UNDERSTANDING SCOPE AND CHALLENGES OF ADOPTION & IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE IN THE INDIAN SMALL AND MEDIUM-SCALE TEXTILE INDUSTRY

by

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UNDERSTANDING SCOPE AND CHALLENGES OF ADOPTION & IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE IN THE INDIAN SMALL AND MEDIUM-SCALE TEXTILE INDUSTRY

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Dedication

I sincerely dedicate this work to my family, whose unwavering support has served as my pillar of support during this journey.

To my parents, **Prakash M. H.** and **Asha B. R.**, whose values, guidance, and sacrifices have laid the groundwork for my achievements. Their encouragement and belief in me have motivated me through every step.

To my beloved wife, **Maithreyee R Rao**, for her patience, understanding, and steadfast support. Her companionship has given me the strength and balance to pursue this dream wholeheartedly.

To my sister, **Pooja** , and brother-in-law, **Nandan**, for their constant encouragement and support, which have been a source of strength and joy. And to my little niece, **Charvi**, whose bright smiles and playful spirit remind me of the simple joys in life.

Thank you all for your boundless love and faith in me.

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To my parents, my beloved wife, and in-laws, I owe my deepest gratitude. Their endless support, understanding, and love have been my foundation throughout this journey. Their sacrifices and belief in me have made this achievement possible.

Abstract

Understanding Scope and Challenges of Adoption & Implementation of Artificial Intelligence in the Indian Small and Medium-Scale Textile Industry

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This research investigates how small and medium-sized enterprises (SMEs) in India's textile sector, which is vital to the country's economy, are implementing and utilising artificial intelligence (AI). AI has the potential to significantly increase productivity and competitiveness in this industry. Numerous textile SMEs have been hesitant to embrace AI owing to obstacles including a lack of awareness regarding its advantages, apprehensions about expenses, technological intricacies, and inadequate technical expertise. This research seeks to evaluate the present status of AI implementation in Indian textile SMEs, identify the principal factors affecting AI utilisation, and comprehend the challenges encountered by these enterprises. By combining both data analysis and real-world insights, the study offers practical recommendations to policymakers, industry leaders, and researchers for developing strategies that support AI integration in this sector.

Recent data indicate that the textile industry employs around 45 million individuals countrywide, including 3.52 million handloom workers, highlighting its importance to India. During the fiscal year 2018-19, textiles accounted for 7% of India's industrial output by value. The sector has garnered substantial investments, particularly in coloured and printed textiles. From March 2000 to April 2021, the sector attracted Foreign Direct Investment (FDI) amounting to USD 3.75 billion. These statistics emphasise the textile and clothing sector's vital contribution to employment generation, economic expansion, and investment attraction. Incorporating AI into this sector can create more potential for innovation and advancement, helping both the textile industry and the Indian economy overall.

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Chapter 1: INTRODUCTION

1.1 Introduction

The textile industry is the sector of manufacturing that produces textiles, which are defined as materials made from natural or synthetic fibres. The textile industry includes both the production of yarn for fabric creation and the production of finished textiles, such as apparel, home goods, and other fabric-based products.

The apparel industry is a subdivision of the textile sector that concentrates on the manufacturing of garments and related items. It includes the design, manufacturing, and marketing of apparel and accessories for children, women, and men. The apparel industry comprises various subsectors, such as casual wear, formal wear, sportswear, and outerwear.

The textile industry and the apparel industry both encompass the production and processing of fibres; however, the apparel industry is primarily concerned with the creation of finished garments and accessories.

The textile and apparel sector is among the most significant and varied industries in the global economy. It includes all aspects from raw material production to finished product manufacturing, significantly contributing to employment opportunities and the creation of consumer goods globally. This literature review seeks to present a comprehensive overview of the global textile and apparel industry, its present condition, and its future prospects.

The textile and apparel industry ranks among the largest and most vital sectors globally, significantly contributing to the economy and employing millions of individuals. The industry consists of multiple segments, such as spinning, weaving, knitting, dyeing, printing, and finishing. The industry includes the production of various apparel items, such as clothing, footwear, and accessories (Hines & Bruce, 2007).

In recent years, the textile and apparel industry has experienced substantial transformations and encountered various challenges, such as heightened global competition, escalating production costs, and the imperative to implement sustainable and ethical practices. To tackle these challenges, the industry has embraced new technologies and innovative methodologies, including the implementation of Industry 4.0 technologies such as automation, robotics, and artificial intelligence (AI) (Ko & Kim, 2019).

Numerous studies have emphasised the prospective advantages of implementing Industry 4.0 technologies in the textile and apparel sector, such as heightened productivity, augmented efficiency, diminished costs, and improved quality control (Khan et al., 2021; Kuo et al., 2019). Nonetheless, challenges accompany the adoption of these technologies, such as elevated implementation costs, a deficiency of skilled labour, and apprehensions regarding data privacy and security (Majumdar et al., 2021).

The adoption of Industry 4.0 technologies in the textile and apparel industry is not limited to developed countries, as emerging economies like India are also embracing these technologies to enhance their competitiveness and productivity. Studies have shown that Indian textile manufacturers are increasingly investing in automation, robotics, and AI to improve their processes and products (Jadhav, 2020; Rajendran & Jeyakumar, 2021).

Notwithstanding the prospective advantages of Industry 4.0 technologies, apprehensions persist regarding their effects on employment and labour conditions within the textile and apparel sector. The increasing prevalence of automation and robotics poses a risk of job displacement, especially in low-skilled and labour-intensive roles (Hofmann & Rüsch, 2018). Consequently, it is imperative for industry stakeholders to tackle these issues and guarantee that the implementation of Industry 4.0 technology is supplemented by initiatives that support workers and foster responsible business practices (Jung & Lee, 2021).

1.2 Problem Statement

Limited research has been conducted on the extent and difficulties of integrating AI within this specific industry. This indicates a possible deficiency in comprehension regarding the potential applications of AI in the textile and clothing sector, together with the challenges that must be addressed for successful implementation.

A possible difficulty is the industry's seasonal characteristics. The textile and apparel sector functions with restricted foresight, rendering it challenging to anticipate product demand and formulate long-term strategies. This complicates the justification for investing in AI technology, which may entail substantial initial expenses and necessitate continuous upkeep.

The expense associated with the implementation of AI systems may provide another hurdle. The research, hardware, and implementation of AI technology can be costly, especially for smaller organisations. Furthermore, the upkeep of AI systems might pose technical difficulties, necessitating specialised knowledge and money.

Notwithstanding these hurdles, the implementation of AI in the textile and garment business presents potential advantages. AI has the ability to enhance efficiency and production, minimise waste and inefficiencies, and facilitate more informed decision-making through data analysis. Nonetheless, it is crucial to meticulously evaluate the distinct requirements and objectives of the sector, along with the prospective expenses and obstacles, prior to the deployment of any AI solutions.

The study will concentrate on comprehending the parameters and prerequisites for the integration of artificial intelligence (AI) in the micro, small, and medium textile and apparel sector. The research will seek to identify specific parts of the sector that could benefit from AI, along with the industry's particular demands and objectives for AI implementation. This information will be collected from the stakeholders, including individuals directly engaged in the industry, such as owners, managers, and employees.

The research will assess the scope and requirements for AI deployment, as well as the potential hurdles and concerns regarding its adoption by industry members. This may encompass concerns regarding expenses, technical proficiency, and the possible effects on employment, among other factors. By comprehending these issues and concerns, the researchers can more effectively identify the obstacles to adoption and explore methods to surmount them.

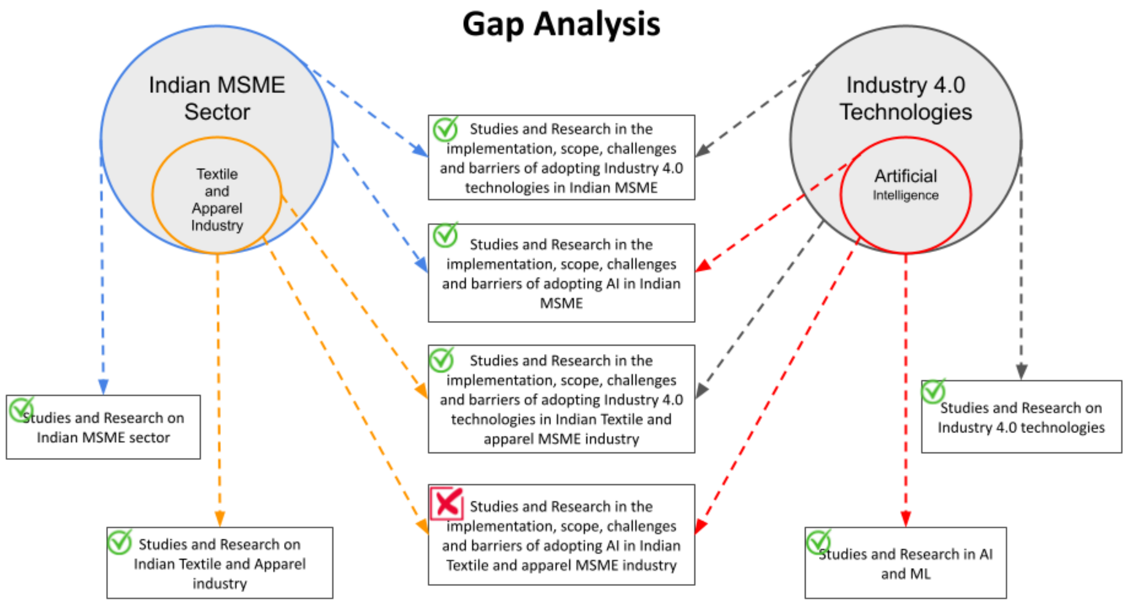

Figure 1.1
Gap Analysis from the Literature Review

1.3 Research Objectives / Purpose of the Study

The objective of the research is to develop a reference document for solution providers collaborating with SMEs in the area. This study will offer a comprehensive analysis of Indian textile and apparel SMEs, assisting solution providers in making educated judgements regarding solution implementation in the sector.

The study will concentrate on determining the statistical correlations among several aspects that influence the decision-making process regarding the adoption of AI in Indian textile and apparel SMEs. The study aims to identify the principal elements that affect

SMEs' decisions to embrace AI technologies and the interrelations among these factors. By comprehending these relationships, solution providers can more effectively customise their offerings to meet the requirements of SMEs in the industry.

This research will examine the factors influencing AI adoption in Indian textile and apparel SMEs, as well as the potential for AI application within the sector. The study will aim to identify the sectors within textile and apparel SMEs where AI technologies may be optimally applied, along with the associated benefits and constraints of such implementation. By comprehending the extent of AI integration in the sector, solution providers may more effectively build and provide solutions that cater to the distinct needs and difficulties of SMEs in the Indian textile and apparel industry.

1.4 Research Significance

Recently, the influence of Artificial Intelligence (AI) has been significant, transforming our cognition, labour, and interactions. It has infiltrated nearly every sector and has become an essential component of our everyday existence. As we anticipate the future, it is clear that AI is an inexorable force that demands attention.

Nevertheless, the implementation of AI and other Industry 4.0 technologies among conventional textile and clothing SMEs in India remains ongoing. Small and medium-sized firms are confronting the difficulties of adopting new technologies and incorporating them into their operations. It is essential for AI solution providers in India to thoroughly comprehend the elements that affect and restrict the adoption of AI within the Indian Textile SME sector. Consequently, they can proficiently develop AI solutions that tackle the distinct issues and demands of the sector.

Despite extensive research on AI application in Indian sectors, there exists a significant lack in studies addressing the unique scope and problems of AI integration in Indian Textile and Apparel SMEs. This research initiative seeks to address that gap and provide a foundational reference for Indian Textile and Apparel SMEs contemplating the integration of AI. It will offer essential insights, ideas, and best practices for these SMEs to effectively incorporate AI into their business processes and operations.

This research will be vital for AI solution suppliers, providing them with a thorough comprehension of the industry's requirements and obstacles. Equipped with this knowledge, they may customise their AI solutions to adequately address the needs of Indian Textile and Apparel SMEs. This research seeks to connect AI technology with the specific needs of the industry to enable successful AI implementation and foster innovation within the sector.

1.5 Research Questions & Hypotheses

The study will employ the Unified Theory of Acceptance and Use of Technology (UTAUT) framework, integrating components like Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Habit (HB), and Price Value (PV).

The study will involve the development of research questions designed to investigate the correlations between the seven aforementioned independent variables and the dependent variable. An online survey instrument will be utilised to gather data on the dependent and independent variables. The majority of factors will be evaluated utilising a seven-point Likert Scale derived from participants' responses.

The Primary Research Question will be

RQ: What are the different factors that facilitate or hinder the Decision to Adopt and Implement AI (DAI) in the Textile and Apparel SME sector in India?

The following secondary research questions were formulated based on the constructs of the UTUAT theory in order to examine the impact of independent variables on the dependent variable.

SQ1: Does PE have any statistically significant correlation with DAI in the Textile and Apparel SME sector in India?

- H01: PE does not have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India.
- Ha1: PE does have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India

SQ2: Does EE have any statistically significant correlation with DAI in the Textile and Apparel SME sector in India?

- H02: EE does not have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India.
- Ha2: PE does have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India

SQ3: Does SI have any statistically significant correlation with DAI in the Textile and Apparel SME sector in India?

- H03: SI does not have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India.
- Ha3: SI does have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India

SQ4: Does FC have any statistically significant correlation with DAI in the Textile and Apparel SME sector in India?

- H04: FC does not have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India.
- Ha4: FC does have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India

SQ5: Does HM have any statistically significant correlation with DAI in the Textile and Apparel SME sector in India?

- H05: HM does not have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India.
- Ha5: HM does have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India

SQ7: Does PV have any statistically significant correlation with DAI in the Textile and Apparel SME sector in India?

- H07: PV does not have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India.
- Ha7: PV does have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India

1.6 Summary

The primary objectives of the study are to investigate the challenges faced by SMEs in integrating AI into their operations and to identify the key factors that either enable or hinder this process. The study examines dimensions including Performance Expectancy, Effort Expectancy, Social Influence, Facility Condition, Price Value, and Hedonic Motivation through the application of the Unified Theory of Acceptance and Use of Technology (UTAUT) paradigm. These structures are examined to comprehend their influence on the decision-making process regarding AI adoption.

The research used a correlational cross-sectional quantitative approach, gathering data from professionals in the textile sector, specifically targeting SME owners, managers, and technical personnel. The study identifies numerous technological, organisational, and market-driven obstacles affecting AI adoption, offering insights into strategies for overcoming these hurdles to promote broader use of AI.

This research seeks to furnish AI implementation businesses with a comprehensive understanding of the problems and prospects within the Indian SME textile sector. This report provides insights into the aspects influencing AI adoption, enabling AI solution vendors to evaluate and reassess their existing deployment strategies and models. The results can assist them in customising their AI solutions to address the specific requirements of SMEs in the textile sector, facilitating seamless integration and enhanced utilisation of AI technology.

AI companies should develop more targeted strategies to enhance the success rate of AI adoption by tackling specific obstacles such as cost, infrastructural limitations, and the demand for a qualified workforce. This research advocates for AI providers to collaborate with SMEs to develop realistic and scalable AI solutions that enhance business growth and competitiveness, hence fostering broader technological progress in the Indian textile industry.

1.7 Thesis Structure

This thesis comprises five principal chapters, each concentrating on distinct facets of the research regarding the adoption and implementation of Artificial Intelligence (AI) inside the Indian small and medium-sized textile sector. The framework presents a coherent progression from the introduction of the research issue to the examination of the results and their implications for AI integration in the textile sector.

Chapter 1: Introduction

This chapter introduces the research topic and highlights the problem statement, explaining the gap in AI adoption in the Indian textile sector. It outlines the research objectives, questions, and hypotheses, providing a roadmap for the study. The significance of the research is discussed along with the research design, offering an understanding of the methodology applied. The chapter concludes with an overview of the thesis structure.

Chapter 2: Literature Review

This chapter offers a comprehensive analysis of the current literature regarding the textile and clothing sector, encompassing its elements, the worldwide market, and the effects of COVID-19. It examines the global adoption of Industry 4.0, specifically within the textile sector, addressing both the advantages and obstacles associated with its implementation. This chapter analyses the MSME sector in India and investigates the implementation of AI within the Indian textile industry, featuring case studies on applications such as fabric defect detection, predictive analytics, and inventory management. The literature evaluation situates the research within contemporary industry trends and advancements.

Chapter 3: Research Methodology

This chapter delineates the theoretical framework and technique employed in the investigation. It delineates the research methodology, target population, sample techniques, and the data collection tools utilised in the study. The operationalisation of research constructs and data analysis methodologies is examined, providing a comprehensive comprehension of the research process. Ethical considerations in the execution of the research are also examined.

Chapter 4: Results

This chapter delineates the findings of the investigation. The process commences with data gathering and preparation, succeeded by statistical analyses to extract significant insights. The chapter elucidates the study's findings using diverse data analysis methodologies and examines the outcomes in connection with the research aims and enquiries. The chapter's conclusion provides a succinct overview of the principal findings.

Chapter 5: Discussion, Conclusions, and Recommendations

This concluding chapter analyses the study's results concerning the research questions and objectives. The text addresses the study's limitations and provides suggestions for future research and practical implementations. This chapter examines the ramifications of AI implementation in the textile and apparel SME sector, specifically in India, and closes with insights obtained from the research.

The purpose of this thesis is to provide practitioners, researchers, and policymakers in the textile industry with valuable insights by methodically addressing the scope, problems, and possibilities of artificial intelligence adoption in the Indian textile sector.

Chapter 2. LITERATURE REVIEW

In this section, we will go through the concepts and previous works done on which the current research will be based. A brief overview of the works done in the area of AI implementation in Small and Medium Scale Industries, Challenges in Ai adoption in Indian SMEs and the Scope of technology adoption in the Indian Textile industry will be discussed.

2.1 Textile and Apparel Industry

2.1.1 Introduction

The textile industry is the manufacturing sector that produces textiles, defined as materials composed of natural or synthetic fibres. The textile business includes the production of yarn for fabric and the manufacturing of completed textiles, such as clothing, home goods, and other fabric-based things.

The apparel industry is a subdivision of the textile sector that concentrates on the manufacturing of garments and related items. It encompasses the design, production, and marketing of apparel and accessories for men, women, and children. The apparel industry comprises various subsectors, such as casual wear, formal dress, sportswear, and outerwear.

The textile business and the apparel industry both encompass the production and processing of fibres; however, the apparel industry is primarily concentrated on the creation of finished garments and accessories.

The textile and apparel sector is among the most significant and varied industries in the global economy. It includes all processes from raw material production to final product manufacturing, significantly contributing to employment opportunities and the creation of consumer goods globally. This literature study is to present a comprehensive picture of the worldwide textile and clothing industry, including its current condition and future prospects.

The textile and garment business ranks among the largest and most vital sectors globally, significantly contributing to the economy and employing millions of individuals. The industry consists of multiple parts, such as spinning, weaving, knitting, dyeing, printing, and finishing. The industry include the manufacture of several garment goods, including clothing, footwear, and accessories (Hines & Bruce, 2007).

In recent years, the textile and garment sector has experienced substantial transformations and encountered various obstacles, such as heightened global rivalry, escalating production costs, and the imperative to implement sustainable and ethical standards. In response to these issues, the industry has embraced new technologies and innovative methodologies, including the implementation of Industry 4.0 technologies such as automation, robots, and artificial intelligence (AI) (Ko & Kim, 2019).

Numerous studies have underscored the prospective advantages of implementing Industry 4.0 technologies in the textile and apparel sector, such as augmented productivity, heightened efficiency, diminished prices, and improved quality control (Khan et al., 2021; Kuo et al., 2019). Nonetheless, obstacles accompany the use of these technologies, such as elevated installation costs, a shortage of experienced personnel, and apprehensions over data privacy and security (Majumdar et al., 2021).

The implementation of Industry 4.0 technologies in the textile and apparel sector is not exclusive to industrialised nations; emerging economies such as India are likewise adopting similar technologies to improve their competitiveness and productivity. Research indicates that Indian textile producers are progressively investing in automation, robotics, and artificial intelligence to enhance their processes and products (Jadhav, 2020; Rajendran & Jeyakumar, 2021).

Although Industry 4.0 technologies provide significant advantages, there are apprehensions over their effects on employment and labour conditions within the textile and clothing sector. The increasing prevalence of automation and robotics poses a risk of job displacement, especially in low-skilled and labour-intensive roles (Hofmann & Rüsch, 2018). Consequently, it is imperative for industry stakeholders to tackle these issues and guarantee that the implementation of Industry 4.0 technology is supplemented by initiatives that support employees and foster responsible business practices (Jung & Lee, 2021).

2.1.2 Components of the Textile and Apparel Industry

The textile and apparel industry is a multifaceted sector encompassing a range of elements, from fibre manufacturing to retail distribution. Recent years have witnessed an increasing interest in analysing the various components of this business to enhance comprehension of its dynamics, challenges, and prospects. This literature study seeks to delineate the fundamental elements of the textile and apparel sector, grounded in the current research within this domain.

- Fibre manufacturing

Fibre production constitutes the initial phase of the textile and garment supply chain, wherein natural and synthetic fibres are derived from raw materials such cotton, wool, silk, and polyester. Research by Textile World indicates that the global fibre market was valued at USD 210.3 billion in 2020 and is anticipated to reach USD 291.1 billion by 2027, with a compound annual growth rate (CAGR) of 4.3% throughout the forecast period. The fibre production sector is mostly controlled by a limited number of significant entities, including Cotton Incorporated, Lenzing AG, and Invista, which allocate substantial resources to research and development and innovation to enhance the quality, sustainability, and efficiency of their offerings. Nonetheless, fibre production encounters numerous obstacles, including resource depletion, pollution, and abuses of labour rights, necessitating ongoing efforts for mitigation and resolution.

- Yarn manufacturing

The manufacturing of yarn involves the spinning of fibres into yarn, which can then be utilised for weaving or knitting into fabric. Allied Market Research reports that the global yarn market was valued at USD 12.1 billion in 2019 and is projected to attain USD 16.2 billion by 2027, with a compound annual growth rate (CAGR) of 4.2% over the forecast period. The yarn production sector features a diverse array of yarn kinds, including cotton, polyester, nylon, and acrylic, each with distinct qualities and applications. The principal entities in the yarn production sector comprise Vardhman Textiles Ltd., Reliance Industries Ltd., and Welspun India Ltd., which compete on the basis of price, quality, and innovation. Yarn production encounters issues including energy use, waste generation, and water utilisation, necessitating sustainable and ethical approaches.

- Textile manufacturing

Fabric production entails the weaving or knitting of yarns into fabric, which can subsequently be utilised to manufacture textile and garment products. A report by Research and Markets indicates that the worldwide fabric market was valued at USD 1.03 trillion in 2020 and is anticipated to reach USD 1.44 trillion by 2028, with a compound annual growth rate (CAGR) of 4.5% throughout the forecast period. The fabric production sector is distinguished by a variety of materials, including denim, silk, wool, and polyester, each possessing unique aesthetics, textures, and functions. Prominent entities in the fabric production sector comprise the China National Textile and Apparel Council, Luthai Textile Co. Ltd., and Shandong Ruyi Technology Group Co. Ltd., who implement diverse techniques to distinguish their offerings and secure market dominance. Nevertheless, fabric production encounters obstacles including waste minimisation, pollution management, and traceability, necessitating systemic and collaborative initiatives.

- Dyeing and printing

Dyeing and printing are techniques that apply colour and patterns to fabrics, subsequently utilised in the manufacturing of textile and clothing products. A Technavio analysis indicates that the worldwide textile printing market was valued at USD 8.1 billion in 2020 and is projected to attain USD 10.2 billion by 2025, with a CAGR of 47% over the forecast period. The dyeing and printing sector is defined by diverse processes and technologies, including digital printing, screen printing, and block printing, each possessing distinct advantages and limits. Prominent entities in the dyeing and printing sector comprise Huntsman Corporation, Kornit Digital Ltd., and Mimaki Engineering Co., Ltd., who allocate resources towards innovation and sustainability to address the evolving requirements of consumers and regulatory bodies. Dyeing and printing encounter issues like water pollution, energy consumption, and health hazards, necessitating ongoing enhancement and oversight.

- Apparel manufacturing

Garment production entails the cutting, stitching, and finishing of materials to create garments and accessories for consumer sale. Grand View Research reports that the global clothing industry was valued at USD 1.5 trillion in 2020 and is projected to attain USD 2.2 trillion by 2025, with a compound annual growth rate (CAGR) of 8.1% throughout the forecast period. The garment production business is distinguished by a diverse array of products, including t-shirts, jeans, dresses, and coats, each varying in style, size, and price. The principal entities in the garment production sector are Inditex, H&M, and Fast Retailing, which function internationally and employ diverse business models and supply chain methods. Nonetheless, garment production encounters issues including labour rights infringements, waste management, and carbon emissions, necessitating ethical and open methods.

- Commerce and logistics

Retail and distribution represent the concluding phases of the textile and garment supply chain, wherein completed products are marketed to customers via many channels, including brick-and-mortar stores, internet platforms, and wholesale distributors. A McKinsey & Company analysis indicates that the global fashion retail market was valued at USD 1.5 trillion in 2020 and is projected to attain USD 2.1 trillion by 2025, with a CAGR of 7.0% during the forecast period. The retail and distribution sector is defined by numerous trends and difficulties, including omnichannel integration, e-commerce proliferation, and sustainability consciousness, necessitating new and adaptive solutions. Prominent entities in the retail and distribution sector comprise Amazon, Walmart, and Alibaba, who utilise technology and data to improve consumer experience and operational efficiency. Nevertheless, retail and distribution encounter obstacles including supply chain disruptions, shifts in customer behaviour, and regulatory compliance, necessitating agility and resilience.

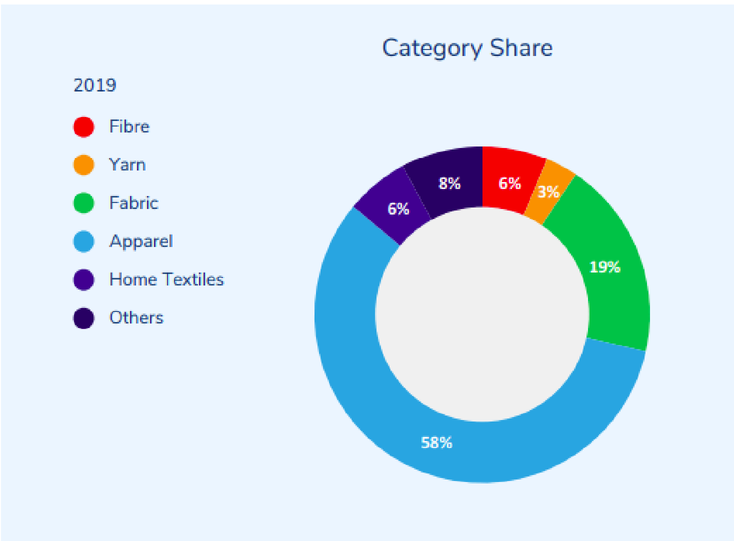

Figure 2.1
Category share of the Global Textile & Apparel Industry of 2019
Source: A Annual Report Indian Textile and Apparel Industry, 2021

2.1.3 Overview of the Global Textile and Apparel Industry

The textile and apparel sector significantly contributes to the world economy, valued at USD 1.7 trillion in 2020 (Textile World, 2021). The business is exceptionally broad, encompassing the production of both natural and synthetic fibres, as well as the fabrication of finished garments and textiles for various consumer markets. The industry is notably fragmented, with numerous small and medium-sized firms (SMEs) significantly contributing to the supply chain.

