interest as it aligned to independent variable MS and determined the ability of the SME sector in India to stay committed and invested in AI adoption.

To summarize, the DOI theory's focuses on analyzing factors associated with innovation characteristics and their impact on the potential adopters, either individuals or organizations. There was a greater emphasis on the innovation adoption by individuals in the DOI theory than on organizations. According to Rogers (2003), leadership traits determine and influence innovation adoption at the organization level. However, other factors, such as organization's size, complexity of the technology involved, organizational slack, and organizational structure also influence the new technology adoption. These organizational impediments were discussed and considered in TOE framework related discussion. In the study, I analyzed AI innovation adoption at the organization level covering decision-makers, implementers, and end-users of the new technology. Thus DOI and TOE both theories were relevant for this study.

DOI-Based Empirical Studies

The DOI had been the basis of many research studies analyzing new technology adoption across various geographies and industries. The DOI model has been enhanced by adding additional contexts and extending the scope from an individual adopter to the organization level. Below section provides the synopsis of some of the studies reviewed as part of the literature review.

Franceschinis et al. (2017) analyzed heating technology's adoption based on renewable energy sources instead of fossil fuel in Italy using DOI theory. Instead of five, in that research three adopters groups early adopters, intermediate adopters, and laggards were found to react differently to the new technology adoption (Franceschinis et al., 2017). The laggards were the most sensitive group of adopters towards RA, where cost was the prime factor for the adoption decision (Franceschinis et al., 2017). The cost factor impacted the RA of the new technology for the adopters at an individual level and organizational level both. The CL of the technology and adoption processes for renewable technologies decreased prospects of faster technology adoption. Intermediate adopters were the most concerned about CL of the technology involved in renewable energy-based heating systems than the other two adapters (Franceschinis et al., 2017).

Sayginer and Ercan (2020) analyzed the Cloud Computing adoption trend in Turkey using the DOI and TOE models. Three constructs, RA, CL, and CP formed part of that study. CL was the primary concern in cloud adopters, followed by CP, and the least affecting factor was RA within Turkey-based organizational cloud adopters (Sayginer & Ercan, 2020). The cloud technology adoption needed changes to the internal IT systems as the data needed to travel outside the organizational boundaries more often. The internal systems needed alteration to leverage hybrid data-sharing models.

The cost was the favorable sub-construct within the RA helping the cloud adoption as the organization moved from a capital expenditure-based model to an operational expenditure-based model (Sayginer & Ercan, 2020).

Yap and Chen (2017) conducted a study about diffused wine consumption in young Chinese consumers using DOI theory. The survey participants ranked CL, CP, RA, observability, and triability in a specific order of their influence on diffused wine consumption (Yap & Chen, 2017). Local traditions and sophisticated manufacturing practices used by local manufacturers challenged modern diffused wine manufacturers. Manufacturing of the diffused wine was relatively costlier for the manufacturers. Thus, the local community depended on local brands. One of the research suggestions were that wine manufacturers must educate wine consumers to reduce the impact of CL and align wine manufacturing practices to increase CP (Yap & Chen, 2017).

According to Nath et al. (2016), a strength of DOI theory was that it was a generic theory that could be easily applied to any innovation by covering most of the aspects of generic technology acceptance theory. However, the DOI theory lacks an adequate organizational level context; and does not consider external environmental aspects such as regulatory framework and law that play a vital role in technology adoption (Nath et al., 2016).

According to Awa and Ojiabo (2016), TOE provided an organizational context with a broader scope covering macro-level factors such as organizational boundaries, resources, and government systems support. However, the theory missed an important micro-level context such as an individual who decides the technology adoption and uses it throughout the technology lifespan (Awa & Ojiabo, 2016). External and internal environmental factors and many organizational contexts are difficult to measure, and it is difficult to understand its impact on technology decision making, implementation, and use at the firm level (Awa & Ojiabo, 2016).

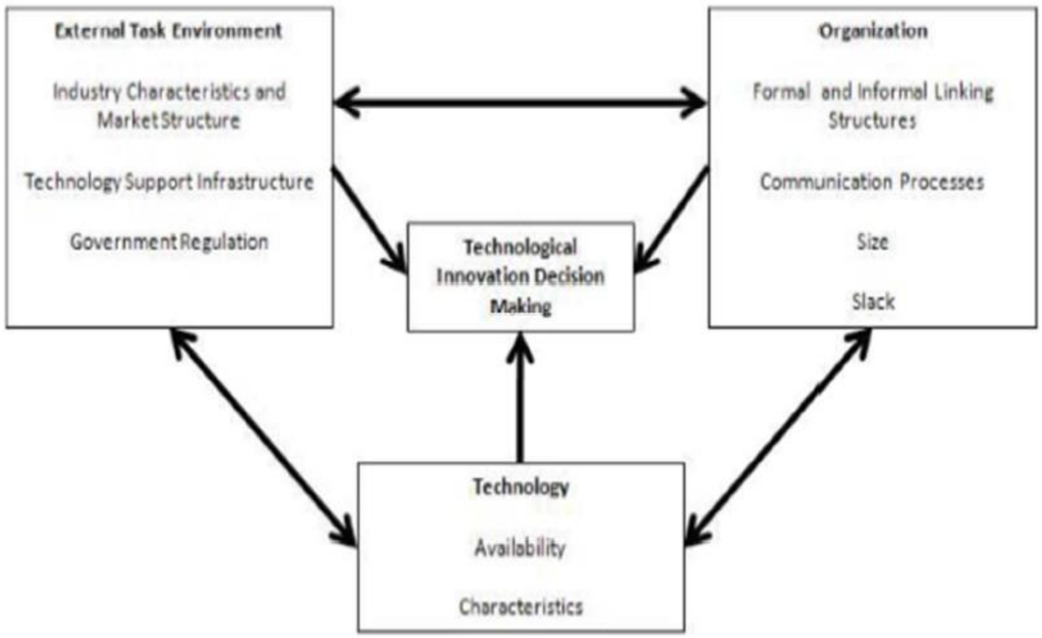
TOE

Tranatsky and Fleisher formed the TOE theory in 1990 to categorize the innovation adoption factors under technology, organization, and environment context. TOE covers the technology innovation adoption at the organizational level. Organization's internal impediments are categorized as technological and organizational, and external impediments are called an environmental construct. According to Tranatsky and Fleisher (1990), it was difficult for a single individual to understand the sophisticated technologies implemented at an organizational level. The TOE framework is useful to study technology adoption at an organizational level.

Within the TOE framework, the technological components such as machinery used for manufacturing and computer systems used for running organizational processes are considered as part of technology. Organizational context contained organization's attributes, such as firm size, managerial processes, and organizational structure. Environmental context referred to industry characteristics, regulatory concern, and competition in the market, nature, and the state of the industrial sector.

Figure 2

TOE Framework



Note. From The Process of Technological Innovation (p. 153), by L. G. Tornatzky and M. Fleischer. Copyright 1990 by Lexington Books. Reprinted with permission from the publisher (see Appendix D).

There were multiple constructs part of the TOE framework, as listed in Figure 2. Either of three categories, technological, organizational, or environmental context, contained at least one of the constructs used in this study. Constructs covered through TOE were ITS, CP, CL, MS, MP, NP, and RC. Table 1 contains innovation characteristics related part of multiple theories including DOI and TOE. I found some overlap between constructs used in DOI and TOE theory that is discussed in sections about research studies involving multiple theories.

Table 1

Innovation Characteristics

#	Innovation Characteristics	#	Innovation Characteristics
1	Relative advantage	2	Association with major enterprises
3	Clarity of results	4	Compatibility
5	Communicability	6	Complexity
7	Continuing cost	8	Cost
9	Divisibility	10	Ease of operation
11	Flexibility	12	Importance
13	Initial cost	14	Mechanical attraction
15	Observability	16	Payoff
17	Pervasiveness	18	Profitability
19	Radicalness	20	Rate of cost recovery
21	Regularity of reward	22	Reliability
23	Riskiness	24	Specificity of evaluation
25	Saving of discomfort	26	Saving of time
27	Scientific status	28	Social approval
29	Triability	30	Visibility

Note. From "Innovation characteristics and innovation adoption-implementation: A meta-analyses of finding," by Tonatzky and Klein, 1982, p. 43. Reprinted with permission by the publisher (see Appendix C).

30 innovation characteristics mentioned in Table 1 possess some overlap in their coverage within TOE framework. Each of the parameters might be important from a specific study. However, for the study, seven parameters from the TOE framework, such as ITS, CL, MS, CP, MP, NP, and RC were chosen. Below paragraphs contains some explanation about importance and relevance for this study. While evaluating the technological context, CL and CP of innovative technology became essential. As part of the organizational context, ITS and MS were critical. In the environmental context, MP, NP, and RC were critical.

The level of readiness of IT systems used within the organization and its IT management's efficiency were impediments that defined the level of IT sophistication (Salleh & Janczewski, 2016). In order to adopt the new technology, the organization must have the required flexibility within the IT systems, the stability of the environment, efficient vendor support, and systems must run on the latest software and hardware support levels (Xu et al., 2017). The IT knowledge and skills of the system administrators, management, and end-users of the organization's technology plays a pivotal role in the organization's ability to embrace the new technology and define experimentation capability. Understanding the organization's financial readiness and technological readiness while analyzing its innovativeness is important for the research related to new technology adoption.

For this study ITS was one of the crucial factors to consider. Due to the organization's size and financial resources availability the SME sector in India and elsewhere have resource crunch. Some of the small companies have funding challenges. These companies lack sophisticated IT infrastructure and corporate work culture to attract the top talent. Along with the legacy systems, many SMEs thus possess user-defined technologies (UDT) and thus require support of expert employees as often they do not have the vendor support for UDTs. When these organizations try to adopt new technologies such as AI, the decision making becomes overly complex due to a lack of sophisticated IT infrastructure, multi-technology scenarios.

Valdebenito and Quelopana (2009) conducted a study about the adoption of cloud-based Enterprise Resource Platform (ERP) offered through software as a Service (SaaS) based model for SME. According to Valdebenito and Quelopana (2009), ITS worked in favor of the SME sector to quickly migrate to the SaaS-based model for ERP packages. The migration to cloud platforms for SME simplified the IT Systems management and increased ITS level as the ERP replaced multiple business applications with a single organization-wide software package (Valdebenito & Quelopana, 2009).

Bergeron et al. (2017) defined ITS as the IT management method and its level of alignment with the organizational strategy. The study involved a comparative analysis of IT companies from the SME sector and their ITS level to adopt the new technology. According to Bergeron et al. (2017), the organization with better ITS level provided an opportunity for enhanced product innovation and improved organizational flexibility in adopting new technologies. The organization's size had proved to be counterproductive in some cases as the lag in the removal of legacy infrastructure and systems made it difficult for organizations to adopt newer technologies (Bergeron et al., 2017).

Syamsuar (2018) conducted a study to understand the resistance to the adoption of Internet Protocol (IP V6) and the preference of companies to remain on IP (V4). The IP (V6) was available in the industry for more than 15 years, but it did not achieve the expected diffusion level in the industry, as many organizations still used the IP (V4) (Syamsuar, 2018). ITS as an organizational context parameter in the TOE structure had been one of the dominant factors of major concern associated with the non-adoption of IP (V6) across the industry (Syamsuar, 2018).

Kim et al. (2018) conducted a study of the adoption of the Semantic Web (SW) (BigData based data analytics technology) by IT professionals. Few drivers of the SW adoption across various organizations were the innovativeness of the firm, data management capabilities of the IT staff, and the applicability of the data management to business applications attributed to ITS (Kim et al., 2018). Organizations where ITS was at a higher level, found to be using SW or similar data analytics platforms to make faster business decisions compared to their peers (Kim et al., 2018).

MS is a vital parameter that determines the success or failure of any initiative or project in an organization. The new technology adoption is not different from it. The executive leadership determines the long-term business strategy and directs the middle-management to execute programs to achieve the strategic goal. While doing so, the middle-management needs top leaders' political blessings and more importantly company's financial and non-financial resources. In the study, MS was considered as an essential factor for AI adoption in India's SME sector. In some cases, the top management makes decisions about the new technology adoption without involving employees at the lower level in their organization. The technical competence and inclination of the top management towards a particular technology, capabilities of middle-management, and technical expertise of the technical staff determines the success of AI adoption.

Customer Relationship Management (CRM) and Enterprise Resource Planning (ERP) were powerful enterprise-wide systems requiring a considerable amount of MS and organizational resources during the implementation and sustained effective use. Cruz-Jesus et al. (2019) found that MS along with ITS (data quality and integration), were one of the most critical factors in 277 firms evaluated for CRM adoption. Whereas, MS and ITS played equally important part in ERP assimilation and helped organizations to reap considerable benefits from ERP implementation in many organizations within China (Xu et al., 2017). In yet another study, Salleh and Janczewski (2016) found that lack of MS required for building the right information security culture and weak organizational learning culture were main impediments prohibiting Big Data adoption in organizations.

The degree to which an adopter finds the new technology, process, or phenomenon challenging to understand and use is called as complexity. There are two crucial factors to consider while discussing CL. The first parameter is the nature of innovation. For example, if too many parameters involved in the technology adoption such as a lengthy process of understanding, prior knowledge about a specific product or technology then the CL level. The number of parameters and pre-requisites were hard to define for every innovation to term. Another vital factor to consider while deciding the complexity was the adopter itself. For an uneducated person, the use of one technology might be a complex phenomenon, but the same technology might be effortless for an educated person. The prior knowledge and other factors sometimes define the complexity of the innovation adoption. AI technology involves various programming languages, massive data analysis, and sophisticated algorithms. In this study, the feedback from the survey participants determined the level of CL involved in AI adoption in the SME sector in Indi.

Ullah and Qureshi (2019), during the study about IT Computer Technology (ICT) adoption by SME, found that the organizational resources, size of the organization, and CL were crucial factors. Managers in the organization play an influential role in ICT adoption in SME sector by reducing the level of CLin decision-making (Ullah & Qureshi, 2019). While in other research related to Cloud Computing adoption, Kandil et al. (2018) defined CL in cloud technology as the effectiveness of data transfer, efficient interface design, and application functionality. Though cloud technology is accessible to individuals easily, but CL level in organizational level cloud adoption impacts negatively (Kandil & et al., 2018).

As defined by Alkhalil et al. (2017), consistency with the experience of using existing systems or products and similarity with the adopters' value system determines the compatibility of the innovation. During the study about cloud technology adoption,CP issues prohibited the migration of extensive data from old legacy systems to cloud-based systems, negatively impacted the cloud technology adoption (Alkhalil et al., 2017). In yet another study, while studying the adoption of BigData Systems (BDS), Salleh and Janczewski (2016) found that existing security systems and controls were perceived to be sufficient by the employees slowed down the adoption of BDS in most of the organizations. Complex systems using BDS needed the data analytics engine to run at the hosting partner premises. Thus, it prohibited using BDS systems as users did not find stringent data security rules and sophisticated data transfer technologies to be compatible with the existing systems.

In the study, I evaluated the CP from the response received from the survey participants. In the SME sector, there is an availability of required agile practices and flexibility. SMEs use AI technology by taking the baby steps like creating a ChatBot for handling the user queries or gathering information from customers. SMEs also use AI in less complicated scenarios to build the necessary competency and then use the technology further to solve complex business problems. AI-based systems focus on automation. Therefore, SMEs might find manual approval processes less compatible with the automation perspective. The participants' feedback was received and analyzed during this study to understand if CP was a concern for AI adoption in the SME sector.

Pressure exerted on the organization due to competition in the market is called Mimetic Pressure. Sometimes, new technology adoption can result in business competition to retain the market share, enhance revenue, cost reduction, and, in extreme cases, just because the competitor adopted the new technology. Ikumoro and Jawad (2019) stated that the use of intelligent conversational agents or Chatbot for sales activities by the SME sector in Malaysia was driven by the MP as large organizations used Chatbot often. Shahzad et al. (2021) quoted that coercive pressure and MP positively influenced the Hospital Information System (HIS) in Pakistan's public sector hospitals for technology innovation.

In this study, survey participants' feedback determined the level of impact exerted by MP. SMEs from India might have limited organizational resources and a shortage of the Indian market's required skillsets to execute AI-related initiatives and projects. However, it would be interesting to know if AI initiatives or projects' initiation is affected by MP or is driven by business requirements only. Successful AI adoption by SMEs in India might exert MP on the broader industry players and other business ecosystem participants.

The out of compliance behavior of an individual or an organization is called normative pressure. Social acceptance was a need of an individual, but a similar need existed at the organization level to remain competent and relevant among their peers and the marketplace. Ikumoro and Jawad (2019) mentioned that in the SME sector of Malaysia, the need to meet the change in the regulatory environment and requirements posed by traders and customers created NP for adopting newer technologies. Di and Xia (2017) stated that NP, MP and CL were among the most influencing factors for adopting Extensible Business Reporting Language (XBRL) in China's financial sector.

For this study, NP was one of the exciting factors to study. Due to the business's competitive nature and high dependency on the human intervention involved in the SME sector, the effective use of disruptive technologies such as Artificial Intelligence was a challenge. It was interesting to find if the AI technologists used in the small companies find its need from their customers' demands, the regulatory requirements, and expectations through compulsion created from NP. It was interesting to know if NP was an impacting factor for AI technology adoption in India's SME sector.

Small organizations globally were among the essential contributors due to their vital role in the global economy. There were many RC about the SME sector those control their financial transactions, ethical behavior, and prohibition of misuse of government aid and schemes while executing business activities. The risk involved for individual and institutional investors, customers of the SME sector in the globally connected markets makes it essential for government bodies to impose various rules and regulations. Many companies falling under the category of SME in India had business tie-ups and customers in multiple geographical locations in the world. RC were of prime importance for these small organizations as non-adherence to regulations could result in considerable financial and reputational loss. It might negatively impact the trust of a vast customer base and can put their money at risk.

TOE and DOI framework was used while analyzing the impact of RC in IT innovation and the adoption of new technology. According to Salleh and Janczewski (2018), data protection-related RC were of prime importance while selecting Big-Data technologies due to unstructured data that makes data protection more complex and challenging. Outsourcing of the work to vendors working from different countries added to RC complexity and applicability of the more stringent data protection acts (Salleh & Janczewski, 2018).

Almubarak (2017) found that Saudi Arabian public sector hospitals' RC negatively impacted cloud technology adoption. The reason cited for this trend by Almubarak (2017) was that the more stringent regulations for managing IT systems and data privacy rules made it more difficult for the hospitals to use the cloud computing technologies. The management in those impacted hospitals showed inclination towards using existing systems instead of migrating to the cloud environment.

TOE Framework-Based Studies

While studying innovation adoption across various industrial sectors, TOE framework solely or in combination of other theories was very useful (Saint & Gutierrez, 2017; Low et al., 2019; Kurse et al., 2019). The industrial sector's unique characteristics and the different needs of the industries altered the speed of innovation adoption across industries. Below were some of the representative examples of related research papers.

Li et al. (2018) researched the use of audit analytics systems in auditing firms by using the TOE framework. From the technology context, ITS, CP, and higher technical capabilities helped to achieve better results in new technology adoption (Li et al., 2018). While from organizational context, significant MS, firm size, and in-house expertise or an ability to seek professional help were essential success factors in the new technology adoption. Whereas favorable environmental factors such as a change in the regulations helped to accelerate the speed of technology adoption or competition in the industry sector (Li et al., 2019).

Saint and Gutierrez (2017) studied the adoption of learning analytics in higher education institutes in the United Kingdom, using TOE framework. They focused on RA, CL, perceived financial cost, MS, firm size, technology competence, NP, and vendor support. After surveying 171 institutes and 385 participants, they found that parameters related to organizational context, namely MS, CP, and firm size, were the most influential factors. In comparison, NP and vendor support were the least influential environmental context factors in technology adoption (Saint & Gutierrez, 2017).

Low et al. (2019) leveraged the TOE framework to understand the adoption of smart living and digital economy in Malaysia's megacities. In that quantitative study, the researchers tried to understand how technology, organizations, and environmental context correlated to the nation's economy, the industrial sector, and citizens of the country? The citizens started using new digital tools and observed that CP and NP were crucial factors that influenced the innovation adoption and use in Malaysia (Low et al., 2019).

Kurse et al. (2019) conducted 22 semi-structured interviews of AI experts from the German financial industry to understand the factors influencing AI adoption. The outcome of these interviews fit within the TOE framework, and they further discussed structural changes and modifications required in these organizations to increase CP and NP for significant AI adoption. Kurse et al. (2019) suggested that additional AI-related training should be given to general users and employees to increase CP and reduce fear about AI. Further, there was a need to increase MS in organizations to reduce regulatory non-compliance and enhance ethical standards by properly managing new technology adoption within the financial sector (Kurse et al., 2019). Within the technological context, CP was the major obstacle for AI adoption, along with the legacy technology as the second level hurdle for and effective use of AI in the financial sector (Kurse et al., 2019).

Usman et al. (2019) used the theory of DOI and TOE together to study the adoption of cloud-based enterprise resource planning (ERP) systems in Nigerian SMEs in manufacturing sector. Instead of focusing on innovation features, they preferred to understand how internal and external adoption factors and their relative advantage to SMEs was influential. Availability of subject matter experts (SME) within the market, and within the organization, financial strength to use well established ERP products were factors affecting the diffusion in SME sectors in Nigeria (Usman et al., 2019).

Multiple factors influence new technology adoption across organizations in various industrial sectors. These factors are related to technology, such as CP and CL. There are other factors such as MS and ITS related to the organizational context. MP, NP, and RC are environment-related constructs that might influence the new technology adoption. However, all these constructs were essential from technology adoption and implementation. There was a need to look at new technology adoption from the user perspective. It was crucial to know whether the users find the technology useful and easy to use. TAM theory discussed in the next section might help in understanding the same.

TAM

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). The theory was based on behavioral studies to understand the adoption and use of information systems by users. According to Sebjan et al. (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 or add another layer of CL in performing the task (Sebjan et al., 2014). Enabling or disabling external factors such as social influence could change the adopter's perspective and enhance the technology adoption.

According to Sebjan et al. (2014), 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 (Sebjan et al., 2014). In TAM theory, social interactions and pressure experienced by the adopter was studied; along with PU and PEU was studied at the individual adopter level to understand usability patterns (Sebjan et al., 2014).

As Gaddam (2019) stated, the MS and organizational CP were the most critical factors in technological adoption in an organizational context. Additionally, leaders' knowledge and capabilities played the critical role in promoting novel technology in their organization (Gaddam, 2019). The leaders were found to be providing the required MS, and helping to influence users' perspective in improving PU in their employees (Gaddam, 2019). These factors were essential for significant and sustained technology adoption within an organization.

TAM-Based Studies

TAM is one of the most important theories used as is or in combination with DOI, TOE, or other innovation adoption models. As PU and PEU were focus points in 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 Sanchez-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 (Sanchez-Prieto et al., 2019).

In another TAM based study about the adoption of smart mobility solutions in Malaysia, the researcher used four core constructs from TAM. According to Ahmed et al. (2020), PU and PEU had a considerable impact on improving attitude towards smart mobility solutions. After the survey, the researchers analyzed the collected data using an Artificial Neural Network (ANN) based simulation model. 93% of private vehicle owners preferred the Radio Frequency Identifier (RFID) based solution in mass parking spaces, whereas, for roadside parking, they did not prefer the same (Ahmed et al., 2020). The ANN-based model was used to suggest further improvements to increase the ease of use and phased rollout of smart mobility solutions (Ahmed et al., 2020).

Kumar and Sachan (2017) conducted an empirical study based on the TAM model to find factors influencing electronic income tax returns filing in India. This quantitative research involved a survey of 294 Indian taxpayers who used the Indian government's e-filing facility, and the researchers used the composite model developed using TAM and DOI theories. According to Kumar and Sachan (2017), citizens based their decision on e-filing based on the evaluation of the e-filing website from PEU and PU. The PEU was the highest impacting factor, followed by PU in the study and some of the DOI related factors such as CL and RA (Kumar & Sachan, 2017). Min et al. (2019) conducted a study about the adoption of Uber Mobile Application for shared rides in DOI and TAM theory based study. Along with sharing mobile mobility applications, using the same app for shared accommodation or similar factors involved studying the sharing economy. DOI constructs RA, CL, CP, and observability influenced TAM constructs PU and PEU among adopters (Min et al., 2017).

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 Suhartanto and Leo (2018), there was a significant presence of multinational retailers using ICT effectively in Indonesia but still there was slow adoption of ICT by smaller firms. The study demonstrated that a lack of awareness about PEU and PU within the small retailers was the biggest roadblock for the effective use of ICT at a mass scale (Suhartanto & Leo, 2018).

AI

Allen Newell and Herbert Simon at Dartmouth Conference in 1956 introduced transformational change named AI for the first time. They both initially developed a generic algorithm to solve any mathematical problem; this lead to the development of WOBOT-1, the first robot in 1972 in Japan. However, till the year 2000, it remained difficult for scientists to simulate the brain's functioning due to many challenges such as lack of funding, limited processing capability of computing resources, no availability of substantial data storage and analytics capabilities, and many more. It was quite evident that AI and its applications were not recent innovations in the market. However, over the past 15-20 years, there had been exponential growth in computing devices' processing and storage capabilities. These advancements removed limitations and restrictions in AI research areas. Computing capabilities, storage capabilities, data abundance, and analytics tools have helped various industry sectors to adopt AI.

According to Duchessi et al. (1993), there were three predominant types of AI-related research; empirical studies, case studies, and technical research. Empirical studies are used to study critical factors and to analyse the impact on the development, implementation and adoption of AI. Case studies are used to develop model of AI implementation and adoption for specific use cases. Whereas, studies those are aligned to technical solutions and theoretical models are used to analyse the impact of AI on management and organization. There were a variety of definitions of AI available in the research field.

According to Nilsson (1998) from Stanford University, intelligent agents' behaviour included creating perception, reasoning, learning new skills, communicating, and decision-making in a complex AI environment. According to Poole and Mackworth (2017), AI was an intelligently acting computational agent that could learn from the experience and possess decision-making capabilities if the environment, goals, and objectives were adequately defined. Tredinnick (2017) stated that the computerized virtual assistant used Natural Language Processing (NLP) and Machine learning (ML) for customer interaction as technologies under AI. Machine Learning was often considered a computational ability to perceive data or images to make or represent knowledge. According to Zerfass et al. (2020), when researchers included abstract and concrete aspects of AI in the definition, non-technical professionals found it easier to understand.

Technology related research in AI focused mainly on solving the business problems by implementing novel AI-based algorithms or technology solutions. AI-related developments in the areas of expert systems, Robotic Process Automation (RPA), Natural Language Processing (NLP), and image processing are impacting multiple business sectors (Purdy & Daugherty, 2016). The primary focus of majority research studies is to analyse a specific AI solution implemented in an organization to make it more meaningful and compelling to reap its benefits and achieve organizational growth. However, AI solutions implementation is a complex process. There were some concerns, such as strategic fitment issues, lack of organizational capabilities, stringent regulatory requirements, and many more (Aboelmaged, 2014).

Artificial Neural Network based solutions that involved complex decision making are dependent on the availability of reliable data and more exceptional analytical ability to support systems. AI adoption in the SME sector is predominantly customer service, fraud detection, and the development of credit distribution algorithms (Bahrammirzaee, 2010). AI adoption had not been the mainstream phenomenon in various industries, specifically in the SME sector, due to various prohibiting factors such as RC, CL level of the technology, and availability of a skilled workforce (O'Leary, 2010).

One of the oldest references to a bidirectional impact of AI on management was available in a research paper published by Duchess, O'Keefe, and O'Leary in 1993. Their research was an empirical study of research conducted from 1961 to 1993. According to Duchessi et al. (1993), three categories of AI research were - case studies focusing on specific AI technology implementation in a single organization, research aligned to theoretical models involving socio-technical management theories, and lastly, research involving in-depth study of specific factor impacting AI adoption.

AI Adoption-Related Studies

In the research study to understand the adoption of AI in Communication Management Zerfass et al. (2020) stated that though professionals possess limited technical knowledge about AI technology; there may be a significant impact on their profession due to AI. During their study, Zerfass et al. (2020) used the TOE framework and selected macro-level variables for the analysis, such as industry structure and communication processes within the organization and the available technology's suitability. The researchers surveyed 2689 communications practitioners and found that the lack of clarity in roles and responsibilities while using AI technology was the more significant challenge that points to a lack of ITS and MS (Zerfass et al., 2020).

Savola et al. (2018) conducted a qualitative study to understand factors related to AI adoption in marketing management in SMEs in neighboring countries, Sweden and Finland. The researchers classified AI-based marketing management systems into three categories, such as Expert Systems (ES), Neural Networks and Predictive Modelling (NNPM), and Case-Based Reasoning (CBR) (Savola et al., 2018). The researchers used TOE and TAM frameworks during their study to understand organizational level influencing factors. CP, MS, firm size, MP, and NP were the influencing factors within the SME sector for the use of AI for marketing management (Savola et al., 2018).

Mahroof (2019) researched about understanding factors that impacted AI adoption in warehousing and supply chain management for a large retailer. The study's mode was a qualitative study using a single case study model where the researcher interviewed multiple executives within the firm to understand their perspective related to AI adoption. During the research, Mahroof (2019) used the TOE framework and the Unified Theory of Acceptance and Use of Technology (UTAUT). AI adoption for supply chain and warehousing activities was not a huge success due to lack of ITS and MS within the operational management crew (Mahroof, 2019).

Pumplun et al. (2019) leveraged the TOE framework for studying the organizational readiness to adopt AI technology using a qualitative study approach. The researchers interviewed 12 AI experts and decision-makers from various organizations in Germany and Ireland. Pumplun et al. (2019) stated that due to a change in the Industry Structure and new regulations like General Data Protection Regulation (GDPR), RC impacted AI adoption. Along with the above findings, Pumplun et al. (2019) also mentioned that the MS, Organizational slack were essential factors to address the skill gap that impacts the AI implementation.

Rao (2018) conducted qualitative research based on DOI theory, Institutional Theory, and TOE framework about AI adoption within South Africa organizations. The researcher studied innovation characteristics of the organizations and technology context-related parameters such as technology integration, CL, and firm readiness. Institutional Theory also had common factors with TOE's environmental context, such as MS, MP or coercive pressure, and NP aligned to competition intensity. Rao (2018) concluded that technology integration, CL, and ITS had the most profound impact on AI adoption. In contrast, MS, organizational innovativeness, and formalization had a medium impact on AI adoption, while MP and NP impact AI adoption in South Africa.

Hong Chen, in 2019 conducted a study about AI adoption in the Chinese Telecom Sector using the TOE and DOI framework. According to Chen (2019), technological context-related attributes such as CP, CL, and RA were used as AI innovation attributes. The researchers used managerial capability, MS, and technical capability from the organizational context. Other environmental context-related variables used in the research were government support, market volatility, competitive environment, and vendor support. Factors in the descending order of their importance regarding AI adoption in the

Chinese Telecom Industry were a RA, CP, MS, government involvement, and vendor support (Chen, 2019).

Ryfors et al. (2019) researched manufacturing SME's AI adoption in Sweeden using the DOI and TOE theory. This qualitative study involved semi-structured interviews of management personals from 10 different SMEs. The revised TOE framework developed by Racherla and Hu in 2008 was used for their research study. The majority of SMEs who participated in the study faced less NP and MP (Ryfors et al., 2019). The deficit in technical know-how and lack of sufficient funds prohibited the Swedish SMEs from greater AI adoption (Ryfors et al., 2019).

AlSheibani et al. (2018) provided guidelines for better AI adoption in Australia's SME sector as part of a quantitative study of 208 companies. The five factors that were of interest due to IT innovation adoption were MS, size of the firm, competition scenario, RA, and RC (AlSheibani et al., 2018). From the organizational context, MS was the most influential factor for AI adoption in Australian SMEs (AlSheibani et al., 2018). The SME sector needed to significantly improve its organizational level AI-related knowledge base to overcome the entry barrier (AlSheibani et al., 2018).

Kang and Westskytte examined AI-based cybersecurity technology adoption in the Financial Sector in 2008. The researchers conducted a qualitative study that involved in-depth analysis and semi-structured interviews of eleven shortlisted companies' executives. The researcher used the DOI and TOE framework during this study to study RA, CP, CL, observability, triability, MS, security readiness, perceived threat, government policies, and social networks. Kang and Westskytte (2018) mentioned that RA impacted positively and CL acted negatively in AI-based cybersecurity innovation adoption. The organization-level and industry-wide skill shortage for experts knowing both AI and cybersecurity was a significant challenge for the financial sector (Kang & Westskytte, 2018).

Summary and Transition

During this literature review, I focused on AI adoption in various industrial sectors, where different innovation adoption models were used to understand enablers and disablers of new technology adoption. There were many research papers providing details about the technical solution and social implications of new technology solutions including AI. Some research papers were useful to understand AI adoption in different industrial sectors. Three major industries that used AI were the high-tech industry, manufacturing companies, and the healthcare industry. SME sector was an industry sector that provided services and was an integral part of these industry segments. Currently, the SME sector was more dependent on human intelligence for providing personalized services and data-driven instant decision making. There was a fragmented adoption of AI in many industrial sectors, including the SME sector. The primary usage of AI was in customer interaction (ChatBOTs) for solving customer queries and process orders involving small decision trees, data analytics for making informed decisions, and using robots for the marketing of services.

In this chapter, I identified the literature gap and provided the outline and direction for the research. The learnings from the past related research have provided the background for avoiding the pitfalls. In the next chapter, I provided details about the research methodology and a detailed data collection plan. I also provides details about the proposed ethical practices and procedures to mitigate the risk to the validity that I discussed in the subsequent section.

Chapter 3: Research Method

This quantitative cross-sectional correlational study involved examining the DOI, TOE, and TAM theoretical models and the extent to which they influence AI adoption, implementation, and use in the SME sector in India. I proposed a survey where expected participants were employees from the SME sector who participated in AI-related projects or initiatives within their organization or otherwise as developers, implementers, or end-users. I proposed using Survey Monkey to design and host the survey.

This chapter includes an explanation of the research methodology and selection process for the research design. It includes a detailed discussion of the survey instruments used and their validity. Further, I discussed the survey questionnaire variables and procedural aspects of the survey in detail. Chapter 3 includes information about proposed precautions and safety measures necessary for the ethical conduct, as these are vital factors for any research involving voluntary participation.

Research Design and Rationale

There are three principal research methodologies available: qualitative, quantitative, and mixed methods. When a qualitative research methodology is used, a single phenomenon is studied and described in detail (Ravitch & Carl, 2019). On the other hand, when quantitative research is used to analyze the numerical data, perform statistical analysis, and draw conclusions based on statistical validity (Ravitch & Carl, 2019). When the research purpose involves a dual purpose, where a combination of quantitative and qualitative research methods becomes essential, a mixed method of research is used (Babbie, 2017). For this study, I proposed a quantitative research methodology because I wanted to study the statistical correlation between 10 factors those can impact the decision of AI adoption, implementation, and use in the SME sector in India.

I wanted to study the AI adoption in SME sector of India, so the cross sectional survey design was suitable. I was able to qualify if the participants were associated with the SME sector through an appropriate question in the survey. Among industries of various size and scale, I wanted to focus on SME sector in India. The cross-sectional survey design is most suitable for quantitative research as to study real-life settings with a focus on a particular set of participants who fulfill the selection criteria (Shikuku at al., 2018). The cross-sectional survey design helps in terms of describing and analyzing a large sample of data and ensuring that results remained statistically significant (Shikuku et al., 2018) Kelemba (2019) stated that a survey can help to gather the participant's views and opinions by asking the right questions, and later the collected information can be used to perform statistical analysis.

The cross-sectional survey design helped to identify common characteristics, attributes, and patterns visible from the vast sample data or even focus on a small population within a large number of participants (Kelemba, 2019). The data collected with the least possible effort and ensuring the data collection's quality was easy to supervise and control in the questionnaire-based survey as part of the quantitative studies (Shikuku et al., 2018). Online surveys have proved to be cost-effective method to reach out to a large number of participants with minimum effort and cost. If designed appropriately, online surveys help collect data related to multiple variables using a single data collection instrument (Fuldeore & Soliman, 2017).

The cross-sectional survey design had some advantages and limitations. One of the significant limitations was that, as cross-sectional studies are point in time studies, they have limited usability in terms of continuous evaluation of phenomena over an extended period (Cartledge et al., 2020). Cross-sectional studies often fail to provide concluding results because of lack of responses from survey participants or researchers misclassifying data (Cartledge et al., 2020).

To ensure the quality of the research and effective use of the survey questionnaire, I used previously validated and tested survey instruments ('Organizational Adoption of Virtual Worlds Survey', 'Cloud Adoption by IT Manager', and 'User Acceptance of Information Technology'). I made few small alterations to the questionnaire as Dr. Yoon used it for data collection about virtual reality-related software usage, and in this study, I proposed to use the same questionnaire for AI-related data collection. I was careful while modifying the questionnaire to ensure the significance of DOI, TOE, and TAM-related constructs. A pilot study was not required as there were no significant modifications to original survey instruments ('Organizational Adoption of Virtual Worlds Survey', 'Cloud Adoption by IT Manager', and 'User Acceptance of Information Technology').

Methodology

To understand AI adoption, implementation, and use in India’s SME sector, I proposed a cross-sectional survey. This provided an opportunity to conduct a point in time study instead of conducting a longitudinal study which involves analyzing the research problem for a longer duration. According to Fuldeore and Soliman (2017) longitudinal studies often take an enormous amount of time and are expensive research approaches compared to point in time studies.

I conducted the study to understand the relationship between DOA, implementation, and use, and 10 independent variables related to various aspects of new technology adoption. I selected the cross-sectional design as it is more suitable method than empirical or experimental studies when selected participants are directly related to or impacted by the subject of the study. The cross-sectional design helped me to reach many participants with minimum effort and meet the minimum number of samples essential for statistical analysis

Population

The target population was technologists involved in adoption, implementation, or use of AI technology who were associated with AI-related projects or initiatives within their organization or in a personal capacity. According to the MSME (2020), there was a total of 1,002,757 registered companies, of which 71.9% (721096) were micro enterprises, 4.3% (43532) were small enterprises, 0.9% (9357) were medium enterprises, and 22.8% (228772) were unclassified companies as of October 30, 2020. Micro enterprises are household or cottage industries with lack funds for investment in niche technologies such as AI due to lack of need and financial strength. For this study, I considered only SMEs. During this research, I did not ask any organization about specific data regarding participants but rather views about technology use in their respective industry sectors.

According to the MSME (2020), there are 10,103,152 employees working in MSMEs in India. However, there was no information available how many employees work in 52889 SMEs. There was no authentic information regarding how many employees within India’s SME sector worked on AI-related initiatives or how many were directly or indirectly involved in AI technology adoption-related decision-making. A question regarding this was added to the survey to understand whether participants had some experience using AI technology and whether they were involved in activities using AI technology.

The primary focus in the study was to understand enablers and limiting factors impacting AI adoption, implementation, and use in India's SME sector. The survey participants were directly or indirectly involved in making decisions and, sometimes, implementing AI technology. I solicited the number of participants by engaging with the participants using social media and the online survey that was rolled out on the Survey Monkey platform.

Sampling and Sampling Procedures

To conduct a study in the required time, meet the quality requirements, and possible within the possible efforts, selecting the correct sample size is very important. According to Sim et al. (2018), there are four approaches for determining the sample size: use of the rule of thumb, use of the conceptual framework, guidelines from comparable past empirical studies, and statistical formulae. The primary criticism about quantitative research is that the trustworthiness of that research reduces significantly if a proper justification or rationale about the sample size decisions are not explained appropriately (Boddy, 2016).

G*Power software is one of the most popular software for calculating the sample size through power analysis in a quantitative study and it also provides graphical display to show an impact of change in the sample size on the statistical validity (Kundra et al., 2016; Dianat, 2016). Cook (2019) used the G*Power software and power analysis to determine the sample size for determining the difference in the managerial perceptions of veterans and non-veterans.

The sampling frame selected for this study used SME sector employees in India who were directly or indirectly involved in the decision-making of AI-related projects or initiatives in their organizations or in personal capacity. According to the MSME (2020) there were 52889 registered SMEs firms in India. There was no authenticate data available about how many employees do work in the small and medium enterprises at the time when the survey was rolled out.

I added a question in the survey questionnaire to understand if the participant had some experience in AI technology as an implementer, decision-maker, or end-user within their organization or if a participant is or has worked on AI technology-related initiatives or projects. To reach all the employees working on AI technology was impossible as this data was not available to me. A sampling technique helped to reach the right representatives within this participant pool and to draw statistically valid conclusions.

As explained by Etikan et al. (2016), convenience sampling was a type of non-probability sampling where the participants were selected just because they were a convenient source of information for the researcher. The convenience sampling method helped to meet the minimum sample requirements and allowed the completion of the research without many complications involved in the randomized sampling (Brewis, 2014). I used the convenience sampling method during the study for the initial reach to the participants using social media.

I published a message in my network on LinkedIn and in LinkedIn groups where I was a member. According to Naderifar et al. (2017), snowball sampling was a convenience sampling method applied when existing participants can help recruit further recruits who were among their quittance and share specialized knowledge or similar entry criteria. I published a post on the LinkedIn platform to request participation to the survey and requested participants to share the message in their social network. Thus, I used chain-referral snowball sampling method as one participant forwarded the participation request to multiple participants.

According to Cribbie et al. (2019), Priori analysis is an effective method to determine the required number of participants in a survey at a given power, and Type-I errors allowed. I used Priori analysis for calculating the required sample size as a type of analysis in the study. I used 10 independent variables for the study: ITS, RA, CP, MS, CL, MP, NP, RC, PU, and PEU. As I was interested in finding the statistically significant correlation between an independent variable and a dependent variable so the correlation bivariate normal model of statistical testing was used during Priori analysis. Input parameters used for Priori analysis using G*Power software are described in Figure 3.

Figure 3

*Parameters Selected for Priori Analysis Conducted Using G*Power*

Exact – Correlation: Bivariate normal model			
Options:	exact distribution		
Analysis:	A priori: Compute required sample size		
Input:	Tail(s)	=	Two
	Correlation ρ H1	=	0.3
	α err prob	=	0.05
	Power (1–β err prob)	=	0.80
	Correlation ρ H0	=	0
Output:	Lower critical r	=	–0.2145669
	Upper critical r	=	0.2145669
	Total sample size	=	84
	Actual power	=	0.8003390

Parameters mentioned in figure 3 were used for conducting Priori analysis for sample size calculation for a Pearson's r correlation as the researcher was interested in understanding correlation between one independent variable and one dependent variable. The evidence based effect size helped to determine the statistical significance of the correlation. As I believed that there might be a moderate treatment effect on the data collected through an online survey, the correlation p H1 was selected as 0.30, and α probability of error as 0.05, Power (1-beta err prob) as 0.80, and correlation P HO as zero were selected.

Priori analysis recommended sample size of 84 for this study as stated in the appendix G. Though the minimum sample size was 84, the data from a minimum of 150+ participants was collected to help achieve statistically valid results. To cover at least 150+ participants, I contacted prospective participants using social media during the survey's rollout. I hosted the survey on the Survey Monkey.

Procedures for Recruitment, Participation, and Data Collection

Preparatory Steps for Creating the Survey on Survey Monkey

I created an online survey on Survey Monkey website. I used questions from the pre-validated survey instrument 'Organizational Adoption of Virtual Worlds Survey', 'Cloud Adoption by IT Manager', and 'User Acceptance of Information Technology'. I conducted the initial functionality testing using the survey web-link. Four members of my family completed the functional testing of the online survey. Once the testing was complete, I requested the Survey Monkey Professional Services team to download the data and then conducted the preliminary testing in SPSS. Once I finished the SPSS data input and successfully tested it, I determined that the “Online Survey” was ready for use. Before the rolling out of the survey to participants, I deleted the testing data.

Rollout of Online Survey

I published a post (appendix E) on social media to request participation in the survey. I shared the request in my LinkedIn professional network. The message on the social media also included a request to participants to forward the request in their professional networks to solicit more participants with similar interest. I sent the message to LinkedIn contacts in my personal and professional network.