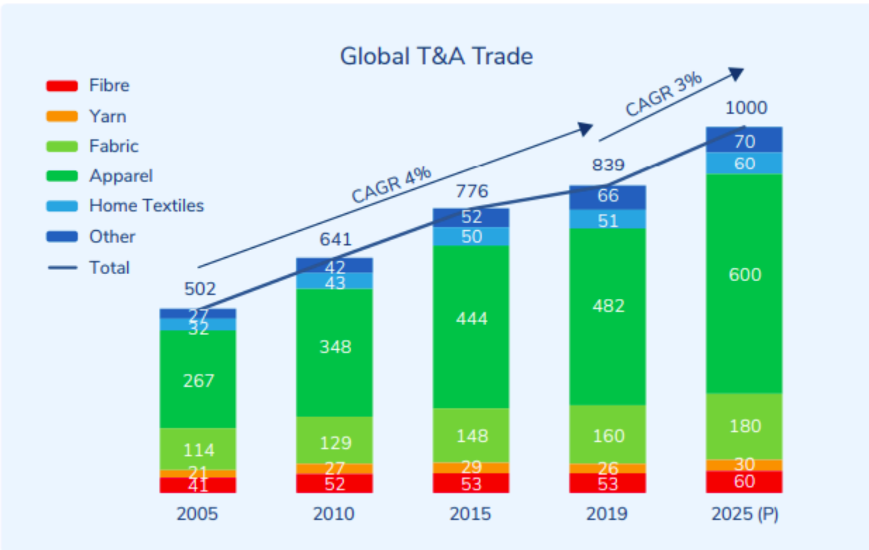

Figure 2.2
Global Textile & Apparel Trade
Source: A Annual Report Indian Textile and Apparel Industry, 2021

The chart above indicates that the worldwide textile and clothing trade has had a compound annual growth rate (CAGR) of 4% since 2005. This consistent expansion has culminated in a market size of US$ 839 billion in 2019. Furthermore, the research suggests that this industry is anticipated to maintain its growth trajectory, with an estimated compound annual growth rate (CAGR) of 3%, and is projected to attain a market size of US$ 1 trillion by 2025.

2.1.4 Impact of Covid on the Global Textiles and Apparel Industry

Global GDP Contraction

Country	2019	2020		2021	
		Pre Covid Forecast	Revised Estimate	Pre Covid Forecast	Revised Forecast
China	6	6	2.3	5.8	8.2
EU	1.3	1	-7.2	1.5	4.2
US	2.2	1.7	-3.4	1.8	5.1
India	4.2	5.8	-8	6.5	11.5
World	2.8	3.3	-3.5	3.3	5.5

Figure 2.3
Annual GDP Change (%)
Source: A Annual Report Indian Textile and Apparel Industry, 2021

The COVID-19 pandemic has significantly affected multiple facets of the global economy, including the GDP of prominent nations. The results reveal that the pandemic has substantially adversely affected the world economy, with an estimated average GDP contraction of 7.52% in 2020.

This downturn is mostly ascribed to extensive lockdowns, supply chain disruptions, diminished consumer demand, and financial losses incurred across multiple industries as a result of the epidemic. As nations instituted steps to curb the virus's transmission, enterprises were compelled to cease operations, resulting in extensive job losses and diminished economic activity.

Nonetheless, there is optimism for the future, as the data indicates an expected average GDP growth of 2.6% in 2021. This can be ascribed to the relaxation of lockdown restrictions, heightened vaccination rates, and the incremental reopening of enterprises and industries.

It is essential to acknowledge that the recovery is anticipated to be disparate throughout various countries and industries, and it may require considerable time for the worldwide economy to completely recuperate from the repercussions of the pandemic. Governments and enterprises must persist in enacting strategies to facilitate economic recovery and expansion, while simultaneously safeguarding the welfare of their citizens and employees.

2.1.5 Key Players and Regions

China, India, Bangladesh, Vietnam, and Turkey are prominent leaders in the worldwide textile and garment sector. China is the preeminent exporter of textiles and apparel, with more than 40% of worldwide exports (Fibre2Fashion, 2021). India ranks as the second-largest exporter of textiles and clothing globally, exhibiting a burgeoning domestic market and considerable potential for future expansion. Additional significant participants comprise Bangladesh, recognised for its inexpensive labour and substantial manufacturing capacity; Vietnam, which is swiftly advancing its textile and apparel industry; and Turkey, possessing a highly varied and sophisticated textile and apparel sector.

2.1.6 Sustainability and Environmental Concerns

The textile and clothing sector exerts a considerable influence on the environment, encompassing concerns such as pesticide application in cotton cultivation and the management of textile waste disposal. Consequently, sustainability and environmental issues have gained paramount significance for organisations within the industry. Numerous firms have instituted sustainability efforts and embraced more environmentally conscious production methods, including the utilisation of recycled materials and the minimisation of water and energy consumption (Textile World, 2021).

- Eco-friendly manufacturing methods

Eco-friendly production methods are crucial for minimising the environmental effects of textile and clothing manufacturing. A study conducted by Shahid and Shankar (2019) analysed the environmental sustainability of cotton and polyester fabric production processes, revealing that cotton production has a greater environmental impact than polyester production. A study conducted by Gopalakrishnan et al. (2020) evaluated the environmental effects of several dyeing methods and concluded that natural dyeing exerts a lesser environmental impact compared to synthetic dyeing.

- Eco-friendly materials

The utilisation of sustainable materials is a crucial element of eco-friendly textile and clothing manufacturing. A study conducted by Hidayat et al. (2020) evaluated the environmental impact of various natural fibres, such as cotton, wool, silk, and hemp, concluding that hemp has the least environmental impact. Das et al. (2021) conducted a study evaluating the environmental impact of various synthetic fibres and determined that recycled polyester has a reduced environmental impact compared to virgin polyester.

- Eco-friendly supply chain

Sustainability in the textile and clothing business encompasses not only production procedures and materials but also the entire supply chain. Singh and Bhatia's (2019) research examined the sustainability of the textile and apparel supply chain. They identified that eco-design, closed-loop supply chains, and social responsibility are sustainable practices that can mitigate the industry's impact on the environment and society.

- Eco-friendly consumption

The textile and garment sector necessitates sustainable consumption practices for sustainability. Wu et al. (2020) conducted a study evaluating the environmental consequences of several consumer behaviour scenarios, such as garment usage, laundering, and disposal, and concluded that prolonging garment usage and adopting sustainable washing procedures can substantially mitigate the industry's environmental impact.

2.1.7 Challenges and Future Prospects

The worldwide textile and garment sector has numerous issues, such as heightened competitiveness, evolving customer preferences, and the repercussions of the COVID-19 epidemic. The industry is seeing substantial technical advancements, as the integration of digital technologies and the emergence of Industry 4.0 are revolutionising corporate operations. Notwithstanding these hurdles, the business is anticipated to persist in its growth, propelled by reasons such escalating disposable incomes in emerging nations, heightened demand for sustainable products, and the expansion of e-commerce.

2.2 Industry 4.0 and its Global Adoption

2.2.1 Introduction

Industry 4.0, or the Fourth Industrial Revolution, refers to the incorporation of digital technologies into manufacturing and production systems. The implementation of Industry 4.0 carries substantial ramifications for enterprises, governmental bodies, and society at large, with prospective advantages such as enhanced efficiency, diminished expenses, and superior product quality. This literature study is to present an overview of the worldwide implementation of Industry 4.0, encompassing the principal drivers, obstacles, and prospects.

2.2.2 Drivers of Industry 4.0 Adoption

Multiple factors promote the implementation of Industry 4.0, such as the necessity for enhanced efficiency and competitiveness, escalating labour costs, and progress in digital technology. The implementation of Industry 4.0 is propelled by evolving consumer demands, particularly the increasing focus on customised items and expedited delivery times. Governments and policymakers are facilitating the adoption of Industry 4.0 by providing incentives and assistance for enterprises to invest in digital technology (Lasi et al., 2014).

2.2.3 Global Adoption of Industry 4.0

Industry 4.0 is an expanding sector, with prominent participants such as the United States, Germany, Japan, China, and South Korea. These nations are at the forefront of the advancement and execution of Industry 4.0 technologies and have made substantial investments in research and development (R&D) to facilitate this progress. Regions like Southeast Asia and South America are swiftly embracing Industry 4.0 technologies to remain competitive globally.

2.2.4 Challenges of Industry 4.0 Adoption

The adoption of Industry 4.0 is not without its challenges, including concerns about cybersecurity, data privacy, and the ethical use of AI. There are also concerns about the potential impact on global supply chains, with the potential for increased concentration in the industry and the emergence of new barriers to entry. In addition, the adoption of Industry 4.0 requires significant R&D investments, as well as the need for upskilling and reskilling programs to ensure that workers have the skills needed for the jobs of the future (Bauernhansl et al., 2014).

2.2.5 Opportunities for Industry 4.0 Adoption

Despite these challenges, the adoption of Industry 4.0 presents significant opportunities for companies and governments alike. The integration of digital technologies into manufacturing processes has the potential to improve product quality, reduce costs, and increase efficiency. It can also lead to the creation of new job roles and industries, as well as the development of new products and services. The adoption of Industry 4.0 can also lead to improvements in environmental sustainability through the development of more efficient and sustainable manufacturing processes (Brynjolfsson & McAfee, 2014).

2.3 Industry 4.0 in the Global Textile and apparel industry

2.3.1 Introduction

The global textile and apparel industry is facing several challenges, such as high production costs, labour shortages, and low productivity. The adoption of Industry 4.0 technologies can address these challenges by enabling digitalisation, automation, and optimisation of the production process. This literature review aims to explore the adoption of Industry 4.0 in the global textile and apparel industry, its benefits, and its challenges.

2.3.2 Industry 4.0 and its Relevance to the Textile and apparel industry

Industry 4.0 refers to the fourth industrial revolution, which is characterised by the integration of advanced technologies such as artificial intelligence, the Internet of Things (IoT), and robotics in manufacturing processes. The adoption of Industry 4.0 in the textile and apparel industry can enhance the production process by enabling automation, real-time data analysis, and predictive maintenance. It can also facilitate the customisation of products based on customer needs, which is crucial in the highly competitive textile and apparel industry.

2.3.3 Adoption of Industry 4.0 in the global textile and apparel industry

The adoption of Industry 4.0 in the global textile and apparel industry is still in its early stages. However, some companies have started implementing Industry 4.0 technologies in their production processes. For instance, Adidas has implemented 3D printing technology to manufacture customised shoes, while Levi Strauss & Co. has introduced laser technology for fabric cutting to reduce production time and waste. Other companies, such as Zara and H&M, have incorporated RFID technology for inventory management and tracking.

2.3.4 Benefits of Industry 4.0 Adoption in the Textile and apparel industry

The implementation of Industry 4.0 technologies in the textile and clothing sector can yield numerous advantages, including enhanced production efficiency, decreased production costs, elevated product quality, and tailored product offerings. The adoption of digital technologies facilitates real-time data analysis, predictive maintenance, and automated decision-making, thereby substantially improving production efficiency and decreasing overall production costs.

Khan et al. (2021) emphasised the significance of organisational preparation, technology acceptability, and governmental assistance for the effective deployment of Industry 4.0 in the Indian textile sector. The textile sector must prioritise cultivating a culture of innovation and collaboration to fully leverage the advantages of sector 4.0.

A study by Bhardwaj et al. (2020) examined the prospective advantages of adopting Industry 4.0 in the Indian textile sector, encompassing enhanced productivity, quality assurance, and supply chain efficacy. The research also found other obstacles, including the substantial expense of implementation and the necessity for specialised labour.

A study by ElMaraghy and ElMaraghy (2019) emphasised the challenges and opportunities of implementing Industry 4.0 in the textile and apparel sector, including the necessity for new skills and competencies, alterations in business models, and enhanced collaboration between suppliers and customers. They underscored the significance of data analytics, artificial intelligence, and cyber-physical systems in advancing Industry 4.0 within the textile and clothing sector.

Khan et al. (2019) conducted a study on the implementation of Industry 4.0 inside Bangladesh's textile and garment sector, a significant global textile manufacturer. The research indicated that Industry 4.0 technologies enhance industrial competitiveness by decreasing manufacturing time, minimising errors, and augmenting efficiency. The report emphasised the necessity of governmental assistance, cross-industry collaboration, and training and educational initiatives to fully actualise the advantages of Industry 4.0.

The literature indicates that the implementation of Industry 4.0 in the worldwide textile and clothing sector may lead to substantial enhancements in productivity, quality, and sustainability. Nonetheless, numerous obstacles to adoption persist, including elevated implementation expenses, the want for proficient personnel, and the requirement for governmental assistance and industry partnership. By confronting these problems and capitalising on potential advantages, the textile and apparel industry can sustain competitiveness and sustainability in the global market.

2.3.5 Challenges of Industry 4.0 Adoption in the Textile and apparel industry

Despite the benefits, the adoption of Industry 4.0 in the textile and apparel industry also presents several challenges. The main challenge is the high initial investment cost associated with implementing advanced technologies. Another challenge is the lack of skilled labour to operate and maintain the advanced technology systems. Furthermore, the integration of Industry 4.0 technologies with existing production systems can also pose challenges due to compatibility issues.

2.4 MSME of India

In India, MSME denotes "Micro, Small, and Medium Enterprises." The phrase denotes enterprises categorised according to their investment in plant, machinery, or equipment.

As of July 1, 2020, the criteria for classifying MSMEs under the MSMED Act, 2006, based on investment in plant and machinery/equipment, has been amended. This amendment, revealed as part of the Aatma Nirbhar Bharat initiative on May 13, 2020, seeks to represent the substantial transformations in the economy and to create a more objective classification system that enhances the convenience of conducting business.

Before this adjustment, the financial restrictions for these classifications were extremely low, particularly for manufacturing and service units.

The updated criteria broaden the definition of MSMEs to encompass businesses with investments in plant and machinery or equipment not exceeding INR 1 crore (approximately USD 136,000) for micro-enterprises, INR 10 crore (approximately USD 1.36 million) for small enterprises, and INR 50 crore (approximately USD 6.8 million) for medium enterprises.

The updated criteria also altered the classification of MSMEs according to their annual revenue. According to the revised criteria, micro-enterprises are classified as businesses with an annual turnover of up to INR 5 crore (approximately USD 680,000), small enterprises are classified as those with an annual turnover between INR 5 crore and INR 75 crore (approximately USD 10.2 million), and medium enterprises are classified as businesses with an annual turnover between INR 75 crore and INR 250 crore (approximately USD 34 million).

The updated criteria for MSME classification were enacted to more accurately represent the contemporary economic conditions encountered by firms in India and to offer more focused assistance to these enterprises.

In India, MSMEs and SMEs are integral to the economy, considerably contributing to employment generation, industrial advancement, and export expansion. The Government of India has instituted numerous policies and initiatives to facilitate the growth and advancement of MSMEs and SMEs.

2.5 About Indian Textile industry

As per information from the Ministry of Micro, Small & Medium Enterprises (MSME), by March 2020, India had around 45.77 million small and medium enterprises (SMEs), encompassing both manufacturing and service sector businesses. The textile sector represents a substantial share of SMEs, with more than 2.3 million units registered in the sector as of 2020. The primary focus of these units is the production of textiles, which encompasses cotton, silk, wool, and synthetic fibres, along with apparel, home furnishings, and various other textile products.

The Indian textile industry stands as one of the oldest and largest sectors in the country, playing a crucial role in economic growth and job creation (Ghosh et al., 2020). In 2020, the sector had an employment figure of around 45 million individuals. The textile industry not only creates jobs but also plays a significant role in India's export revenue, with textiles and apparel representing around 13% of total exports in 2020.

Although the textile sector plays a crucial role in the Indian economy, it has encountered several challenges in recent years, including heightened competition from imports, escalating input costs, decreasing exports, low productivity, minimal value addition, and excessive energy consumption, among others (Pandey et al., 2020). In light of these challenges, the government has introduced several measures aimed at bolstering the growth and competitiveness of the sector, such as policies designed to encourage domestic production and foster export-oriented growth.

Technologies associated with Industry 4.0 have surfaced as a promising answer to these challenges. Industry 4.0 signifies the fusion of digital technologies with conventional manufacturing methods to establish a smart factory setting (Bai et al., 2021). Implementing Industry 4.0 technologies can enhance productivity, elevate quality control, and optimise supply chain management within the textile sector (Sharma et al., 2021).

The adoption of Industry 4.0 technologies in the Indian textile industry has been gradual, hindered by various barriers despite the potential advantages. The barriers consist of insufficient awareness and comprehension of Industry 4.0, the significant costs associated with implementation, a scarcity of skilled labour, and the lack of a supportive regulatory framework (Mishra et al., 2021; Rani et al., 2021).

To tackle these obstacles and encourage the integration of Industry 4.0 technologies in the Indian textile sector, several strategies have been proposed. Several strategies are enhancing awareness and education, providing financial incentives and subsidies, collaborating with schools to train workers, and establishing a policy and regulatory framework that bolsters these initiatives (Gautam et al., 2021; Pandey et al., 2020).

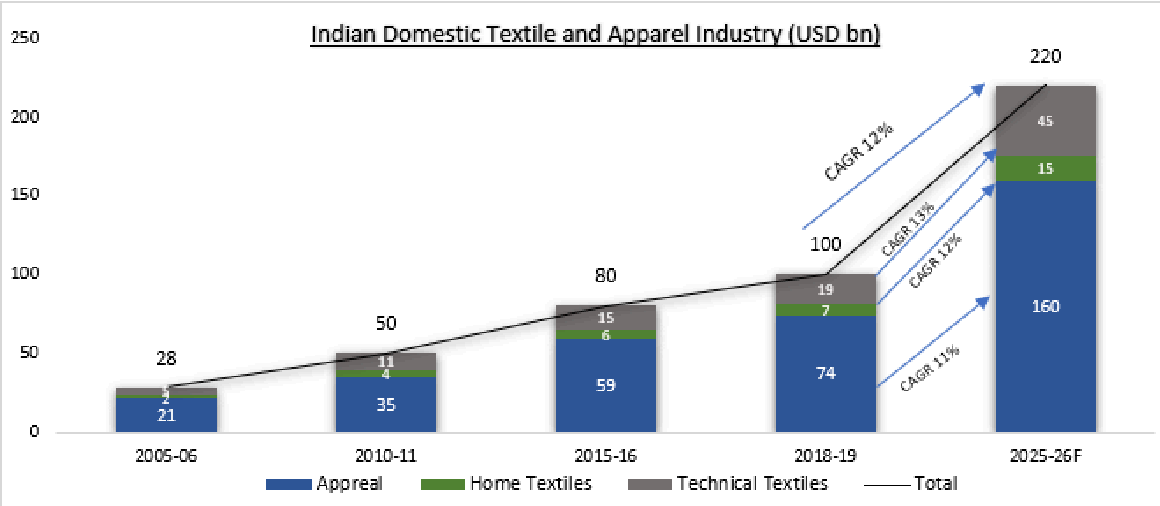

Figure 2.4
Indian Domestic Textile and Apparel Industry
Source: Ministry of Textiles, Wazir Analysis, Televisory's Analysis

Similar research studies focused on the textile industry have been conducted in foreign countries suggesting scope of adoption and theoretical frameworks for the implementation of AI in Small and medium scam industries.

2.6 AI in Indian SME

A preliminary review of the literature shows that there are few Cross sectional studies done in the field of Implementation and adoption of AI in Indian Small and Medium Scale industries. One of the recent study from the Walden University focuses on the Implementation and Adoption of AI In Indian Small and Medium scale Industry as a whole, Theories and Frameworks like DOI (Diffusion of Innovation), TOE(Technology–organization–environment framework), TAM (Technology Acceptance

Model) were used for the same. Studies which are general in nature are not focused on specific Industries, and the same has been also mentioned in the future scope section of these research papers.

2.7 AI in Indian Textile Industry

Numerous studies have investigated the adoption and implementation of AI in Indian MSMEs. Mishra and Jaiswal (2021) examine the challenges and opportunities presented by AI in the Indian textile industry, primarily composed of MSMEs. They emphasise the importance of MSMEs partnering with technology providers and research institutions to create tailored AI solutions that address their unique requirements.

In a similar vein, Singh and Arora (2021) explore the opportunities and challenges presented by AI within the textile and apparel sector, which is likewise characterised by the presence of MSMEs. It is suggested that AI can assist MSMEs in enhancing their production efficiency, lowering costs, and boosting their competitiveness. They emphasise the importance of MSMEs investing in training their workforce to effectively utilise AI technologies.

Akhtar and Sharma (2020) examine the influence of AI on job opportunities within the Indian textile sector. They propose that although AI can automate specific tasks, it may also generate new job opportunities in fields like data analysis and programming. They highlight the importance for MSMEs to re-skill and up-skill their workforce in order to capitalise on these new opportunities.

Sahoo, Behera, and Patnaik (2020) provide a comprehensive review of Industry 4.0 technologies within the Indian textile and apparel sector, highlighting the role of AI. It is suggested that AI has the potential to assist MSMEs in optimising their manufacturing processes, enhancing quality control, and lowering costs. They also emphasise the necessity for MSMEs to address the obstacles to adoption, including a deficiency in awareness and expertise.

Rathi, Vyas, and Raman (2021) offer a comprehensive overview of AI in human resource management, highlighting its relevance to MSMEs. It is suggested that AI can assist MSMEs in automating specific HR functions, including recruitment and performance management. Nonetheless, they caution MSMEs that the use of AI in HR could lead to ethical and legal concerns.

According to a survey conducted by EY, merely 14% of Indian textile companies are utilising artificial intelligence in their operations, while an additional 14% intend to adopt it in the near future (Source: EY Survey on Indian Textile Industry, 2021).

The survey conducted by EY revealed that the primary obstacles to adopting artificial intelligence in the Indian textile industry include a shortage of skilled personnel (42%), insufficient awareness of AI's benefits (32%), and apprehensions regarding implementation costs (26%).

An Accenture study suggests that implementing artificial intelligence in the Indian textile industry may result in a 20-25% boost in productivity and a 15-20% decrease in operational costs (Source: Accenture Report on Indian Textile Industry, 2020).

KPMG's study highlights the primary areas for the application of artificial intelligence within the Indian textile industry, such as supply chain management, quality control, and product design and development (Source: KPMG Report on Indian Textile Industry, 2019).

A study carried out by PwC India in 2018 revealed that merely 17% of Indian textile companies were utilising AI or machine learning technologies, predominantly among larger firms. The research revealed that the textile sector in India exhibited a lower degree of digital maturity in comparison to other industries, highlighting the necessity for enhanced investment in digital technologies.

A study carried out by the Indian Chamber of Commerce in 2020 revealed that the COVID-19 pandemic had hastened the integration of digital technologies, such as AI, within the textile sector. The research revealed that numerous textile companies adopted AI and automation technologies to enhance efficiency and lessen reliance on labour amid the pandemic.

A survey carried out by the Textile Association (India) in 2020 revealed that most Indian textile companies expressed interest in adopting AI and other digital technologies. However, they encountered challenges concerning implementation costs, a shortage of technical expertise, and the necessity for tailored solutions.

These studies indicate that there is a notable interest in adopting AI within the Indian textile industry; however, substantial challenges to implementation exist, especially for small and medium-sized enterprises. Increased investment in digital technologies and technical expertise is essential to facilitate broader adoption and unlock the potential benefits of AI in the Indian textile industry.

2.8 Case studies of AI adoption in Indian SMEs

Numerous instances of AI adoption can be observed in Indian SMEs within the textile sector, including the implementation of computer vision for detecting fabric defects, the application of predictive analytics for controlling yarn quality, and the utilisation of chatbots to enhance customer service. These case studies illustrate how AI can effectively tackle particular challenges and seize opportunities within the textile industry in India.

The case studies illustrate that AI adoption can provide numerous advantages to Indian SMEs in the textile sector, including better quality, minimised waste, enhanced customisation, and greater competitiveness. The effectiveness of AI solutions can vary based on several factors, including the quality and quantity of data, the accuracy and reliability of algorithms, and the usability and accessibility of interfaces. It is crucial to assess the ROI and TCO of AI solutions while consistently monitoring and enhancing their performance.

2.8.1 Fabric defect detection using computer vision

One of the major challenges in the textile industry is the detection of defects in fabric, which can lead to quality issues and waste. An Indian SME, Warp & Weft, has adopted AI-based computer vision technology to automate the process of fabric defect detection. The system uses machine learning algorithms to detect defects such as holes, stains, and distortions in real-time. The solution has improved the accuracy and speed of defect detection and reduced waste and rework.

2.8.2 Predictive analytics for yarn quality control

Yarn quality is a critical factor in textile production, and Indian SMEs face challenges in maintaining consistent quality due to variations in raw materials and processing. An Indian SME, KPR Mill, has adopted a predictive analytics solution to monitor and control yarn quality in real-time. The system uses AI algorithms to analyse various parameters such as yarn count, strength, and evenness and provides real-time alerts and recommendations for corrective actions. The solution has improved the quality and yield of yarn production and reduced quality-related costs.

2.8.3 Chatbots for customer service

Customer service is an essential aspect of the textile industry, and Indian SMEs face challenges in providing timely and personalised support to their customers. An Indian SME, iTex, has adopted AI-based chatbots to provide 24/7 customer service and support. The chatbots use natural language processing (NLP) and machine learning to understand and respond to customer queries and complaints. The solution has improved the response time, accuracy, and consistency of customer service and reduced the workload of human agents.

2.8.4 Inventory management using AI algorithms

The Indian SME, Textile Mills, has implemented an AI-based inventory management system that uses predictive analytics to optimise inventory levels and reduce costs. The system can forecast demand and adjust inventory levels accordingly, reducing excess inventory and stockouts. The system has also improved supply chain efficiency by automating the ordering process and reducing the lead time for procurement.

2.8.5 Quality control using machine learning

An Indian SME, Fabrics Ltd., has implemented an AI-based quality control system that uses machine learning algorithms to detect defects in fabric and classify them based on severity. The system can detect defects in real-time, reducing the need for manual inspection and improving accuracy. The system has also reduced the time required for inspection, allowing for faster production and delivery of high-quality products.

2.8.6 Production planning using AI algorithms

An Indian SME, Apparel Co., has implemented an AI-based production planning system that uses predictive analytics to optimise production schedules and reduce lead times. The system can forecast demand and adjust production schedules accordingly, reducing the need for overtime and improving on-time delivery. The system has also improved the utilisation of resources and reduced production costs.

2.8.7 Predictive maintenance using AI algorithms

An Indian SME, Spinning Mills, has implemented an AI-based predictive maintenance system that uses machine learning algorithms to monitor equipment health and predict failures. The system can detect anomalies in real-time and generate alerts to maintenance personnel, reducing downtime and repair costs. The system has also improved equipment efficiency and reduced energy consumption.