I provided the participants with brief details about the research concept and an online survey questionnaire. If the participant wanted to know more about the research study, they were encouraged to contact me on the email address published in the social media post and the survey questionnaire on the Survey Monkey website. I proposed to answer any questions or concerns raised by any participant while participating in the survey. I ensured that the Survey Monkey Team deleted the preliminary testing data before opening the survey to participants.

Data Collection

I monitored the Survey Monkey website's progress to ensure the number of participants (150) complete the survey. I extracted the survey data from the Survey Monkey website daily to know the number of responses and checked if the responses were valid. I also checked if each participant had answered all the questions in the survey. I kept the survey open until the 150 plus valid responses were gathered before closing the survey. Though the required sample size was 84 only, the data from a minimum of 150 participants was collected to avoid any challenges or rejection of data due to invalid responses or incomplete surveys. Then, I published a social media post (appendix F) to announce the survey's closure and to thank participants for their support and help. I downloaded the data in a spreadsheet, then copied it to SPSS software and proceeded with the data analysis.

Instrumentation and Operationalization of Constructs

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 provides the participants' flexibility to attempt the survey at a convenient time and place (Hatchison et al., 2014). According to Schoenherr et al. (2015), email is 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, the researcher used social media and I was not required to use email as a method to send the survey questionnaire to the individual participants.

Use of Validated Instrument

The survey instrument used for this study was created using three different survey instruments ('Organizational Adoption of Virtual Worlds Survey', 'Cloud Adoption by IT Manager', and 'User Acceptance of Information Technology'). The first survey instrument ('Organizational Adoption of Virtual Worlds Survey') was adopted for Dr. Tom Yoon. It was developed in 2009 for studying factors affecting the adoption of Virtual World software by various organizations. The original survey instrument contained 10 constructs associated with DOI and TOE theory. Four constructs from this survey instrument were used by AlKhater et al. in 2014 for Cloud adoption related research.

According to Yoon (2009), the theoretical constructs included in the survey instrument were tested by conducting the confirmatory factor analysis. As all of the constructs aligned to independent variables are multi-item constructs it was important to know the result of validity. Yoon (2009) provided the confirmatory factor analysis result table that included convergent validity and t-statistics for all the constructs along with the accepted value of 0.6 and significance level of 0.01. It was found that all the constructs selected in this study showed the adequate internal consistency (Yoon, 2009).

For the study, small alterations without touching the core constructs were made to the survey instrument to make it more suitable for gathering the data related to AI adoption, implementation, and use instead of the Virtual World software package. The permission received from Dr. Yoon for the use of survey instruments and small modifications is available in Appendix B. Care has been taken to maintain the relevance to DOI, TOE, and TAM theoretical constructs. Yoon (2009) validated the survey instrument during the research and included the research paper's validation testing results. The researcher used IBM SPSS software to conduct detailed statistical testing and analysis to validate the questionnaire's internal reliability. Bandalos and Finney (2018) mentioned that the researcher must conduct the factor analysis and alpha item analysis to validate the survey instrument's scale.

The second survey instrument ('Cloud Adoption by IT Manager') that was referred and used for this study was created by Dr. Opala in 2012. I used demographic data collection related six questions from this survey. These questions helped me to collect information about participant’s title, industry sector, gender, age group, education level, and experience in using AI technology. I modified some of the questions to remove the facility of accepting free flow text from survey participants. This helped me in avoiding collection of any unsolicited personal data from the participants.

The third survey instrument ('User Acceptance of Information Technology') was developed by Venkatesh et al. in 2003. I used two questions from this survey that helped me to collect information about two constructs (PU and PEU) from TAM theory. These questions were vital to understand how AI technology is used by end users and implementers in the SME sector in India.

Operationalization of the Research Constructs

In this study, there were 10 independent variables related to DOI, TOE, and TAM theory. There was one dependent variable decision of AI adoption, implementation, and use in India's SME sector. Table 2 contains measurement items for variables.

Table 2

Instrumentation and Operationalization of Constructs

Question No.	Question	Theoretical Model	Context if any	Variable assigned
7	In my industry sector, there are standardized processes for IT innovation.	DOI / TOE	Organizational context	ITS1
8	My industry sector has the ability to quickly integrate Artificial Intelligence in existing infrastructure.	DOI/TOE	Organizational Context	ITS2
9	IT strategies in my industry sector support business strategies.	DOI / TOE	Organizational Context	ITS3
10	Adopting Artificial Intelligence will allow better communication with customers.	DOI	NA	RA1
11	Adopting Artificial Intelligence will increase the profitability.	DOI	NA	RA2
12	Adopting Artificial Intelligence will reduce costs.	DOI	NA	RA3
13	Adopting Artificial Intelligence will allow to enter new businesses or markets.	DOI	NA	RA4
14	Adopting Artificial Intelligence will improve the web presence.	DOI	NA	RA5
15	Artificial Intelligence adoption is consistent with organizational beliefs and values in my industry sector.	DOI / TOE	Technological Context	CP1
16	The attitude towards Artificial Intelligence adoption in organizations in my industry	DOI / TOE	Technological Context	CP2

	sector is favorable.			
17	Artificial Intelligence adoption is generally compatible with Information technology (IT) infrastructure.	DOI / TOE	Technological Context	CP3
18	Artificial Intelligence adoption is consistent with the business strategy	DOI / TOE	Technological Context	CP4
19	In my industry sector, top management is interested in adopting Artificial Intelligence	DOI / TOE	Organizational Context	MS1
20	In my industry sector, top management considers Artificial Intelligence adoption important	DOI / TOE	Organizational Context	MS2
21	In my industry sector, top management shows the support in Artificial Intelligence adoption	DOI / TOE	Organizational Context	MS3
22	Many of the competitors are currently adopting or will be adopting Artificial Intelligence in near future	DOI / TOE	Environmental Context	MP1
23	Competitors that have adopted Artificial Intelligence are perceived favorably by others in our industry	DOI / TOE	Environmental Context	MP2
24	Many of the customers are currently adopting or will be adopting Artificial Intelligence in near future	DOI / TOE	Environmental Context	NP1
25	Many of the suppliers are currently adopting or will be adopting Artificial Intelligence in near future	DOI / TOE	Environmental Context	NP2
26	Customers can switch to another company for similar services/products without much difficulty	DOI / TOE	Environmental Context	NP3
27	Adopting Artificial Intelligence innovation involves high cost.	DOI / TOE	Technological Context	CL1
28	Adopting Artificial Intelligence innovation takes long time.	DOI / TOE	Technological Context	CL2

29	Artificial Intelligence technology does/will significantly improve IT compliance.	TOE	Environmental Context	RC1
30	Artificial Intelligence is inherently reliable and meets IT compliance requirement.	TOE	Environmental Context	RC2
31	Artificial Intelligence can increase revenue and profitability.	TAM	NA	PU1
32	Artificial Intelligence can increase employee productivity	TAM	NA	PU2
33	Artificial Intelligence can improve customer service	TAM	NA	PU3
34	Adopting Artificial Intelligence innovation lacks application maturity.	TAM	NA	PEU1
35	Inappropriate staffing and personnel shortfalls are big challenges for Artificial Intelligence adoption.	TAM	NA	PEU2
36	Artificial Intelligence can better utilize IT resources and applications	TAM	NA	PEU3
37	Most of the organizations in my industry intent to adopt Artificial Intelligence	DOI/ TOE/ TAM	NA	DOA1
38	It is likely that organization in my industry sector will take steps to adopt Artificial Intelligence in future.	DOI/ TOE/ TAM	NA	DOA2
39	In my opinion how soon organizations in my industry sector will adopt Artificial Intelligence?	DOI/ TOE/ TAM	NA	DOA3

Data Analysis Plan

I aimed to understand whether there was a significant corrrelation between various constructs related to DOI, TOE, and TAM theories and the decision of AI adoption, implementation, and use in the SME sector in India. Data collected through the cross-sectional survey was fed to IBM SPSS software version 25 to evaluate the relationship between the dependent and independent variables. Correlational bivariate normal distribution analysis is important to find whether the independent variable and a dependent variable had statistically significant correlation (Cronrath, 2020).

I downloaded the survey data from the Survey Monkey website and analyzed it using the IBM SPSS software version 25. This data analysis was aimed to understand the potential relationship between the independent variables and the dependent variable. Before conducting the data analysis, I collected the descriptive statistics from the survey data such as gender, age, role or title of the participant, type of business, educational level, and years of experience using AI technology. I performed the descriptive analysis to such as range, min, max, frequency, mean, median, and mode to understand the central tendency of the data collected. I also conducted other statistical tests to find out the standard deviation and performed inferential analysis to find out whether the data distribution was normal or non-normal.

After the initial descriptive statistics was derived, I conducted further statistical testing to find out patterns and correlation in the collected data. Depending on the distribution of the data a combination of parametric and non-parametric statistical tests were selected. I was interested in finding an association between the dependent variable and independent variable. To understand the strength of the relationship between the independent variable and dependent variable, a Pearson Correlation was calculated.

According to Mu et al. (2018), correlational studies are aimed at finding the differences in the collected data samples exposed to an event in a naturalistic setting where the researcher collects the data without any interference. As mentioned by Arora and Garg (2018), correlational studies do not involve comparative analysis as the researcher do not expose the participants to different controlled groups or interfere during the data collection period. In this study, I used the pre-defined or pre-assigned variables and performed statistical tests for understanding the relations between the dependent variable and independent variable. According to Mu et al. (2018), choice of the research design, selection bias, reporting inconsistencies are some of the challenges those can impact the internal and external validity in the correlational study.

This was a point-in-time study where I collected the data from the participants during a short period of time (4 days). I conducted statistical tests such as Pearson's r, and liner regression tests during the data analysis phase. Pearson's r was used to find out the standard correlation coefficient essential for conducting the correlational analysis.

According to Arora and Garg (2018), the Pearson r correlation involves a major assumption that the data is normally distributed. In order to assure that the data was normally distributed, all the incomplete survey responses were removed from the analysis as it could have skewed the data distribution. I considered and tested to check if other two assumptions such as linearity and homoscedasticity hold true during this study. According to Mu et al. (2018), the linearity is proved by a straight line relationship between two variables and homoscedasticity is proved by finding whether the data was equally distributed at both the sides of the regression line.

The residual error across ten independent variables was either less significant or equally distributed across the variables. Interrelation across two or more independent variables did not significantly alter the results. During the testing, I tested the relationship between ten independent variables (ITS, RA, CL, MS, MP, NP, CP, RC, PU, and PEU) with the dependent variable DOA by performing various tests.

RQ: What are the various factors that enable and limit DOA, implementation, and use in the SME sector in India?

The following secondary research questions were used related to technology help in terms of understanding the DOI and TOE contexts of AI adoption in the SME sector in India.

SQ1: Does ITS have any statistically significant correlation with DOA in the SME sector in India?

$H_0$1: ITS does not have a statistically significant correlation with DOA in the SME sector in India.

H_a1: ITS does have a statistically significant correlation with DOA in the SME sector in India.

SQ2: Does RA have any statistically significant correlation with DOA in the SME sector in India?

$H_0$2: RA does not have a statistically significant correlation with DOA in the SME sector in India.

H_a2: RA does have a statistically significant correlation with DOA in the SME sector in India.

SQ3: Does CP have any statistically significant correlation with DOA in the SME sector in India?

$H_0$3: CP does not have a statistically significant correlation with DOA in the SME sector in India.

H_a3: CP does have a statistically significant correlation with DOA in the SME sector in India.

The following secondary research questions related to organizational context were used to understand the DOI and TOE frameworks related to AI adoption in the SME sector in India.

SQ4: Does MS have any statistically significant correlation with DOA in the SME sector in India?

$H_0$4: MS does not have any statistically significant correlation with DOA in the SME sector in India.

H_a4: MS does have a statistically significant correlation with DOA in the SME sector in India.

SQ5: Does CP have any statistically significant correlation with DOA in the SME sector in India?

$H_0$5: CP does not have any statistically significant correlation with DOA in the SME sector in India.

H_a5: CP does have a statistically significant correlation with DOA in the SME sector in India.

The following secondary research questions related to environmental context were used to understand the TOE framework related to AI adoption in the SME sector in India.

SQ6: Does MP have any statistically significant correlation with DOA in the SME sector in India?

$H_0$6: MP does not have any statistically significant correlation with DOA in the SME sector in India.

H_a6: MP does have a statistically significant correlation with DOA in the SME sector in India.

SQ7: Does NP have any statistically significant correlation with DOA in the SME sector in India?

$H_0$7: NP does not have any statistically significant correlation with DOA in the SME sector in India.

H_a7: NP does have a statistically significant correlation with DOA in the SME sector in India.

SQ8: Does RC have any statistically significant correlation with DOA in the SME sector in India?

$H_0$8: RC does not have any statistically significant correlation with DOA in the SME sector in India.

H_a8: RC does have a statistically significant correlation with DOA in the SME sector in India.

The following secondary research questions were related to the TAM theory and understanding AI adoption in the SME sector in India.

SQ9: Does PU have any statistically significant correlation with DOA in the SME sector in India?

$H_0$9: PU does not have any statistically significant correlation with DOA in the SME sector in India.

H_a9: PU does have a statistically significant correlation with DOA in the SME sector in India.

SQ10: Does PEU have any statistically significant correlation with DOA in the SME sector in India?

$H_0$10: PEU does not have any statistically significant correlation with DOA in the SME sector in India.

H_a10: PEU does have a statistically significant correlation with DOA in the SME sector in India.

I discussed, summarized, and interpreted the correlational bivariate normal distribution analysis results of the continuous data measured using the Likert-scale. I provided a detailed explanation of the research findings in the results section using the descriptive statistical analysis, including the graphical representation of the demographic data presented as part of the results.

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). Precisely, the discussions about the threats to validity becomes the most crucial factor in quantitative research while using statistical methods to find answers to questions or validate the researcher's claim (Cruzes & Othmane, 2017). It is essential to discuss threats to the validity to sufficient depth, as it became difficult to prove the applicability of research in one setting to another, or the results' generalization becomes impossible otherwise (Steckler & McLeroy, 2008; Cruzes & Othmane, 2017).

There are four types of research validities that the researcher must be cognizant about: measurement (construct), conclusion, internal, and external validity threat (Steckler & McLeroy, 2008). External validity is about knowing whether constructs apply to each participant, called population validity and whether constructs are valid and applicable even during the experimental settings (Devroe & Wauters, 2019). The Internal validity helps to understand if an evidence provided by the researcher is sufficient to prove the claim or not.

External Validity

According to Cruzes and Othmane (2017), external validity proves the generalization of the results, and external validity threats limit this generalization. By conducting the pilot test, Yoon validated the survey instrument ('Organizational Adoption of Virtual Worlds Survey') and addressed external validity threats. I rolled out the survey to all participants simultaneously, and no participant was subjected to repetitive surveys and thus I addressed the threat to external validity.

The participant selection criteria was that the participant must be directly or indirectly involved in AI-related project or initiative-related decision-making and working in the SME sector. I shared the criteria with the participants though a social media post and in the consent form during the survey. To address the threat of the setting's representation, I rolled out the survey to participants simultaneously. To minimize the impact of time and location threat, I rolled-out the survey simultaneously to all the participants and allocated the similar timeframe to respond.

Internal Validity

When the researcher addresses the threat to internal validity, the environmental conditions or settings do 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 to internal validity such as history, mutation, imitation of treatment, and motivation (Cruzes & Othmane, 2017).

As part of this research, a point in time study was conducted instead of an elongated study. That is why the history related internal validity threat did not apply to this study. Threats related to mutation were applicable if studies conducted at different times to deliver quite similar results. The researcher conducted 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 completed the survey in a single sitting. Each participant took the survey only once. Also, a participant did not require to answer similar questions multiple times in the survey; thus, it adequately addressed the testing threats.

The study was used to understand factors impacting the decision of AI adoption, implementation, and use in SME sector of India. The participant population in the study were, the employees directly or indirectly involved in the decision making about the AI project or initiative; thus, it was a homogeneous population. There was no significant difference across survey participants working for different SME in India.

The participant selection threat criteria addressed subject selection related threats to internal validity. The researcher rolled out the survey to all of the participants at 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 designed 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 of the participants did complete the survey in a single sitting. These factors mitigated the challenge of a lack of motivation as a threat to internal validity.

Construct Validity

According to Cruzes and Othmane (2017), construct validity was all about the researcher believing that the dependent and independent variables accurately represented the theoretical concept used as the backbone of the research. Along with the statistical testing, the literature review about similar research proved that the selection of variables was proved in different settings and was well tested at different times by different researchers in the past.

I used a validated and proven survey instruments ('Organizational Adoption of Virtual Worlds Survey', 'Cloud Adoption by IT Manager', and 'User Acceptance of

Information Technology') for this study. I 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. As a pilot study was not involved, all the participants took the survey during the 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 participant received the brief information about the research, they did not know the actual hypothesis tested 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. I addressed the participants' evaluation apprehension by selecting a considerably large sample size than the minimum sample size required for the research. The minimum sample size required is 84; however, I collected the response from 152 survey participants. All of the participants were able to complete the survey in a single sitting, and thus there were fewer chances that experimenter expectations threat to construct validity impacting the participant's response.

Ethical Procedures

Ethical conduct in social research is of paramount importance. Ethical standards help to form a sturdy base so that future researchers could depend on a reliable research (Eyarfe & Sansui, 2019). Many countries defined guidelines and regulations about the ethical standards for social studies. As human subjects were involved in the quantitative study, I strictly followed all required ethical standards and practices applicable. No questions were helping in the collection of the personalized and confidential data of the participants. The Survey Monkey Professional Services did not share any personalized data about the participant with the researcher. The data provided by the Survey Monkey Professional Services was only related to the survey response. I stored the data in a password protected spreadsheet and folder on a personal laptop until the dissertation process was complete. After the dissertation process was complete, the data was stored in a password-protected folder and file on Google Drive for five years as per the IRB guidelines.

While conducting the research, primarily during I the data collection, rolling out the survey to all the participants I followed all the required ethical practices. All the necessary information such as the purpose of the research and its outline were readily provided to all the participants before they participate in the data collection. The participants became aware of the research scope by reading the first section of the survey questionnaire and then provided their consent before attempting the survey. I contacted all the participants only after the formalities and approval from the Institutional Review Board (IRB) were received. I published the entry and exit criteria in a social media post (appendix E) to solicit participation in the survey. The participant were aware of AI selection, implementation, or use in their industry or personal capacity. The survey questionnaire contained a disclaimer that the participants were free to exit the survey at any time. I did not use the data from the incomplete surveys during the data analysis phase.

Summary and Transition

This chapter started with a detailed analysis of the selection criteria used for selecting the research methodology. Then the sampling techniques and selection of population were discussed. After that, it contained a run-through of the data collection process. It contained an explanation about the need for conducting a pilot study and its relevance to the study. Furthermore, some discussion about how the instrumentation and operationalization of the constructs happens was provided. Later on, details about data analysis, along with the threat to validity, were presented. At last, the epilog of ethical procedures that the researcher were followed during the research.

This study contained a cross-sectional survey to understand which factors influence the AI adoption, implementation, and use in India's SME sector. Three different theories namely DOI, TOE, and TAM formed the theoretical foundation. The DOI theory helped in finding the individual level acceptance of the new technology like AI. Whereas, TOE model was a logical extension of the DOI theory from an individual perspective to organizational factors. While DOI and TOE frameworks helped to understand the decision method for technology adoption and some aspects of implementation, TAM theory provided the usability factor from the individual user perspective.

Forming a research framework based on a robust theoretical model is not enough for any successful research. It must be followed by a sound data collection policy when a quantitative study method. The targeted population for this study were employees working in the SME sector who had some exposure to AI technology and were involved directly or indirectly in decision-making about the technology adoption and implementation in their respective organizations or otherwise. The sample size was determined based on the number of independent variables involved and the threshold for good statistical results.

Qualitative studies were prone to four types of validity threats related to the conclusion, construct, external and internal validity. Applicability of these different threats and plans to mitigate those threats were part of the discussion. Adhering to ethical standards was very much essential to achieve reliable and trustworthy results. Following the ethical standards reduced the threat to participants in the data collection and increased the research quality. The next chapter in this dissertation contains a detailed discussion of the data collection output, statistical tests conducted on the collected data, and conclusions.

Chapter 4: Results

The purpose of this quantitative cross-sectional correlational study was to study the existence and extent of the relationship between ITS, RA, CP, CL, MS, MP, NP, RC, PU, and PEU and decision to adopt, implement, and use AI technology in the SME sector in India. AI technology has been a useful and favorable technology among SME sectors. The main research question and 10 sub questions guided this study. The focus of the leading research question was to understand whether there is any statistically significant relationship between the independent variables and the dependent variable DOA. Each of the 10 secondary research questions were used to assess correlations between one independent variable and the dependent variable:

SQ1: Does ITS have any statistically significant correlation with DOA in the SME sector in India?

H_01: ITS does not have a statistically significant correlation with DOA in the SME sector in India.

H_a1: ITS does have a statistically significant correlation with DOA in the SME sector in India.

SQ2: Does RA have any statistically significant correlation with DOA in the SME sector in India?

H_02: RA does not have a statistically significant correlation with DOA in the SME sector in India.

H_a2: RA does have a statistically significant correlation with DOA in the SME sector in India.

SQ3: Does CP have any statistically significant correlation with DOA in the SME sector in India?

H_03: CP does not have a statistically significant correlation with DOA in the SME sector in India.

H_a3: CP does have a statistically significant correlation with DOA in the SME sector in India.

SQ4: Does MS have any statistically significant correlation with DOA in the SME sector in India?

H_04: MS does not have any statistically significant correlation with DOA in the SME sector in India.

H_a4: MS does have a statistically significant correlation with DOA in the SME sector in India.

SQ5: Does CP have any statistically significant correlation with DOA in the SME sector in India?

H_05: CP does not have any statistically significant correlation with DOA in the SME sector in India.

H_a5: CP does have a statistically significant correlation with DOA in the SME sector in India.

SQ6: Does MP have any statistically significant correlation with DOA in the SME sector in India?

$H_0$6: MP does not have any statistically significant correlation with DOA in the SME sector in India.

H_a6: MP does have a statistically significant correlation with DOA in the SME sector in India.

SQ7: Does NP have any statistically significant correlation with DOA in the SME sector in India?

$H_0$7: NP does not have any statistically significant correlation with DOA in the SME sector in India.

H_a7: NP does have a statistically significant correlation with DOA in the SME sector in India.

SQ8: Does RC have any statistically significant correlation with DOA in the SME sector in India?

$H_0$8: RC does not have any statistically significant correlation with DOA in the SME sector in India.

H_a8: RC does have a statistically significant correlation with DOA in the SME sector in India.

SQ9: Does PU have any statistically significant correlation with DOA in the SME sector in India?

$H_0$9: PU does not have any statistically significant correlation with DOA in the SME sector in India.

H_a9: PU does have a statistically significant correlation with DOA in the SME sector in India.

SQ10: Does PEU have any statistically significant correlation with DOA in the SME sector in India?

$H_0$10: PEU does not have any statistically significant correlation with DOA in the SME sector in India.

H_a10: PEU does have a statistically significant correlation with DOA in the SME sector in India.

I developed alternative and null hypotheses to answer each of the secondary research questions. According to Nachmias and Leon-Guerrero (2018), a hypothesis is often used to state a temporary answer to the research question and that answer is validated through statistical testing. I verified a total 20 hypotheses (10 alternative hypotheses and 10 null hypotheses) to confirm the relationship between each of the 10 independent variables and dependent variable.

This chapter is divided into two sections. I explained the data collection process used during this research. The data collection process includes participant recruitment process, rate of response, and information about any deviations from procedures explained in Chapter 3. I also included details about the data preparation process, participants' demographic statistical information, and other baseline details about the research sample. Chapter 4 includes findings of this study involving various tables and figures. I provided descriptive statistics and correlational bivariate normal distribution analysis. This analysis included the results of the t-test, Pearson's r, and regression tests. The concluding section contains a summary and transition to Chapter 5 explaining conclusions derived from research analysis, limitations, implications, and recommendations of this study.

Data Collection

I used an online survey method to collect the required data about AI adoption, implementation, and use in India's SME sector. The data collected through the online survey to find the correlation between 10 independent variables and the dependent variable. I used questions from three pre-validated and tested survey instruments ('Organizational Adoption of Virtual Worlds Survey', 'Cloud Adoption by IT Manager', and 'User Acceptance of Information Technology') developed by Yoon, Opala, and Venkatesh et al.. There were no significant alterations to the original survey instruments, so it did not require the pilot study. The data collection process started after the IRB approval (01-26-021-0580508). I set up the online survey on the Survey Monkey platform based on the survey instrument included in appendix A.

On February 27, 2021, I put the request on LinkedIn for participation in the survey. There were 938 views of the LinkedIn post that helped I seek the survey's required response. The online survey included the IRB-approved consent form on the first page. The participants were required to proceed with the survey only when they agree to the consent. The participants were free to exit the study at any moment during their participation. I set up the task in a way that all participants could take the survey anonymously. The anonymous response option helped exclude the participant's personal information, such as IP address, first name, last name, and e-mail address of the survey results.

I removed the facility of using the free flow text box from the survey. This facility was available for question 1 when the participant selects none of the above options, question 2 when the participant chooses the industry sector as other, and question 5 when the participant selects the educational level as other. The free flow text box would have allowed the participant to enter any unsolicited information or personal details while answering those questions. I removed the free flow text box facility to avoid any violations in the data collection processes.

Recruitment Timeframe

I created a web-link-based collector and mentioned it on the social media post. The required sample size was 84, but as described in chapter 3, I kept the survey open until minimum 150 complete responses. The data collection window was from January 27, 2021, to January 30, 2021. During this period, the social media post requesting participation helped gather the survey's required response. I monitored the survey on the Survey Monkey platform to track the response rates.

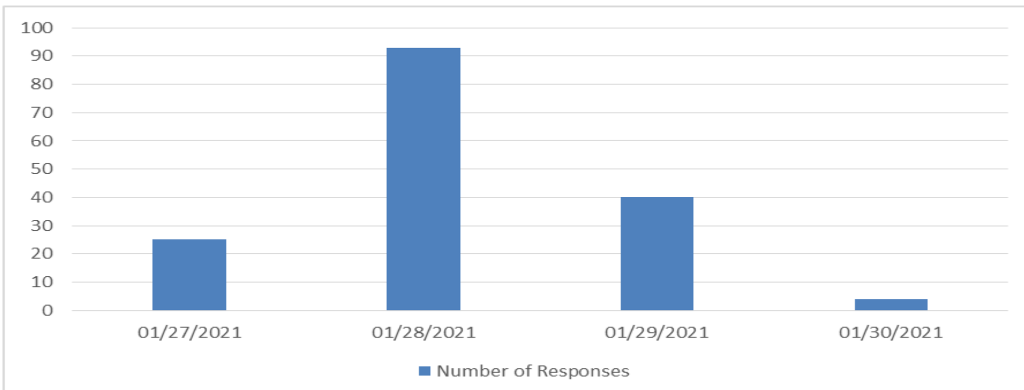
Survey Recruitment Rates

I opened the survey to participants on January 27, 2021, and I received 25 responses. One response was incomplete as the participant skipped question no. 27. The disqualification rate was 4% on the first day of the data collection. At the end of the second day, January 28, 2021, the total number of responses was 118. I found two more incomplete answers as two participants skipped a few of the questions related to demographic information. The disqualification rate was 2.54% on the second day of the data collection. At the end of the third day, January 29, 2021, the total responses were

158. However, there were six invalid responses out of 158 as two more participants skipped a few of the demographic information-related questions, and one participant skipped question no. 14. The disqualification rate was 3.79% at the end of the third day of the data collection.

Figure 4

Survey Response by Day

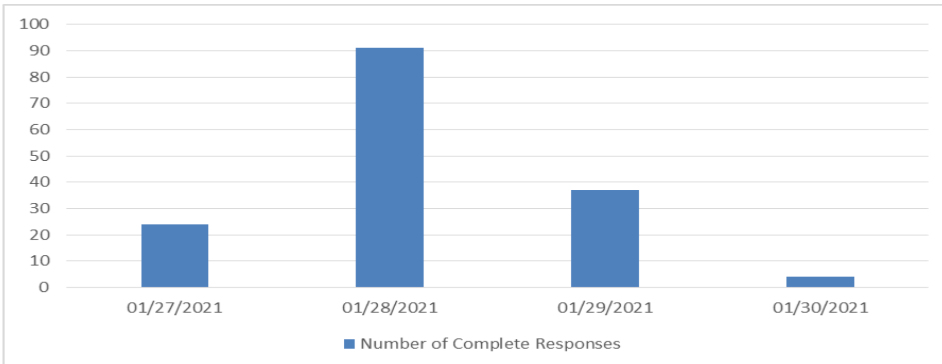


On day four, January 30, 2021, I closed the collector and disabled the Survey Monkey Platform survey; there were four more valid responses. The disqualification rate was 3.70% when the collector is locked. I explained the survey recruitment rate in figure 4. The final count of valid responses was 156. The overall survey recruitment rate was 96.29%, on the first day it was 96%, on the second day it was 97.45%, on the third day it was 96.20%.

I downloaded the data in a spreadsheet format to a password-protected personal computer and revalidated the data to ensure the count of valid responses was indeed 156. I meticulously followed the data collection procedure explained in chapter 3. There was no deviation from the mentioned procedure.

Figure 5

Complete Survey Response Per Day



Data Preparation

I downloaded the data from the Survey Monkey platform in a password protected spreadsheet and stored it in a personal laptop. While screening for the missing values in 162 responses I found 6 responses those were missing answers to at least one of the 40 questions. One of the participant did not answer the question number 13 making it impossible to calculate score of relative advantage. Two participants did not answer the question about the education level making it difficult to decide whether the response was suitable for the research as answers to questions related to AI were having a recognizable pattern. One participant answered only one question out of 40. Rest two participants did not answer more than two AI implementation related questions. Due to the missing data points, these six records were not considered so total 156 complete responses were considered during the data analysis.

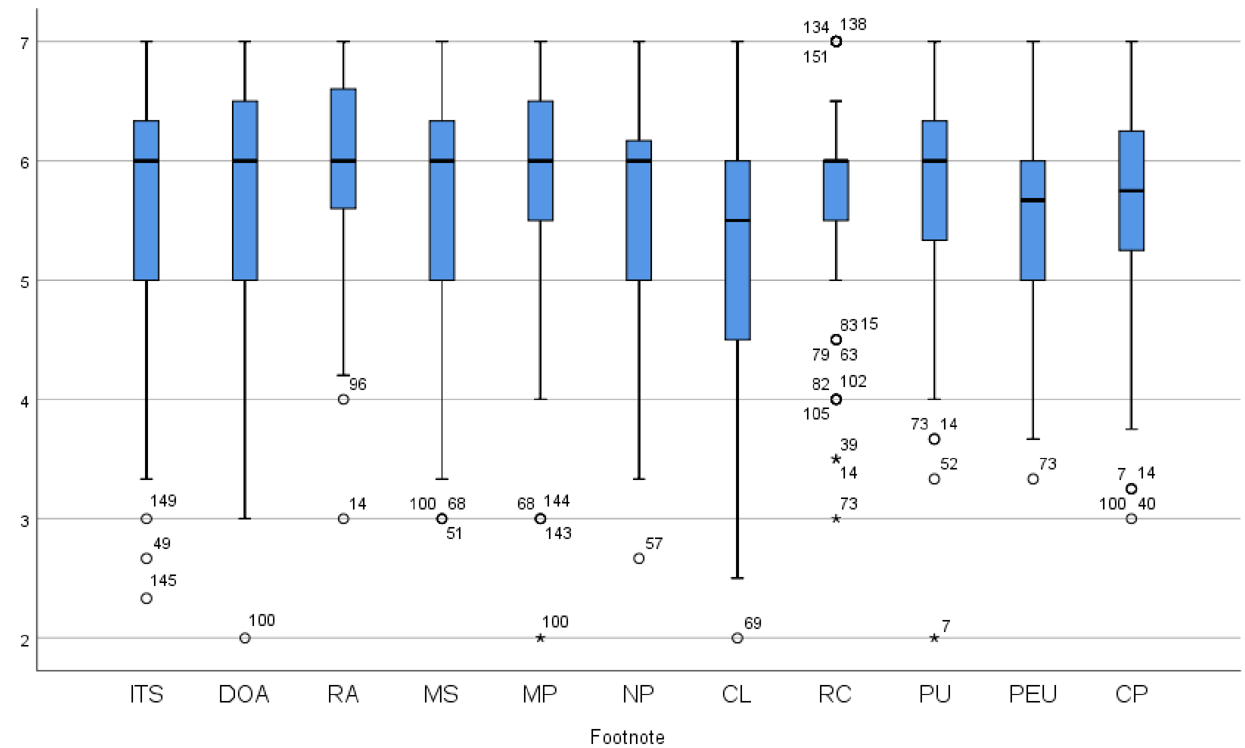
I renamed column headings for columns containing the demographic data to make it easier for the data analysis. The renamed column headings were title, industry sector, gender, age group, level of the school, and AI-related experience. Further, the columns related to the research constructs were renamed as mentioned in the Appendix H to help writing descriptions during the data analysis. Then I recorded the response values for all the associated variables for question number seven to 39 to the scale unit such as one (strongly agree), two (agree), three (somewhat agree), four (neither agree nor disagree), five (somewhat disagree), six (disagree), and seven (strongly disagree) in IBM SPSS V25 dataset.

I constructed 10 composite variables those were aligned to ten independent variables and stored those in the columns named as ITS, RA, CL, MS, MP, NP, CP, RC, PU, and PEU. Also, I constructed a composite variable for dependent variable DOA. The ITS composite variable was constructed by calculating the average of ITS1, ITS2, and ITS3 those were respectively answers to question number seven to nine. The RA composite variable was constructed by calculating the average of RA1, RA2, RA3, RA4, and RA5 those were respectively answers to question number 10 to 14. The CP composite variable was constructed by calculating the average of CP1, CP2, CP3, and CP4 those were respectively answers to question number 15 to 18. The MS composite variable was constructed by calculating the average of MS1, MS2, and MS3 those were respectively answers to question number 19 to 21. The MP composite variable was constructed by calculating the average of MP1and MP2 those were respectively answers to question number 22 to 23. The NP composite variable was constructed by calculating the average of NP1, NP2, and NP3 those were respectively answers to question number 24 to 26. The CL composite variable was constructed by calculating the average of CL1 and CL2 those were respectively answers to question number 27 to 28. The RC composite variable was constructed by calculating the average of REG1 and REG2 those were respectively answers to question number 29 to 30. The PU composite variable was constructed by calculating the average of PU1, PU2, and PU3 those were respectively answers to question number 31 to 33. The PEU composite variable was constructed by calculating the average of PEU1, PEU2, and PEU3 those were respectively answers to question number 34 to 36. The DOA composite variable was constructed by calculating the average of DOA1 and DOA2 those were respectively answers to question number 37 to 38.

I created a box plot to find out the outliers in the collected data. As depicted in the below figure the 10 independent variables and one dependent variable was measured using the 7 scale Likert Scale. These responses were within the Likert Scale limit one (strongly agree), two (agree), three (somewhat agree), four (neither agree nor disagree), five (somewhat disagree), six (disagree), and seven (strongly disagree)

Figure 6

Box Plot for 10 Independent Variables and One Dependent Variable



The outliers were not visually observed in the histogram and particularly in the scatterplot. The box plot identified 24 unique records as outliers and four extreme outliers (case seven for PU, case 39 and 73 for RC, and case 100 for MP).It was decided that these four outlier cases (case seven, 39, 73 and 100) be removed from the data to be analyzed. Due to this the total number of complete survey responses for the data analysis were reduced from 156 to 152.

This activity helped me to simplify the description of items in different sections. The final research sample of 152 complete responses was securely saved in the personal laptop in a password-protected folder to conduct the statistical analysis using IBM SPSS

Version 25.I later safely kept the collected data on Google Drive for five years. I shall delete the data after five years as per the guidelines of Walden IRB.

Baseline Descriptive Statistics

I calculated the measure of central tendency using mean and standard deviation for the 10 independent variables (ITS, RA, CL, CP, MS, MP, NP, RC, PU, and PEU) and dependent variable (DOA). Table 3 depicts that the means of all the independent variables varied from 5.31 and 6.02, whereas the standard deviation ranged from .74 and .94. It was observed that all the independent variables had negative skew statistics indicating that all the distributions were platykurtic. But the values were in normal range. I observed that the kurtosis values for two variables (relative advantage and mimetic pressure) were outside the normal ±1 range and it indicated small or moderate violation of normal bell curve distribution.

Table 3

Descriptive Statistics for Independent and Dependent Variables

Variable	Mean	Median	Std. Deviation	Minimum	Maximum	Skewness	Kurtosis
ITS	5.66	6.00	0.96	2	7	-1.044	0.989
RA	6.02	6.00	0.74	3	7	-0.77	1.013
CP	5.74	6.00	0.80	3	7	-0.739	0.817
MS	5.76	6.00	0.98	3	7	-0.646	-0.094
MP	5.89	6.00	0.84	3	7	-0.957	1.588
NP	5.70	6.00	0.84	2	7	-0.642	0.357
CL	5.31	5.50	0.99	2	7	-0.389	0.249

RC	5.82	6.00	0.75	3	7	-0.603	0.329
PU	5.84	6.00	0.85	3	7	-0.676	0.051
PEU	5.51	5.67	0.77	3	7	-0.188	-0.575
DOA	5.79	6.00	0.89	3	7	-0.947	0.845

Before performing the descriptive statistics, I conducted the Reliability Analysis using Cronbach's Alpha analysis. The purpose of the Cronbach's Alpha analysis was to check the reliability of the 7 point Likert Scale and whether any of the independent variables measured using these scale had any undue influence. The Reliability Statistics provided in Table 4 below revealed the Cronbach's Alpha was .857 that was well above .7 means the results are reliable. I also checked the impact on Cronbach's Alpha if each of the independent variable measured using the scale was removed. The results are depicted in the Table 5 below. All the independent variables had the similar impact on the Cronbach's Alpha.

Table 4

Result of Cronbach's Alpha Analysis

Cronbach's Alpha	Cronbach's Alpha based on the standardized items	N of items
.857	.862	10

Table 5

Result of Cronbach's Alpha Analysis: Impact of Deletion of Item

Variable	Cronbach's Alpha if item deleted
ITS	.853

RA	.833
CP	.837
MS	.833
MP	.834
NP	.830
CL	.875
RC	.839
PU	.837
PEU	.853

Proportionality to Larger Population

152 complete responses out of 162 participants who attempted the online survey provided 93.82% of response completion rate. According to Survey Monkey (2019), there are approximately 500,000 participants available on the Survey Monkey Online Survey Platform. Hence I reached out to 0.0304% of the participants using the convenience and snowball sampling method.

Descriptive Statistics

In this section, I provided some insights those were collected using six demographic questions. I added the consent form on the first screen of the online survey, and participants were instructed to read through and then proceed to the first question if they agree. 162 survey participants agreed to the consent and then proceeded to attempt the survey.

I targeted this study to employees of Small and Medium Scale Enterprises in India. Table 6 below shows that 6% of participants were one of the top executives in their organization. Around 10% of participants were IT application managers, and 17% were IT infrastructure managers. 21% of participants were holding other IT management positions. Lastly, 47% of participants were individual contributors and were not having any non-managerial positions.

Table 6

Frequency and Percentages of Demographic Characteristics of Participants

Category	**Title**	**Frequency**	**Percentage**
Title	Chief Information Officer (CIO)	5	3%
	Chief Security Officer (CSO)	4	3%
	IT Application Manager	15	10%
	IT Infrastructure Manager	27	18%
	None of the above	70	46%
	Other IT Management Position	31	20%
Total		152	100%
Gender	Female	49	32%
	Male	102	67%

	Other	1	.7%
Total		152	100%
Age Range	18 to 30	39	26%
	31 to 44	87	57%
	45 to 60	25	16%
	More than 60	1	.7%
Total		152	100%
Level of school	Bachelor’s degree	76	50%
	Doctorate degree	3	2%
	Master’s degree	69	46%
	Other	2	1%
	Secondary School	2	1%
Total		152	100%
Experience in Artificial Intelligence Technology	2 years to less than 5 years	34	22%
	5 years or more	20	13%
	Less than 2 years	71	47%
	None	27	18%
Total		152	100%
Industry Sector	Construction	2	1%
	Education	5	3%
	Energy/Utilities	6	4%

	Financial Services/Banking	33	22%
	Government	1	1%
	Healthcare	12	8%
	IT-Services	74	49%
	Other	19	12%
Total		152	100%

Table 6 showed more female participants (67%) who attempted the survey compared to 32% male participants. Whereas adults between ages 31 to 44 accounted for the largest population 57% among the participants followed by 26% participants falling in the age group of 18 to 30. There were 16% of the participants from the age group 45 to 60, and there was only one participant who was above age 60.

As reflected in the Table 6 above 50% percent of participants owned a bachelor's degree, and another set of 46% of participants attained a master's degree. About the participants' experience in AI technology, 22% of participants had two to five years of experience, and 47% had less than two years of experience. About 13% of the participants had more than five years of experience in AI technology, and about 18% of participants did not have any experience in implementing or using AI technology.

As indicated, 49% of the participants worked for IT Services firms, and 22% of the participants were working in the Financial Industry. 8% of the participants were from the Healthcare sector, and 12% of the participants were from uncategorized firms in this survey. The participants working in the construction industry, education sector, energy/utilities, and government constituted 9% of the participants.

Study Results

I conducted this correlational cross-sectional quantitative study to gain insights into the AI technology adoption, implementation, and use in India's SME sector. The purpose of this correlational cross-sectional quantitative study to find out whether there is any correlation between the 10 constructs (ITS, RA, CP, CL, MS, MP, NP, RC, PU, and PEU) from theories such as DOI, TOE, and TAM and the decision to adopt, implement, and use AI in SME sector in India. The main research question (RQ) and 10 sub research questions along with their deriving 20 hypotheses were formulated as below.

Descriptive Analysis

I used the IBM SPSS Statistics version 25 software to study the characteristics of the data collected and computed standard deviation, frequency, percentage, and mean of all independent and dependent variables involved in the study. I provided details of the demographic characteristics of the research data based on the tests conducted.

Characteristics of Participants and Industry Sector

There were six parameters: title, level of education, gender, age group, industry sector, and experience related to AI technology. These details are described in table 6. The results indicated that most of the respondents were from 18 to 44 with bachelor's or master's degrees. Most of the participants were working for IT-Services companies or in the financial services sector and had up to five years of experience in implementing or using AI technologies. About 47% of participants were technologists’ workings on AI technologies in individual contributors' capacity, and 21% of the participants held managerial positions.

Descriptive Characteristics of the Research Variables

I studied the central tendency, how the variables are distributed, and the variation of distribution within the variables used in this correlational cross-sectional quantitative research. According to Ruxton and Neuhäuser (2018), mode, which helps measure central tendency, median that allows in describing diversity and variation of the distribution of research data are useful statistical analysis tools. I calculated mean (M), variance (V), and standard deviation (SD) for 10 independent variables (IT sophistication, relative advantage, complexity, compatibility, management support, mimetic pressure, normative pressure, regulatory concern, perceived usefulness, and perceived ease of use) and one dependent variable (decision of AI adoption) that is shared it in Table 8 below. All the variables were composite variables created using two or more variables measured using a seven-point Likert scale with values ranging from 1 for strongly disagree and 7 for strongly agree.

The items ITS1, ITS2, and ITS3 of the IT sophistication variable presented in Table 8 had roughly equal scores of mean, median, standard deviation, min, and max. The standard deviation values were between .992 and 1.397. The mean of three variables varied between 5.40 and 5.91, indicating that the average response for ITS1, ITS2, and ITS3 was between somewhat agree and agree on a seven-point Likert scale. The same was visible as depicted in Table 8, where the mean of the calculated composite variable IT sophistication was 5.66.

The RA1, RA2, RA3, RA4, and RA5 of the relative advantage variable presented in Table 8 had roughly equal scores of mean, median, standard deviation, min, and max.