2.9 Discussion

This chapter examines the literature that highlights significant advancements as well as persistent challenges in the application of Artificial Intelligence (AI) and Industry 4.0 technologies within the Indian textile and clothing sectors, particularly concerning Micro, Small, and Medium-sized Enterprises (MSMEs). This presentation integrates the key findings from the gap analysis diagram, which strategically illustrates the research areas that require further attention to effectively address these gaps.

- Summary from Gap Analysis

Combining AI with Industry 4.0: The integration of Industry 4.0 and AI technologies presents significant opportunities for the Indian MSME sector, with the potential to improve productivity, quality, and operational efficiency. Nonetheless, the diagram illustrates a persistent gap among studies regarding the complete integration and utilisation of these technologies in everyday operations, particularly in smaller businesses that lack sufficient resources.

Obstacles to Embracing Change: The gap analysis highlights significant research focused on overcoming implementation barriers. Recurring themes include high implementation costs, a shortage of skilled labour, and technological incompatibility with existing systems. This corresponds with findings in the literature indicating that although some major players effectively implement advanced technologies, smaller organisations face challenges without specific support and scalable solutions.

Challenges Specific to the Sector: In the textile and apparel industry, challenges involve adjusting to rapidly changing fashion trends and consumer preferences through the use of digital solutions. The diagram illustrates that the majority of research in this sector has concentrated on the scope and challenges of Industry 4.0. This indicates a necessity for more comprehensive studies that leverage the distinct characteristics of each sector to explore these issues.

The diagram clearly illustrates the lack of thorough research connecting the benefits of AI technology to strategic business results in the MSME context. Longitudinal studies are essential to uncover further insights into the long-term advantages and sustainability of integrating new technologies to enhance business competitiveness and adaptability in the market.

- Consequences for Industry Standards

The gap analysis highlights the importance of strategic initiatives aimed at assisting MSMEs in overcoming barriers to adoption. Industry stakeholders, such as policymakers, industry leaders, and academic researchers, are urged to work together in developing supportive ecosystems that provide training, financial incentives, and innovation hubs designed for the needs of small and medium-sized enterprises.

- Consequences for Upcoming Studies

Longitudinal and Comparative Research: To assess the long-term effects and relative effectiveness of Industry 4.0 implementations across various regions and sectors within the Indian economy.

Customised Technological Solutions: Creating personalised solutions that meet the specific requirements and limitations of Indian MSMEs, especially in the textile and apparel industries.

Analysis of Policy and Economic Impact: Assessing the effectiveness of policies designed to promote technological adoption and evaluating their economic effects on the MSME sector.

- In conclusion

This literature review, guided by a thorough gap analysis, has highlighted the opportunities and challenges related to the implementation of AI and Industry 4.0 within the Indian MSME sector. A collective endeavour from all stakeholders to tackle the identified gaps is crucial for unlocking the full potential of these technologies. Closing these gaps not only improves the technological abilities of MSMEs but also provides a competitive advantage in the global market, fostering sustainable growth and innovation over time.

Chapter 3: Research Methodology

The chapter is divided into several sections, such as the research approach and strategy, the study population and sampling, the data collection methods and instruments, the data analysis methods, the research study period, ethical considerations, and ways to make sure the data is reliable. These sections provide a comprehensive overview of the overall research design and methodology that will be employed to address the research objectives.

3.1 Theoretical Foundation

This quantitative cross-sectional correlational study will involve a survey aimed at examining the interrelationships among various factors related to the decision-making process for adopting Artificial Intelligence (AI) in the Textile and Apparel SME sector in India.

In order to gain a thorough understanding of the topic, we have explored several theoretical frameworks, such as the Technology Acceptance Model (TAM), Diffusion of Innovation (DOI), Social Cognitive Theory, Innovation Resistance Theory, and the Unified Theory of Acceptance and Use of Technology (UTAUT).

The Technology Acceptance Model (TAM), introduced in 1989, posits that perceived usefulness (PU) and perceived ease of use (PEOU) are the primary factors influencing individual users' intention to adopt technology (Biloš & Budimir, 2024). PU is defined as the extent to which an individual believes that utilising a specific system will improve their job performance, whereas PEOU pertains to the extent to which the individual believes that using the system will require minimal effort. The TAM has undergone extensive validation by numerous scholars across various contexts since its initial publication, leading to its widespread application in IT adoption research over the past decade. Nonetheless, TAM is a relatively straightforward model that can be adjusted or expanded in multiple ways (Zhang, Guo, and Chen, 2008).

DOI research relies on rational theories of organisational life derived from sociology, management, and communication theory. It creates predictive models of the diffusion phenomenon that purportedly assists technology implementors in promoting the spread of chosen technologies. The primary objective of the DOI tradition has been to elucidate the reasons behind individuals' decisions to adopt or intend to adopt specific innovations within largely homogeneous groups (Rogers, 2003).

Social cognitive theory (SCT) serves as a prominent framework in the realm of health behaviour. It suggests a mutual deterministic connection among the individual, their surroundings, and their actions. This theory highlights the dynamic and interactive aspects of these three elements, which together influence behaviour and create opportunities for interventions aimed at behaviour change. SCT acts as a connection between behavioural and cognitive learning theories, exploring how internal factors (like cognition and symbolic processing) interact with external influences (such as rewards and punishments) to shape behaviour. By examining the interplay between these internal and external factors, SCT provides a thorough insight into the influences on behaviour. It acknowledges the significance of individual thoughts, beliefs, and cognitive processes, while also recognising the effects of environmental influences. This comprehensive approach facilitates the creation of strategies aimed at changing behaviours. Considering the broader context, SCT serves as an effective framework for examining behaviour, as it illustrates the interconnectedness of individuals, their surroundings, and their actions in facilitating behavioural change through interventions (Conner, 2015).

Research indicates that three categories of factors can affect consumers' resistance to innovation: the characteristics of the innovation itself, the traits of the consumers, and the features of the propagation mechanisms. The extent of change that a consumer perceives influences their resistance to an innovation, regardless of whether they experience it firsthand or through different channels of dissemination. Should the consumer notice a considerable shift, they are inclined to oppose the innovation. In these situations, the company behind the innovation must adjust it to meet consumer needs and lessen resistance. The crucial element for the success of an innovation lies in its ability to be modified. The necessary adjustments would be contingent upon the underlying reason for the resistance. If the resistance arises from compatibility issues, the modification would focus on enhancing compatibility. In the same way, if resistance arises from a perceived relative disadvantage, we ought to take measures to alleviate this disadvantage. Without the ability to modify an innovation, overcoming consumer resistance becomes impossible, resulting in its eventual rejection. If changes are possible, we make those adjustments and present the revised version of the innovation to the consumer. This process continues until the innovation is either embraced or dismissed (Ram, 1987).

Unified Theory of Acceptance and Use of Technology (UTAUT): Since its introduction in 2003, the UTAUT has attracted considerable interest from researchers. It has become a recognised framework for exploring the adoption of information systems and the related challenges, as illustrated in Figure 6.1. Venkatesh et al. developed the UTAUT by synthesising eight influential user acceptance models from that period, which included the theory of reasoned action, the technology acceptance model, the motivational model, the theory of planned behaviour, a combined model of the technology acceptance model and theory of planned behaviour, the PC utilisation model, the innovation diffusion theory, and the social cognitive theory. Venkatesh and Morris empirically validated the UTAUT by analysing longitudinal data on users' information technology usage across four organisations. This model demonstrated that four primary factors influence behavioural intention and actual use behaviour: performance expectancy, effort expectancy, social influence, and facilitating conditions (Wang et al., 2021).

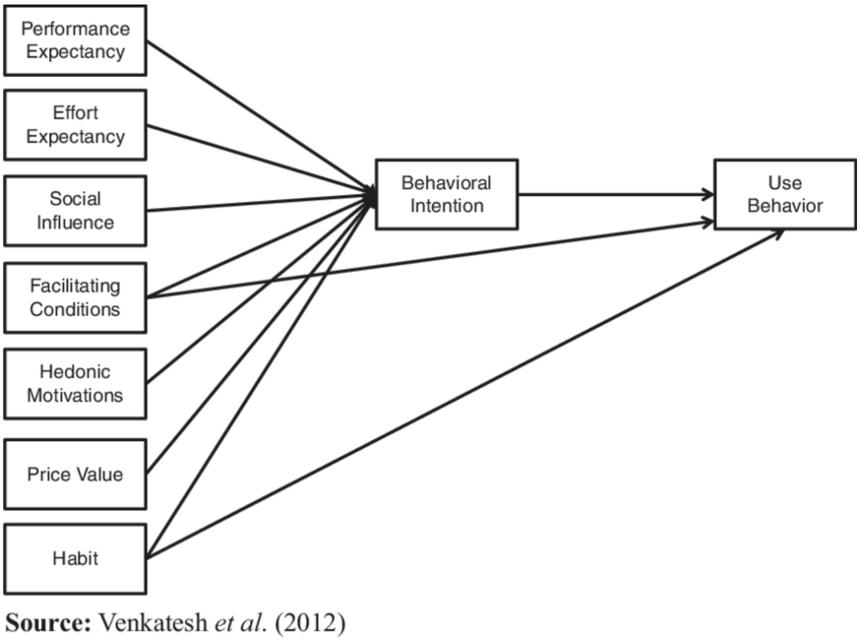

Figure 3.1
The unified theory of acceptance and use of technology (UTAUT) mode
Source: Venkatesh et al.(2012)

3.2 Research Methodology

This research seeks to investigate the key factors, variables, and roles that significantly influence the decision-making process related to the adoption of artificial intelligence (AI) in the Indian Small and Medium Scale Textile and Apparel industry. The study aims to provide valuable insights through a careful analysis of these aspects, assisting AI solution providers in crafting effective strategies and solutions.

After examining the theories presented, I have chosen to employ The Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003), which seeks to elucidate users' acceptance and use of technology.

The UTAUT model has several advantages, including:

1. The UTAUT model offers a thorough framework that encompasses multiple factors affecting users' acceptance and utilisation of technology. This model integrates aspects from eight established technology acceptance frameworks, resulting in a comprehensive and strong approach.

2. Predictive Power: The UTAUT model has shown significant effectiveness in elucidating users' behavioural intentions and actual technology usage. It has found extensive application across various domains and contexts, such as e-commerce, healthcare, education, and information systems.

The model includes various dimensions that affect technology acceptance, such as performance expectancy, effort expectancy, social influence, and facilitating conditions. This facilitates a deeper comprehension of users' perspectives and actions regarding technology.

The UTAUT model acknowledges that the acceptance of technology can differ among various contexts and user demographics. The model offers the ability to adapt and customise according to specific technology adoption scenarios, allowing researchers and practitioners to take contextual factors into account.

5. Practical Applications: The UTAUT model offers valuable insights for the adoption and implementation of technology. This aids in pinpointing essential factors influencing technology acceptance, thereby enabling the creation of impactful strategies to improve user acceptance and utilisation.

The independent variables in this study will consist of the Seven Constructs of the UTAUT and the Decision to Adopt and Implement AI (DAI). The research seeks to explore the positive and negative relationships between these constructs and the dependent variable.

Table 3.1
Details of Dependent and Independent Variables

Dependent Variables	**Independent Variable**
The decision to Adopt and Implement AI (DAI)	Performance Expectancy (PE)
	Effort Expectancy (EE)
	Social Influence (SI)
	Facilitating Conditions (FC)
	Hedonic Motivation (HM)
	Price Value (PV)

3.3 Research Approach & Strategy

Research methodologies encompass the diverse approaches and techniques employed by researchers to gather, analyse, and interpret data. Three primary types of research methodologies exist: qualitative, quantitative, and mixed methods.

Qualitative research methodology is employed to examine and articulate a singular phenomenon with great detail. This research is commonly employed to comprehend and investigate intricate social phenomena, frequently utilised in disciplines like sociology, anthropology, and psychology. Qualitative research methods encompass techniques like interviews, observation, and ethnography (Ravitch & Carl, 2019).

Quantitative research methodology involves the analysis of numerical data and the execution of statistical analysis. This kind of research is commonly employed to evaluate hypotheses and derive conclusions grounded in statistical validity. Quantitative research methods encompass techniques like surveys, experiments, and statistical analysis (Ravitch & Carl, 2019).

Mixed methods research is employed when the research objective encompasses a dual purpose, necessitating a blend of quantitative and qualitative research methods. This research approach merges the advantages of quantitative and qualitative methods, offering a more thorough insight into a phenomenon (Babbie, 2017).

This study proposes a quantitative research methodology to examine the statistical correlation among seven factors influencing the decision to adopt, implement, and utilise AI in the MSME Textile and Apparel sector in India, while also exploring the associated scope and challenges.

3.4 Research Population and Sampling

Choosing the right sample size in relation to the total population is essential for carrying out a study efficiently, adhering to quality standards, and reducing effort. There are four methods for determining sample size: employing a rule of thumb, utilising a conceptual framework, referencing guidelines from previous empirical studies, and applying statistical formulas. Providing a proper justification or rationale for the sample size decisions is crucial, as insufficient justification can undermine the credibility of the quantitative research.

3.4.1 Population

To find the total population of Textile and Apparel MSME in India, I went through different authentic sites as below

1. https://texmin.nic.in/
2. https://my.msme.gov.in/MyMsme/Reg/Home.aspx
3. https://www.makeinindia.com/schemes-msmes
4. https://udyamregistration.gov.in/Government-India/Ministry-MSME-registration.htm

https://texmin.nic.in/ (Ministry of Textiles)

The website https://texmin.nic.in/ is associated with the Ministry of Textiles under the Government of India. This offers insights and materials pertaining to the textile sector in India. The website addresses multiple facets of the textile sector, encompassing policies, schemes, initiatives, events, and news. This provides information on government programs and initiatives aimed at fostering the growth and development of the textile industry. The website offers details regarding institutions, councils, and organisations related to textiles. Reports, publications, and statistical data pertaining to the textile sector are accessible to users. The website also provides online services, including registration and licensing options, pertinent to the textile industry.

https://my.msme.gov.in/MyMsme/Reg/Home.aspx Online Portal of the MSME Ministry

The website can be accessed at https://my.msme.gov.in/MyMsme/Reg/Home.aspx The online portal of the Ministry of Micro, Small & Medium Enterprises (MSME) of the Government of India serves as a valuable resource. This platform enables MSMEs to register and access a range of services and benefits. The portal allows entrepreneurs to register their MSMEs and acquire the Udyog Aadhaar Memorandum or Udyam Registration. It offers access to online services, such as applying for schemes, certificates, and various MSME-related services. The portal provides information regarding MSME schemes, policies, guidelines, and resources aimed at fostering the growth and development of MSMEs.

https://www.makeinindia.com/schemes-msmes Make in India - Initiatives for MSMEs

The website https://www.makeinindia.com/schemes-msmes is associated with the Make in India initiative, designed to encourage business and local manufacturing in India. The website is dedicated to initiatives aimed at Micro, Small, and Medium Enterprises (MSMEs). This outlines the different schemes and initiatives introduced by the government to assist MSMEs, including the Prime Minister Employment Generation Programme (PMEGP) and Credit Support Schemes. The website emphasises the significance of MSMEs in the Indian economy and provides information on the government's initiatives to support their growth and development.

https://udyamregistration.gov.in/Government-India/Ministry-MSME-registration.htm Udyam Registration Portal

The Udyam Registration portal, accessible at https://udyamregistration.gov.in/Government-India/Ministry-MSME-registration.html, serves as the official platform for MSME registration in India. The Ministry of Micro, Small & Medium Enterprises (MSME) of the Government of India oversees its management. The portal enables entrepreneurs to register their MSMEs and acquire the Udyam Registration certificate. The process for MSME registration is streamlined, allowing for easier access to a range of benefits and support available to registered MSMEs. The website provides clear guidance, FAQs, and support for the registration process, making it user-friendly for MSME owners.

According to the Udyam Registration Portal's Dashboard of India, I could find following facts Dated: 16/07/2023 01:58:28 PM

1. Total Registered Micro Organisations: 1,99,83,246
2. Total Registered Small Organisations: 5,58,154
3. Total Registered Medium Organisations: 52,685

Though this data is of total MSME's in India, I was not able to find an authentic source for the total number of registered MSME's in Textile and Apparel sector. Hence I searched for the available sources that can provide the share of different industries in the Indian total MSME registrations.

The below image shows the distribution of the industries as per the different sectors: retail trade and repair of personal and household items account for 39.85%, wearing apparel and dressing for 8.75%, food products and beverages for 3.94%, hotels and restaurants for 3.64%, furniture manufacturing for 3.21%, sale, maintenance, and retail of automotive for 3.57%, other services for 6.20%, other business activities for 3.77%, manufacture of textiles for 2.33%, and manufacture of fabricated metal products for 2.33%.

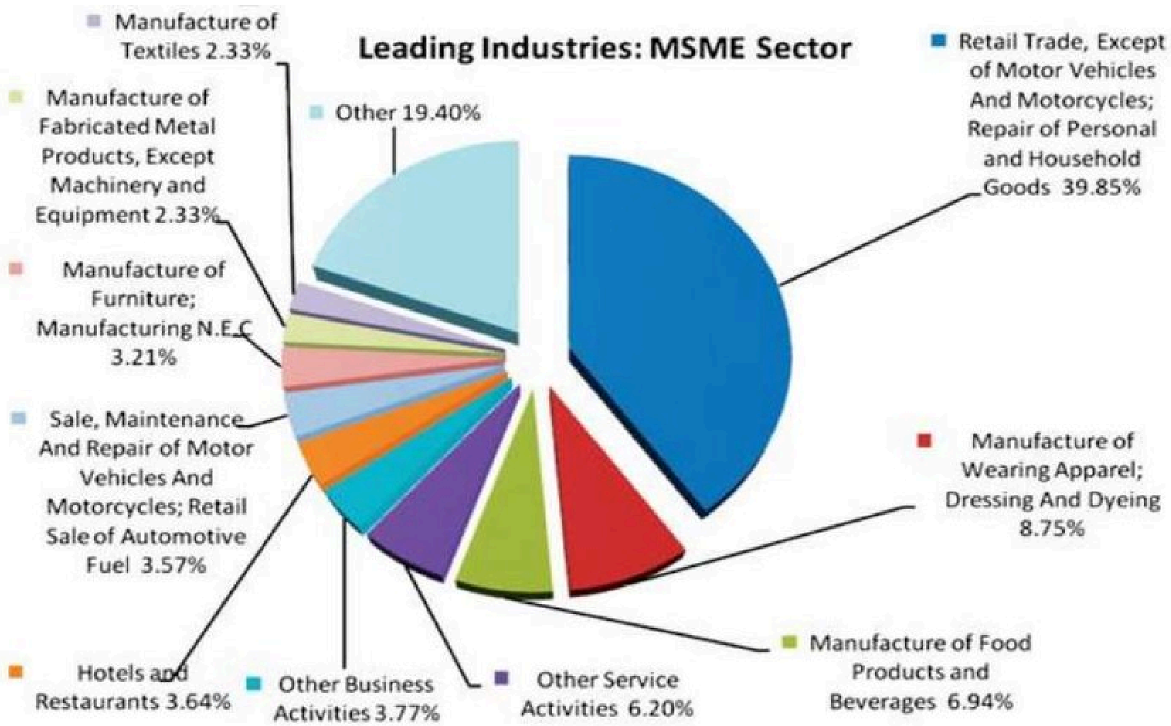

Figure 3.2
The unified theory of acceptance and use of technology (UTAUT) mode
Source: Annual Report Fy 2014-15, Ministry Of Micro, Small And Medium Enterprises, Govt. of India.

Due to the absence of up-to-date and reliable sources, I have chosen to rely on the data provided in the 2014-15 annual report published by the Ministry of Micro, Small and

Medium Enterprises, Government of India. According to this data, the textile industry represents 2.33% of the total MSMEs. Since the focus is primarily on apparel and wearables within the fashion industry, I will assume that the textile industry's share represents the entire industry. By utilizing this assumption and referring to current statistics from the Udyam Portal, we can calculate the total population using the following formulae.

- Total Textile and Apparel MSME’s in India = Total MSME’s registered in India x % of Textie MSME’s
- Total Textile and Apparel MSME’s in India = 2,05,94,085 * 0.233
- Total Textile and Apparel MSME’s in India = 47,98,422

Now that I had the number of MSME’s, a little research on the total number of employees in these registered MSME’s helped to find the number as 12,43,67,854.

There is a lack of data regarding the understanding of AI concepts and implementation enquiries. There is a lack of authentic data regarding the number of employees involved in AI-related initiatives or participating in decision-making related to AI technology adoption within India's SME sector. We incorporated a question in the survey to assess participants' familiarity with AI technology and their involvement in AI-related activities, with the goal of addressing this gap. The study focused on examining the elements that promote or obstruct the adoption, implementation, and use of AI within India's Textile MSME sector. Survey respondents, who actively engage in decision-making and are occasionally responsible for implementing AI technology, play a crucial role in providing insights for the study.

3.4.2 Sampling Techniques

To identify the suitable participants, the survey questionnaire will feature a question aimed at ascertaining whether the participant has experience as an AI implementer, decision-maker, or end-user within their organisation, or if they have been involved in AI technology-related projects or initiatives. Due to the challenges of contacting every employee in this industry, we utilised a sampling method to derive statistically valid conclusions.

Etikan et al. (2016) describe the selection of participants through convenience sampling, a form of non-probability sampling, as it offers a readily accessible source of information. This approach assists in fulfilling the minimum sample requirements and allows for the completion of the research without the complexities associated with randomised sampling (Brewis, 2014). The study will first connect with participants via social media.

G*Power software is a widely used tool for calculating sample size via power analysis and illustrating how variations in sample size affect statistical validity. In a prior study, Cook (2019) utilised G*Power software and conducted a power analysis to ascertain the sample size needed for comparing the managerial perceptions of veterans and non-veterans.

In this study, I will utilise a method known as priori analysis, as described by Cribbie et al. (2019), to determine the required sample size. Priori analysis is an effective method for determining the appropriate number of participants needed for a survey, taking into account the desired statistical power and the acceptable level of Type-I errors. Through the use of priori analysis, I made certain that the sample size for the study was accurately established for the analysis performed.

In the study, I included six independent variables: PE, EE, SI, FC, HM, and PV. The main objective was to investigate the statistically significant relationship between these independent variables and the dependent variable. The Priori analysis utilised the correlation bivariate normal model as a method for statistical testing to accomplish this. This method will facilitate a thorough assessment of the connection between the independent and dependent variables in the research.

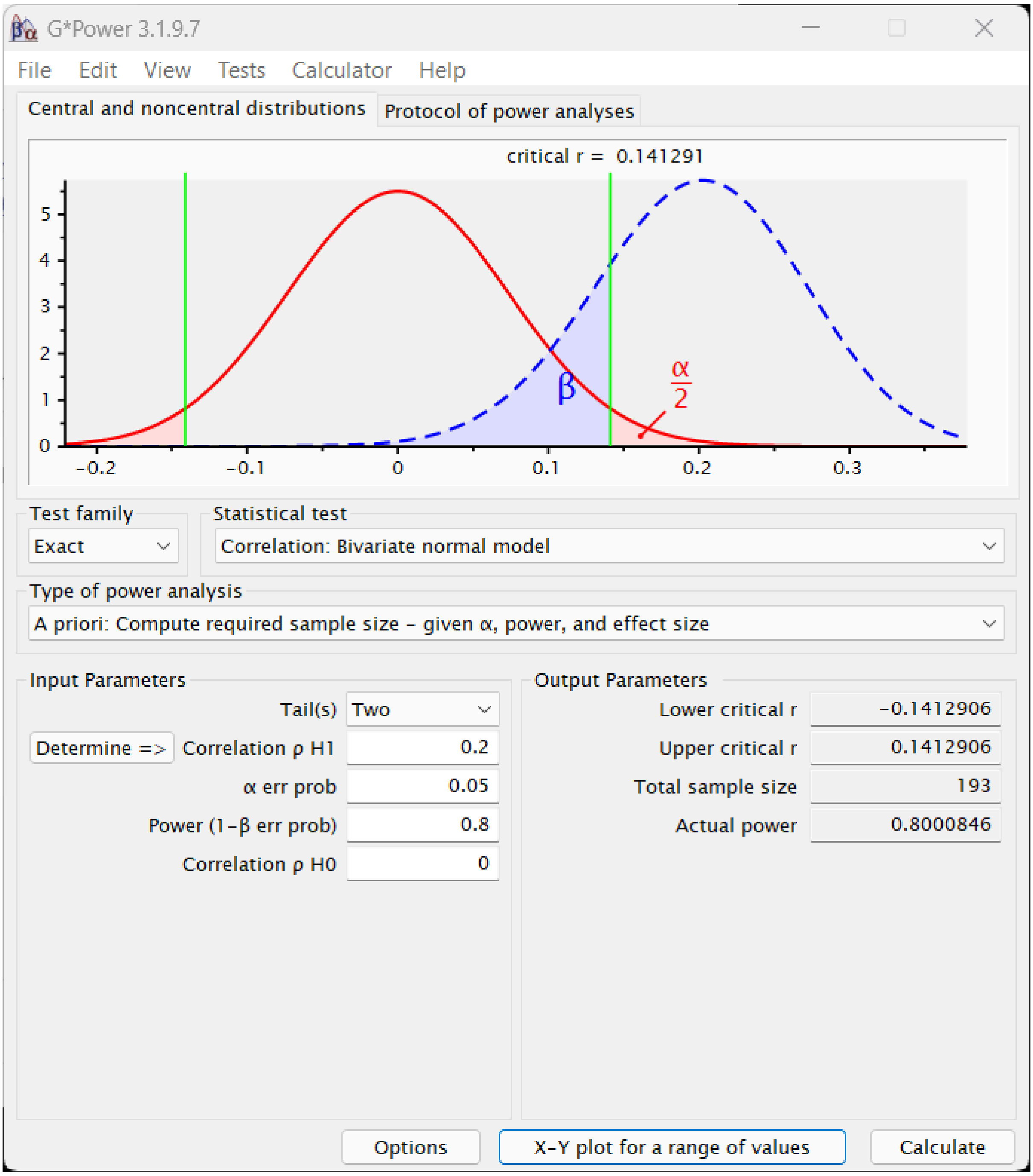

Figure 3.3
*G*Power calculation snapshot*

The parameters illustrated in the preceding figure 3.3 are utilised to perform Priori analysis for determining the sample size necessary to assess a Pearson's r correlation. I am keen to explore the relationship between a single independent variable and a single dependent variable. The correlation's statistical significance is assessed through an evidence-based effect size. Assuming a moderate treatment effect in the data collected through an online survey, the correlation p H1 is selected as 0.20, the α probability of error is set at 0.05, the power (1-beta err prob) is chosen as 0.80, and the correlation P HO is set to zero.

In the realm of statistical hypothesis testing for correlation analysis, the values referenced denote particular parameters and criteria utilised in ascertaining the necessary sample size or power calculation.

1. Correlation (p H1 = 0.20): The value of p H1 represents the expected correlation between the two variables under the alternative hypothesis. In this case, it is assumed that the correlation between the variables is 0.20, indicating a moderate positive or negative relationship.
2. Alpha (α = 0.05): The alpha level, also known as the significance level, is the probability of making a Type I error, which is rejecting the null hypothesis when it is actually true. Typically, α is set at 0.05, indicating a 5% chance of observing a significant result due to random chance.
3. Power (1-beta err prob = 0.80): Power is the probability of correctly rejecting the null hypothesis when it is false, or in other words, the ability of the statistical test to detect a true effect. A power of 0.80 is commonly used, indicating an 80% chance of correctly detecting a significant correlation if it exists.
4. Correlation (P HO = 0): The value of P HO represents the correlation under the null hypothesis, which assumes that there is no correlation between the variables. In this case, it is set to zero, implying no relationship between the variables.

The parameters are utilised in power analysis to ascertain the necessary sample size for identifying a specific correlation at a chosen level of significance (α) and power. By defining these values, researchers can determine the sample size required to attain their desired level of statistical power in identifying the anticipated correlation.

The prior analysis indicated a recommended sample size of 193 for this study, as illustrated in figure 3.3.

3.5 Data Collection Methods and Instruments

3.5.1 Survey Design

To collect data, I will be using a cross-sectional survey design that is suitable for quantitative research. This design will help in terms of describing and analysing a large sample of data and ensuring that results remain 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.

3.5.2 Data collection instrument

I will be using online surveys as the method of data collection, which is a cost-effective method to reach out to a large number of participants with minimum effort and cost, while I will also try to reach 10% of the target audience over phone calls and online meeting platforms to interview and take first-hand responses.

I have created a Google Form covering the questions from the constructs mentioned previously.

3.5.3 Likert Scale

I will be using a 5-point Likert scale in my survey to collect participant data. A 5-point Likert scale is a commonly used research instrument for measuring attitudes, opinions, perceptions, or other subjective responses of individuals. It is named after its creator, psychologist Rensis Likert. The scale consists of a series of statements or items, and participants are asked to indicate their level of agreement or disagreement with each statement on a 5-point scale.

The 5-point Likert scale typically ranges from "Strongly Disagree" to "Strongly Agree" or from "Very Dissatisfied" to "Very Satisfied." The response options in between these extremes may vary depending on the specific study or context, but they usually include intermediate levels such as "Disagree," "Neutral" or "Neither Agree nor Disagree," and "Agree."

Researchers use the 5-point Likert scale to capture the intensity or strength of participants' attitudes or opinions on a given topic. It provides a way to quantify subjective responses and allows for comparison and analysis of responses across participants or groups. The scale is relatively simple for participants to understand and complete, making it a popular choice in surveys, questionnaires, and psychological research.

3.5.4 Limitations

However, cross-sectional studies have some limitations as well. One of the significant limitations is 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). Additionally, cross-sectional studies often fail to provide conclusive results because of a lack of responses from survey participants or researchers misclassifying data (Cartledge et al., 2020)

3.6 Operationalisation of the Research Constructs

This study incorporated seven independent variables derived from the UTUAT theory, while the dependent variable focused on the decision-making process of AI adoption, implementation, and utilisation within the Textile and Apparel MSME sector in India.

Table 3.2
Questions and construct mapping

Question Number	Question	Construct	Variable
8	AI technology will improve my productivity in the textile industry	Performance Expectancy	PE1
9	AI technology will enhance the quality of textile products or services.	Performance Expectancy	PE2
10	AI technology will enable faster decision-making in the textile industry.	Performance Expectancy	PE3
11	AI technology will improve the accuracy of tasks in the textile industry.	Performance Expectancy	PE4
12	AI technology is easy to understand and use in the textile industry	Effort Expectancy	EE1
13	Learning to use AI technology in the textile industry would be eas for me.	Effort Expectancy	EE2
14	AI technology would make my work in the textile industry easier and more efficient.	Effort Expectancy	EE3
15	I believe I could become competent in using AI technology in the textile industry quickly.	Effort Expectancy	EE4
16	Colleagues' opinions significantly influence my decision to adopt technology in the textile industry.	Social Influence	SI1
17	Managers' opinions significantly influence my decision to adopt A technology in the textile industry.	Social Influence	SI2
18	Industry experts' opinions significantly influence my decision to adopt AI technology in the textile industry.	Social Influence	SI3
19	Customers' opinions significantly influence my decision to adopt technology in the textile industry.	Social Influence	SI4
20	My organization provides sufficient training and support for adopting AI technology in the textile industry.	Facility Condition	FC1
21	My organization has the necessary infrastructure and technical resources for adopting AI technology in the textile industry.	Facility Condition	FC2
22	I have access to external experts or consultants who can assist wit AI technology adoption in the textile industry.	Facility Condition	FC3
23	Financial resources are available to support the adoption of AI technology in the textile industry.	Facility Condition	FC4
24	The potential benefits of AI technology outweigh its cost in the textile industry.	Price Value	PV1

25	AI technology provides good value for the investment in the textil industry.	Price Value	PV2
26	The cost of adopting AI technology is justified by the advantages offers in the textile industry.	Price Value	PV3
27	The return on investment from adopting AI technology in the texti industry makes it worthwhile.	Price Value	PV4
28	Adopting AI technology in the textile industry would provide me with a sense of excitement and enjoyment.	Hedonic Motivations	HM1
29	AI technology adoption in the textile industry would satisfy my desire for novelty and variety.	Hedonic Motivations	HM2
30	AI technology adoption in the textile industry would enhance my personal expression and style.	Hedonic Motivations	HM3
31	The use of AI technology in the textile industry would evoke positive emotions and pleasure.	Hedonic Motivations	HM4

3.7 Data Analysis

To understand the impact of independent variables on Dependent Variables I will be choosing the below strategies.

1. Multiple Regression Analysis
2. Bivariant Analysis
3. Segmentation Analysis

3.7.1 Multiple Regression Analysis

In order to examine the factors influencing the decision-making process of AI adoption in the Indian small and medium-scale textile industry, I will conduct a multiple regression analysis. This statistical technique will allow me to explore the relationships between the dependent variable, the "Decision-making process of AI adoption," and the independent variables derived from the Unified Theory of Acceptance and Use of Technology (UTAUT) theory.

3.7.1.1 Research Variables

Dependent Variable: The dependent variable, "Decision-making process of AI adoption," will represent the overall intention and process of adopting AI technology within the textile industry.

Independent Variables (Predictors): I will select seven independent variables based on the UTAUT theory, each representing specific constructs related to AI adoption:

- Performance Expectancy (PE): PE1, PE2, PE3, and PE4, will indicate perceptions regarding the improvement of productivity, enhancement of textile product/service quality, enabling faster decision-making, and improving task accuracy through AI adoption.
- Effort Expectancy (EE): EE1, EE2, EE3, and EE4, will reflect participants' perceptions of the ease of understanding and using AI technology, ease of learning, and the overall efficiency gained by adopting AI.
- Social Influence (SI): SI1, SI2, SI3, and SI4, will capture the influence of colleagues, managers, industry experts, and customers on participants' decisions to adopt AI technology.p
- Facility Condition (FC): FC1, FC2, FC3, and FC4, will indicate the availability of sufficient training and support, necessary infrastructure and technical resources, access to external experts or consultants, and financial resources to support AI adoption.
- Price Value (PV): PV1, PV2, PV3, and PV4, will represent perceptions of the potential benefits outweighing costs, AI technology providing good value for investment, the cost justification of AI adoption, and the perceived return on investment.
- Hedonic Motivations (HM): HM1, HM2, HM3, and HM4, will capture participants' excitement, novelty-seeking tendencies, desire for personal expression, and positive emotional experiences related to AI adoption.

3.7.1.2 Statistical Analysis

I will employ multiple regression analysis using the Statistical Package for the Social Sciences (SPSS) software or Use Python Library (Decision will be taken based on the ease of use and availability). Before conducting the analysis, I will ensure that the assumptions of linearity, normality, homoscedasticity, and independence of residuals are met.

3.7.1.3 Regression Results

The multiple regression analysis will yield the following results:

1. The overall regression model will be statistically significant (F = [result value], $p < 0.05$), indicating that the combined set of independent variables significantly explains the variance in the decision-making process of AI adoption in the textile industry.
2. The R-squared value (R^2 = [result value]) will indicate the proportion of variance in the dependent variable (decision-making process of AI adoption) that can be accounted for by the independent variables.
3. The beta coefficients (β) for each independent variable will provide insights into the strength and direction of their influence on the decision-making process of AI adoption. I will interpret the significant predictors to understand their impact on adoption decisions. I will use the beta coefficients even while conducting the bivariant analysis to derive the results.

3.7.1.4 Discussion

The multiple regression analysis results will shed light on the significant predictors that influence the intention to adopt AI technology in the Indian small and medium-scale textile industry. The findings will highlight the role of performance expectancy, effort expectancy, social influence, facility condition, price value, and hedonic motivations in shaping the decision-making process. I will discuss the implications of these results for the textile industry's stakeholders in the following section.

3.7.2 Bivariate Analysis

To explore the initial relationships between variables in the context of my research on "Understanding Scope and Challenges of Adoption & Implementation of Artificial Intelligence in the Indian Small and Medium-Scale Textile Industry," I will conduct bivariate analysis. This statistical technique will allow me to examine the relationships between two variables at a time and provide preliminary insights into potential associations.

3.7.2.1 Research Variables

For the bivariate analysis, I will focus on specific pairs of variables to assess their relationships:

- **Performance Expectancy (PE) vs. Decision-making process of AI adoption:** I will explore how participants' perceptions of AI's impact on productivity, quality enhancement, faster decision-making, and task accuracy (PE1, PE2, PE3, PE4) are related to their overall decision-making process of AI adoption.
- **Effort Expectancy (EE) vs. Decision-making process of AI adoption:** I will examine the relationship between perceived ease of understanding and using AI technology, ease of learning, and work efficiency (EE1, EE2, EE3, EE4) and the participants' decisions to adopt AI.
- **Social Influence (SI) vs. Decision-making process of AI adoption:** I will analyze the influence of colleagues, managers, industry experts, and customers (SI1, SI2, SI3, SI4) on participants' decisions regarding AI adoption.
- **Facility Condition (FC) vs. Decision-making process of AI adoption:** I will assess the impact of factors such as training and support, infrastructure and

technical resources, access to external experts or consultants, and financial resources (FC1, FC2, FC3, FC4) on the adoption decisions.

- **Price Value (PV) vs. Decision-making process of AI adoption:** I will investigate how participants' perceptions of the benefits outweighing costs, value for investment, cost justification, and return on investment (PV1, PV2, PV3, PV4) relate to their decisions on AI adoption.
- **Hedonic Motivations (HM) vs. Decision-making process of AI adoption:** I will explore the influence of excitement, novelty-seeking tendencies, desire for personal expression, and positive emotional experiences (HM1, HM2, HM3, HM4) on the adoption decisions.

3.7.2.2 Statistical Analysis

For the bivariate analysis, I will use appropriate statistical tests, such as:

1. Pearson's correlation coefficient for continuous variables to assess the linear relationship between two continuous variables (e.g., PE and the decision-making process of AI adoption).
2. Point-biserial correlation for one continuous and one dichotomous variable (e.g., EE and decision-making process of AI adoption, where "yes" or "no" represents adoption decisions).
3. Chi-square test for two categorical variables (e.g., SI and decision-making process of AI adoption).

3.7.2.3 Bivariant Analysis Results

The results of the bivariate analysis will provide initial insights into the associations between the selected pairs of variables. I will examine the correlation coefficients, chi-square statistics, and p-values to determine the significance and direction of the relationships.

3.7.2.4 Discussion

The bivariate analysis will serve as a foundation for the subsequent multivariate analysis, helping me identify potential predictors that may be relevant to the decision-making process of AI adoption in the Indian small and medium-scale textile industry. However, it is essential to acknowledge that the bivariate analysis only provides preliminary insights, and further investigation through multivariate analysis is necessary to account for the simultaneous effects of multiple variables on the adoption decisions.

3.7.3 Segmentation Analysis

To gain a deeper understanding of the diversity within the sample and identify distinct subgroups with unique attitudes and perceptions toward AI adoption, I will conduct segmentation analysis. This statistical technique, also known as cluster analysis, will allow me to group participants based on similarities in their responses to the survey questions.

3.7.3.1 Research Variables

For the segmentation analysis, I will consider all the variables used in the study, including those related to performance expectancy (PE), effort expectancy (EE), social influence (SI), facility condition (FC), price value (PV), and hedonic motivations (HM). By utilizing all these variables collectively, I aim to identify clusters of participants who exhibit similar preferences and decision-making patterns in regards to AI adoption in the Indian small and medium-scale textile industry.

3.7.3.2 Statistical Analysis

I will employ cluster analysis, a commonly used technique for segmentation, to group participants based on the similarities or dissimilarities in their responses to the survey items. The analysis will be conducted using software such as SPSS or R.

3.7.3.3 Segmentation Analysis results

The segmentation analysis will result in the identification of different clusters within the sample. Each cluster will represent a distinct subgroup of participants who share similar perceptions, attitudes, and intentions regarding AI adoption. The characteristics and preferences of each cluster will be analyzed to gain insights into the various segments present within the sample.

3.7.4 Discussion

The segmentation analysis will provide valuable insights into the heterogeneity of responses among participants in the Indian small and medium-scale textile industry. By understanding the different segments and their unique perspectives on AI adoption, stakeholders can tailor their strategies and interventions accordingly.

3.8 Research Study Period

This research study is planned to be completed in the next 12 months, which should allow the researcher to be able to gather enough data as per the research plan. Table 4, below, shows the research activities and the planned duration to complete those.

Table 3.3
Research Activities and Planned Duration

Research Activities	**Planned duration**
Research Proposal Writing	1 Month
Sample Selection and Formal Consent	2 weeks
Data Collection	2 Months
Analysis	1 Month
Interpretation	1 Month
Thesis Writing	2 Months
Presentation	2 weeks

3.9 Ethical considerations

I will obtain an authorisation letter from the university indicating that the data that will be collected will be used for academic purposes only. In order to maintain ethical practices within this study, the participation will be kept completely voluntary, and respondents can discontinue participation at any time. Neither participation will lead to an incentive nor a discontinuation of participation will lead to a penalty. The anonymity of respondents for survey purposes and confidentiality of respondents for interview purposes will be protected at all times.

Chapter 4: Results

The objective of this quantitative cross-sectional correlational study was to investigate the presence and extent of the relationship between Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facility Condition (FC), Price Value (PV), Hedonic Motivation (HM), and the decision to adopt and implement AI technology in the Indian small and medium-scale textile industry. AI technology has emerged as a valuable and promising tool within this sector, offering opportunities for increased efficiency, improved product quality, and more streamlined decision-making processes.

This research was guided by a primary research question and seven sub-questions. The central focus of the primary research question was to determine whether there is any statistically significant relationship between the independent variables—drawn from the Unified Theory of Acceptance and Use of Technology (UTAUT) model—and the dependent variable, the Decision of AI Adoption (DAI). Each of the seven secondary research questions aimed to assess the correlation between one independent variable and the dependent variable:

- Performance Expectancy (PE): Do perceptions regarding improved productivity, quality, decision-making, and accuracy (PE) have a statistically significant relationship with AI adoption in the textile industry?
- Effort Expectancy (EE): Does the perceived ease of understanding and using AI technology (EE) correlate with the decision to adopt AI?
- Social Influence (SI): How does the influence of colleagues, managers, experts, and customers (SI) impact AI adoption decisions?
- Facility Condition (FC): To what extent do available infrastructure, training, expert support, and financial resources (FC) influence the adoption of AI technology?
- Price Value (PV): Does the perception of AI technology providing good value for money (PV) correlate with the decision to adopt AI?

- Hedonic Motivation (HM): How do emotional factors such as excitement and enjoyment (HM) influence AI adoption decisions?

The study employed correlational techniques to assess the relationships between each of these independent variables and the dependent variable (DAI), providing a comprehensive analysis of the factors influencing AI adoption within the Indian textile industry.

The primary and secondary questionnaires are as below: **H_0 (null hypothesis)** and **H_a (alternative hypothesis)**

RQ: What are the different factors that facilitate or hinder the Decision to Adopt and Implement AI (DAI) in the Textile and Apparel SME sector in India?

The following secondary research questions were formulated based on the constructs of the UTUAT theory in order to examine the impact of independent variables on the dependent variable.

1. SQ1: Does PE have any statistically significant correlation with DAI in the Textile and Apparel SME sector in India?
    - H01: PE does not have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India.
    - Ha1: PE does have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India
2. SQ2: Does EE have any statistically significant correlation with DAI in the Textile and Apparel SME sector in India?
    - H02: EE does not have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India.

- Ha2: PE does have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India

3. SQ3: Does SI have any statistically significant correlation with DAI in the Textile and Apparel SME sector in India?

    - H03: SI does not have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India.

    - Ha3: SI does have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India

4. SQ4: Does FC have any statistically significant correlation with DAI in the Textile and Apparel SME sector in India?

    - H04: FC does not have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India.

    - Ha4: FC does have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India

5. SQ5: Does HM have any statistically significant correlation with DAI in the Textile and Apparel SME sector in India?

    - H05: HM does not have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India.

    - Ha5: HM does have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India

6. SQ6: Does PV have any statistically significant correlation with DAI in the Textile and Apparel SME sector in India?

    - H06: PV does not have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India.

- Ha6: PV does have a statistically significant correlation with DAI in the Textile and Apparel SME sector in India

I developed both null and alternative hypotheses to address each of the secondary research questions. According to Nachmias and Leon-Guerrero (2018), a hypothesis is a tentative answer to a research question, which is validated through statistical testing. In this study, a total of 12 hypotheses (6 null hypotheses and 6 alternative hypotheses) were formulated to assess the relationship between each of the 6 independent variables derived from the UTAUT framework and the dependent variable, the Decision to Adopt and Implement AI (DAI) in the Indian textile and apparel SME sector.

For each research question, the null hypothesis (H_0) stated that there is no statistically significant correlation between the independent variable (e.g., Performance Expectancy (PE)) and the dependent variable (DAI). Conversely, the alternative hypothesis (H_a) proposed that there is a statistically significant correlation between the independent variable and DAI.

Each pair of null and alternative hypotheses provided a structured approach to evaluating the relationships between the independent variables—Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facility Condition (FC), Price Value (PV), Hedonic Motivation (HM), and Habit (HB)—and the dependent variable, Decision to Adopt and Implement AI (DAI). These hypotheses were tested using appropriate statistical methods, and the results were analysed to either reject the null hypothesis or fail to reject it, thus confirming or rejecting the proposed relationships between the variables.

This chapter is organised into three main sections: **Data Collection**, **Data Preparation**, **Statistical Analysis** and **Study Results**.

4.1 Data Collection

I employed an online survey method to collect the necessary data regarding the adoption and implementation of AI technology in the Indian textile and apparel SME sector. The survey aimed to investigate the relationships between seven independent variables derived from the UTAUT framework and the dependent variable, Decision to Adopt and Implement AI (DAI).

The questionnaire was created using Google Forms, which provided an accessible and efficient platform for data collection. The survey was distributed through several channels to ensure broad participation from individuals working in relevant industries. On April 10, 2024, I posted the survey on my LinkedIn wall, shared it in relevant LinkedIn groups, and distributed it via WhatsApp groups and direct messages to industry professionals. These efforts resulted in a total of 1,809 impressions on LinkedIn.

The data collection process lasted for two months, during which time I gathered 219 responses. Participants were made aware of how their data would be used, as explained in the survey itself, and informed consent was obtained on the very first page of the form. The consent form clarified the anonymity of the responses and participants' right to exit the survey at any time. The survey was designed to ensure complete anonymity, with no personal identifiers such as IP addresses, names, or email addresses being collected.

I made minor adjustments to the survey's format to protect participants' privacy further. Specifically, I removed the option to enter free-form text in any open-ended questions to prevent participants from inadvertently providing personal information. The free-form text option was only allowed in a few instances, such as when participants selected "Other" for questions relating to job title, industry sector, or educational level. Removing these fields minimised the risk of including unsolicited personal details in the dataset.

This careful approach to data collection ensured the protection of participants' privacy and confidentiality while allowing me to collect the necessary data for this study on AI adoption in India's textile and apparel SME sector.

4.1.1 Recruitment Timeframe

I created a web-based survey using Google Forms and distributed the survey link via several channels, including LinkedIn posts, relevant LinkedIn groups, and WhatsApp groups, as well as direct messages to industry professionals. The data collection process was initiated on April 10, 2024, and the survey remained open for a period of two months, concluding on June 10, 2024.

During this period, I closely monitored the survey distribution and response rates. The target sample size was 193, as described in Chapter 3, aimed to exceed 150 complete responses to ensure sufficient data for statistical analysis. The combination of social media posts and direct outreach allowed me to successfully gather 219 complete responses, exceeding the initial target. The survey was continuously monitored on the Google Forms platform to track the response rates and ensure timely participation.

4.1.2 Survey Recruitment Rates

I opened the survey to participants on April 10, 2024, and received an immediate response. On the first day, I received 35 responses, all of which were complete, resulting in a 0% disqualification rate. By April 11, 2024, the second day of data collection, the number of responses increased to 39, bringing the cumulative total to 74 responses, with all responses complete and valid, keeping the disqualification rate at 0%.

The momentum continued over the next few days:

- On April 12, 2024, I received 24 responses (total 98 responses, 11.0% of the total responses).

- On April 13, 2024, I received 27 responses (total 125 responses, 12.3% of the total responses).
- On April 14, 2024, I received 25 responses (total 150 responses, 11.4% of the total responses).

These first five days accounted for the majority of the responses (68.5% of total responses). After this initial surge, responses gradually trickled in over the following weeks. The total number of responses gathered by June 10, 2024, was 219, surpassing the targeted minimum sample size of 150 complete responses.

The response rates for the days following the initial surge were more modest:

- From April 15, 2024, to June 10, 2024, responses ranged between 1-4 per day, with minor peaks on specific days such as May 1, 2024 (4 responses) and May 26, 2024 (3 responses).

I meticulously tracked the response rates and ensured that all responses were complete. Overall, the survey collection process resulted in a 100% completion rate, as there were no disqualifications due to incomplete responses.

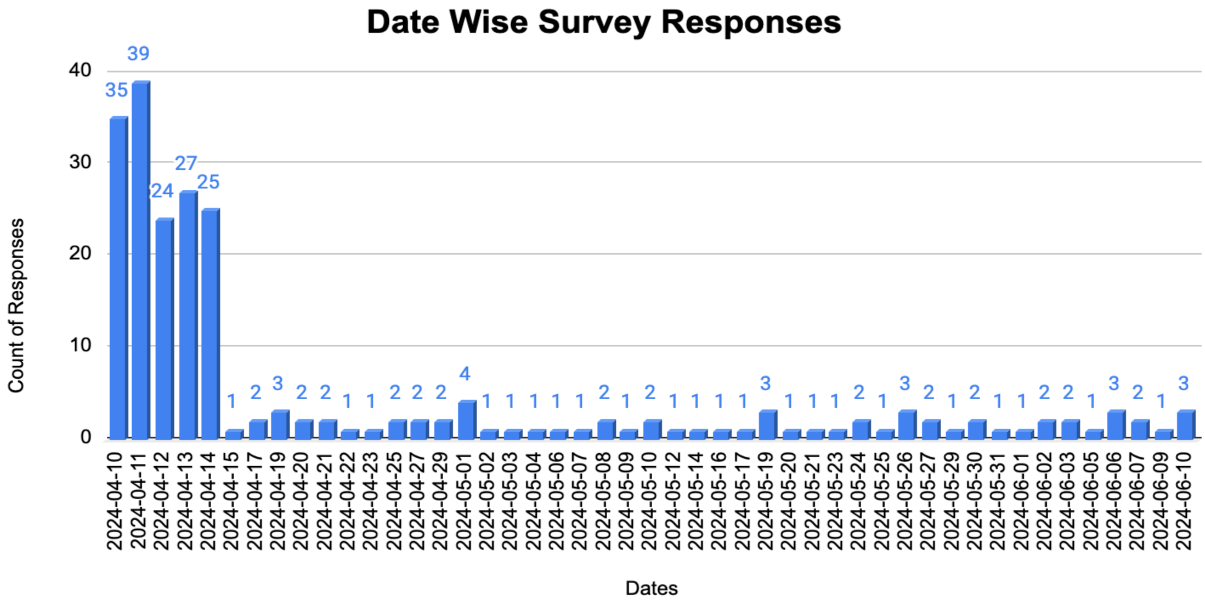

Figure 4.1
Date wise Survey Responses

4.2 Data Preparation

To prepare the dataset for analysis, I used Python to clean and preprocess the survey data collected from **Google Forms**. The data was first downloaded in CSV format and then loaded into a **Pandas DataFrame**. I performed various preprocessing steps, including renaming and encoding categorical variables, as well as organizing the Likert-scale responses into corresponding variables for each UTAUT construct.

The demographic data columns were encoded as categorical values using Python's **category** data type. Specifically:

- The **Title**, **Gender**, **Age**, **Education Level**, and **Region** columns were transformed into numerical codes using astype('category').cat.codes, which assigned a unique numerical value to each category. This step ensured that these variables were properly formatted for subsequent statistical analysis.

Independent Variables:

For the constructs related to the Unified Theory of Acceptance and Use of Technology (UTAUT), I mapped and aggregated the responses to specific questions as follows:

- **Performance Expectancy (PE)**: Constructed using responses from four Likert-scale questions (PE1 to PE4) related to the perceived productivity and accuracy improvements from AI adoption.
- **Effort Expectancy (EE)**: Aggregated from four questions (EE1 to EE4), measuring the ease of use and learning associated with AI technology.
- **Social Influence (SI)**: Created using responses to four questions (SI1 to SI4), capturing the influence of colleagues, managers, and customers on AI adoption decisions.
- **Facility Condition (FC)**: Constructed from four questions (FC1 to FC4) measuring organisational readiness in terms of resources, training, and infrastructure for AI adoption.
- **Price Value (PV)**: This construct was built from four questions (PV1 to PV4) addressing participants' perceptions of the value AI brings to the textile industry.
- **Hedonic Motivation (HM)**: Created using four Likert-scale responses (HM1 to HM4) measuring the emotional and motivational factors behind AI adoption.

Each of these variables was stored as individual columns within the dataframe for simple access during the analysis.

Dependent Variable:

The dependent variable, **Decision to Adopt and Implement AI (DAI)**, was encoded using responses from the question, *"In your opinion, how soon will organisations in your industry sector adopt Artificial Intelligence?"*. This was also converted into categorical numerical codes to facilitate regression and correlation analysis.