The standard deviation values were in the range of .860 to 1.025. The mean of three variables varied between 5.89 and 6.17, indicating that the average response for RA1, RA2, RA3, RA4, and RA5 was very close to agreeing on a seven-point Likert scale. The same was visible as depicted in Table 8, where the mean of calculated composite variable relative advantage was 6.02.

The CP1, CP2, CP3, and CP4 of the compatibility variable presented in Table 8 had roughly equal scores of mean, median, standard deviation, min, and max. The standard deviation values were in the range of .902 to 1.144. The mean of these variables varied between 5.72 and 5.76, indicating that the average response for CP1, CP2, CP3, and CP4 was between somewhat agree and agree on a seven-point Likert scale. The same was visible as depicted in Table 8, where the mean of calculated composite variable compatibility was 5.74.

The items MS1, MS2, and MS3 of the management support variable presented in Table 8 had roughly equal scores of mean, median, standard deviation, min, and max. The standard deviation values were in the range of 1.007 to 1.146. The mean of three variables varied between 5.69 and 5.80, indicating that the average response for MS1, MS2, and MS3 was between somewhat agree and agree on a seven-point Likert scale. The same was visible as depicted in Table 8, where the mean of calculated composite variable management support was 5.76.

The items MP1 and MS2 of the management support variable presented in Table 8 had roughly equal scores of mean, median, standard deviation, min, and max. The standard deviation values were in the range of .975 to .949. The mean of three variables varied between 5.76 and 6.03, indicating that the average response for MP1 and MP2 was between somewhat agree and agree on a seven-point Likert scale. The same was visible as depicted in Table 8, where the mean of calculated composite variable management support was 5.89.

The NP1, NP2, and NP3 of the normative pressure variable presented in Table 8 had roughly equal scores of mean, median, standard deviation, min, and max. The standard deviation values were in the range of .895 to 1.189. The mean of these variables varied between 5.45 and 5.83, indicating that the average response for NP1, NP2, and NP3 was between somewhat agree and agree on a seven-point Likert scale. The same was visible as depicted in Table 8, where the mean of calculated composite variable normative pressure was 5.70.

The items CL1 and CL2 of the complexity variable presented in Table 8 had roughly equal scores of mean, median, standard deviation, min, and max. The standard deviation values were in the range of 1.118 to 1.168. The mean of these variables varied between 5.22 and 5.41, indicating that the average response for CL1 and CL2 was between somewhat agree and agree on a seven-point Likert scale. The same was visible as depicted in Table 8, where the mean of calculated composite variable normative pressure was 5.31.

The items RC1 and RC2 of the regulatory concern variable presented in Table 8 had roughly equal scores of mean, median, standard deviation, min, and max. The standard deviation values were in the range of .789 to .953 The mean of these variables varied between 5.64 and 6.00, indicating that the average response for RC1 and RC2 was between somewhat agree and agree on a seven-point Likert scale. The same was visible as depicted in Table 8, where the mean of calculated composite variable regulatory concern was 5.82.

The items PU1, PU2, and PU3 of the perceived usefulness variable presented in Table 8 had roughly equal scores of mean, median, standard deviation, min, and max. The standard deviation values were in the range of .864 to 1.190. The mean of these variables varied between 5.62 and 6.06, indicating that the average response for PU1, PU2, and PU3 was between somewhat agree and agree on a seven-point Likert scale. The same was visible as depicted in Table 8, where the mean of calculated composite variable PU was 5.84.

The PEU1, PEU2, and PEU3 of the perceived ease of use variable presented in Table 8 had roughly equal scores of mean, median, standard deviation, min, and max. The standard deviation values were in the range of 1.048 to 1.279. The mean of these variables varied between 4.99 and 5.97, indicating that the average response for PEU1, PEU2, and PEU3 was between neither agree nor disagree and agree on a seven-point Likert scale. The same was visible as depicted in Table 8, where the mean of calculated composite variable perceived ease of use was 5.51.

The items DOA1 and DOA2 of the decision of AI adoption variable presented in Table 8 had roughly equal scores of mean, median, standard deviation, min, and max. The standard deviation values were in the range of .865 to 1.070. The mean of these variables varied between 5.68 and 5.89, indicating that the average response for DOA1 and DOA2 was between somewhat agree and agree on a seven-point Likert scale. The same was visible as depicted in Table 8, where the mean of calculated composite variable decision of AI adoption was 5.79.

Table 7

Descriptive Statistics for Study Constructs (N = 152)

Variable	Mean	Median	Std. Deviation	Minimum	Maximum
ITS1	5.68	6	1.188	1	7
ITS2	5.40	6	1.397	2	7
ITS3	5.91	6	0.992	2	7
RA1	6.17	6	0.860	3	7
RA2	6.05	6	1.025	2	7
RA3	5.89	6	0.998	2	7
RA4	5.99	6	0.980	2	7
RA5	6.01	6	0.884	3	7
CP1	5.73	6	1.042	3	7
CP2	5.74	6	1.144	1	7
CP3	5.78	6	1.003	2	7
CP4	5.72	6	0.902	3	7
MS1	5.80	6	1.100	1	7
MS2	5.79	6	1.007	3	7
MS3	5.69	6	1.146	2	7
MP1	6.03	6	0.949	2	7
MP2	5.76	6	0.975	2	7

NP1	5.83	6	1.015	2	7
NP2	5.82	6	0.895	3	7
NP3	5.45	6	1.189	2	7
CL1	5.41	6	1.118	2	7
CL2	5.22	5	1.168	2	7
RC1	6.00	6	0.789	3	7
RC2	5.64	6	0.953	2	7
PU1	5.86	6	0.864	4	7
PU2	5.62	6	1.190	1	7
PU3	6.06	6	0.998	1	7
PEU1	4.99	5	1.279	1	7
PEU2	5.56	6	1.132	2	7
PEU3	5.97	6	1.048	2	7
DOA1	5.68	6	1.070	2	7
DOA2	5.89	6	0.865	3	7
ITS	5.66	6.00	0.96	2	7
RA	6.02	6.00	0.74	3	7
CP	5.74	6.00	0.80	3	7
MS	5.76	6.00	0.98	3	7
MP	5.89	6.00	0.84	3	7
NP	5.70	6.00	0.84	2	7

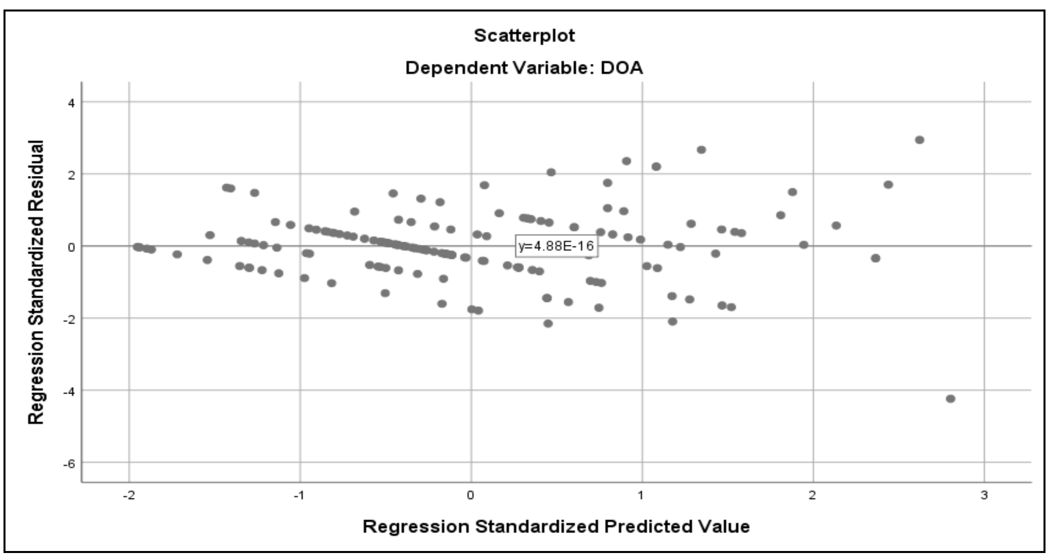
CL	5.31	5.50	0.99	2	7
RC	5.82	6.00	0.75	3	7
PU	5.84	6.00	0.85	3	7
PEU	5.51	5.67	0.77	3	7

Preliminary Data Screening

Preliminary data screening steps were to test assumptions such as homoscedasticity, undue influence, normal distribution of error, independence of the errors, and linearity. Also, I conducted the bivariate correlational analysis with a two-tailed test of significance and calculated Pearson correlation along with the normal probability plot of the standardized residuals, scatterplot, and histogram.

Figure 7

Scatterplot of Standardized Residuals



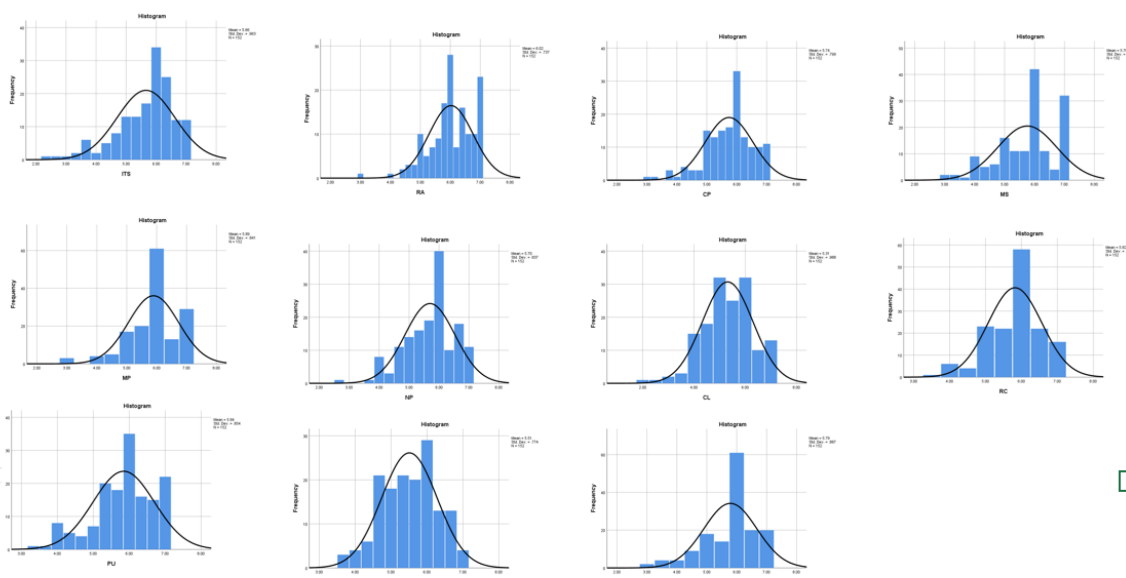
Assumption of Homoscedasticity

I analyzed the scatterplot in figure 7 that contained Regression Standard Predictor Variable plotted on the X-axis and Regression Standardized Variable plotted on the Y-axis. It was observed that the reference line created almost equal half and the scatter plot did not show any grouping of scatter with noticeable patterns. Hence the assumption of homoscedasticity was met.

Assumption of Linearity

The scatterplot in figure 7 had Regression Standardized Predictor Variable on the X-axis and Regression Standardized Variable on the Y-axis. It was observed that the one reference line creates an even divide between the upper half and the lower half. Thus the assumption of linearity was met that depicted a linear equation that represents the existence of the linear relationship.**Figure 8**

Histogram for 10 Independent Variables and One Dependent Variable



Assumption of Independence of Observations

To check for the independence of observation, I performed a Durbin-Watson test on the predictor variables. The results of the Durbin-Watson values ranged between 1.587 and 1.971. Thus, I concluded that the assumption of independence of observation was satisfied.

Table 8

Results of Test of Independence of Observations

Variable	**R**	**R-square**	**Adjusted R-square**	**SE**	**Durbin-Watson** Average (Score 1-5)
ITS	.387	.150	.144	.86419	1.804
RA	.438	.192	.187	.84252	1.709
CP	.473	.224	.219	.82577	1.625
MS	.597	.357	.353	.75161	1.962
MP	.541	.292	.288	.78831	1.744
NP	.549	.302	.297	.78304	1.971
CL	.122	.013	.006	.93120	1.639
RC	.407	.166	.160	.85606	1.691
PU	.398	.158	.153	.85983	1.825
PEU	.319	.102	.096	.88829	1.587

Assumption of Multicollinearity

In assessing the multicollinearity, I performed VIF analysis. The result of this analysis showed that all of the predictor variables were below 10. Thus, it was concluded that there is no problem with multicollinearity in this particular dataset.

Table 9

Results of Multicollinearity Analysis for Independent Variables

Variable	**T**	**VIF**
ITS	.592	1.688
RA	.453	2.210
CP	.514	1.946
MS	.335	2.984
MP	.414	2.417
NP	.448	2.231
CL	.686	1.458
RC	.519	1.926
PU	.441	2.268
PEU	.621	1.611

Note. Tolerance is defined as T = 1 – R square. Variance Inflation Factor (VIF) is defined as VIF = 1 / T.

Assumption of undue influence

Cook’s distance on the residual statistics ranged from .094 to .556. As Cook’s distance was lower than 1.0, this assumption was met as there was no undue influence on the model.

Table 10

Results of Undue Influence Analysis for Independent Variables

Variable	Cook’s distance
ITS	.179
RA	.160
CP	.440
MS	.411
MP	.556
NP	.338
CL	.141
RC	.126
PU	.307
PEU	.094

Assumption of Normal Distribution of Errors

Figure 9 depicted a normal distribution of the data. As observed, the peak is not at zero. The histogram represented a skewed distribution aligned with the expectation of symmetrical distribution. Also, the normal probability plot below contained the points at the top right. The bottom left of the straight line supported the assumption of meeting the normality in the data without any significant deviation. Based on the preliminary data screening, there is some evidence to support the assumptions of homoscedasticity, linearity, and normal distribution of errors. The Meeting of these assumptions confirmed the validity of the correlational cross-sectional quantitative study.

Figure 9

Histogram of Regression Standardized Correlation

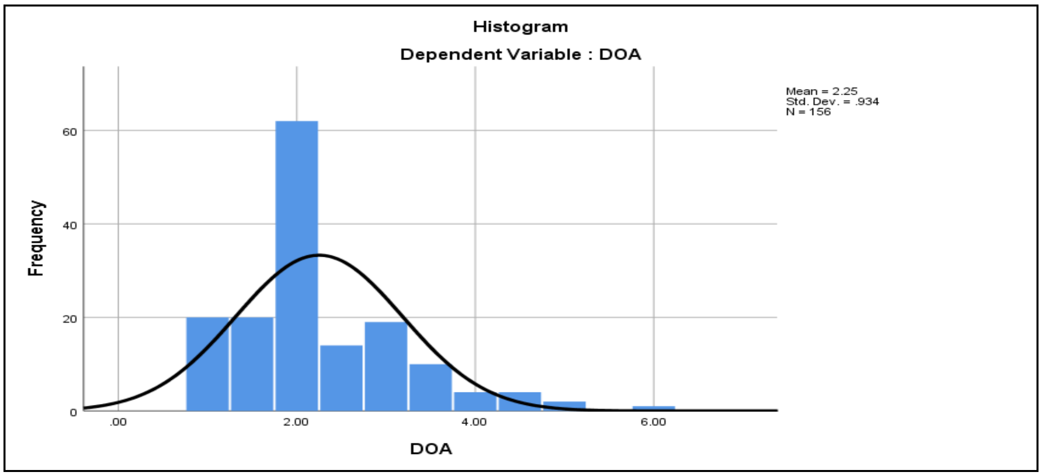
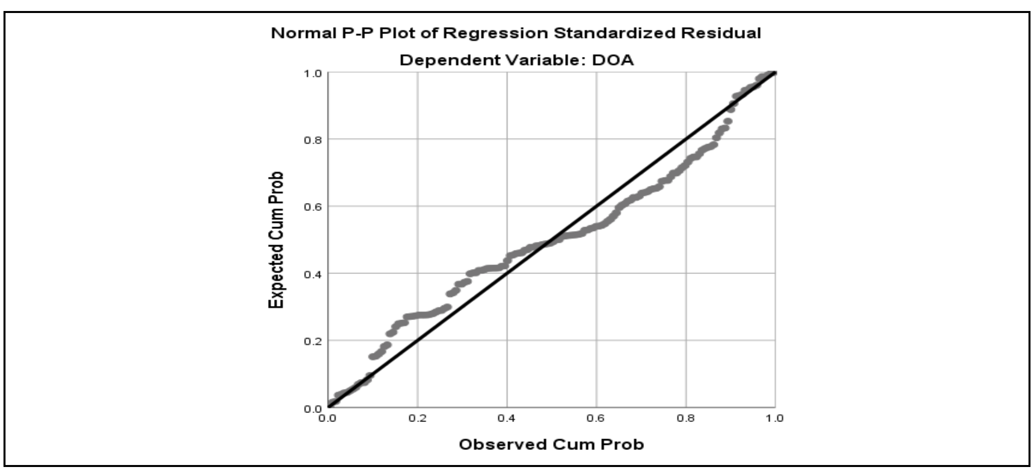


Figure 10

Normal P/P of the Regression Standardized Residual



Inferential Statistics

I was interested in understanding whether there is a correlation between each of the 10 independent variables and one dependent variable. The Pearson coefficient test was performed to answer all the secondary research questions. The Pearson correlation test helps I understand the strength of the correlation between two variables and is easy to perform and analyze results when used to test a probable correlation (Wagner, 2016; Ruxton & Neuhäuser, 2018; Frankfort-Nachmias & Leon-Guerrero, 2016). The survey instrument contained the seven-point Likert scale where the numerical value from 1 to 7 was assigned to each response: 1 for Strongly Disagree, 2 for Disagree, 3 for Somewhat Disagree, 4 for Neither Agree nor Disagree, 5 for Somewhat Agree, 6 for Agree, and 7 for Strongly Agree.

RQ: What are the various factors that enable and limit the decision of AI adoption, implementation, and use in SME sector in India?

This research question was answered after completing the hypothesis testing for 10 secondary research questions. The hypothesis testing revealed that 9 out of 10 independent variables (ITS, RA, CP, MS, MP, NP, RC, PU, and PEU) had some impact on the dependent variable (DOA). Thus these nine independent variables (ITS, RA, CP, MS, MP, NP, RC, PU, and PEU) enabled and one independent variable (complexity – CL) limited the impact AI adoption, implementation, and use in the SME sector in India.

SQ1: Does ITS have any statistically significant correlation with DOA in SME sector in India? The null hypothesis (Ho1) stated that ITS does not have statistically significant correlation with DOA in SME sector in India. The research hypothesis (Ha1) stated that ITS does have statistically significant correlation with DOA in SME sector in India.

The Pearson correlations in ITS (r) in Table 12 were found to have a low positive correlation and statistically significant ($r = .379$, $p < .001$). Hence, the research hypothesis (Ha1) was supported, and the null hypothesis (H1o) is rejected. The histogram shows the normal distribution of the data and the scatter plot shows that an increase in ITS would lead to a low increase in DOA in the SME sector in India.

Table 11

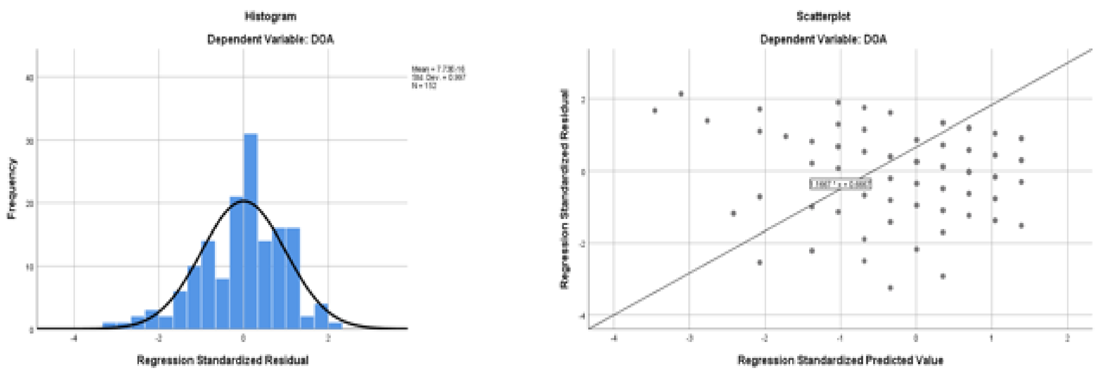
Pearson Correlation Coefficient ITS and DOA

Variable		ITS	DOA
IT Sophistication (ITS)	Pearson Correlation	1	.379**
	Sig. (2 tailed)		.000
	N	152	152
Decision of AI Adoption (DOA)	Pearson Correlation	.379**	1
	Sig. (2 tailed)	.000	
	N	152	152

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

Figure 11

Histogram and Scatter Plot of ITS Versus DOA



SQ2: Does RA have any statistically significant correlation with DOA in SME sector in India? The null hypothesis (Ho2) stated that RA does not have statistically significant correlation with DOA in SME sector in India. The research hypothesis (Ha2) stated that RA does have statistically significant correlation with DOA in SME sector in India.

The Pearson correlation of RA in Table 13 was found to be a low positive correlation and statistically significant ($r = .408$, $p < .001$). Hence, the research hypothesis (Ha2) was supported, and the null hypothesis (H2o) is rejected. The histogram below shows the normal distribution of the data and the scatter plot shows that an increase in RA would lead to a low increase in DOA in the SME sector in India.