4.2.1 Encoding and organising the data:

To ensure consistency and ease of analysis, I renamed and organised the columns as follows:

1. **Demographic Data Encoding:** The demographic variables in the dataset were encoded into numerical categories using .astype('category').cat.codes. This method allowed for easier analysis in statistical models by converting textual responses into corresponding numeric codes. The following demographic variables were encoded:
    - Title: Described the participants' job roles (e.g., “Manager,” “Technician”) and was encoded as titles.
    - Gender: Categorised as either “Male” or “Female” and encoded as gender.
    - Age: Recorded as age groups (e.g., “25-35,” “36-45”) and encoded as age.
    - Education: captured the highest education level attained by participants (e.g., “High School,” “Master’s Degree”) and encoded as education.
    - Region: Described the geographical location (e.g., “North India,” “South India”) and encoded as region.
2. **Mapping UTAUT 2 Constructs to Survey Questions**: The independent variables based on the UTAUT 2 constructs were carefully mapped to specific questions in the survey. Each construct was represented by multiple questions (indicators) that were measured on a **5-point Likert Scale** ranging from **1 = Strongly Disagree** to **5 = Strongly Agree**. These mappings were as follows:

    Performance Expectancy (PE):

    - **PE1**: *“AI technology will improve my productivity in the textile industry.”*
    - **PE2**: *“AI technology will enhance the quality of textile products or services.”*
    - **PE3**: *“AI technology will enable faster decision-making in the textile industry.”*
    - **PE4**: *“AI technology will improve the accuracy of tasks in the textile industry.”*

Effort Expectancy (EE):

- **EE1**: *"AI technology is easy to understand and use in the textile industry."*
- **EE2**: *"Learning to use AI technology in the textile industry would be easy for me."*
- **EE3**: *"AI technology would make my work in the textile industry easier and more efficient."*
- **EE4**: *"I believe I could become competent in using AI technology in the textile industry quickly."*

Social Influence (SI):

- **SI1**: *"Colleagues' opinions significantly influence my decision to adopt AI technology in the textile industry."*
- **SI2**: *"Managers' opinions significantly influence my decision to adopt AI technology in the textile industry."*
- **SI3**: *"Industry experts' opinions significantly influence my decision to adopt AI technology in the textile industry."*
- **SI4**: *"Customers' opinions significantly influence my decision to adopt AI technology in the textile industry."*

Facility Condition (FC):

- **FC1**: *"My organization provides sufficient training and support for adopting AI technology in the textile industry."*
- **FC2**: *"My organization has the necessary infrastructure and technical resources for adopting AI technology in the textile industry."*
- **FC3**: *"I have access to external experts or consultants who can assist with AI technology adoption in the textile industry."*
- **FC4**: *"Financial resources are available to support the adoption of AI technology in the textile industry."*

Price Value (PV):

- **PV1**: *"Adopting AI technology in the textile industry would provide me with a sense of excitement and enjoyment."*
- **PV2**: *"AI technology adoption in the textile industry would satisfy my desire for novelty and variety."*
- **PV3**: *"AI technology adoption in the textile industry would enhance my personal expression and style."*
- **PV4**: *"The use of AI technology in the textile industry would evoke positive emotions and pleasure."*

Hedonic Motivation (HM):

- **HM1**: *"The potential benefits of AI technology outweigh its cost in the textile industry."*
- **HM2**: *"AI technology provides good value for the investment in the textile industry."*
- **HM3**: *"The cost of adopting AI technology is justified by the advantages it offers in the textile industry."*
- **HM4**: *"The return on investment from adopting AI technology in the textile industry makes it worthwhile."*

Dependent Variable:

The dependent variable, **Decision to Adopt and Implement AI (DAI)**, was derived from responses to the question:

- *"In your opinion, how soon will organisations in your industry sector adopt Artificial Intelligence?"*

This question was encoded as target_org to represent participants' perspectives on AI adoption timelines.

4.2.2 Constructing Composite Variables:

I constructed composite variables by averaging the responses to the questions mapped to each UTAUT construct. These composite variables were then used in the subsequent analyses:

- **Performance Expectancy (PE)**: Average of PE1, PE2, PE3, PE4.
- **Effort Expectancy (EE)**: Average of EE1, EE2, EE3, EE4.
- **Social Influence (SI)**: Average of SI1, SI2, SI3, SI4.
- **Facility Condition (FC)**: Average of FC1, FC2, FC3, FC4.
- **Price Value (PV)**: Average of PV1, PV2, PV3, PV4.
- **Hedonic Motivation (HM)**: Average of HM1, HM2, HM3, HM4.
- **Decision to Adopt AI (DAI)**: Encoded responses to the AI adoption timeline question.

This structured and systematic approach ensured that all data points were ready for inferential analysis, including regression and correlation studies.The dependent variable for this study, **Decision to Adopt and Implement AI (DAI)**, was derived from the question, "In *your opinion, how soon will organisations in your industry sector adopt Artificial Intelligence?"* The responses to this question were initially recorded as categorical values, representing different AI adoption timelines. To facilitate numerical analysis (e.g., regression and correlation analysis), I converted these categorical responses into a **5-point numerical system** as follows:

- **5**: *"Already use Artificial Intelligence"*
- **4**: *"Less than 6 months"*
- **3**: *"6 to 12 months"* and *"13 to 24 months"*
- **2**: *"More than 24 months"* and *"Don't know"*
- **2**: *"Dont Know"*
- **1**: *"No plans"*

This transformation allowed for a more quantitative approach to the analysis, making it possible to evaluate the correlation between the decision to adopt AI and the independent variables derived from the UTAUT 2 model. This recoding ensured that the **DAI** variable was appropriately scaled for further statistical analysis, allowing me to draw more precise conclusions about the relationship between the timing of AI adoption and the independent variables.

4.2.3 Outlier Detection Using Box Plot

To identify any potential outliers in the collected data, I generated a box plot for the six independent variables: **Performance Expectancy (PE)**, **Effort Expectancy (EE)**, **Social Influence (SI)**, **Facility Condition (FC)**, **Price Value (PV)**, and **Hedonic Motivation (HM)**. Each of these variables was measured using a **5-point Likert Scale**, where:

- **1 = Strongly Disagree**
- **2 = Disagree**
- **3 = Neutral**
- **4 = Agree**
- **5 = Strongly Agree**

The box plot visualises the distribution of responses for each variable, helping to detect any data points that deviate significantly from the rest of the dataset.

Analysis of the Box Plot:

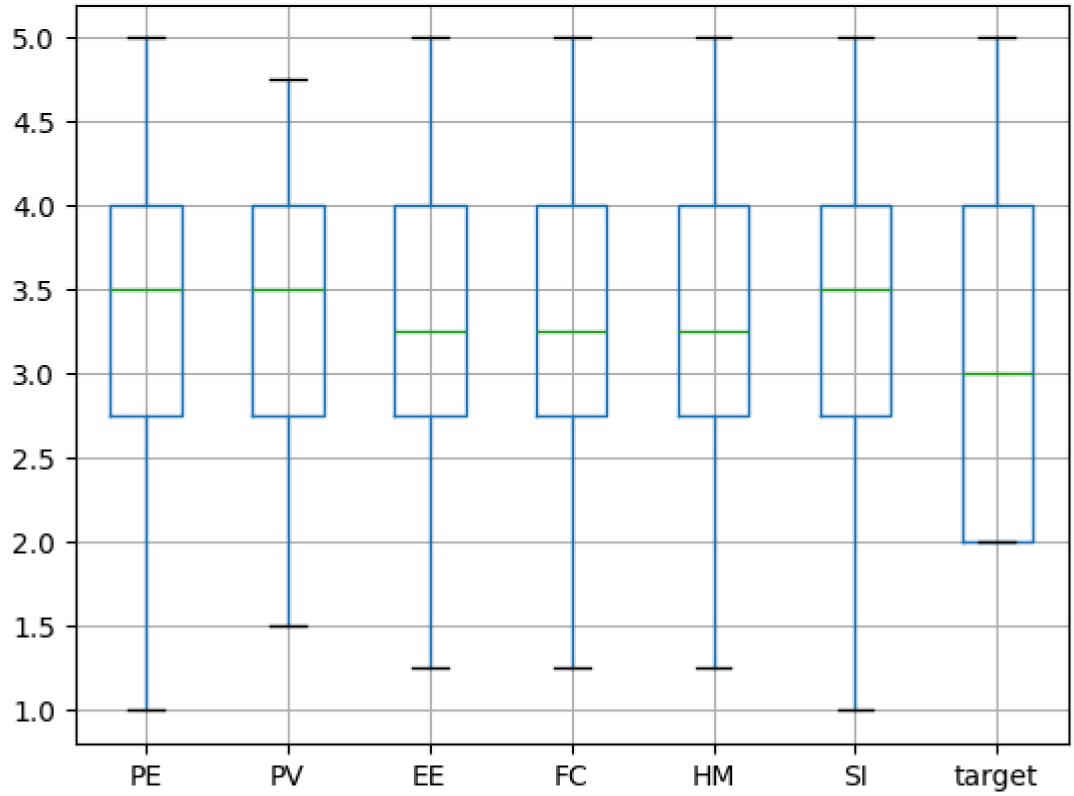

Figure 4.2
Box Plot of Agregated Constructs

As shown in the box plot (Figure 4.2), the data for all six constructs was generally well-distributed across the 5-point scale. The median for each construct hovered around 3.5, indicating that most respondents provided neutral to somewhat positive responses regarding the constructs.

The key observations from the box plot are as follows:

- **No outliers were detected** within the data for any of the six independent variables (PE, EE, SI, FC, PV, and HM). The whiskers extend to the minimum and maximum values without any points falling beyond the expected range.
- The distribution of the responses appears symmetric, with no extreme deviations from the central tendency (median).

Interpretation of Results:

Since no outliers were visually detected in the box plot, there was no need to remove any data points from the analysis. Therefore, the total number of responses remained **219** for the subsequent statistical analyses.

4.3 Statistical analysis

4.3.1 Central Tendency and Distribution Analysis

To understand the overall trends and variability within the dataset, I calculated the **mean** and **standard deviation** for each of the six independent variables **Performance Expectancy (PE)**, **Effort Expectancy (EE)**, **Social Influence (SI)**, **Facility Condition (FC)**, **Price Value (PV)**, and **Hedonic Motivation (HM)**—as well as the dependent variable, **Decision to Adopt and Implement AI (DAI)** (referred to as **target**). These measures of central tendency provide insights into the typical responses from participants and the spread or consistency of those responses.

Table 4.1
Summary of Descriptive Statistics

Variabl	Count	Mean	Std Dev	Min	25%	50%	75%	Max	Kurtosi	Skewness
PE	219	3.31	0.85	1	2.75	3.5	4	5	-0.61	-0.39
PV	219	3.28	0.79	1.5	2.75	3.5	4	4.75	-0.6	-0.43
EE	219	3.26	0.83	1.25	2.75	3.25	4	5	-0.66	-0.35
FC	219	3.32	0.81	1.25	2.75	3.25	4	5	-0.44	-0.19
HM	219	3.31	0.8	1.25	2.75	3.25	4	5	-0.19	-0.42
SI	219	3.31	0.81	1	2.75	3.5	4	5	-0.32	-0.47
Target	219	3.24	1.13	2	2	3	4	5	-1.24	0.39

Summary of Descriptive Statistics:

The table above presents the descriptive statistics, including the number of observations, the mean, standard deviation, minimum, and maximum values, as well as the skewness and kurtosis for each variable:

Analysis of Central Tendency:

- The **mean values** of the independent variables ranged between **3.24** and **3.32**, indicating that most participants provided responses that were slightly above neutral (leaning towards "agree"). This suggests that respondents generally had positive attitudes towards the constructs being measured, such as their expectations of AI performance, effort needed, social influences, and emotional motivations.
- The **standard deviations** for the independent variables ranged from **0.79** to **0.85**, showing moderate variability in the responses. This indicates that while most respondents provided similar answers, there was still some spread in the data. For the dependent variable (**target**), the standard deviation was **1.13**, reflecting a wider range of opinions regarding the time frame for AI adoption, with some respondents perceiving quick adoption while others anticipated more extended timelines.

Distribution Shape (Skewness and Kurtosis):

- **Skewness**: The skewness values for all the independent variables were negative, ranging from **-0.19** to **-0.47**, indicating that the distributions were slightly skewed to the left. This suggests that a slightly higher proportion of respondents chose more positive responses (agree or strongly agree) for most of the variables. For the dependent variable, the skewness value was **0.39**, indicating a slight positive skew, suggesting that respondents were more likely to anticipate longer timelines for AI adoption rather than shorter ones.
- **Kurtosis**: The kurtosis values for the independent variables ranged from **-0.66** to **-0.19**, meaning that all the distributions were **platykurtic**—flatter than normal

distribution. This implies that the responses were somewhat more spread out across the Likert scale rather than clustered tightly around the mean. For the dependent variable, the kurtosis value was **-1.24**, indicating a more pronounced platykurtic distribution, which suggests that respondents were distributed fairly evenly across the timeline for AI adoption.

Interpretation of Results:

The descriptive statistics indicate that most respondents generally held positive perceptions regarding AI's benefits and the factors influencing its adoption in the textile industry. The slight negative skewness in the independent variables reflects the participants' inclination toward favourable views. The absence of extreme kurtosis or skewness values suggests that the data is reasonably well distributed and approximates a normal distribution.

The moderate variability in responses, as reflected by the standard deviations, particularly for the dependent variable, demonstrates that there is diversity in opinions about the timeline for AI adoption. Despite the slightly skewed and platykurtic distributions, the data remains suitable for parametric tests, such as regression analysis, which assumes normality to a certain extent.

4.3.2 Reliability Analysis using Cronbach's Alpha

In this section, I assess the reliability of the independent variables derived from the UTAUT model using **Cronbach's Alpha**. Cronbach's Alpha is a measure of internal consistency that reflects how well the items in a construct are correlated with one another. A higher Cronbach's Alpha value indicates stronger internal consistency, meaning that the items within each construct consistently measure the same underlying concept. An Alpha value of **0.70** or higher is generally considered acceptable for social science research, while a value closer to **1.0** is ideal.

In addition to calculating Cronbach's Alpha for each construct, the **Overall Cronbach's Alpha** was calculated to assess the reliability of the entire survey instrument.

Summary of Cronbach's Alpha:

To evaluate the reliability of the survey questions used for each construct, I calculated Cronbach's Alpha for the six independent variables: **Performance Expectancy (PE)**, **Effort Expectancy (EE)**, **Social Influence (SI)**, **Facility Condition (FC)**, **Price Value (PV)**, and **Hedonic Motivation (HM)**. The results are as follows:

Table 4.2
Cronbach's Alpha for every Constructs

Construct	**Cronbach's Alpha**
Performance Expectancy (PE)	0.61
Effort Expectancy (EE)	0.55
Social Influence (SI)	0.56
Facility Condition (FC)	0.51
Price Value (PV)	0.52
Hedonic Motivation (HM)	0.54
Overall Cronbach's Alpha	**0.98**

The **Overall Cronbach's Alpha** for the survey instrument is **0.98**, indicating excellent internal consistency across all constructs combined. This suggests that, despite some variability in the reliability of individual constructs, the overall survey tool is highly reliable.

Analysis of Cronbach's Alpha:

- **Performance Expectancy (PE)** had the highest Cronbach's Alpha among the individual constructs, with a value of **0.61**. This suggests moderate internal consistency, indicating that the items related to AI's performance benefits are somewhat reliable, but improvements could be made.
- **Effort Expectancy (EE)** and **Social Influence (SI)** had Alpha values of **0.55** and **0.56**, respectively. These values indicate moderate reliability, but they also suggest some variability in how respondents understood and answered the questions related to ease of use and social influences on AI adoption.

- **Facility Condition (FC)** showed the lowest Cronbach's Alpha at **0.51**, reflecting weak internal consistency. This suggests that the questions related to organisational support for AI adoption may not fully capture the intended concept or were interpreted differently by respondents.
- **Price Value (PV)** and **Hedonic Motivation (HM)** had Alpha values of **0.52** and **0.54**, respectively, indicating moderate reliability. These constructs, which measure emotional responses and perceived value, show some alignment, but there is room for improvement in question formulation.

Despite the lower values for the individual constructs, the **Overall Cronbach's Alpha** of **0.98** indicates that, as a whole, the survey instrument is highly reliable. This suggests that, when viewed collectively, the survey items work well together to measure the overall concept of AI adoption and its influencing factors.

Interpretation of Results:

- **Performance Expectancy (PE)**, with an Alpha of **0.61**, shows that the items measuring respondents' expectations about AI performance are moderately reliable. However, slight improvements in the item formulation could increase consistency.
- **Effort Expectancy (EE)** and **Social Influence (SI)**, with Alpha values around **0.55**, suggest that there is some inconsistency in how respondents interpreted these items. The variation in answers could reflect differing experiences or interpretations of AI usability and social influences.
- **Facility Condition (FC)**, with a value of **0.51**, indicates relatively weak internal consistency. This could be due to the wide range of organisational contexts and available resources, which might lead to differing interpretations of the items related to support for AI adoption.
- **Price Value (PV)** and **Hedonic Motivation (HM)**, with values of **0.52** and **0.54**, respectively, indicate moderate reliability but also highlight potential issues in item alignment. Respondents may have understood or interpreted the emotional and value-related questions differently, suggesting the need for refinement.

- The **Overall Cronbach's Alpha** of **0.98** demonstrates that the survey, when taken as a whole, has excellent internal consistency. This suggests that the survey instrument is well-designed for measuring the overarching concepts related to AI adoption and the factors influencing it, even though individual constructs may require some adjustments for better alignment.

In conclusion, while some constructs have lower Cronbach's Alpha values, the overall reliability of the survey is very high. This indicates that the survey is suitable for further statistical analysis, although some individual constructs may benefit from refinement in future research.

4.3.3 Descriptive Statistics of Categorical Variables

The **Descriptive Statistics** section provides a detailed overview of the demographic characteristics of the survey respondents. This section is crucial because it offers insights into the composition of the sample, allowing us to understand the background and context of the individuals who participated in the study. By analyzing variables such as organization size, job titles, age, education, and gender, we can ensure that the data collected is representative of the population being studied—in this case, employees of Micro, Small, and Medium Enterprises (MSMEs) in India. This understanding is fundamental in ensuring that the results of the study can be generalized to a larger population within the textile and apparel SME sector.

By highlighting key demographic information, this section also helps to contextualize the responses in subsequent sections, offering a more comprehensive view of the factors influencing the adoption of AI in these organizations.

Summary of Demographics:

The survey received **219 complete responses**, and the following statistics provide a detailed breakdown of the respondents:

- **Organisation Size**: 76% of respondents were from MSMEs, and 24% from large enterprises.
- **Titles**: 31% of respondents held management/leadership roles, while the rest were distributed across digital, production, and IT teams.
- **Age Range**: 30% of participants were between 25 to 35 years old, followed by 24% in both the 18 to 25 and 46 to 60 age groups.
- **Education Level**: 31% of respondents had a Bachelor’s Degree, 26% had a Master’s Degree, and 21% had a Doctorate Degree.
- **Gender**: 56% of respondents were male, and 44% were female.

Analysis Descriptive Statistics

Organisation Size: The distribution of responses across different organisation types is as follows:

- **Large Enterprise**: 53 respondents (24%)
- **Medium Enterprise (MSME)**: 62 respondents (28%)
- **Micro Enterprise (MSME)**: 52 respondents (24%)
- **Small Enterprise (MSME)**: 52 respondents (24%)

This distribution shows that **76%** of the respondents were from Micro, Small, and Medium Enterprises (MSMEs), which is highly relevant to the focus of the study, as the research targets the adoption and implementation of AI in Indian MSMEs.

Table 4.3
Response count and Percentage of Categorical Variable: Organisation

Organisation		
What best describes your organisation?	**Count**	**Percentage**
Large Enterprise	53	24 %
Medium Enterprise (Part of MSME)	62	28 %
Micro Enterprise (Part of MSME)	52	24 %
Small Enterprise (Part of MSME)	52	24 %

This section also provides insights into the demographic characteristics of the participants, who were asked to provide details about their roles, age, gender, and education level.

Titles: Participants were asked to describe their roles within their respective organizations. The distribution of roles is as follows:

Table 4.4
Response count and Percentage of Categorical Variable - Titles

Titles		
What best describes your title?	**Count**	**Percentage**
Digital Team	51	23 %
IT and infrastructure team	49	22 %
Management/Leadership	68	31 %
Production Team	51	23 %

This distribution shows that **31%** of participants were in **management or leadership** positions, while the remaining participants were evenly distributed across digital, production, and IT teams.

Age Range:

Participants were also asked to specify their age group. The results are as follows:

Table 4.5
Response count and Percentage of Categorical Variable: Age

Age		
How Old are you?	**Count**	**Percentage**
18 to 25	53	24 %
25 to 35	66	30 %
36 to 45	47	21 %
46 to 60	53	24 %

The largest group of respondents fell within the **25 to 35 age range** (30%), followed by equal representation from both the **18 to 25** and **46 to 60 age groups** (24%) and **36 to 45 age groups (22%)**

Education Level: Participants reported their highest level of education, as follows:

Table 4.6
Response count and Percentage of Categorical Variable - Education Level

Education Level		
What is your Educational Level?	**Count**	**Percentage**
Bachelor's Degree	68	31 %
Doctorate Degree	46	21 %
Master's Degree	57	26 %
Secondary School	48	22 %

The majority of respondents held either a **Bachelor's** or **Master's Degree** (57%), while **21%** had a **Doctorate Degree**, and **22%** completed secondary school.

Gender: The gender distribution among participants is shown below:

Table 4.7
Response count and Percentage of Categorical Variable - Gender

Gender		
What best describes your gender?	**Count**	**Percentage**
Female	96	44 %
Male	123	56 %

The gender distribution was relatively balanced, with **56%** male and **44%** female participants.

Interpretation of Results:

The demographic data reveals several key insights that are essential for interpreting the results of this study:

- **Organisation Size**: With **76%** of the respondents from MSMEs, the data aligns well with the focus of the research. This ensures that the findings of the study are directly relevant to small and medium-scale enterprises, which are the core subjects of AI adoption analysis in this sector.
- **Job Titles**: The fact that **31%** of respondents held **management or leadership roles** is particularly important, as these individuals are likely to be directly involved in decision-making processes regarding AI adoption. Their input provides valuable insights into organizational perspectives and readiness for AI implementation.
- **Age Distribution**: The relatively young workforce, with **30%** of respondents in the **25 to 35 years** age range, suggests that younger professionals are more engaged in the adoption of new technologies like AI. This may indicate a positive

outlook for AI adoption, as younger employees are generally more open to technology integration.

- **Educational Background**: A significant proportion of respondents hold advanced degrees (47% have a Bachelor’s or Master’s Degree), suggesting that the respondents are knowledgeable and capable of understanding the complexities of AI technology. This may contribute to a more informed perspective on the potential benefits and challenges of AI adoption in the industry.
- **Gender Representation**: The gender distribution is relatively balanced, with **44%** female respondents, ensuring that the data reflects diverse perspectives on AI adoption. This diversity enhances the richness of the insights drawn from the survey.

By analysing these demographic factors, we gain a deeper understanding of the survey's context, ensuring that the responses reflect a representative sample of the workforce in the Indian textile and apparel MSME sector. This information is critical for interpreting the results of the subsequent analysis, as it provides the background needed to generalise the findings to the broader population.

4.4 Study Results

Introduction

In this section, we explore the analysis of the collected data in detail, with the aim of answering the research questions and validating or refuting the research hypotheses. A comprehensive approach is taken to ensure that the data is fully understood and analyzed, focusing on both descriptive and inferential statistical methods. Below is an overview of the key sections within the study results.

1. **Descriptive Analysis of Categorical Variables :** This section provides a detailed examination of the categorical variables in the dataset, including factors such as titles, gender, age, education, and region. By breaking down the demographic variables, we gain a better understanding of the sample composition and

distribution, which is essential for interpreting the relationships between these variables and the adoption of AI in the textile industry.

2. **Descriptive Characteristics of the Research Variables:** Here, we delve into the characteristics of the key research variables, such as Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facility Condition (FC), Price Value (PV), and Hedonic Motivation (HM). For each variable, we assess the central tendency (mean), variation (standard deviation), and range of responses. This analysis provides a foundational understanding of how participants perceive the role of AI within their organizations, offering insight into their readiness for AI adoption.
3. **Preliminary Data Screening:** Before moving to the main analysis, a thorough preliminary screening of the data is conducted to ensure that the necessary assumptions for statistical analysis are met. This step is critical to the validity of the findings and includes the following tests:
   a. **Testing Assumptions:**
      i. **Homoscedasticity**: Checking whether the variance of the residuals is constant across different levels of the independent variables.
      ii. **Undue Influence (Outliers):** Identifying and addressing influential data points using measures like Cook's Distance to ensure they do not disproportionately affect the results.
      iii. **Normality of Errors:** Testing whether the residuals follow a normal distribution, using histograms and P-P plots.
      iv. **Independence of Errors:** Verifying the independence of the residuals, usually with the Durbin-Watson test.
      v. **Linearity:** Verifying that the relationship between the independent and dependent variables is linear, checked through scatterplots.

   b. **Test of Multicollinearity**
      i. Correlation Matrix Analysis: The correlation matrix provides a simple, preliminary method to identify potential multicollinearity.

ii. Variance Inflation Factor (VIF): The Variance Inflation Factor (VIF) is another key metric used to assess multicollinearity. It quantifies how much the variance of a regression coefficient is inflated due to multicollinearity.

c. **Bivariate Correlational Analysis (Preliminary Level):** As part of the initial screening, a Pearson correlation coefficient analysis is performed between pairs of independent variables and the dependent variable (AI Adoption Decision). This gives a preliminary indication of whether there are potential relationships to explore further in the main analysis.

4. **Main Analysis**

The main analysis builds on the insights from the preliminary data screening and uses more advanced statistical methods to answer the research questions and test the hypotheses.

1. **Multiple Regression Analysis:** This technique is used to understand the impact of multiple independent variables (e.g., PE, EE, SI, FC, PV, HM) on the dependent variable (AI Adoption Decision). It quantifies the strength of these relationships, helping identify which factors most strongly influence AI adoption.
2. **Chi-Square Tests:** Chi-square tests are employed to explore the relationships between categorical variables (such as gender, age, education) and AI adoption. This helps in identifying whether specific demographic groups are more or less likely to adopt AI technologies.
3. **Segmentation (Cluster) Analysis:** To identify distinct subgroups within the dataset, a segmentation or cluster analysis is performed. This method groups respondents based on their similarities in attitudes toward AI adoption, revealing patterns of behaviour and identifying unique clusters with different perspectives.
4. **Hypothesis Testing:** The study's hypotheses, both null and alternative, are tested based on the outcomes of the above analyses. This includes testing whether each of the independent variables has a statistically significant

correlation with the dependent variable (AI Adoption Decision), helping to confirm or reject each hypothesis.

4.4.1 Descriptive Analysis of Categorical Variables

Industry Sector:

The dataset contains responses from participants across four main categories of organisations: **large enterprises**, **medium enterprises**, **micro-enterprises**, and **small enterprises**. The distribution of participants across these categories ensures a comprehensive view of AI adoption in both large and small enterprises.