Table 12

Pearson Correlation Coefficient RA and DOA

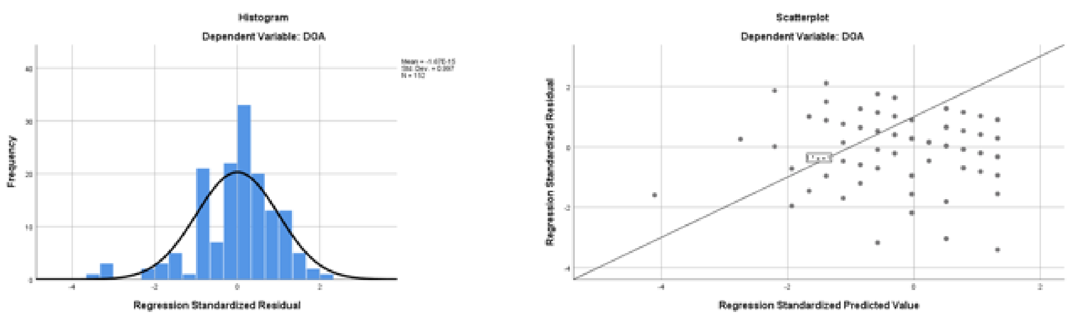
Variable	RA	DOA

Relative Advantage (RA)	Pearson Correlation	1	.408**
	Sig. (2 tailed)		.000
	N	152	152
Decision of AI Adoption (DOA)	Pearson Correlation	.408**	1
	Sig. (2 tailed)	.000	
	N	152	152

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

Figure 12

Histogram and Scatter Plot of RA Versus DOA



SQ2: Does CP have any statistically significant correlation with DOA in SME sector in India? The null hypothesis (Ho3) stated that CP does not have statistically significant correlation with DOA in SME sector in India. The research hypothesis (Ha3) stated that CP does have statistically significant correlation with DOA in SME sector in India.

The Pearson correlation of DOA in the Table 14 was found to be low positive correlation and statistically significant ($r = .442$, $p < .001$). Hence, the research hypothesis (Ha3) was supported and the null hypothesis (Ho3) is rejected. The histogram below shows the normal distribution of the data and the scatter plot shows that an increase in CP would lead to a low increase in DOA in the SME sector in India.

Table 13

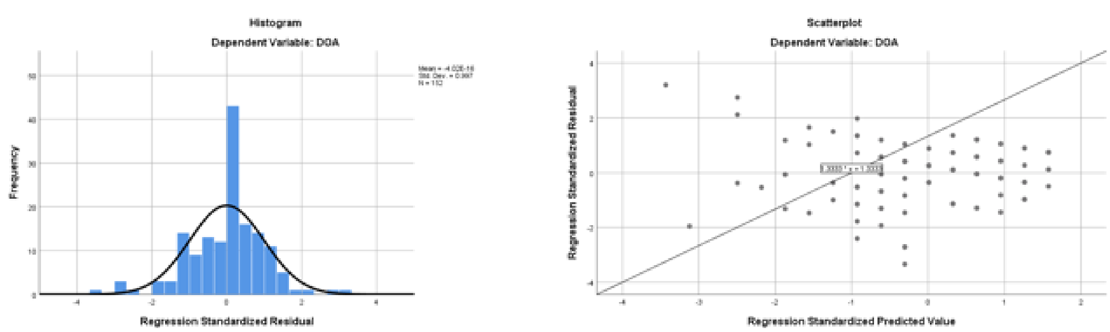
Pearson Correlation Coefficient CP and DOA

Variable		CP	DOA
Compatibility (CP)	Pearson Correlation	1	.442**
	Sig. (2 tailed)		.000
	N	152	152
Decision of AI Adoption (DOA)	Pearson Correlation	.442**	1
	Sig. (2 tailed)	.000	
	N	152	152

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

Figure 13

Histogram and Scatter Plot of CP vs DOA



SQ4: Does MS have any statistically significant correlation with DOA in SME sector in India? The null hypothesis (Ho4) stated that MS does not have statistically significant correlation with DOA in SME sector in India. The research hypothesis (Ha4) stated that MS does have statistically significant correlation with DOA in SME sector in India.

The Pearson correlation of MS in the Table 15 was found to be moderate positive correlation and statistically significant ($r = .568$, $p < .001$). Hence, the research hypothesis (Ha4) was supported and the null hypothesis (Ho4) was rejected. The histogram below shows the normal distribution of the data and the scatter plot shows that an increase in MS would lead to a moderate increase in DOA in the SME sector in India.

Table 14

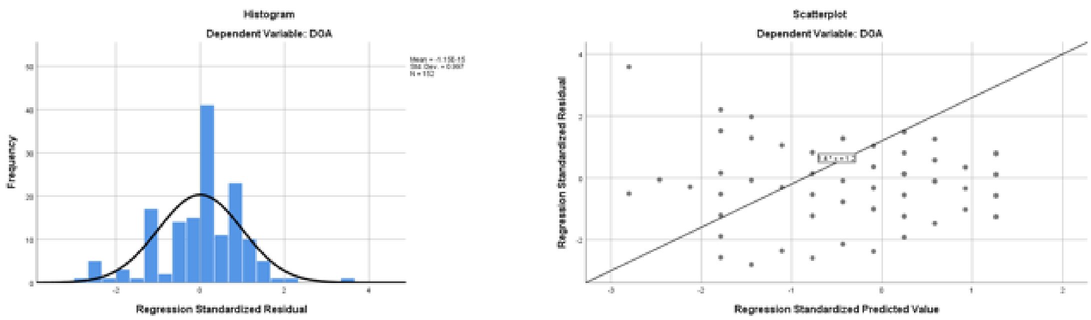
Pearson Correlation Coefficient MS and DOA

Variable		MS	DOA
Management Support (MS)	Pearson Correlation	1	.568**
	Sig. (2 tailed)		.000
	N	152	152
Decision of AI Adoption (DOA)	Pearson Correlation	.568**	1
	Sig. (2 tailed)	.000	
	N	152	152

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

Figure 14

Histogram and Scatter Plot of MS Versus DOA



RQ5: Does CL has any statistically significant correlation with DOA in SME sector in India? The null hypothesis (Ho5) stated that CL does not have statistically significant correlation with DOA in SME sector in India. The research hypothesis (Ha5) stated that CL does have statistically significant correlation with DOA in SME sector in India.

The Pearson correlation of CL in Table 16 was found to have no correlation and statistically not significant ($r = .149$, $p > .001$). Hence, the null hypothesis (Ho5) was supported and the research hypothesis (Ha5) was rejected. The histogram below shows the normal distribution of the data and the scatter plot shows that an increase in CL would not lead to an increase or decrease in DOA in the SME sector in India.

Table 15

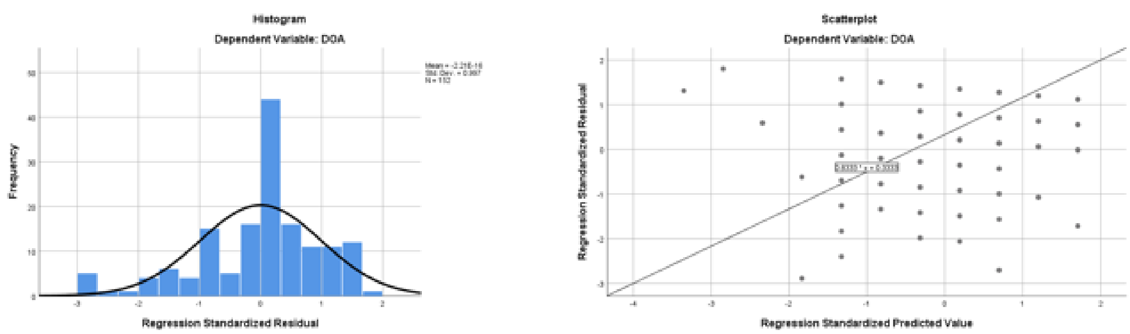
Pearson Correlation Coefficient CL and DOA

Variable		CL	DOA
Complexity (CL)	Pearson Correlation	1	.149
	Sig. (2 tailed)		.068
	N	152	152
Decision of AI Adoption (DOA)	Pearson Correlation	.149	1
	Sig. (2 tailed)	.068	
	N	152	152

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

Figure 15

Histogram and Scatter Plot of CL vs DOA



I conducted the post hoc power analysis as the Pearson Coefficient for the independent variable CL showed no statistically significant correlation with the dependent variable DOA. The G* Power analysis recommended the sample size of 84 participants for the study. However, I collected the data from 152 participants. As depicted in the appendix I, the post hoc power analysis indicated an observed power of 1.0000000 for complexity using the calculated effect size of 0.707, with the sample size of the study as 152. The probability of committing the type II error (beta) was negligible. Additional details of the post hoc power analysis were included in the Appendix I.

SQ6: Does MP have any statistically significant correlation with DOA in SME sector in India? The null hypothesis (Ho6) stated that MP does not have statistically significant correlation with DOA in SME sector in India. The research hypothesis (Ha6) stated that MP does have statistically significant correlation with DOA in SME sector in India.

The Pearson correlation of MP in the Table 17 was found to be moderate positive correlation and statistically significant ($r = .478$, $p < .001$). Hence, the research hypothesis (Ha6) was supported and the null hypothesis (Ho6) is rejected. The histogram below shows the normal distribution of the data and the scatter plot shows that an increase in MP would lead to a moderate increase in DOA in the SME sector in India.

Table 16

Pearson Correlation Coefficient MP and DOA

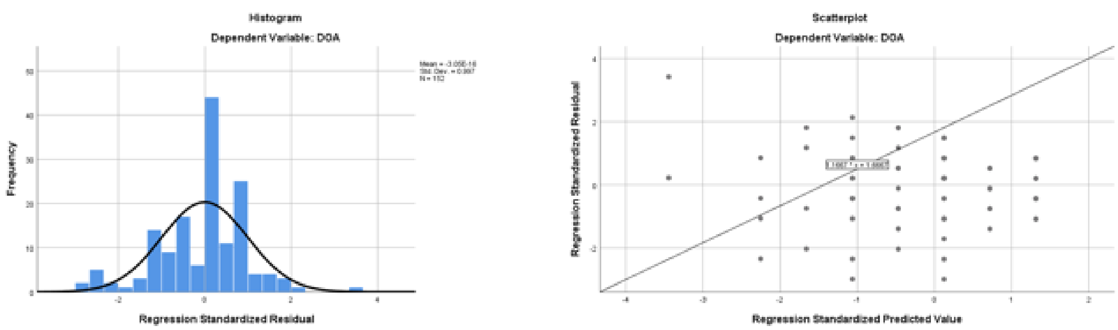
Variable		MP	DOA
Mimetic Pressure (MP)	Pearson Correlation	1	.478**
	Sig. (2 tailed)		.000
	N	152	152

Decision of AI Adoption (DOA)	Pearson Correlation	.478**	1
	Sig. (2 tailed)	.000	
	N	152	152

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

Figure 16

Histogram and Scatter Plot of MP Versus DOA



SQ7: Does NP have any statistically significant correlation with DOA in SME sector in India? The null hypothesis (Ho7) stated that NP does not have statistically significant correlation with DOA in SME sector in India. The research hypothesis (Ha7) stated that normative pressure does have statistically significant correlation with DOA in SME sector in India.

The Pearson correlation of NP in the Table 18 was found to be moderate positive correlation and statistically significant ($r = .553$, $p < .001$). Hence, the research hypothesis (Ha7) was supported and the null hypothesis (Ho7) is rejected. The histogram below shows the normal distribution of the data and the scatter plot shows that an increase in NP would lead to a moderate increase in DOA in the SME sector in India.

Table 17

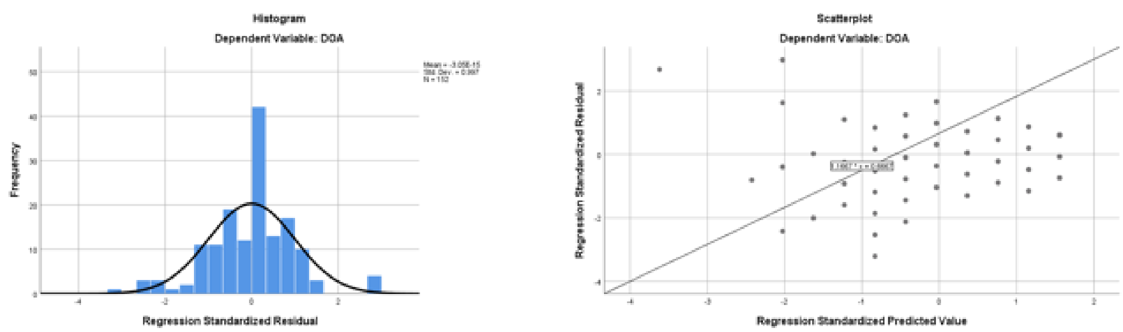
Pearson Correlation Coefficient NP and DOA

Variable		NP	DOA
Normative Pressure (NP)	Pearson Correlation	1	.553**
	Sig. (2 tailed)		.000
	N	152	152
Decision of AI Adoption (DOA)	Pearson Correlation	.553**	1
	Sig. (2 tailed)	.000	
	N	152	152

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

Figure 17

Histogram and Scatter Plot of NP vs DOA



SQ8: Does RC have any statistically significant correlation with DOA in SME sector in India? The null hypothesis (Ho8) stated that RC does not have statistically significant correlation with DOA in SME sector in India. The research hypothesis (Ha8)

stated that RC does have statistically significant correlation with DOA in SME sector in India.

The Pearson correlation of RC in the Table 19 was found to be low positive correlation and statistically significant ($r = .388$, $p < .001$). Hence, the research hypothesis (Ha8) was supported and the null hypothesis (Ho8) was rejected. The histogram below shows the normal distribution of the data and the scatter plot shows that an increase in RC would lead to a low increase in DOA in the SME sector in India.

Table 18

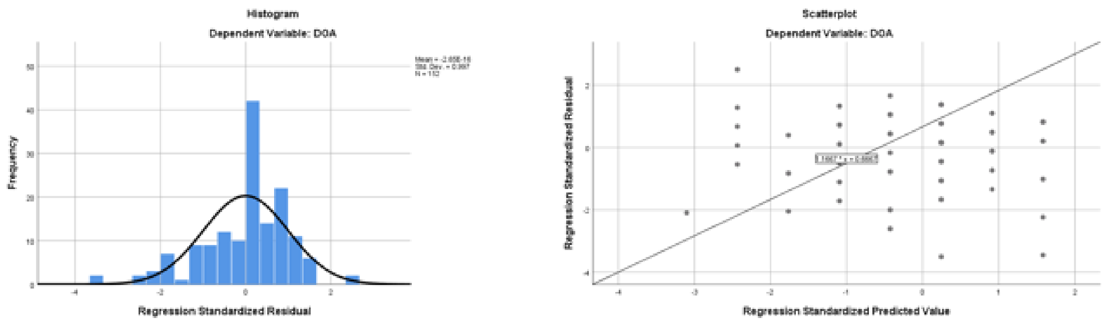
Pearson Correlation Coefficient RC and DOA

Variable		RC	DOA
Regulatory Concern (RC)	Pearson Correlation	1	.388**
	Sig. (2 tailed)		.000
	N	152	152
Decision of AI Adoption (DOA)	Pearson Correlation	.388**	1
	Sig. (2 tailed)	.000	
	N	152	152

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

Figure 18

Histogram and Scatter Plot of RC vs DOA



SQ9: Does PU have any statistically significant correlation with DOA in SME sector in India? The null hypothesis (Ho9) stated that PU does not have statistically significant correlation with DOA in SME sector in India. The research hypothesis (Ha9) stated that PU does have statistically significant correlation with DOA in SME sector in India.

The Pearson correlation of PU in the Table 20 was found to be low positive correlation and statistically significant ($r = .412$, $p < .001$). Hence, the research hypothesis (Ha9) was supported and the null hypothesis (Ho9) is rejected. The histogram below shows the normal distribution of the data and the scatter plot shows that an increase in PU would lead to a low increase in DOA in the SME sector in India.

Table 19

Pearson Correlation Coefficient PU and DOA

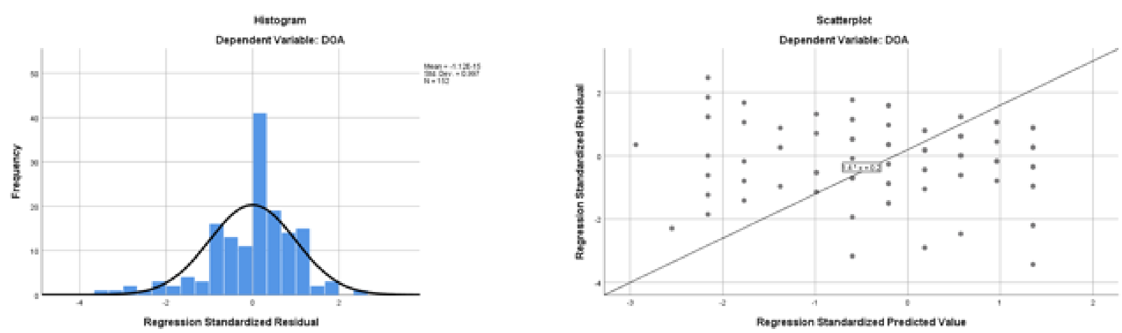
Variable		PU	DOA
Perceived Usefulness (PU)	Pearson Correlation	1	.412**

	Sig. (2 tailed)		.000
	N	152	152
Decision of AI Adoption (DOA)	Pearson Correlation	.412**	1
	Sig. (2 tailed)	.000	
	N	152	152

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

Figure 19

Histogram and Scatter Plot of PU Versus DOA



RQ10: Does PEU have any statistically significant correlation with DOA in SME sector in India? The null hypothesis (Ho10) stated that PEU does not have statistically significant correlation with DOA in SME sector in India. The research hypothesis (Ha10) stated that PEU does have statistically significant correlation with DOA in SME sector in India.

The Pearson correlation of perceived ease of use in the Table 21 was found to be low positive correlation and statistically significant ($r = .352$, $p < .001$). Hence, the research hypothesis (Ha10) was supported and the null hypothesis (Ho10) is rejected. The histogram below shows the normal distribution of the data and the scatter plot shows that an increase in PEU would lead to a low increase in DOA in the SME sector in India.

Table 20

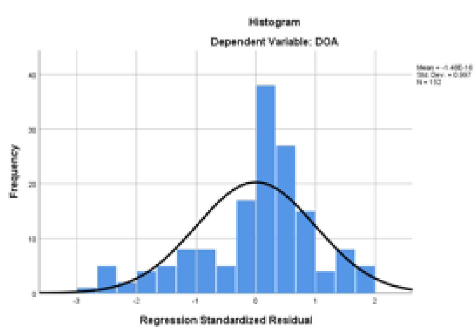
Pearson Correlation Coefficient PEU and DOA

Variable		PEU	DOA
Perceived ease of Use (PEU)	Pearson Correlation	1	.352**
	Sig. (2 tailed)		.000
	N	152	152
Decision of AI Adoption (DOA)	Pearson Correlation	.352**	1
	Sig. (2 tailed)	.000	
	N	152	152

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

Figure 20

Histogram and Scatter Plot of PEU Versus DOA



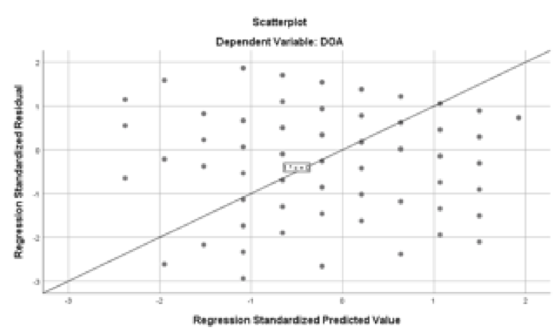


Table 21

Summary of Results

Variable	Pearson Correlation Coefficient (r)
ITS	.379
RA	.408
CP	.442
MS	.568
MP	.478
NP	.553
CL*	.149
RC	.388
PU	.412
PEOU	.352

As depicted in the Table 22 above; 10 independent variables were analyzed individually: MS, MP, and NP showed the moderate positive correlation with DOA. Six independent variables ITS, RA, CP, RC, PU, and PEU showed low positive correlation with DOA. Similar was the trend observed in the predictability of the dependent variable. Three independent variables with moderate correlation were found to have better ability to predict the variance in the dependent variable compared to six independent variables with low positive correlation.

Summary

The main goal of this correlational cross-sectional quantitative research study was to understand the various factors that enable and limit the impact on AI adoption, implementation, and use in the SME sector in India. In the first section of this chapter, I provided details about the data collection process. These descriptions included details about the online survey setup process, the process of soliciting participants to the survey, the information on the response received to the online survey.

Further, I described the data preparation process and included details about the baseline descriptive statistics and demographic details derived from the initial analysis of the data. I provided results explaining descriptive characteristics from the demographic information about the survey participants. I described the process adopted to derive the inferential statistics, and importantly some elaboration of the data screening process followed.

There were 162 responses to the survey; out of those, 152 survey responses were considered for further data analysis. The data's descriptive analysis revealed that 67% of male participants, 50% of participants were having bachelor's degrees, and 46% master's degree. There were 83% participants in the age group of 18 to 44 years, 49% of participants were from IT Services companies. There were 22% of participants from the financial industry, and 82% of participants were having up to 5 years of experience in AI technology.

I detailed testing of assumptions and indicated that there were no significant violations to report. The Pearson correlation analysis revealed that 9 out of 10 independent variables (ITS, RA, CP, MS, MP, NP, RC, PU, and PEU) had low to moderate correlation with the dependent variable DOA. There was only one independent variable named compatibility that did not show any correlation with the dependent variable DOA.

In Chapter 5, I analyze, interpret, and discuss findings provided in this chapter. I also include details about limitations of the study, recommendations for future studies, and potential positive social change.

Chapter 5: Discussion, Conclusions, and Recommendations

The primary purpose of this quantitative cross-sectional correlational study was to study the impact of TOE factors on the adoption, implementation, and use of AI technology in the SME sector in India. AI has started receiving attention of business leaders in the SME sector as the technology of choice to solve their critical business problems. I focused on finding correlations between each of the independent variables: ITS, RA, CP, MS, MP, NP, CL, REC, PEU, and PU and the dependent variable DOA in the SME sector in India.

As indicated in Chapter 4, results indicate that nine out of 10 independent variables show varied level of correlations with DOA. When only DOA is compared with independent variables, ITS (r = .379, p < .001), RA (r = .408, p < .001), CP (r = .442, p < .001), RC (r = .388, p < .001), PU (r = .412, p < .001), and PEU (r = .352, p < .001) showed low positive correlations with DOA. Three independent variables MS (r = .568, p < .001), MP (r = .478, p < .001), and NP (r = .553, p < .001) showed moderate positive correlations with DOA. There was one variable CL (r = .149, p > .001) which showed no correlation with DOA and was not statistically significant.

In this chapter, I provide interpretations of results by conducting a quantitative analysis. Further, I address the study's limitations and possible contributions to positive social change. Further, I provide recommendations for future studies and include a conclusion at the end of the chapter.

Interpretation of Findings

This correlational cross-sectional quantitative study was conducted to understand the correlation between 10 independent variables (ITS, RA, CP, MS, MP, NP, CL, RC, PU, and PEU) and the dependent variable (DOA). The statistical analysis such as Pearson Correlation is useful in finding correlations between each independent variable and the dependent variable when considered separately (Arora, & Garg, 2018, Xu, & Deng, 2017). When the data analysis was performed using Pearson correlation, I found no serious violations of assumptions.

Descriptive statistics revealed there were three independent variables (RA, MP, and PU) with a larger mean as compared to other 7 independent variables (ITS, CP CL, NP, RC, PU, and PEU). The first variable was RA (M = 6.02), which showed that participants felt organizations may get a competitive edge against their competitors and enhance their market positions. The second variable was MP (M = 5.89), which demonstrated that organizations have pressure to mimic the behavior of AI adoption of their competitors to stay relevant in the market. The third variable was PU (M = 5.84), and participants felt that the adoption of AI technology helped organizations improve profitability, productivity, and customer service.

Main Research Question

I used Pearson correlation to understand which variables have a positive or negative correlation with the dependent variable, strengths of correlations, and whether they were statistically significant. MS (r = .568, p < .001) showed significant statistical correlation with the DOA and thus proved that providing necessary approvals as well as financial and nonfinancial resources for adopting the AI technology was crucial. NP (r = .553, $p < .001$) showed significant statistical correlation with the DOA and thus proved that many customers and suppliers are adopting AI technology, so businesses are obliged to adopt AI technology to remain relevant. MP (r = .478, $p < .001$) showed significant statistical correlation with the DOA and thus proved that companies in SME sector in India need to adopt AI to offer AI based products and services due to peer pressure as a result of competition in the industry. These results were substantiated by previous research where MS, MP, and NP were found to be crucial factors in adoption of new technologies such as AI, Internet of Things (IoT) and Cloud Technologies (Ingaldi, & Ulewicz, 2020; Ingalagi, et al., 2021; Ing, et al., 2020).

Secondary Research Questions

There were 10 secondary research questions in this study. Each of the secondary questions was used to evaluate if an independent variable has any correlation with the dependent variable. There were 10 research hypotheses and 10 null hypotheses aligned to 10 secondary research questions. I conducted Pearson correlation analysis to determine the existence or nonexistence of correlations between each of the independent and dependent variable.

ITS

The availability of the standard IT processes and IT management capabilities developed within the organization to seamlessly integrate the new technology determines ITS. As the Pearson correlation analysis results revealed, ITS (r = .379, $p < .001$) showed a moderate positive correlation with DOA, and the results was statistically valid. These results were substantiated by previous research where ITS was found to be significant to the new technology adoption such as AI, IoT, and Cloud computing (Salleh & Janczewski, 2016; Bergeron et al., 2017; Sysmsuar, 2018; Kim at al., 2018; Zerfass et al., 2020).

RA

RA in this involves enhanced communication with customers, increased profitability, cost reduction, entry into new markets, and improved web presence. RA a construct from the DOI theory. As the results of Pearson correlation analysis revealed, RA (r = .408, p < .001) a moderate positive correlation with DOA, and the results was statistically valid. These results were substantiated by previous research where RA was found to be significant to the new technology adoption such as AI, IoT, and Cloud computing (Franceschinis et al., 2017; Sayginer & Ercan, 2020; Yap & Chen, 2017; Sanchez-Prieto et al., 2019; Kumar & Sachan, 2017).

CP

CP involves consistency in terms of organizational beliefs and values, attitudes towards new technology adoption, compatibility with existing IT infrastructure, and alignment with business strategies. As the Pearson correlation analysis results revealed, CP (r = .442, p < .001) a moderate positive correlation with DOA, and the results was statistically valid. These results were substantiated by previous research where CP was found to be significant to the new technology adoption such as AI, IoT, and Cloud computing (Sayginer & Ercan, 2020; Yap & Chen, 2017; Alkhalil et al., 2017; Salleh & Janczewski, 2016).

MS

MS in this correlational cross-sectional quantitative study was attributed to the positive attitude of top management towards AI adoption, the importance of AI technology in top management's perspective, the considerate approach of management towards AI adoption. The Pearson correlation analysis results revealed that Management Support ($r = .568$, $p < .001$) a strong positive correlation with DOA, and the results was statistically valid. These results were substantiated by previous research where MS was found to be significant to the new technology adoption such as AI, IoT, and Cloud computing (Cruz-Jesus et al., 2019; Saint, & Gutierrez, 2017; Rao, 2018; Usman et al., 2019).

MP

MP in this correlational cross-sectional quantitative study was attributed to the competitor's behavior towards AI adoption and pressure on the organization. As the Pearson correlation analysis results revealed, Mimetic Pressure ($r = .478$, $p < .001$) showed a moderate positive correlation with DOA, and the results was statistically valid. These results were substantiated by previous research where MP was found to be significant to the new technology adoption such as AI, IoT, and Cloud computing (Shahzad et al.,2021; Ikumoro, & Jawad, 2019; Di, & Xia, 2017; Savola et al., 2018).

NP

In this correlational cross-sectional quantitative study, NP was attributed to pressure on the organization due to customers adopting AI-based products, the eagerness of customers to adopt AI-based products, and the threat that customers will shift to other suppliers to adopt AI-based products. The results of Pearson correlation analysis revealed, Normative Pressure ($r = .553$, $p < .001$) showed a strong positive correlation with DOA, and the results was statistically valid. These results were substantiated by previous research where NP was found to be significant to the new technology adoption such as AI, IoT, and Cloud computing (Di & Xia, 2017; Saint, & Gutierrez, 2017; Rao, 2018; Savola et al., 2018).

CL

CL in this correlational cross-sectional quantitative study was attributed to entry-level barriers such as the high cost of AI adoption, long time, and preparation needed for AI adoption at the organizational level. As the Pearson correlation analysis results revealed, CL ($r = .149$, $p > .001$) showed no correlation between Complexity and the decision of AI adoption, and the relationship was statistically not significant. This was not in line with the previous findings where the Complexity negatively impacted the new technology adoption such as AI, IoT, and Cloud Computing (Kandil & et al., 2018; Di, & Xia, 2017; Kurse et al., 2019).

RC

RC in this correlational cross-sectional quantitative study was attributed to AI improving the organization's compliance posture and inherent capabilities within AI solutions to meet the regulatory compliance. The regulatory concern was part of TOE theory. As the Pearson correlation analysis results revealed, RC ($r = .388$, $p < .001$) showed a moderate positive correlation with DOA, and the results was statistically valid. These results were substantiated by previous research where RC was found to be significant to the new technology adoption such as AI, IoT, and Cloud computing (Saint, & Gutierrez, 2017; Almubarak, 2017; Rao, 2018; Usman et al., 2019).

PU

PU in this correlational cross-sectional quantitative study was attributed to the belief that AI will improve the employees' productivity and improve customer service, increasing revenue and profitability. The perceived usefulness was part of TAM theory. The results of Pearson correlation analysis revealed, PU ($r = .412$, $p < .001$) showed a moderate positive correlation with DOA, and the results was statistically valid. These results were substantiated by previous research where PU was found to be significant to the new technology adoption such as AI, IoT, and Cloud computing (Sanchez-Prieto et al., 2019; Ahmed et al., 2020; Kumar & Sachan, 2017; Min et al., 2017).

PEU

PEU in this correlational cross-sectional quantitative study was attributed to the perception that AI adoption will enhance the utilization of IT infrastructure and business applications. AI adoption needs an increase in Application maturity and improved staff availability with the right skillsets. The results of Pearson correlation analysis revealed, PEU ($r = .352$, $p < .001$) showed a moderate positive correlation with DOA, and the results was statistically valid. These results were substantiated by previous research where PEU was found to be significant to the new technology adoption such as AI, IoT, and Cloud computing (Ahmed et al., 2020; Kumar & Sachan, 2017; Min et al., 2017; Suhartanto & Leo, 2018).

Limitations of the Study

Limitations were found during the data collection and data analysis phases. I focused on the correlation of individual independent variables (ITS, RA, CP, MS, MP, NP, CF, RC, PU, and PEU) with the dependent variable (DOA). I chose only 10 constructs from DOI, TOE, and TAM theories. To address this limitation, I selected questions from three prevalidated survey instruments ('Organizational Adoption of Virtual Worlds Survey', 'Cloud Adoption by IT Manager', and 'User Acceptance of Information Technology').

In the survey questionnaire, I avoided the use of free flow text box in three questions. Though it has prohibiting survey participants from sharing the personal information, it did result in the limitation. I did not accept the free flow text for this question as I wanted to avoid receiving unsolicited inputs or sensitive data from the participants. The participants could not share specific information about their job title. Instead of providing the specific information the participants were required to select options such as other management position. Similar was the limitation while specifying industry sector. The participant was required to select other industry sector as option instead of entering the specific text. The information collected about education level also had similar limitation. The participant was required to select other industry sector as option instead of entering the specific text. I categorized participants only into the managerial and non-managerial categories and focused only to specific industry sectors available as options to select.

I used question number six to understand the number of years of experience on the AI technology of the participant. I did not add a screening question to restrict participants with no experience in AI technology. Future studies may gather information from participants with more significant experience in AI technology.

This study's focus was to understand factors impacting or influencing AI adoption in the SME sector in India. Question number 2 in the survey collected information about the industry sector. Most of the participants were part of the IT Services and Financial Industry. In future studies, there can be a particular focus on specific industry sector to get more insights.

Recommendations

I focused on India's SME sector as it is one of the most prominent sectors offering jobs. According to the MSME Ministry of India (2020), as of 10/30/2020, there were 43532 Small enterprises, 9357 number of Medium scale industries, and 721096 Micro enterprises. The AI technology implementation needs a considerable amount of investment thus it might not be suitable for Microenterprises those operate at a very small scale and in a very small setup without the need of the sophisticated IT system and technologies. However, I recommends the future studies focus on these companies as it might provide different insights about the possible technology leverage in a cost effective manner.

I did not prefer specific industry types within the SME during this correlational cross-sectional quantitative study. However, most of the participants were from IT-Service and Financial Services companies. I recommend conducting Industry Sector focused studies where along with technological needs, management aspects, and specific needs of the Industry and insights would be found.

I used three theories (DOI, TOE, and TAM) for this correlational cross-sectional quantitative study. There are many other theories available those can help to understand various aspects of the new technology adoption. I recommend that future researchers use other studies to focus on the only usability, or only implementation, or technology evaluation methodologies and decision-making around it.

According to the MSME Ministry of India (2020), there are 1002757 companies in the MSME sector in India. I conducted a survey involving 152 participants. I recommend that future researchers increase the researcher's scope to Micro Enterprises and try to increase the participant pool. I recommend using secondary data whenever possible if the MSME Ministry of India or Niti Ayog of India conducts some surveys about AI adoption in the MSME sector in India in the future.

I conducted correlational cross-sectional quantitative research to understand how each variable correlated with the dependent variable. I recommend that future studies evaluate how these 10 independent variables interact with each other and if they influence AI adoption decision-making.

During this study, I focused on the SME sector in India. There are other developing countries and developed countries where the SME sector is vital for the economy's growth and contributes to the world economy. I recommend that future researchers conduct similar cross-sectional studies in other countries and other parts of the world. It would help to extend the knowledge gained and help various communities across the world.

Implications

AI is a technology that might have a profound impact on humankind as it directly connects the machine to human beings and can potentially alter many aspects of human contribution within the Industry. The new technology adoption throws difficult challenges to the Industry and society together. It alters the dynamics of product development, product offerings, customer behavior, and many other aspects. Findings of this research extend the knowledge and information found through research to the SME sector in India and other similar countries. As the SME sector is of prime importance for the world economy, these research findings might help the decision-makers within the Industry and the society at large to make an informed decision about AI adoption.

Significance to the Theory

There were three theoretical frameworks (DOI, TOE, and TAM) used during this correlational cross-sectional quantitative study. Out of 10 constructs, RA was solely aligned to DOI theory while ITS, MS, CP, and CL were common to DOI and TOE theory. MP, NP, and RC were aligned to only TOE framework and PU and PEU were part of TAM theory. Six out of 10 independent variables ITS, RA, CP, RC, PU, and PEU showed low positive correlation with the dependent variable DOA. Three independent variables MS, MP, and NP showed the moderate positive correlation with the dependent variable DOA. There was one variable CL that showed no correlation with the dependent variable DOA and was not statistically significant. These findings have supported the

DOI, TOE, and TAM framework's applicability in analyzing the new technology adoption.

Significance to Practice

Small and medium scale enterprises worldwide have been fast embracing new technologies such as Artificial Intelligence and observed various challenges adopting such technologies (Purdy & Daugherty, 2016; Ingalagi et al., 2021; Ing et al., 2020). The technologists and decision-makers in the SME sector in India and other countries may find the results of this correlational cross-sectional quantitative study to make decisions about the AI technology adoption, implementation, and use in their organizations. This study's findings can be a founding factor for the organization-wide or Industry-specific studies within India and other similar countries. The sources cited in chapter 2 of the literature review would also be useful sources to further insight the subject matter to decision-makers within the Industry and academicians or future researchers.

Significance to Social Change

This study revealed that the management support, pressure due to industry partners and competitors, and increased customer expectations about the services are key drivers that positively impact the AI technology adoption within India. The potential implications for the social change extended beyond the SME sector in India as it included factual information about the adoption of new disruptive technologies such as AI that can help reduce business failure. This study's findings would help the SME sector and contribute to making sustainable development possible while enhancing the Industry's performance. The adoption of AI will help the SME sector to come up with novel product offerings that would help to solve critical social problems such as hunger, environment-friendly solutions, and sustainable growth.

Conclusions

AI is 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. This correlational cross-sectional quantitative research study was conducted to understand the correlation between the constructs such as ITS, RA, CP, MS, MP, NP, CL, RC, PU, and PEU and the decision to adopt, implement and use AI technology in the SME sector in India. The theoretical model for this study was based on three theories: DOI, TOE, and TAM.

The DOI theory helped to set the individual perspective about AI adoption. The TOE theory helped to set the organizational perspective from technology, organizational, and environment-related constructs. Whereas TAM theory helped in understanding the perspective of AI technology users from the usability perspective. The earlier research in AI focused on AI technological research, finding the technical solution to the business problem using AI technology, and an impact of AI technology use on employment generation or similar social concerns. I focused on the constructs considered enablers or prohibiting factors for the new technology adoption in an organizational setting.

The data collection for this correlational cross-sectional quantitative research involved using a survey questionnaire derived from three different prevalidated survey instruments ('Organizational Adoption of Virtual Worlds Survey', 'Cloud Adoption by IT Manager', and 'User Acceptance of Information Technology'). The researcher hosted the survey on the online surveying platform Survey Monkey. The participation for this anonymous survey was solicited using the social media platform LinkedIn. 162 participants attempted the survey, and there were 152 complete responses considered for the data analysis.

Data analysis was designed to analyze the correlation between an individual independent variable and the dependent variable. I conducted Pearson correlation analysis testing during the data analysis phase using the IBM SPSS version 25 software. I provided descriptive statistics, including demographic analysis of the variables collected through an online survey that contained 39 questions. There were 67% male participants and 32% female participants, most of whom were either graduate or postgraduate. 84% of participants from the age group 18 to 44 worked mostly in IT-services or financial services sectors. Most of the online survey participants had up to 5 years of experience using or implementing AI technology.

The findings of this correlational cross-sectional quantitative study revealed that three out of 10 independent variables (MS, MP, and NP) had a moderate positive correlation with the dependent variable (DOA). There were six independent variables (ITS, RA, CP, RC, PU, and PEU) that showed a low positive correlation with DOA. One variable CL showed no statistically significant correlation with DOA.

Results from this study may help future researchers, academicians, and scholars by providing a base and guideline for extending the similar new technology adoption-related study to a different cross-section of Industry, geography, or technology sector. I hope that this study may also help decision-makers and technologists in India's SME sector and other geographies evaluate parameters for decision-making about AI technology carefully. Any help to the industry leaders to build new products and innovative services may accelerate the process of bringing a positive social change.

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Appendix A: AI Adoption Survey

Welcome to the Study.

CONSENT FORM

You are invited to take part in a research study about "Understanding Artificial Intelligence adoption, implementation, and use in Small and Medium Enterprises in India". The researcher is inviting employees working in Small and Medium Enterprises in India with having awareness about AI selection, implementation, or use in their industry or in their personal capacity to be in the study. This form is part of a process called "informed consent" to allow you to understand this study before deciding whether to take part.

This study is being conducted by a researcher named "Dipak Sadashiv Jadhav", who is a Ph.D. student at Walden University.

Background Information:
The purpose of the quantitative cross-sectional correlational study is to understand technology related and business environment related factors, impacting adoption of Artificial Intelligence (AI) in the SME sector in India. This research will help the leaders in the SME sector to take an informed decision about AI adoption.

Procedures:
This study involves the following steps:

- The participant attempts the online survey.
- The researcher will close the survey when approximately 150 participants attempt the survey.
- The researcher will collect the data from the survey website and complete the analysis.

Here are some sample questions:

- In my industry sector, there are standardized processes for IT innovation.
- My industry sector has the ability to quickly integrate Artificial Intelligence in existing infrastructure.
- IT strategies in my industry sector support business strategies.

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 at Walden University whether or not you join the study. If you decide to join the study now, you can still change your mind later. You may stop at any time. The researcher seeks 150 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. The aim of this study is to benefit society by the leaders in the SME sector to take an informed decision about AI adoption.

Payment:
No financial benefit 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 your name or identity at any stage of the research. The researcher will not use your personal information 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 is 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 in personal computer. Data will be kept for a period of at least 5 years, as required by the university.

Contacts and Questions:
You can ask questions of the researcher by email on dipak.jadhav@waldenu.edu. If you want to talk privately about your rights as a participant or any negative parts of the study, you can call Walden University's Research Participant Advocate at 612-312-1210. Walden University's approval number for this study is **01-26-021-0580508** and it expires on **January 25, 2022.**

You might wish to retain this consent form for your records. You may ask the researcher or Walden University for a copy at any time using the contact info above.

Obtaining Your Consent

If you feel you understand the study and wish to volunteer, please indicate your consent by proceeding to the first question in the survey.

This has been approved by the Institutional Review Board of
WALDEN UNIVERSITY
as acceptable documentation of the informed consent process and is valid for one year after the stamped date.

Section I		
Item No.	Demographic Information	Value
1.	What best describes your title?	☐ Chief Information Officer (CIO) ☐ Chief Security Officer (CIO) ☐ IT Application Manager ☐ IT Infrastructure Manager ☐ Other IT Management Position
2	In which Industry Sector do you work?	☐ Construction ☐ Education ☐ Energy/Utilities ☐ Financial Services/Banking ☐ Government ☐ Healthcare ☐ IT-Services ☐Other
3	What best describes your gender?	☐ Male ☐ Female ☐ Other
4	How old are you?	☐ 18 to 30

		☐ 31 to 44 ☐ 45 to 60 ☐ More than 60						
5	What is your educational level?	☐ Secondary School ☐ Bachelor's degree ☐ Master's degree ☐ Doctorate degree ☐ Other						
6	How many years of experience do you have implementing or using Artificial Intelligence technologies?	☐ None ☐ Less than 2 years ☐ 2 years to less than 5 years ☐ 5 years or more						
Section II								
Please indicate how much you agree or disagree with each of the following statements based on a scale ranging from 7 (strongly disagree) to 1 (strongly agree)								
Item No.	Item Description	1 Strongly Agree	2 Agree	3 Somewhat agree	4 Neither agree nor disagree	5 Somewhat disagree	6 Disagree	7 Strongly disagree
IT Sophistication (ITS)								
7	In my industry sector, there are standardized processes for IT innovation.	☐	☐	☐	☐	☐	☐	☐
8	My industry sector has the ability to quickly integrate Artificial Intelligence in existing infrastructure.	☐	☐	☐	☐	☐	☐	☐
9	IT strategies in my industry sector support business strategies.	☐	☐	☐	☐	☐	☐	☐
Relative Advantage (RA)								
10	Adopting Artificial Intelligence will allow better communication with customers.	☐	☐	☐	☐	☐	☐	☐
11	Adopting Artificial Intelligence will increase the profitability.	☐	☐	☐	☐	☐	☐	☐
12	Adopting Artificial Intelligence will reduce costs.	☐	☐	☐	☐	☐	☐	☐
13	Adopting Artificial Intelligence will allow to enter new businesses or markets.	☐	☐	☐	☐	☐	☐	☐
14	Adopting Artificial Intelligence will improve the web presence.	☐	☐	☐	☐	☐	☐	☐
Compatibility (CP)								
15	Artificial Intelligence adoption is consistent with organizational beliefs and values in my industry sector.	☐	☐	☐	☐	☐	☐	☐
16	The attitude towards Artificial Intelligence adoption in organizations in my industry sector is favorable.	☐	☐	☐	☐	☐	☐	☐
17	Artificial Intelligence adoption is generally compatible with Information technology (IT) infrastructure.	☐	☐	☐	☐	☐	☐	☐
18	Artificial Intelligence adoption is consistent with the business strategy	☐	☐	☐	☐	☐	☐	☐
Management Support (MS)								
19	In my industry sector, top management is interested in adopting Artificial Intelligence	☐	☐	☐	☐	☐	☐	☐
20	In my industry sector, top management considers Artificial Intelligence adoption important	☐	☐	☐	☐	☐	☐	☐
21	In my industry sector, top management shows the support in Artificial Intelligence adoption	☐	☐	☐	☐	☐	☐	☐
Mimetic Pressure (MP)								
22	Many of the competitors are currently	☐	☐	☐	☐	☐	☐	☐

	adopting or will be adopting Artificial Intelligence in near future							
23	Competitors that have adopted Artificial Intelligence are perceived favorably by others in our industry	☐	☐	☐	☐	☐	☐	☐
Normative Pressure (NP)								
24	Many of the customers are currently adopting or will be adopting Artificial Intelligence in near future	☐	☐	☐	☐	☐	☐	☐
25	Many of the suppliers are currently adopting or will be adopting Artificial Intelligence in near future	☐	☐	☐	☐	☐	☐	☐
26	Customers can switch to another company for similar services/products without much difficulty	☐	☐	☐	☐	☐	☐	☐
Complexity (CL)								
27	Adopting Artificial Intelligence innovation involves high cost.	☐	☐	☐	☐	☐	☐	☐
28	Adopting Artificial Intelligence innovation takes long time.	☐	☐	☐	☐	☐	☐	☐
Regulatory Concerns (RC)								
29	Artificial Intelligence technology does/will significantly improve IT compliance.	☐	☐	☐	☐	☐	☐	☐
30	Artificial Intelligence is inherently reliable and meets IT compliance requirement.	☐	☐	☐	☐	☐	☐	☐
Perceived Usefulness (PU)								
31	Artificial Intelligence can increase revenue and profitability.	☐	☐	☐	☐	☐	☐	☐
32	Artificial Intelligence can increase employee productivity	☐	☐	☐	☐	☐	☐	☐
33	Artificial Intelligence can improve customer service	☐	☐	☐	☐	☐	☐	☐
Perceived Ease of Use [PEU]								
34	Adopting Artificial Intelligence innovation lacks application maturity.	☐	☐	☐	☐	☐	☐	☐
35	Inappropriate staffing and personnel shortfalls are big challenges for Artificial Intelligence adoption.	☐	☐	☐	☐	☐	☐	☐
36	Artificial Intelligence can better utilize IT resources and applications	☐	☐	☐	☐	☐	☐	☐
Decision to Adopt Artificial Intelligence (DOA)								
37	Most of the organizations in my industry intent to adopt Artificial Intelligence	☐	☐	☐	☐	☐	☐	☐
38	It is likely that organization in my industry sector will take steps to adopt Artificial Intelligence in future.	☐	☐	☐	☐	☐	☐	☐
39	In my opinion how soon organizations in my industry sector will adopt Artificial Intelligence?	☐ Already use Artificial Intelligence ☐ Less than 6 months ☐ 6 to 12 months ☐ 13 to 24 months ☐ More than 24 months ☐ No plans ☐ Don’t know						

Appendix B: Approvals for Using Survey Instrument

02/11/2019 Mail - Dipak Jadhav - Outlook

RE: Permission for your survey questionnaire

Tom Yoon <yoont@wcsu.edu>
Mon 10/21/2019 10:16 PM
To: Dipak Jadhav <dipak.jadhav@waldenu.edu>

Hi Dipak,

Yes, you have my permission to use the survey instrument.
Your topic sounds very interesting. Good luck with your dissertation.