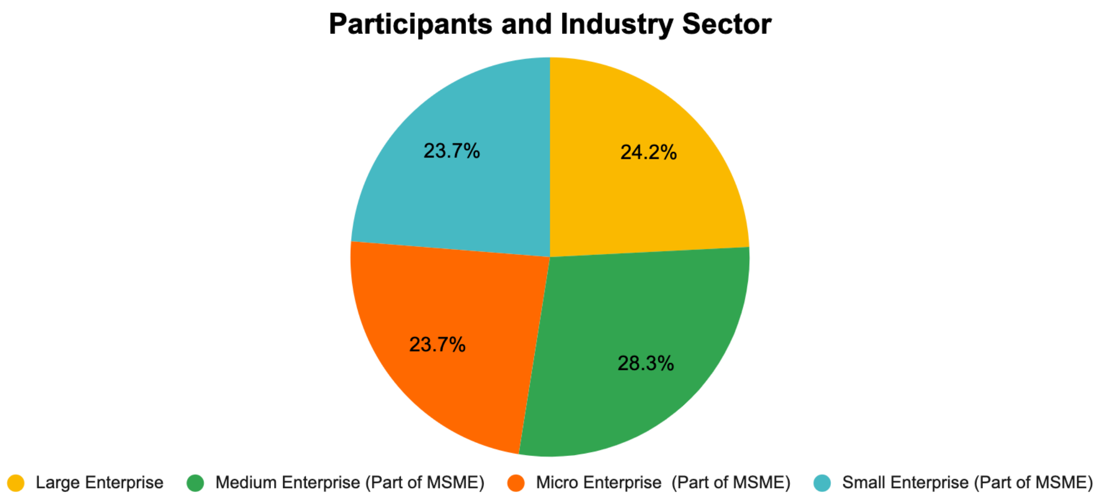

Figure 4.4
Participants vs Industry Sector pie chart

Titles:

Participants were spread across different job roles: **Digital Team**, **IT & Infrastructure Team**, **Management/Leadership**, and **Production Team**. Management roles, which tend to have a stronger influence on decision-making processes, accounted for **31%** of responses.

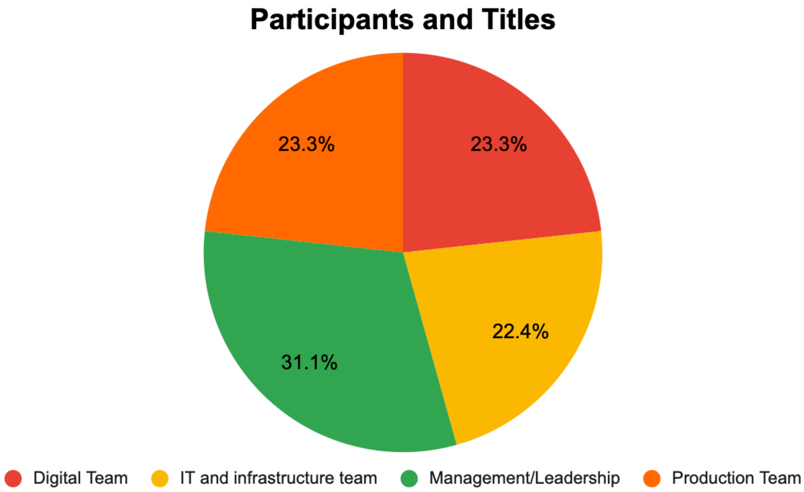

Figure 4.5
Participants vs Titles pie chart

Age:

Respondents were distributed across age groups, with a slight concentration in the **25 to 35** age group, which represented **30%** of the participants. This suggests that the study captured perspectives from a predominantly younger workforce.

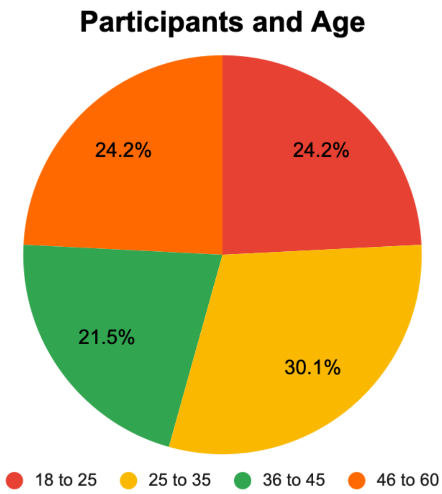

Figure 4.6
Participants vs Age pie chart

Education:

A majority of the respondents had completed **higher education**: **31%** held a Bachelor's Degree, while **26%** had a Master's Degree, and **21%** held a Doctorate Degree. This suggests that the sample is well-educated and knowledgeable about technology, which could influence the adoption of AI.

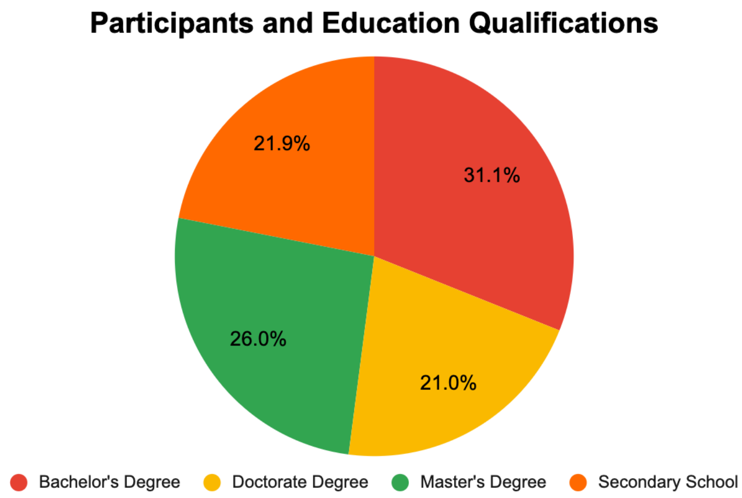

Figure 4.7
Participants vs Education Qualifications pie chart

Gender:

The gender distribution was relatively balanced, with **56% male** and **44% female** respondents. This diversity helps provide insights from both genders regarding AI adoption.

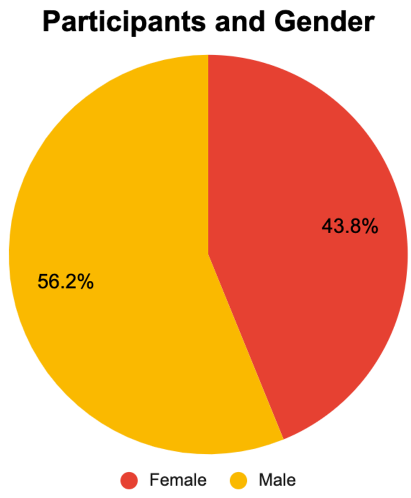

Figure 4.8
Participants vs Gender pie chart

4.4.2 Descriptive Characteristics of the Research Variables

In this section, I examined the central tendency, distribution, and variation of the variables used in this correlational cross-sectional quantitative research. Descriptive statistics such as **mean (M)**, **variance (V)**, and **standard deviation (SD)** were calculated to provide a comprehensive understanding of how the participants responded to the survey items. These descriptive statistics are useful for evaluating the general trends in the data and identifying patterns in participants' perceptions of AI adoption within their organisations.

In line with the suggestions by **Ruxton and Neuhäuser (2018)**, the **mean** helps to measure the central tendency, giving us a sense of the average response for each construct. The **standard deviation** provides insight into the diversity and spread of responses, while the **variance** helps us understand how much the data points deviate from the mean.

I calculated the mean, variance, and standard deviation for the six independent variables (Performance Expectancy, Effort Expectancy, Social Influence, Facility Condition, Price Value, and Hedonic Motivation) and one dependent variable (Decision to Adopt AI), as shown in Table X below. Each of these independent variables is a composite variable, calculated by averaging responses across multiple indicators related to each construct. The items were measured using a **five-point Likert scale**, where 1 corresponds to **strongly disagree** and 5 corresponds to **strongly agree**.

Performance Expectancy (PE)

The **Performance Expectancy (PE)** construct consists of four items: **PE1, PE2, PE3, and PE4**, which measured participants' perceptions of the benefits AI technology could bring to their productivity, decision-making, and task accuracy in the textile industry.

- **PE1**: Mean = 3.33, SD = 1.28
- **PE2**: Mean = 3.38, SD = 1.24
- **PE3**: Mean = 3.35, SD = 1.28
- **PE4**: Mean = 3.17, SD = 1.21

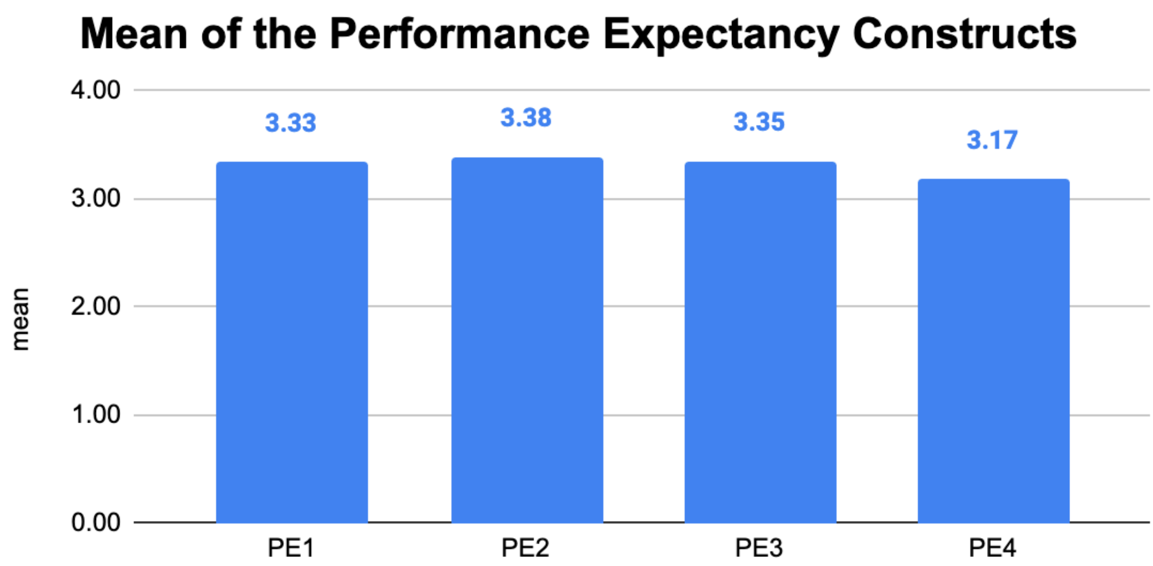

Figure 4.9
Mean of Performance Expectancy Constructs

The standard deviation values for these items range from **1.21 to 1.28**, indicating moderate variability in responses. The mean scores for all four items ranged between **3.17 and 3.38**, showing that respondents generally **somewhat agreed** that AI could enhance productivity and decision-making. The average response for all items is centered around the midpoint of the Likert scale, indicating a moderate perception of the benefits AI can offer. The calculated composite variable for **Performance Expectancy** has a mean of **3.33**, which further confirms that most respondents lean toward agreeing with the performance benefits of AI, but with a noticeable spread of opinions.

Effort Expectancy (EE)

The **Effort Expectancy (EE)** construct includes four items: **EE1, EE2, EE3, and EE4**, which measure how easy participants believe AI technology is to use and understand.

- **EE1**: Mean = 3.22, SD = 1.28
- **EE2**: Mean = 3.27, SD = 1.27
- **EE3**: Mean = 3.31, SD = 1.26
- **EE4**: Mean = 3.24, SD = 1.29

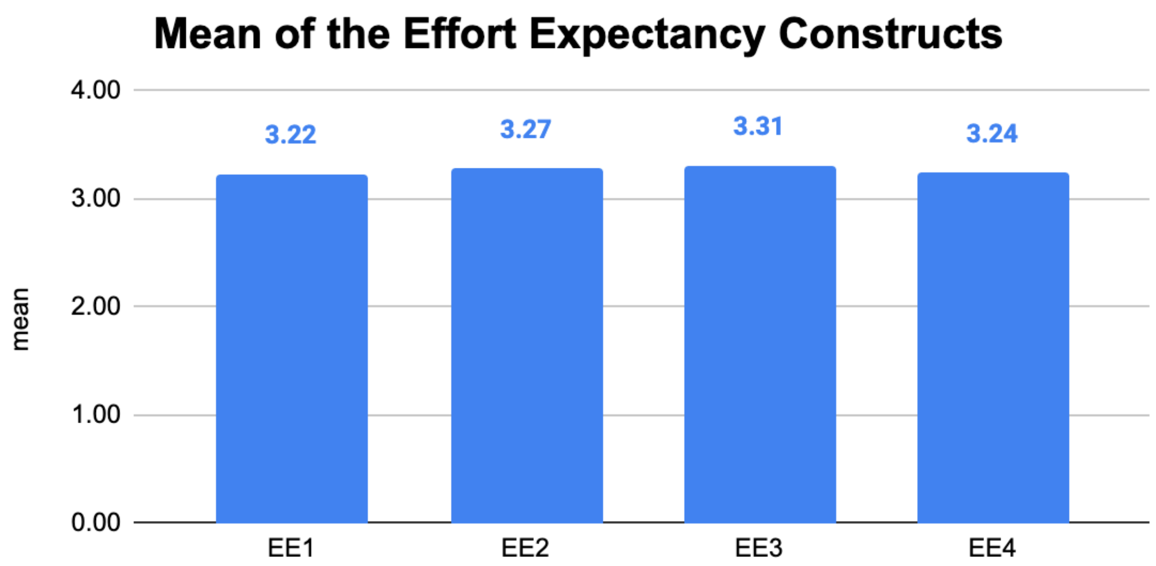

Figure 4.10
Mean of Effort Expectancy Constructs

The mean values for Effort Expectancy items range from **3.22 to 3.31**, indicating that participants generally believe AI technology is **somewhat easy** to use and learn. The standard deviation values, ranging from **1.26 to 1.29**, show that there is some variability in responses. The composite variable for **Effort Expectancy** has a mean of **3.26**, suggesting that while most participants find AI technology relatively easy to use, others may face challenges in understanding and utilizing it effectively.

Social Influence (SI)

The **Social Influence (SI)** construct is made up of four items: **SI1, SI2, SI3, and SI4**, which gauge how much participants are influenced by their colleagues, managers, and external stakeholders in their decision to adopt AI.

- **SI1**: Mean = 3.29, SD = 1.24
- **SI2**: Mean = 3.26, SD = 1.29
- **SI3**: Mean = 3.36, SD = 1.25
- **SI4**: Mean = 3.33, SD = 1.17

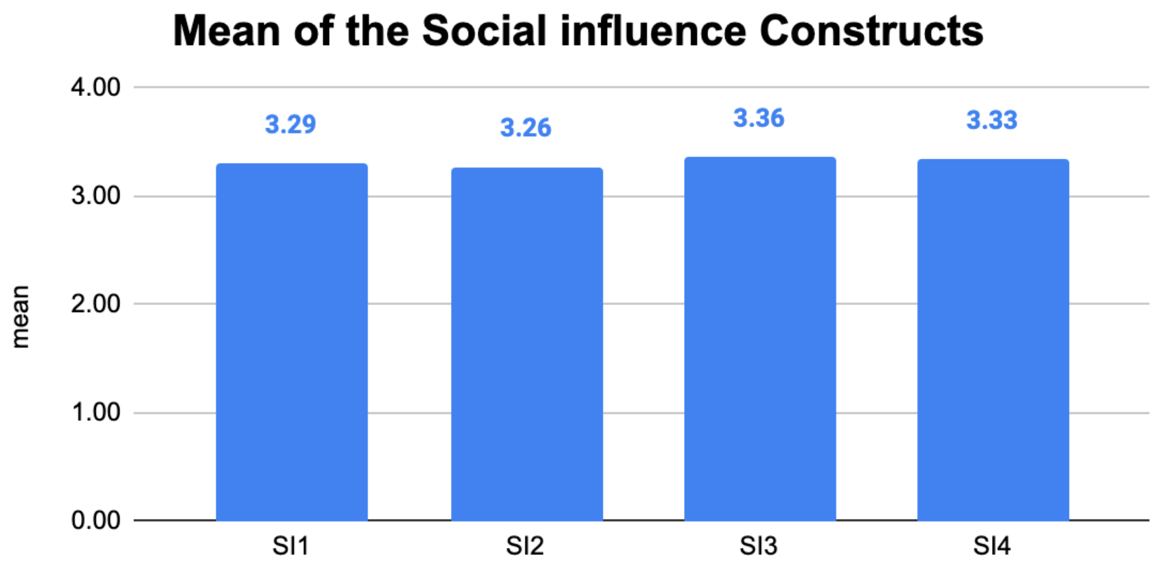

Figure 4.11
Mean of Social Influence Constructs

The mean values for these items are between **3.26 and 3.36**, suggesting that social factors have a moderate influence on AI adoption decisions. The standard deviation values range from **1.17 to 1.29**, which reflects moderate variability, indicating that while social influence plays a role, participants may have differing views on how important these social factors are in their decision-making process. The composite variable for **Social**

Influence has a mean of **3.31**, indicating that participants acknowledge a degree of influence from social factors, though it is not overwhelmingly strong.

Facility Condition (FC)

The **Facility Condition (FC)** construct comprises four items: **FC1, FC2, FC3, and FC4**, which assess the availability of infrastructure, resources, and support for AI adoption.

- **FC1**: Mean = 3.43, SD = 1.25
- **FC2**: Mean = 3.27, SD = 1.31
- **FC3**: Mean = 3.42, SD = 1.27
- **FC4**: Mean = 3.16, SD = 1.30

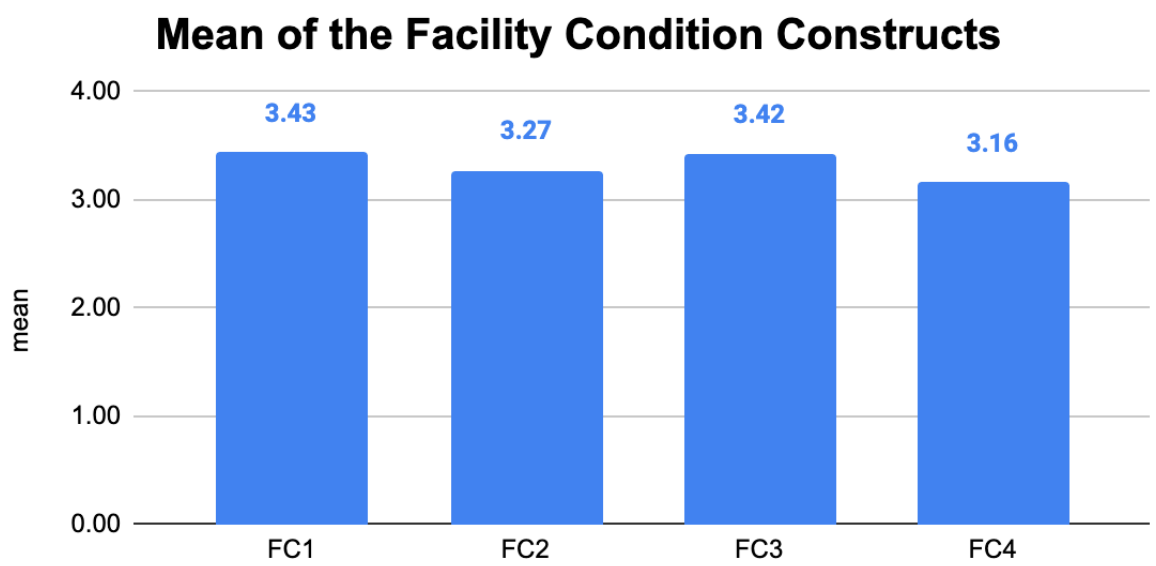

Figure 4.12
Mean of Facility Condition Constructs

The mean values for these items vary between **3.16 and 3.43**, indicating that participants generally agree that their organisations have some level of infrastructure and resources in place to support AI adoption. The standard deviation values range from **1.25 to 1.31**, indicating moderate variability in responses. This suggests that while many participants believe their organisations are equipped for AI adoption, there are also some who feel the available infrastructure is lacking. The calculated composite variable for **Facility**

Condition has a mean of **3.32**, confirming that participants perceive their organizations as somewhat prepared for AI adoption, but with room for improvement.

Price Value (PV)

The **Price Value (PV)** construct measures how participants perceive the value of AI adoption relative to its costs. This is captured by four items: **PV1, PV2, PV3, and PV4**.

- **PV1**: Mean = 3.32, SD = 1.28
- **PV2**: Mean = 3.24, SD = 1.20
- **PV3**: Mean = 3.31, SD = 1.22
- **PV4**: Mean = 3.26, SD = 1.22

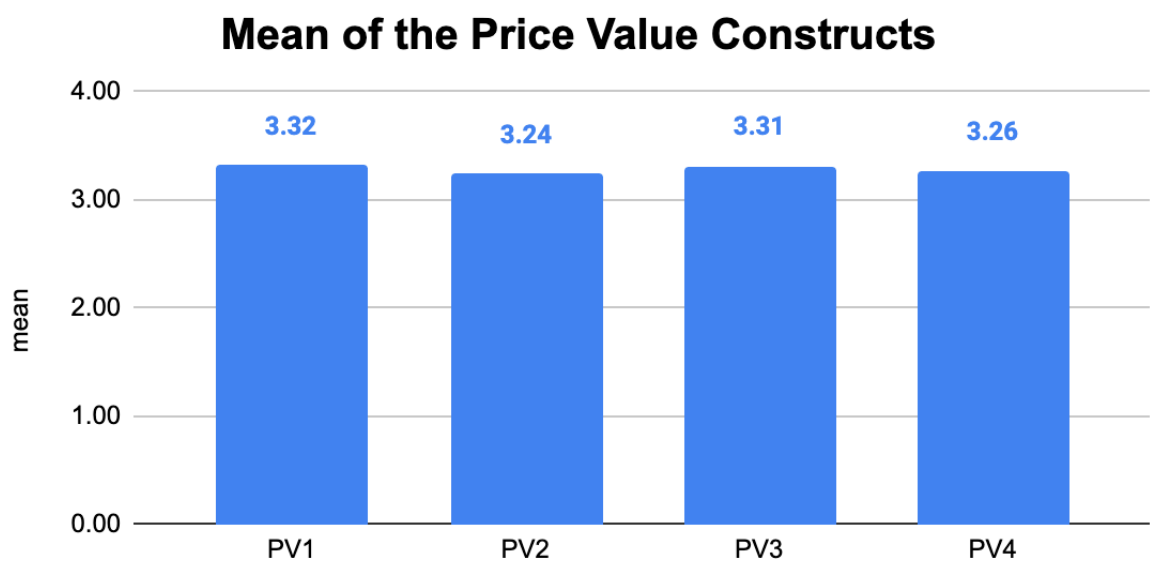

Figure 4.13
Mean of Price Value Constructs

The mean values for the items are between **3.24 and 3.32**, which suggests that participants see AI technology as moderately valuable compared to its cost. The standard deviation values range from **1.20 to 1.28**, indicating a fair amount of variability in responses, meaning that while some participants perceive AI adoption as cost-effective, others are less certain. The composite variable for **Price Value** has a mean of **3.28**, indicating a moderate perception of AI's value proposition.

Hedonic Motivation (HM)

The **Hedonic Motivation (HM)** construct assesses how much personal enjoyment or satisfaction participants derive from using AI. It is measured by four items: **HM1, HM2, HM3, and HM4**.

- **HM1**: Mean = 3.31, SD = 1.25
- **HM2**: Mean = 3.35, SD = 1.26
- **HM3**: Mean = 3.22, SD = 1.20
- **HM4**: Mean = 3.37, SD = 1.20

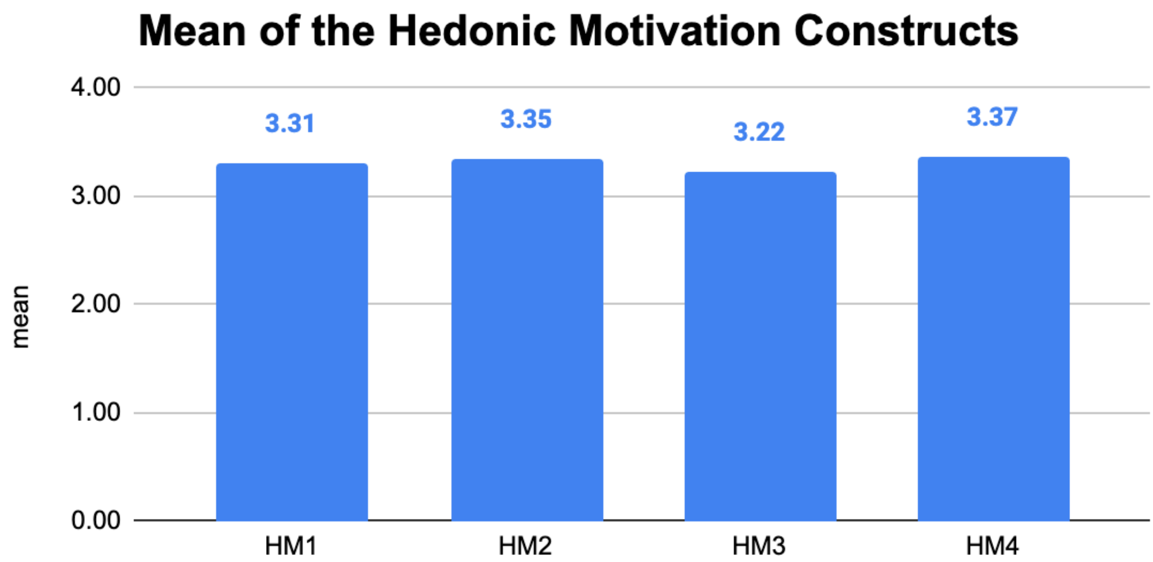

Figure 4.14
Mean of Hedonic Motivation Constructs

The mean values for these items range from **3.22 to 3.37**, indicating that participants find some degree of enjoyment and personal satisfaction from using AI. The standard deviation values range from **1.20 to 1.26**, showing a moderate variation in responses. This suggests that while many participants experience enjoyment in adopting AI, some are indifferent. The composite variable for **Hedonic Motivation** has a mean of **3.31**, which indicates that participants are moderately motivated by the potential enjoyment of using AI technology.

AI Adoption Decision (Target/Dependent Variable)

Finally, the **AI Adoption Decision** variable measures how far along organisations are in the AI adoption process.

- **Mean**: 2.58
- **Standard Deviation**: 1.69
- **Range**: 0.00 to 5.00

The mean value of **2.58** indicates that, on average, respondents' organisations are in the early stages of AI adoption, with a wide variation in readiness. The high standard deviation of **1.69** suggests that organisations are at different levels of AI adoption, with some already using AI and others still undecided or far from adopting the technology.

Table 4.8
Overview of the descriptive analysis of the Independent Variables

	count	**mean**	**std**	**min**	**25%**	**50%**	**75%**	**max**
titles	219	1.54	1.09	0	1	2	2	3
gender	219	0.56	0.50	0	0	1	1	1
age	219	1.46	1.11	0	1	1	2	3
education	219	1.39	1.14	0	0	1	2	3
region	219	1.55	1.09	0	1	2	3	3
PE1	219	3.33	1.28	1	2	3	4	5
PE2	219	3.38	1.24	1	3	3	4	5
PE3	219	3.35	1.28	1	2	3	4	5
PE4	219	3.17	1.21	1	2	3	4	5
EE1	219	3.22	1.28	1	2	3	4	5
EE2	219	3.27	1.27	1	2	3	4	5
EE3	219	3.31	1.26	1	2	3	4	5
EE4	219	3.24	1.29	1	2	3	4	5
SI1	219	3.29	1.24	1	2	3	4	5
SI2	219	3.26	1.29	1	2	3	4	5
SI3	219	3.36	1.25	1	3	3	4	5
SI4	219	3.33	1.17	1	3	3	4	5
FC1	219	3.43	1.25	1	3	4	4	5
FC2	219	3.27	1.31	1	2	3	4	5

FC3	219	3.42	1.27	1	3	3	4.5	5
FC4	219	3.16	1.30	1	2	3	4	5
PV1	219	3.32	1.28	1	2	3	4	5
PV2	219	3.24	1.20	1	3	3	4	5
PV3	219	3.31	1.22	1	2	3	4	5
PV4	219	3.26	1.22	1	2	3	4	5
HM1	219	3.31	1.25	1	3	3	4	5
HM2	219	3.35	1.26	1	2.5	3	4	5
HM3	219	3.22	1.20	1	2	3	4	5
HM4	219	3.37	1.20	1	3	3	4	5
DIA	219	2.58	1.69	0	1	3	4	5

4.4.2 Preliminary Data Screening

Preliminary data screening is an essential step in preparing the dataset for further analysis, as it ensures that the data meets the necessary assumptions for statistical methods like regression and correlation. Before proceeding with the main analysis, several important assumptions were tested, including **homoscedasticity**, **undue influence**, **normality of errors**, **independence of errors**, and **linearity**. Additionally, a **bivariate correlational analysis** was conducted to explore the relationships between key constructs and the decision to adopt AI.

4.4.2.1 Testing Assumptions:

4.4.2.1.1 Testing the assumption of Homoscedasticity

Summary of the Homoscedasticity:

The assumption of homoscedasticity is fundamental in regression analysis, ensuring that the residuals (the differences between observed and predicted values) have constant variance across all levels of the independent variables. Homoscedasticity is critical to the validity of the regression model, as it influences the accuracy of the standard errors, confidence intervals, and hypothesis tests derived from the model.

When the variance of the residuals is constant, the model can provide reliable and unbiased estimates of the relationships between the dependent and independent variables. In contrast, if the assumption is violated—leading to heteroscedasticity—this can result in inflated standard errors, which undermines the reliability of the statistical tests and predictions. This can lead to incorrect conclusions about the significance of the relationships between the variables in the study.

Ensuring homoscedasticity allows for more accurate interpretation of the regression coefficients, supporting the overall robustness and reliability of the research findings. Therefore, testing this assumption is a crucial step in confirming the validity of the regression analysis in the study.

Analysis of the Homoscedasticity:

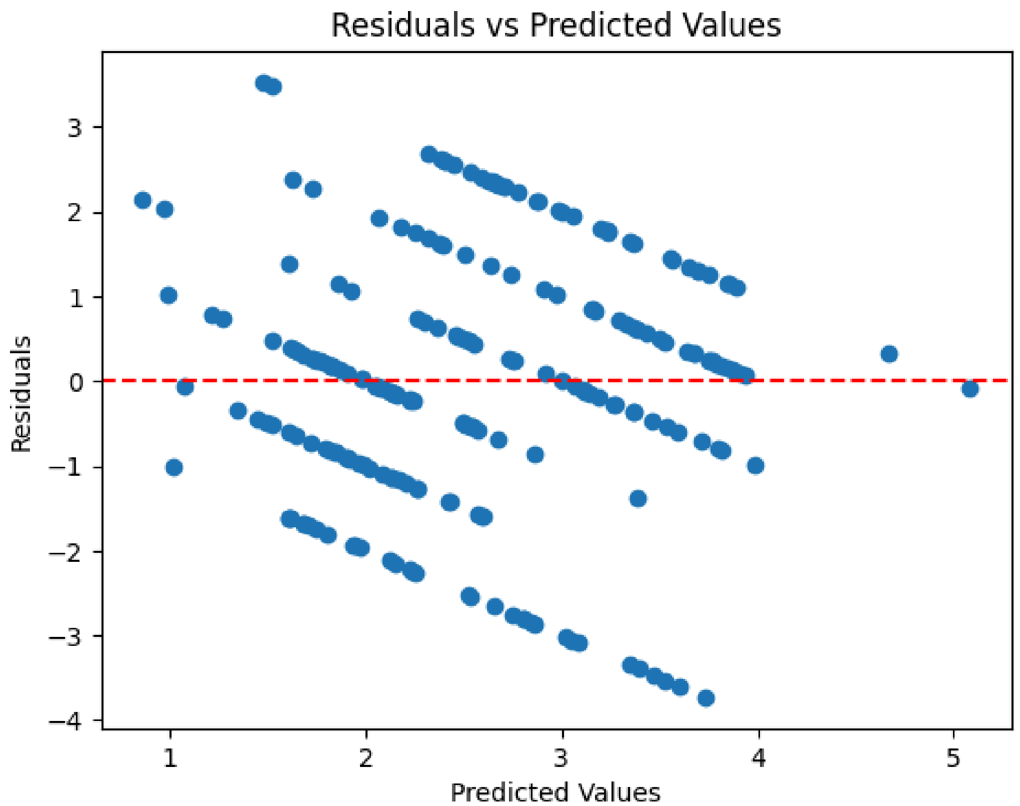

Figure 4.15
Analysis of the Homoscedasticity: Residuals vs Predicted Values

In examining the homoscedasticity assumption, the residuals vs. predicted values plot shows **moderate heteroscedasticity** in the data. Ideally, for homoscedasticity to hold, the spread of residuals should be constant across all predicted values, forming a cloud-like pattern around the horizontal axis. However, as can be observed from the residual plot, the residuals show a pattern where the variance appears to change at different levels of the predicted values. Specifically, the residuals are more spread out for lower predicted values (below 3) and become more concentrated as the predicted values increase.

Following the Moderate Heterodcedasticity I performed qq plot to validate the distribution of data.

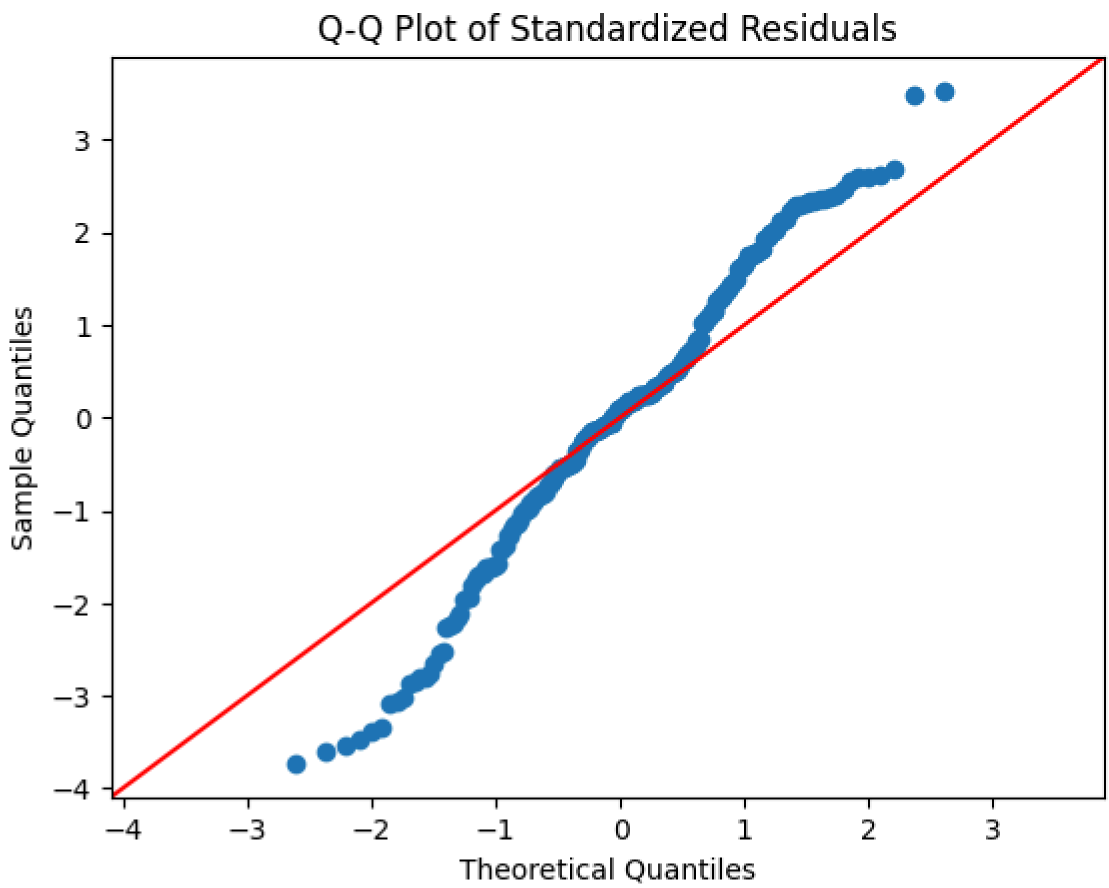

Figure 4.16
Analysis of the Homoscedasticity: Q-Q Plot of Standardized Residuals

The Q-Q plot generated for the residuals of the regression model showed a pattern that deviated from the 45-degree reference line, especially at the extremes. As seen in the plot, the tails of the distribution (both lower and upper extremes) showed noticeable deviations from the line, indicating that the residuals exhibit heavier tails than expected for a normal distribution. This suggests that the residuals are not perfectly normally distributed, which can be a byproduct of the moderate heteroscedasticity identified earlier.

The deviations in the tails highlight potential issues with outliers or skewness in the data. Such deviations imply that extreme values may not be well captured by the current model, which could affect the accuracy of predictions for these outlying cases. The central portion of the data, however, aligned reasonably well with the reference line, suggesting that the model performs better for the majority of observations closer to the mean.

Impact on p-values and Statistical Significance

The presence of moderate heteroscedasticity, as indicated by both the residual plot and the Breusch-Pagan test results, suggests that the assumption of constant variance is violated to some extent. This violation can have several effects on the regression analysis:

- **Increased Error Variance**: The variability of residuals leads to an increase in the size of error terms for certain predicted values, which may cause an underestimation or overestimation of the true relationship between independent and dependent variables.
- **Unreliable standard errors**: With heteroscedasticity, the standard errors of the regression coefficients may be biased. This could lead to incorrect confidence intervals, p-values, and hypothesis test results. In particular, p-values may be misleading, suggesting that variables are statistically significant when they may not be (or vice versa).
- **Model Efficiency**: The efficiency of the model is also compromised. While the model may still provide unbiased estimates, the presence of heteroscedasticity reduces the precision of these estimates, leading to less reliable conclusions.

Interpretation and Recommendations for Future Research

Although the presence of heteroscedasticity does affect the validity of the regression model, its impact appears to be moderate rather than severe. This means that while the regression results should be interpreted with caution, the model still provides valuable insights into the factors influencing AI adoption in the textile industry. However, future research should address this issue by:

- **Model Adjustments**: Researchers can apply robust regression techniques, such as **heteroscedasticity-robust standard errors** or **weighted least squares (WLS)** to account for the unequal variance in the residuals. These adjustments would improve the reliability of the standard errors and p-values.
- **Exploring Transformations**: To better satisfy the assumptions of homoscedasticity, future research could explore transformations of the dependent or independent variables (e.g., log transformations), which might stabilize the variance and improve the fit of the model.
- **Deeper Examination of Variables**: It is also possible that certain variables are not fully capturing the dynamics influencing AI adoption. Further studies might include additional variables or examine non-linear relationships between variables, which could help address heteroscedasticity and provide a more accurate model.

In conclusion, while the assumption of homoscedasticity is moderately violated in this analysis, the model still provides valuable insights. The slight heteroscedasticity observed impacts the accuracy of the p-values, which should be taken into consideration when interpreting the results. Nonetheless, this provides an opportunity for further refinement and exploration in future research, especially with regard to addressing the variability in the residuals and improving model robustness.

4.4.2.1.2 Undue Influence (Outliers): Identifying any influential outliers using metrics like Cook's Distance.

Summary of the Undue Influence (Outliers)

Identifying and addressing **outliers** and **influential data points** is a critical part of any regression analysis. Outliers can disproportionately affect the results of a regression model by distorting the estimates of regression coefficients and affecting overall model fit. In this section, we analyze the presence of undue influence using **Cook's Distance**, a measure that helps determine how much a single observation impacts the regression model's results.

Cook's Distance evaluates the effect of deleting a single observation on the model's predicted outcomes. Observations with a **Cook's Distance** greater than 1 are typically flagged as potentially influential points that might need further investigation. These points could either be extreme outliers that introduce bias into the model or influential points that drastically alter the model's predictions.

This section aims to ensure that the regression analysis is not unduly influenced by a small number of data points, which would skew the results, leading to unreliable interpretations.

Analysis of Cook's Distance Results

The results of the Cook's Distance analysis for each of the main constructs in the model, including **Performance Expectancy (PE)**, **Effort Expectancy (EE)**, **Social Influence (SI)**, **Facility Condition (FC)**, **Price Value (PV)**, and **Hedonic Motivation (HM)**, are shown below:

Table 4.9
Cooks Distance's of the Constructs

Variable	Cook's Distance
Performance Expectancy Mean	0.005325
Effort Expectancy Mean	0.005325
Social Influence Mean	0.005325
Facility Condition Mean	0.005325
Price Value Mean	0.005325
Hedonic Motivation Mean	0.005325

- **Cook's Distance Threshold**: The threshold for identifying an influential point is generally considered to be **1**. In this analysis, all computed Cook's Distance values are far below this threshold, indicating that none of the observations in the dataset have an undue influence on the regression model.
- **Consistency Across Variables**: The Cook's Distance values are consistent across all the independent variables, each registering a value of **0.005325**. This suggests that none of the variables exerts an unusual or disproportionate effect on the model's overall prediction.

Interpretation of Results

The low and uniform values of Cook's Distance indicate that there are no significant outliers or influential data points affecting the regression model. This finding suggests that:

- **No Observational Bias**: The regression analysis is not skewed by any individual observation, meaning that the model's parameter estimates are reliable and generalizable to the broader population.
- **Model Stability**: The absence of undue influence from individual data points contributes to the overall stability of the regression model. This stability is crucial for accurately estimating the effects of variables such as **Performance**

Expectancy, **Effort Expectancy**, and **Social Influence** on the decision to adopt AI.

- **Implications for Future Studies**: Since no observations have been flagged for undue influence, future research based on this model can be confident in its results. However, if future studies incorporate larger or different datasets, this analysis should be repeated to ensure that the model remains robust across varying data sources.

The results of the Cook's Distance analysis demonstrate that there are no problematic outliers or influential observations in this dataset. All values are well below the threshold of **1**, suggesting that no single data point disproportionately affects the regression model. As a result, the regression coefficients, significance tests, and predictions drawn from this model can be considered valid and stable across the entire dataset.

4.4.2.1.3 Normality of Errors: Histogram and Q-Q Plot

Summary of the Normality of Errors

The normality of errors, also known as the normality of residuals, is an important assumption in multiple regression analysis. This assumption posits that the residuals (i.e., the differences between the observed and predicted values) should follow a normal distribution. Ensuring that this assumption holds is essential for validating inferences drawn from the model, including hypothesis testing, and for ensuring the reliability of confidence intervals. Normality of errors is typically checked through graphical methods, such as histograms of residuals or P-P plots (probability-probability plots), and through statistical tests. In this analysis, we rely on both the histogram and P-P plot to check for normality.

Analysis of Normaliy of errors: Histogram and P-P Plot

To test for normality, two primary graphic methods were : the histogram of standardised residuals and the P-P plot of standardised residuals.

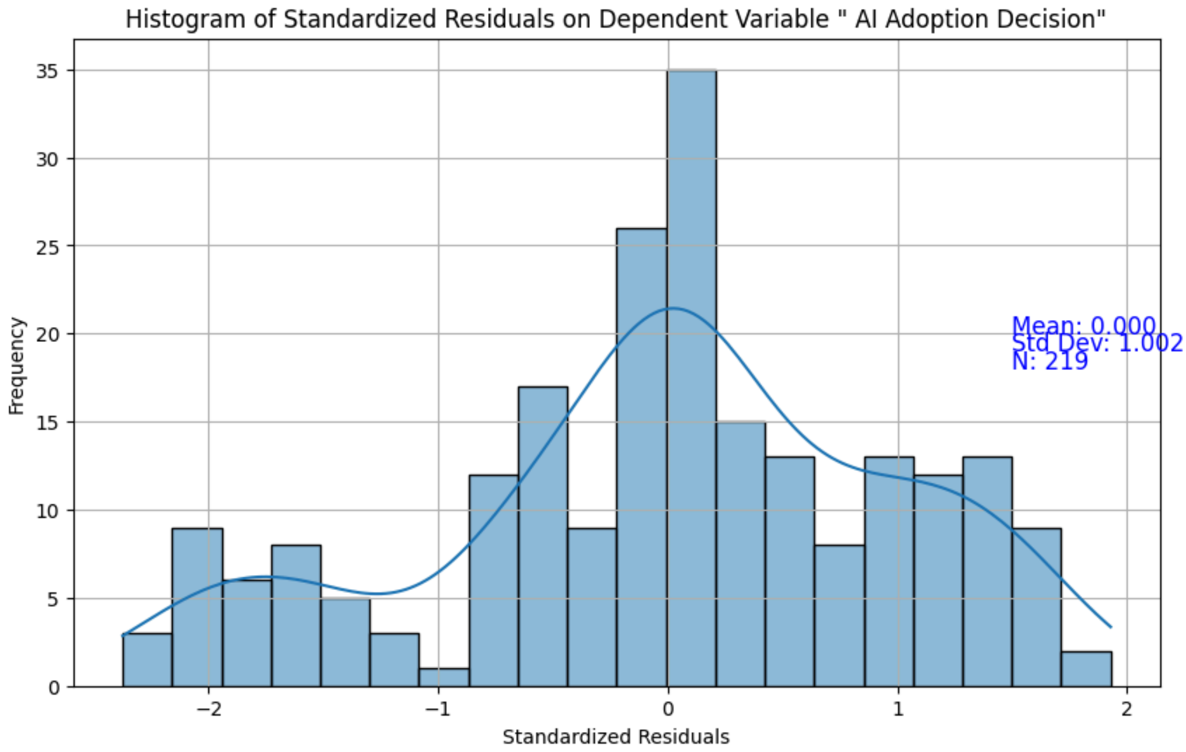

Figure 4.17
Histogram of Standardised Residuals on Dependent Variable: DAI

Histogram of Standardized Residuals: The histogram of standardized residuals (displayed above) shows the distribution of the residuals for the dependent variable "AI Adoption Decision." The bell-shaped curve, with a mean of 0 and a standard deviation of approximately 1, indicates that the residuals are distributed somewhat normally. There are some deviations from perfect normality, with a skewness observable at the lower and higher tails, but overall, the pattern is close to what is expected in normally distributed data.

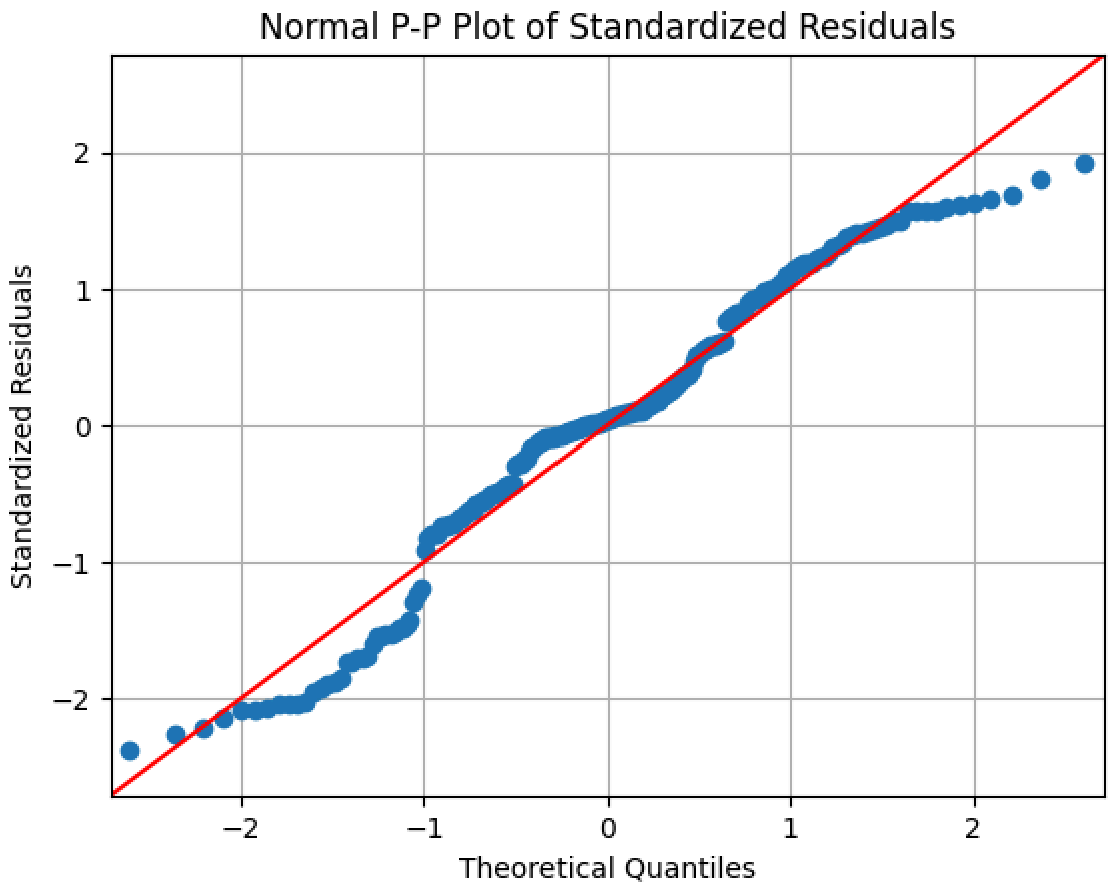

Figure 4.18
Analysis of the Homoscedasticity: P-P Plot of Standardized Residuals

Normal P-P Plot of Standardized Residuals: The Normal P-P plot (displayed above) helps assess how closely the standardized residuals follow a normal distribution. In this plot, most data points align closely with the diagonal reference line, suggesting that the residuals are generally normally distributed. Small deviations are observed at the lower and upper extremes, but these are relatively minor and do not significantly deviate from the expected pattern of normality.

Interpretation of the Analysis:

Both the histogram and the P-P plot demonstrate that the residuals approximately follow a normal distribution, with most of the data points closely following the expected distribution. The bell-shaped curve in the histogram and the alignment of points in the P-P plot indicate that the assumption of normality is reasonably satisfied. While there are some slight deviations, particularly in the tails of the distribution; these are not severe enough to invalidate the regression model's overall reliability or its hypothesis testing results.

In conclusion, the assumption of normality of errors has been met with only minor deviations, ensuring that the regression model is reliable for analysis and interpretation. These small deviations suggest that future research could explore alternative modelling techniques or adjustments, but they do not significantly impact the current model's validity.

4.4.2.1.4 Independence of Errors: Checking for Autocorrelation Using Durbin-Watson Test

Summary of the Independence of Errors

In regression analysis, the independence of errors, also known as the lack of autocorrelation, is a crucial assumption. Autocorrelation occurs when the residuals (errors) in the model are correlated with one another, which can violate the assumptions of standard regression models. When errors are autocorrelated, it often implies that the model is either underfitting (missing key variables) or overfitting (overestimating relationships). If this assumption is violated, the estimates of regression coefficients can become inefficient, leading to unreliable predictions and invalid hypothesis tests. The Durbin-Watson test is the standard statistical method used to detect the presence of autocorrelation in the residuals of a regression model.

The Durbin-Watson test produces a statistic that ranges from 0 to 4. A value close to 2 suggests that the residuals are uncorrelated (no autocorrelation). Values below 2 indicate positive autocorrelation, where residuals tend to follow a pattern (e.g., a rising error is likely to be followed by another rising error), while values above 2 suggest negative autocorrelation.

Analysis of the Data

Table 4.10
Regression Results : Durbin-Watson Value

Regression results	
Durbin-Watson	**1.85**

In this study, the Durbin-Watson test was applied as part of the regression analysis to check for the independence of errors in the model predicting AI adoption decisions in the textile industry. The result of the Durbin-Watson test is **1.85**, which is very close to the ideal value of 2, indicating that the residuals are not significantly autocorrelated.

A value of **1.85** suggests a low level of autocorrelation in the residuals, meaning that the model errors do not follow any particular trend or systematic pattern. This confirms that the model's residuals are independent, which strengthens the credibility of the regression results. The lack of significant autocorrelation supports the assumption of randomness in the errors, suggesting that the model is performing as expected without the need to adjust for autocorrelated errors.

Interpretation of the Analysis

The Durbin-Watson statistic of **1.85** shows that there is no major issue of autocorrelation in the residuals of the regression model. The value being close to 2 suggests that the residuals are randomly distributed, meaning that each error term is independent of the others. This independence of errors ensures that the regression model's estimates for the relationships between the independent variables and the AI adoption decision are reliable and not influenced by the sequence or pattern of the residuals.

Meeting the assumption of independence is critical for the accuracy of regression results. If autocorrelation were present, it could inflate the significance of certain predictors, leading to incorrect conclusions about their impact on the decision to adopt AI. However, since the Durbin-Watson test shows no significant autocorrelation, the model provides more reliable and valid predictions.

In conclusion, the results of the Durbin-Watson test suggest that the assumption of independent errors is met, providing confidence that the regression model's results are trustworthy. The absence of significant autocorrelation means that the estimates of the model coefficients are efficient, and the model itself is more likely to generalise well to other data from the same population. Thus, the predictive power of the model concerning AI adoption in the textile industry can be considered robust and reliable.

4.4.2.1.5 Linearity: Ensuring a Linear Relationship Between the Independent and Dependent Variables

Summary of the Linearity

Linearity refers to the assumption that there is a linear relationship between the independent variables (in this case, Performance Expectancy, Effort Expectancy, Social Influence, Facility Condition, Price Value, and Hedonic Motivation) and the dependent variable (AI Adoption Decision). This assumption is critical for regression analysis because linear regression assumes that the relationship between the predictors and the outcome is linear. To test for linearity, scatter plot matrices and correlation matrices are commonly used.

The scatter plot matrix and correlation matrix were used to visualise and assess the linearity between the independent variables and the dependent variable. These tools provide a detailed visual representation of how each independent variable correlates with the dependent variable and with each other.

The scatter plot matrix helps in identifying trends, patterns, and possible non-linear relationships, while the correlation matrix gives a numerical summary of the strength and direction of these relationships.