Thanks,

Tom Yoon, Ph.D.
Professor, MIS Department
Ancell School of Business
Western Connecticut State University
yoont@wcsu.edu
203-837-3963

John Opala <john@opalanet.com>
Mon 8/24/2020 10:28 PM
To: Dipak Jadhav

Hi Dipak,
You have my permission to use the Instrument.

Thanks,
John

Dr. Omondi John Opala, PhD| CISM | CISSP| C|CISO |ITIL |CCNP |CRISC
Tel: 919- 607-9517
Email: john@opalanet.com
LinkedIn

Gordon Davis <davis001@umn.edu>
Fri 8/21/2020 6:58 AM
To: Dipak Jadhav

The instrument is in the public domain. You may use it in your research.
Gordon B Davis

Appendix C: Permission to Use Figure 1

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Title: Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings

Author: Louis G. Tornatzky

Publication: Engineering Management, IEEE Transactions on

Publisher: IEEE

Date: Feb. 1982

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Appendix D: Permission to Use Figure 2

RE: Urgent: Permission for using the copyright material for academic purpose

You replied on Sun 9/6/2020 7:22 AM

Rachel Twombly <RTwombly@rowman.com>
Sat 9/5/2020 8:51 AM
To: Dipak Jadhav

Dear Dipak,

I apologize for the delay. Permission is granted non-exclusive and no fee to reprint the figure "The technology-organization-environment framework" from *Processes of Technological Innovation* in your academic research proposal, provided that the research is only published in a research publication. If you wish to publish your research commercially, a fee of $45 will be required. Please cite by title, author, publisher, all rights reserved.

Best,
Rachel

Rachel Twombly
Rights & Permissions Assistant
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T: 301-459-3366 ext. 5420
F: 301-429-5748

Appendix E: Social Media Post for Requesting Participation in the Survey

Dear All,

I am writing this post to request your participation in an online survey for my academic research project.

About the researcher:

A working professional with ~21+ years of experience in Information Technology (IT Infrastructure Management, Business Application Development and Maintenance) in Financial Sector. Currently pursuing Doctorate in Management, from Walden University, USA. I am working on a research project "Understanding Artificial Intelligence adoption, implementation, and use in Small and Medium Enterprises (SME) in India".

Brief details of the research project:

The purpose of the quantitative cross-sectional correlational study is to understand technology related and business environment related factors, impacting adoption of Artificial Intelligence (AI) in the SME sector in India. This research will help the leaders in the SME sector to take an informed decision about AI adoption.

Expected participants (Entry and Exit Criteria):

- The survey is voluntary and does not include any monetary benefits.
- The participant should be having awareness about AI selection, implementation, or use in their industry or in their personal capacity.
- The survey participant should be working in the SME sector in India.
- A participant can exit the survey at any time during the participation before completing the survey.
- No personal / critical / commercial / business information will be captured during the survey.
- The researcher expects to collect the data from approximately 150 participants.
- There researcher does not expect any risk or discomfort to the participant by participating in the survey.

Details about the Survey:

A web-based survey hosted on the Survey Monkey platform. It contains 40 close ended questions. The participant need to spend approximately maximum 30 minutes to complete the survey. The questions are intended towards understanding the business factors and their impact on the AI adoption and related decision making.

Survey Link

Please free to contact me for any questions or clarifications needed on
Dipak.jadhav@waldenu.edu

Thanks in advance for your participation…!

Yours sincerely

Dipak Jadhav

Appendix F: Social Media Post Announcing Closure of the Survey

Dear All,

Thank you very much for your overwhelming response to the survey. I have received the response from the required number of participants. The survey will be closed now.

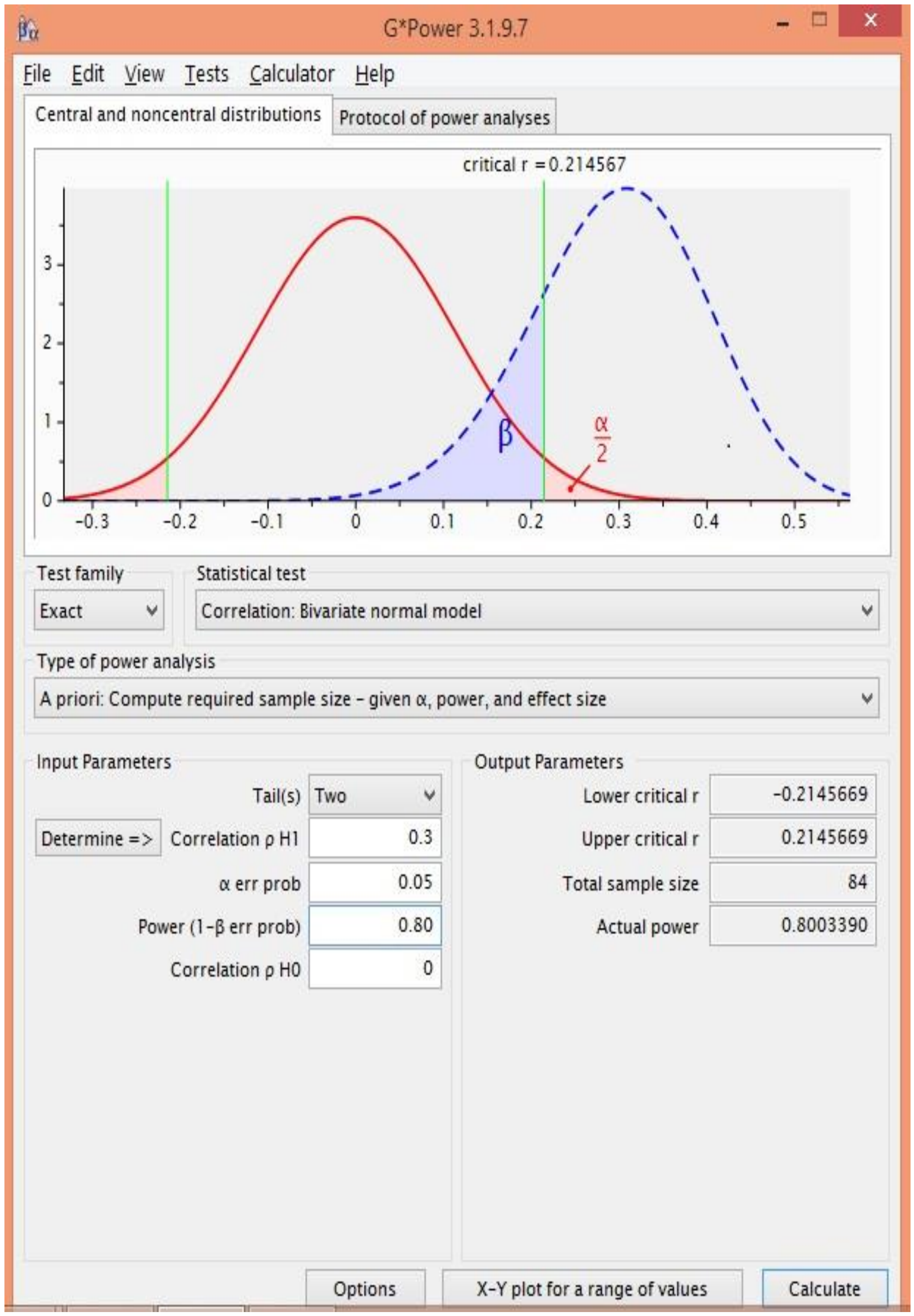
Thanks for all the participants and also those who encouraged others to participate in the survey. Your participation will be of great help to me in achieving the research goals.

Thanks you very much again for your participation…!

Yours sincerely

Dipak Jadhav

Appendix G: G*Power Analysis for Sample Size Calculation



Appendix H: Codes of Construct Items

Question No.	Question	Variable assigned
7	In my industry sector, there are standardized processes for IT innovation.	ITS1
8	My industry sector has the ability to quickly integrate Artificial Intelligence in existing infrastructure.	ITS2
9	IT strategies in my industry sector support business strategies.	ITS3
10	Adopting Artificial Intelligence will allow better communication with customers.	RA1
11	Adopting Artificial Intelligence will increase the profitability.	RA2
12	Adopting Artificial Intelligence will reduce costs.	RA3
13	Adopting Artificial Intelligence will allow to enter new businesses or markets.	RA4
14	Adopting Artificial Intelligence will improve the web presence.	RA5
15	Artificial Intelligence adoption is consistent with organizational beliefs and values in my industry sector.	CP1
16	The attitude towards Artificial Intelligence adoption in organizations in my industry sector is favorable.	CP2
17	Artificial Intelligence adoption is generally compatible with Information technology (IT) infrastructure.	CP3
18	Artificial Intelligence adoption is consistent with the business strategy	CP4
19	In my industry sector, top management is interested in adopting Artificial Intelligence	MS1
20	In my industry sector, top management considers Artificial Intelligence adoption important	MS2
21	In my industry sector, top management shows the support in Artificial Intelligence adoption	MS3
22	Many of the competitors are currently adopting or will be adopting Artificial Intelligence in near future	MP1
23	Competitors that have adopted Artificial Intelligence are perceived favorably by others in our industry	MP2
24	Many of the customers are currently adopting or will be adopting Artificial Intelligence in near future	NP1
25	Many of the suppliers are currently adopting or will be adopting Artificial Intelligence in near future	NP2
26	Customers can switch to another company for similar	NP3

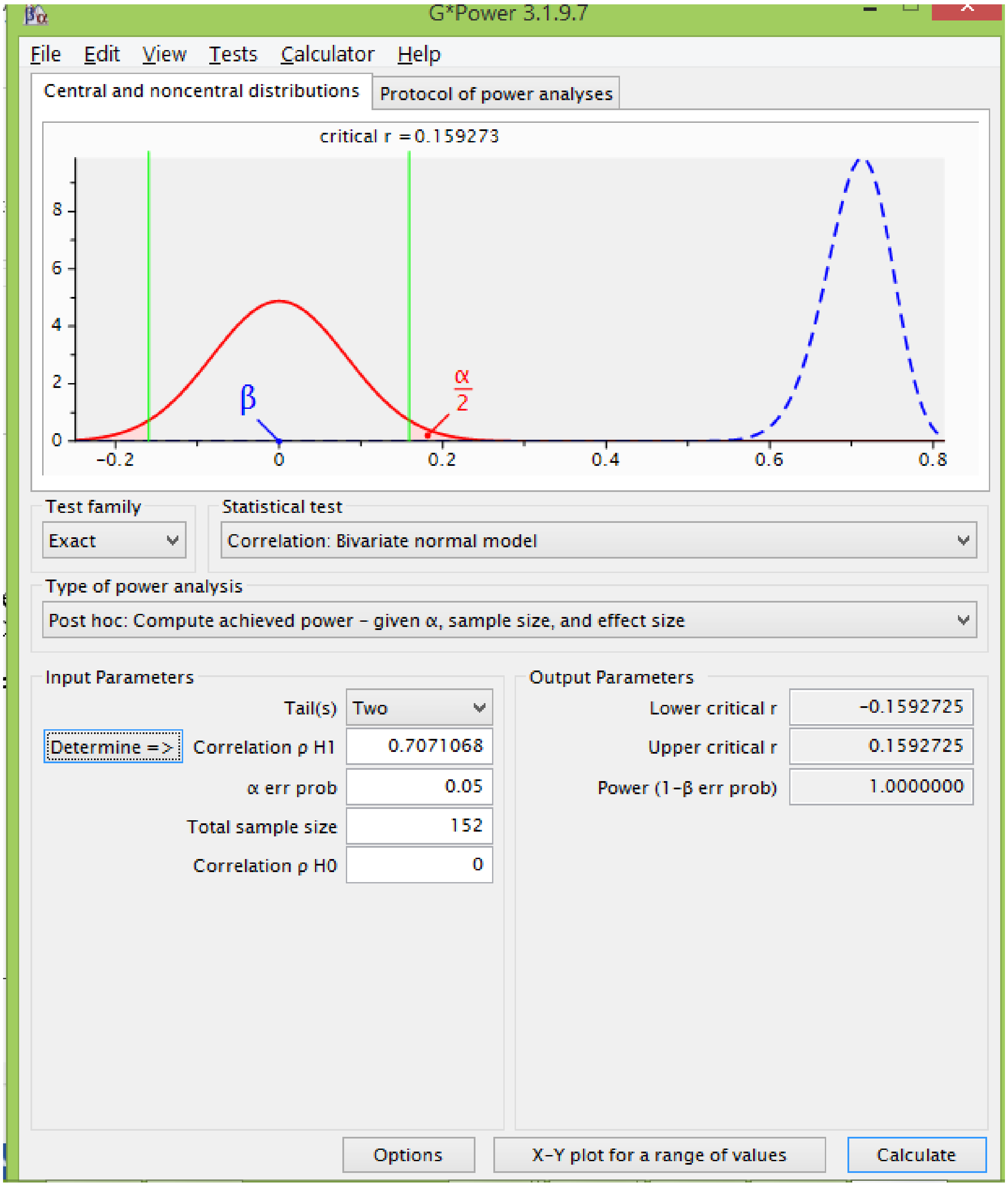
	services/products without much difficulty	
27	Adopting Artificial Intelligence innovation involves high cost.	CL1
28	Adopting Artificial Intelligence innovation takes long time.	CL2
29	Artificial Intelligence technology does/will significantly improve IT compliance.	REG1
30	Artificial Intelligence is inherently reliable and meets IT compliance requirement.	REG2
31	Artificial Intelligence can increase revenue and profitability.	PU1
32	Artificial Intelligence can increase employee productivity	PU2
33	Artificial Intelligence can improve customer service	PU3
34	Adopting Artificial Intelligence innovation lacks application maturity.	PEU1
35	Inappropriate staffing and personnel shortfalls are big challenges for Artificial Intelligence adoption.	PEU2
36	Artificial Intelligence can better utilize IT resources and applications	PEU3
37	Most of the organizations in my industry intent to adopt Artificial Intelligence	DOA1
38	It is likely that organization in my industry sector will take steps to adopt Artificial Intelligence in future.	DOA2
39	In my opinion how soon organizations in my industry sector will adopt Artificial Intelligence?	DOA3

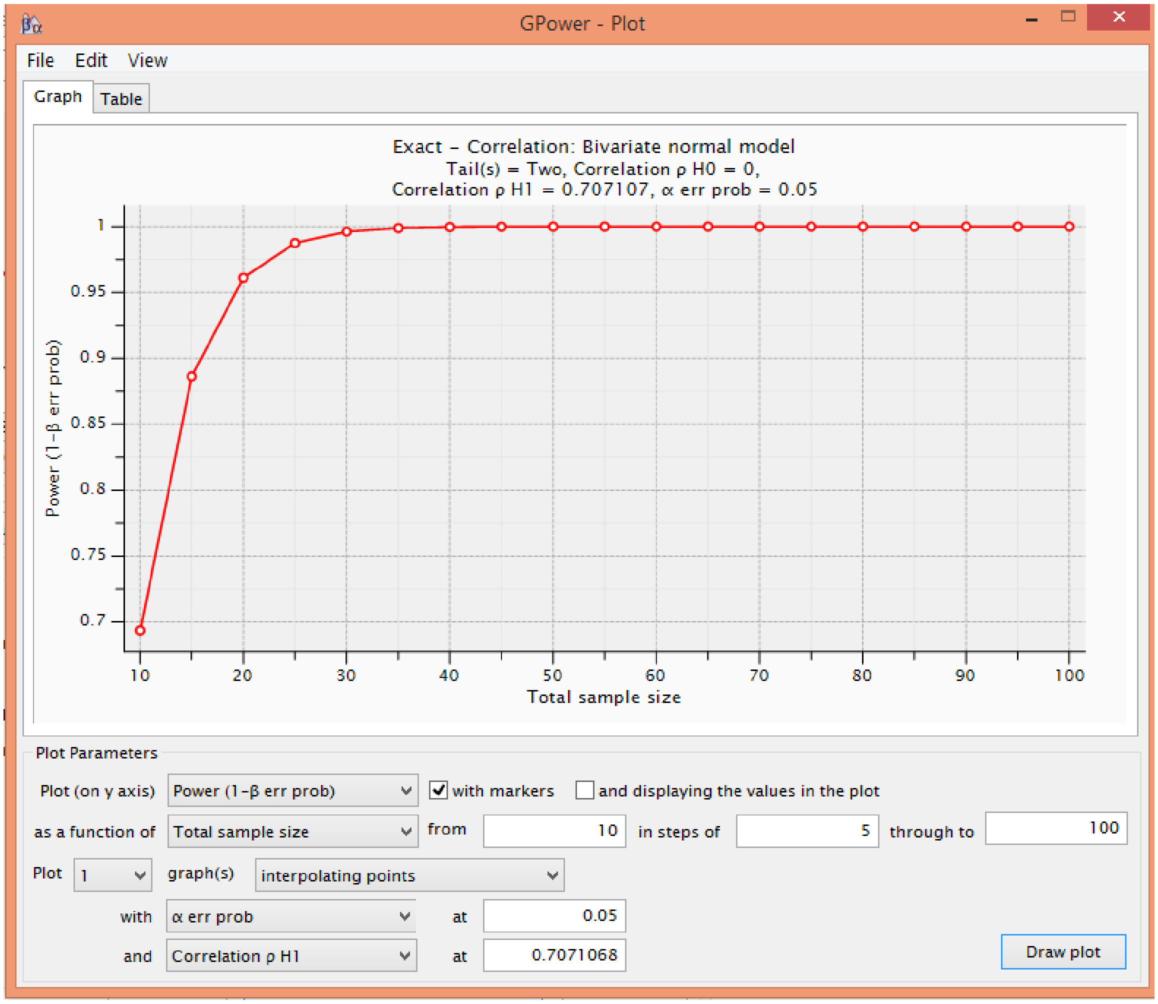
Appendix I: Post Hoc Power Analysis Results

[1] -- *Sunday, May 02, 2021 -- 11:52:35*

Exact – Correlation: Bivariate normal model

Options:	exact distribution		
Analysis:	Post hoc: Compute achieved power		
Input:	Tail(s)	=	Two
	Correlation ρ H1	=	0.7071068
	α err prob	=	0.05
	Total sample size	=	152
	Correlation ρ H0	=	0
Output:	Lower critical r	=	−0.1592725
	Upper critical r	=	0.1592725
	Power (1−β err prob)	=	1.0000000


G*Power 3.1.9.7
File Edit View Tests Calculator Help
Central and noncentral distributions
Protocol of power analyses
critical r = 0.159273
β
α/2
-0.2 0 0.2 0.4 0.6 0.8
0 2 4 6 8
Test family
Exact
Statistical test
Correlation: Bivariate normal model
Type of power analysis
Post hoc: Compute achieved power – given α, sample size, and effect size
Input Parameters
Tail(s) Two
Determine =>
Correlation ρ H1 0.7071068
α err prob 0.05
Total sample size 152
Correlation ρ H0 0
Output Parameters
Lower critical r -0.1592725
Upper critical r 0.1592725
Power (1-β err prob) 1.0000000
Options
X-Y plot for a range of values
Calculate


GPower - Plot
File Edit View
Graph Table
Exact – Correlation: Bivariate normal model
Tail(s) = Two, Correlation ρ H0 = 0,
Correlation ρ H1 = 0.707107, α err prob = 0.05
Power (1-β err prob)
1
0.95
0.9
0.85
0.8
0.75
0.7
10 20 30 40 50 60 70 80 90 100
Total sample size
Plot Parameters
Plot (on y axis) Power (1-β err prob)
with markers
and displaying the values in the plot
as a function of Total sample size from 10 in steps of 5 through to 100
Plot 1 graph(s) interpolating points
with α err prob at 0.05
and Correlation ρ H1 at 0.7071068
Draw plot