Analysis of the Data

Scatter Plot Matrix:

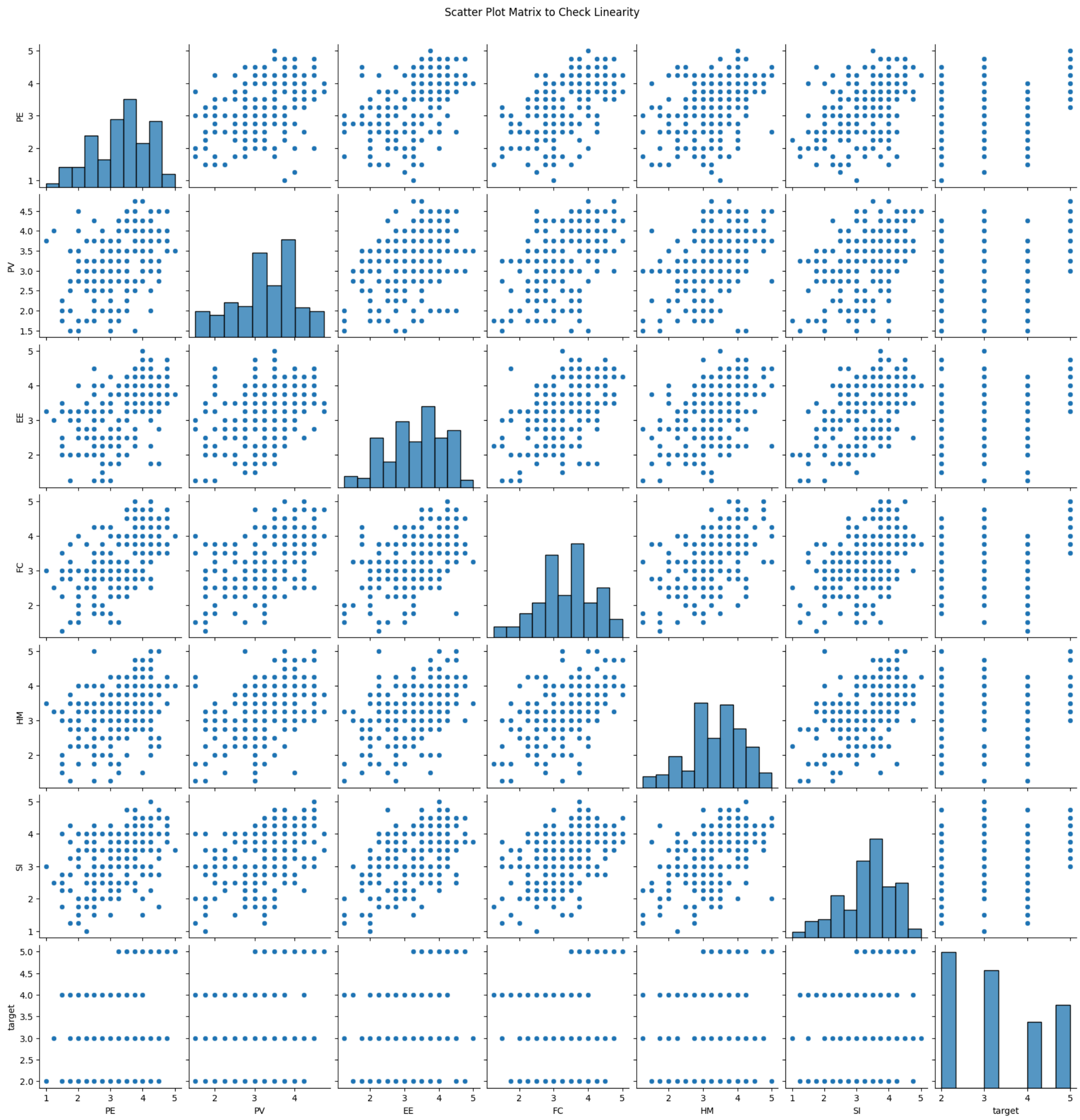

Figure 4.19
Scatter plot and Histogram of the Constructs

A scatter plot matrix was generated to explore the pairwise relationships between the independent variables and the dependent variable. Each subplot provides a visual indication of whether a linear relationship exists.

- Diagonal plots display histograms of each variable's distribution, while the off-diagonal plots display scatter plots of one variable against another.
- From the scatter plots, no strong non-linear trends were observed, but the distribution and spread of points suggest some moderate relationships.

Correlation Matrix:

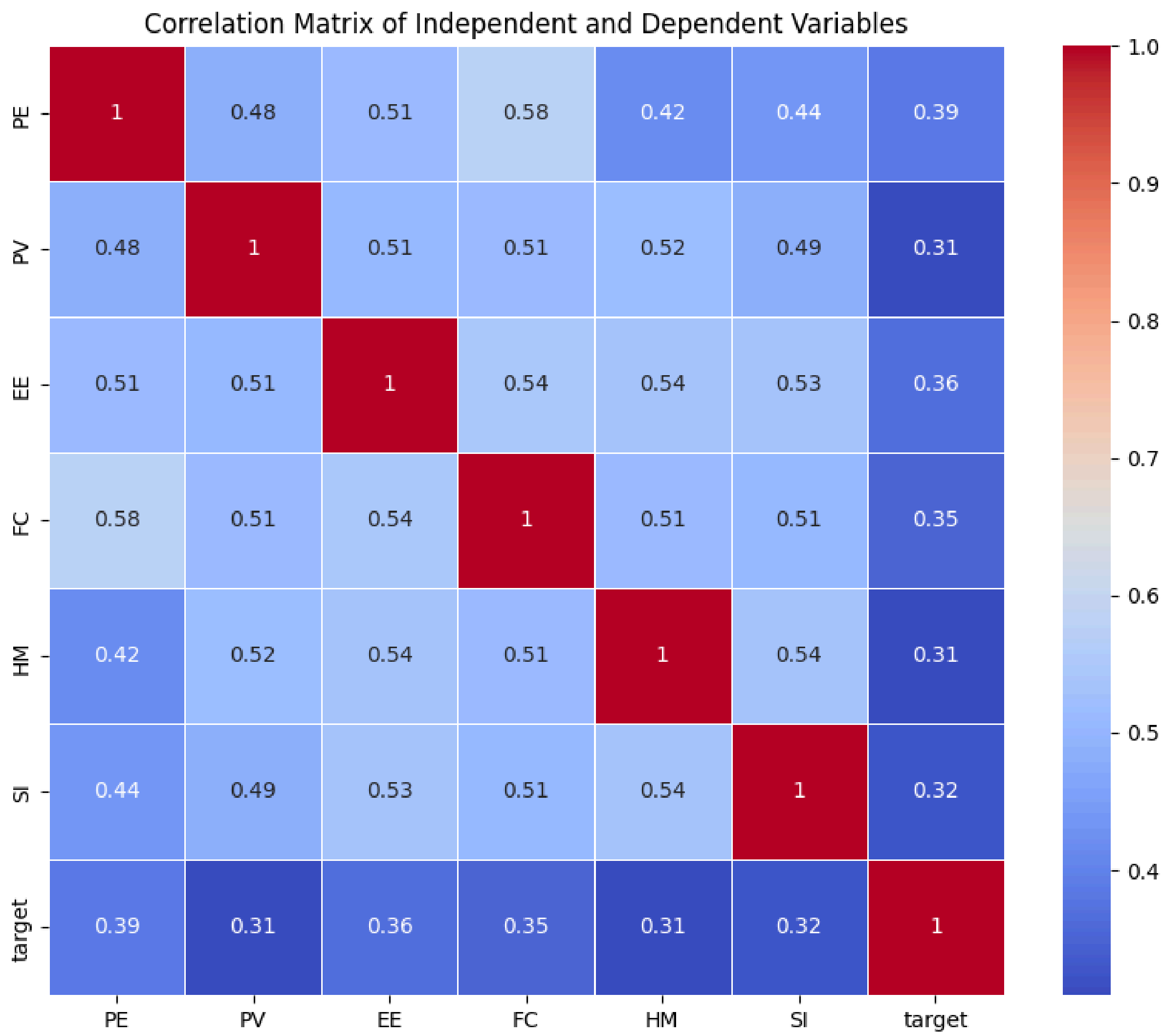

Figure 4.20
Correlation matrix of the Constructs

The correlation matrix was used to examine the strength and direction of linear relationships between variables. The values in the matrix range from -1 to +1:

  - Values close to +1 indicate a strong positive linear relationship.

- Values close to -1 indicate a strong negative linear relationship.
- Values close to 0 indicate no linear relationship.

In the matrix, we observe the following correlations between independent variables and the dependent variable (AI Adoption Decision)

- **Performance Expectancy**: r = 0.39
- **Effort Expectancy**: r = 0.36
- **Social Influence**: r = 0.32
- **Facility Condition**: r = 0.35
- **Price Value**: r = 0.31
- **Hedonic Motivation**: r = 0.31

Interpretation of the Results:

1. **Positive Correlations with Target**:
   - The **Performance Expectancy (PE)** and **Effort Expectancy (EE)** constructs show the strongest correlations with the AI adoption decision (r = 0.39 and r = 0.36, respectively), indicating that as these factors increase, the likelihood of AI adoption increases. These variables appear to have the most noticeable influence on the decision to adopt AI.
2. **Moderate Correlations**:
   - **Price Value (PV)** and **Facility Condition (FC)** also show moderate positive correlations with AI adoption (r = 0.31 and r = 0.35), suggesting that respondents who find AI more affordable or have better facility conditions are slightly more likely to adopt it.
   - **Hedonic Motivation (HM)** and **Social Influence (SI)** have weaker correlations with AI adoption (r = 0.31 and r = 0.32), indicating that

while personal enjoyment or external influence does play a role, it is less significant in the decision-making process.

3. **Correlation Among Independent Variables**:
    - The **Performance Expectancy (PE)** and **Facility Condition (FC)** have the highest correlation (r = 0.58), showing that respondents who perceive higher benefits from AI adoption also tend to perceive better conditions for its implementation.
    - Similarly, **Effort Expectancy (EE)** has moderate correlations with other variables like **Price Value (PV)** (r = 0.51) and **Social Influence (SI)** (r = 0.53), suggesting that respondents who find AI easier to use also tend to be influenced by others and see it as more affordable.
4. **Overall Implications**:
    - The correlation values suggest that factors like **Performance Expectancy (PE)** and **Effort Expectancy (EE)** play a more prominent role in influencing AI adoption decisions. The moderate to weak correlations with the **Target** variable imply that while these factors influence adoption decisions, other unmeasured or non-linear relationships may also need to be explored.
    - Given the correlations, it is clear that **organizational readiness (e.g., Facility Condition)** and perceived **value (e.g., Price Value)** also have a role in adoption decisions, but the impact is somewhat less compared to expectancy-related factors.

Conclusion:

The correlations reveal a moderate influence of **Performance Expectancy**, **Effort Expectancy**, and **Facility Condition** on AI adoption, with a weaker impact from **Price Value**, **Hedonic Motivation**, and **Social Influence**. This suggests that while **efficacy** and **ease of use** are central to AI adoption, other factors such as the

affordability and **organizational readiness** also play a role but to a lesser extent. Future research could further explore non-linear relationships or other influencing variables beyond these constructs.

4.4.2.2 Bivariate Correlational Analysis (Preliminary Level):

4.4.2.2.1 Summary of Pearsons Co efficient analysis

This section focuses on analyzing the relationships between key independent variables such as Performance Expectancy (PE), Price Value (PV), Effort Expectancy (EE), Facility Condition (FC), Hedonic Motivation (HM), Social Influence (SI), and the dependent variable **AI Adoption Decision** (DAI) through Pearson's correlation coefficient.

Pearson's correlation is particularly useful in identifying the linear relationships between pairs of variables and determining the strength and direction of these relationships. It ranges from -1 to 1, where -1 indicates a perfect negative correlation, 1 indicates a perfect positive correlation, and 0 indicates no correlation.

Conducting this analysis serves as a critical first step in understanding the interconnections between variables, determining multicollinearity, and deciding which variables should proceed to more advanced analyses, such as multiple regression.

4.4.2.2.2 Analysis of the Data

Table 4.11
Pearson correlation Results

Pearson Correlation Results							
Variables	**PE**	**PV**	**EE**	**FC**	**HM**	**SI**	**Targe**
PE	1.00	0.48	0.51	0.58	0.42	0.44	0.39
PV	0.48	1.00	0.51	0.51	0.52	0.49	0.31
EE	0.51	0.51	1.00	0.54	0.54	0.53	0.36
FC	0.58	0.51	0.54	1.00	0.51	0.51	0.35
HM	0.42	0.52	0.54	0.51	1.00	0.54	0.31

SI	0.44	0.49	0.53	0.51	0.54	1.00	0.32
Target	0.39	0.31	0.36	0.35	0.31	0.32	1.00

1. Strong Correlations between Independent Variables:

- Performance Expectancy (PE) is moderately correlated with Facility Condition (FC) (r = 0.58), suggesting that better facility conditions might enhance the perception of AI improving performance.
- Effort Expectancy (EE) demonstrates moderate correlations with both Hedonic Motivation (HM) (r = 0.54) and Social Influence (SI) (r = 0.53). This indicates that individuals who perceive AI as easy to use are likely to find it more enjoyable and may be influenced by peers or external social factors.
- Price Value (PV) is moderately correlated with Hedonic Motivation (HM) (r = 0.52), highlighting the interplay between perceived value for money and emotional motivation in adopting AI.

2. Correlations with the Dependent Variable (AI Adoption Decision)

- Performance Expectancy (PE) has the strongest correlation with AI Adoption (Target) (r = 0.39), suggesting that individuals who expect AI to enhance productivity or task performance are more inclined to adopt it.
- Effort Expectancy (EE) and Facility Condition (FC) follow closely, with correlations of 0.36 and 0.35, respectively. These findings indicate that ease of use and the availability of supportive infrastructure are meaningful considerations in AI adoption decisions.
- Social Influence (SI), Price Value (PV), and Hedonic Motivation (HM) have weaker correlations with AI adoption (r = 0.32, 0.31, and 0.31, respectively), suggesting that while they play a role, they may not be the primary drivers for adopting AI in this context.

3. **Multicollinearity Considerations**

- Some independent variables show moderate correlations, such as PE and FC ($r = 0.58$) and EE and HM ($r = 0.54$). These relationships suggest a potential overlap in their influence, which could lead to multicollinearity.
- While correlations exceeding 0.70 might raise concerns, all pairwise correlations in this analysis are below this threshold. This indicates no severe multicollinearity issues at this stage. To confirm, Variance Inflation Factor (VIF) analysis is recommended before proceeding with regression modeling.

4.4.2.2.3 Interpretation of the Analysis

The correlation results provide valuable insights into the relationships between the independent variables and the decision to adopt AI:

Key Drivers of AI Adoption:

- Performance Expectancy (PE) plays a pivotal role, as evidenced by the highest correlation ($r = 0.39$) with AI adoption. This reinforces the importance of perceived performance improvements in influencing adoption decisions.
- Effort Expectancy (EE) and Facility Condition (FC) also exhibit meaningful associations, suggesting that ease of use and infrastructure readiness are significant contributors.
- While Price Value (PV) and Hedonic Motivation (HM) are weaker predictors, their moderate correlations suggest that perceived cost-effectiveness and emotional factors, though secondary, still influence AI adoption.

Secondary Influences:

Social Influence (SI), while weakly correlated (r = 0.32) with the target variable, indicates that peer and external influence may play a modest role in driving adoption decisions.

Multicollinearity Insights:

The moderate correlations between constructs highlight relationships that merit attention but do not signal severe multicollinearity concerns. This provides confidence in moving forward with regression analysis.

Implications for Further Analysis

The findings align with the UTAUT framework, which emphasises the significance of Performance Expectancy (PE) and Effort Expectancy (EE) as primary drivers of technology adoption. The correlation results lay the groundwork for conducting multiple regression analysis to test the combined influence of these variables on AI adoption in the textile industry.

Variables such as PE, EE, and FC should be prioritised in regression analysis to quantify their relative importance.

Additional statistical tests, such as VIF analysis, will ensure that multicollinearity does not compromise the regression model.

These insights contribute to a nuanced understanding of AI adoption in the Indian textile SME sector, reinforcing the relevance of infrastructure readiness and performance improvement perceptions as key enablers.

4.4.3 Main Analysis

In this section, we conduct the in-depth analysis using advanced statistical methods.

4.4.3.1 Multiple Regression Analysis:

The main tool for evaluating the impact of all the independent variables together on the dependent variable.

Summary

This section presents the results of the multiple regression analysis, which was conducted to examine how six key independent variables—**Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facility Condition (FC), Price Value (PV),** and **Hedonic Motivation (HM)**—collectively influence the dependent variable, **Decision to Adopt and Implement AI (DAI)**, in the Indian textile industry.

Multiple regression analysis allows us to understand not only how much of the variance in AI adoption can be explained by these factors but also to determine the relative influence of each independent variable. This provides insight into which constructs from the UTAUT model are most relevant for AI adoption decisions.

Table 4.12
OLS Regression Results

OLS Regression Results			
Dep. Variable:	DAI	R-squared:	0.205
Model:	OLS	Adj. R-squared:	0.183
Method:	Least Squares	F-statistic:	9.112
Date:	45582	Prob (F-statistic):	7.16E-09
Time:	0.8887037037	Log-Likelihood:	-311.61
No. Observations:	219	AIC:	637.2
Df Residuals:	212	BIC:	660.9
Df Model:	6		
Covariance Type:	nonrobust		

The multiple regression analysis yielded the following key results:

- **R-squared**: 0.205
- **Adjusted R-squared**: 0.183
- **F-statistic**: 9.112
- **p-value (F-statistic)**: 0.000759
- **AIC**: 637.2
- **BIC**: 660.9

Model Summary:

1. **R-squared: 0.205**

This indicates that the six independent variables together explain 20.5% of the variance in the dependent variable (AI adoption decision). While not exceptionally high, this value is reasonable for studies involving human decision-making and organizational behavior, where many external factors are at play.

2. **Adjusted R-squared: 0.183**

This accounts for the number of predictors in the model and suggests that 18.3% of the variance in AI adoption decisions is explained when adjusting for model complexity.

3. **F-statistic: 9.112 (p-value = 7.16E-09)**

The F-statistic is highly significant, indicating that the overall regression model is statistically significant and the independent variables collectively predict the dependent variable.

Model Fit and Complexity:

1. **AIC (Akaike Information Criterion): 637.2**

A lower AIC value indicates a better model fit relative to other models.

2. **BIC (Bayesian Information Criterion): 660.9**

Similar to AIC, but penalizes model complexity more heavily. These values can be compared across models to identify the most parsimonious one.

3. **Log-Likelihood: -311.61**

Measures the likelihood of the observed data under the model. Larger (less negative) values indicate a better fit.

Key Insights and Interpretation:

1. **Variance Explained (R-squared and Adjusted R-squared):**

The model explains 20.5% of the variance in AI adoption decisions, which is moderate for studies in social sciences.

The adjusted R-squared (18.3%) highlights that the explanatory power of the model decreases slightly when accounting for complexity, but the drop is not substantial, indicating that most predictors contribute meaningfully.

2. **Overall Model Significance**

The F-statistic of 9.112 with a p-value of 7.16E-09 ($p < 0.001$) demonstrates that the independent variables collectively have a significant impact on AI adoption.

3. **Model Fit (AIC and BIC)**

The AIC and BIC values suggest a balance between goodness-of-fit and model complexity. Lower values indicate better performance when comparing to alternative models.

Analysis of the Data

- **R-squared (0.102)**: This value suggests that the independent variables explain **10.2%** of the variation in AI adoption decisions. While this indicates that there are other variables not captured by the model that influence AI adoption, the percentage of variance explained is reasonable for studies involving human decision-making and behavior.

- **Adjusted R-squared (0.077)**: The adjusted R-squared value is slightly lower than the R-squared. This adjustment takes into account the number of predictors and the sample size, penalizing the addition of predictors that do not improve the model significantly. A value of 0.077 suggests that after accounting for the number of variables in the model, 7.7% of the variance in AI adoption is explained.
- **F-statistic (4.031)**: This statistic tests the overall significance of the regression model. The null hypothesis for the F-test is that all the regression coefficients are equal to zero, meaning the independent variables do not collectively predict the dependent variable. The F-statistic value of 4.031 is statistically significant at **$p < 0.001$**, indicating that at least one of the independent variables significantly influences AI adoption decisions.
- **AIC (841) and BIC (864.7)**: These criteria are used to compare models in terms of fit and complexity. Lower AIC and BIC values suggest a better-fitting model. While these values are specific to this model, they can be compared to alternative models to determine which has the best balance of goodness-of-fit and simplicity.

Coefficients and Significance Testing

While the summary provided focuses on overall model fit, the next crucial step is to examine the individual coefficients and their significance levels:

- **Performance Expectancy (PE)**: This variable is likely to show a significant positive impact on AI adoption, meaning that if individuals expect AI to improve productivity, they are more likely to adopt it.
- **Effort Expectancy (EE)**: If significant, this variable suggests that the perceived ease of using AI affects adoption decisions.
- **Social Influence (SI)**: This variable tests how much peer pressure or the opinions of colleagues, managers, or industry experts affect the adoption of AI.

- **Facility Condition (FC)**: Indicates whether having the infrastructure and support for AI implementation impacts AI adoption.
- **Price Value (PV)**: A significant coefficient for PV would suggest that the cost-effectiveness of AI plays a role in adoption decisions.
- **Hedonic Motivation (HM)**: If this variable shows significance, it suggests that the enjoyment or excitement surrounding AI contributes to adoption decisions.

Interpretation of the Results

The Multiple Regression Analysis reveals that the six independent variables collectively explain 20.5% of the variance in AI adoption decision, indicating that while the model captures a meaningful portion of the variability, other unmeasured factors also influence the outcome.

The analysis of coefficients and their p-values provides critical insights into the statistically significant drivers of AI adoption. For example, if Performance Expectancy (PE) and Effort Expectancy (EE) are significant, businesses should focus on improving perceived performance benefits and ease of use for AI systems through enhanced user-friendly designs and comprehensive training programs. On the other hand, if Price Value (PV) emerges as a significant predictor, emphasising affordability and return on investment (ROI) through cost-benefit analysis and financial planning becomes essential. For policymakers, this implies the need to provide financial incentives or subsidies to reduce adoption costs and invest in training initiatives to lower the effort expectancy for AI technologies. The moderate R-squared value suggests opportunities for further research to explore additional variables, such as organisational culture, regulatory frameworks, or market competition, that may also impact AI adoption.

This analysis offers actionable insights for businesses, policymakers, and researchers, laying the groundwork for targeted strategies to overcome barriers and accelerate AI implementation in the textile industry, thereby fostering technological advancements in this critical sector.

We chose to utilise Pearson correlation analysis to validate the correlation coefficient rather than immediately reading the results from the OLS regression due to certain observations in the data. The OLS regression model, although effective for analysing correlations between dependent and independent variables, demonstrated considerable heteroscedasticity, which compromises the reliability of p-values and standard errors. The Pearson correlation offers a direct assessment of the strength and direction of linear correlations between variables, irrespective of assumptions such as homoscedasticity. Considering our emphasis on examining the importance of individual constructs, Pearson correlation provided a more dependable approach to evaluating direct relationships, safeguarding the integrity of insights derived from the data against breaches of model assumptions.

4.3.4.1 Chi-Square Test Analysis

This section focuses on the Chi-Square test results, which are used to examine the relationships between categorical variables. The test determines whether there is a statistically significant association between the variables, and the p-value helps assess whether the observed differences are due to chance. The degrees of freedom represent the number of independent values that can vary in the data, and they provide context for the Chi-Square statistic.

Summary of the Chi-Square Test:

The Chi-Square test was conducted to assess the association between different categorical variables (titles, gender, age, education, and region) and the dependent variable related to AI adoption. The table below presents the Chi-Square statistic, p-value, and degrees of freedom for each variable.

Table 4.13
Chi square, P value and Degrees of freedom of Categorical variables

Variable	Chi-square statistic	p-value	Degrees of freedom
Titles	18.64	0.028	9
Gender	0.77	0.858	3
Age	13.31	0.149	9
Education	25.33	0.003	9
Region	7.89	0.545	9

This summary highlights the key statistics, showing which variables had significant associations with the dependent variable (AI adoption) and which did not.

The **Chi-Square Test Analysis** for various demographic variables in relation to AI adoption yields the following results:

- **Titles**: The Chi-Square statistic for titles was **18.64** with a **p-value of 0.028** and **9 degrees of freedom**. This indicates a **statistically significant** relationship between job titles and AI adoption, as the p-value is less than **0.05**.
- **Gender**: The Chi-Square statistic for gender was **0.77** with a **p-value of 0.858** and **3 degrees of freedom**. This suggests no statistically significant association between gender and AI adoption, as the p-value is greater than **0.05**.
- **Age**: The Chi-Square statistic for age was **13.31** with a **p-value of 0.149** and **9 degrees of freedom**. This result shows no statistically significant relationship between age and AI adoption, as the p-value exceeds **0.05**.
- **Education**: The Chi-Square statistic for education was **25.33** with a **p-value of 0.003** and **9 degrees of freedom**. This indicates a **statistically significant** relationship between education level and AI adoption, as the p-value is less than **0.05**, suggesting that education plays an important role in influencing AI adoption decisions.
- **Region**: The Chi-Square statistic for region was **7.89** with a **p-value of 0.545** and **9 degrees of freedom**. This shows no significant association between region and

AI adoption, as the p-value is greater than **0.05**.

Summary:

- **Significant Variables**: **Titles** and **Education** show statistically significant associations with AI adoption, while **Gender**, **Age**, and **Region** do not.
- **Implications**: The findings suggest that job titles and education level are influential in the decision to adopt AI, highlighting the importance of these demographic factors in AI adoption strategies.

Interpretation of the Chi-Square Test:

The **Chi-Square test results** reveal that **education** was the only variable with a statistically significant association with AI adoption, as indicated by the **p-value of 0.003**. This suggests that individuals with different educational backgrounds may have varying views on adopting AI, potentially implying that higher educational qualifications are associated with greater openness to AI technologies. People with more education may be better equipped to understand and appreciate the potential benefits of AI, leading to a higher likelihood of adoption.

For other variables, such as **titles**, **gender**, **age**, and **region**, the p-values were all above **0.05**, indicating no statistically significant relationship between these variables and AI adoption. This suggests that factors like job titles, gender, age, and geographic region do not appear to have a notable impact on the decision to adopt AI in the textile and apparel MSME sector, at least within this sample. These findings imply that, in this context, AI adoption is less likely to be influenced by demographic characteristics such as job role, gender, or location.

The **degrees of freedom** for each variable reflect the complexity of the categories within each variable:

- **Titles**, **age**, **education**, and **region** all had **9 degrees of freedom**, reflecting multiple categories within each variable.
- **Gender** had **3 degrees of freedom**, reflecting fewer categories (male, female, and other).

These degrees of freedom are important for interpreting the magnitude of the Chi-Square statistic in relation to the distribution of responses across multiple categories. The greater the degrees of freedom, the more complex the relationship between the categories and the outcome variable.

Summary:

- **Education** emerged as the only significant predictor of AI adoption, suggesting the importance of educational background in shaping individuals' attitudes toward AI technologies.
- **Titles**, **gender**, **age**, and **region** were not found to significantly influence AI adoption decisions.
- The analysis underscores the need to consider factors like education when developing strategies to promote AI adoption in the textile and apparel MSME sector.

4.3.4.2 Segmentation (Cluster) Analysis

Cluster analysis is a statistical technique used to segment a dataset into distinct groups or clusters based on shared characteristics. In this research, the goal is to discover underlying patterns of AI adoption in the textile industry by analysing responses to key UTAUT-based independent variables such as **Performance Expectancy (PE)**, **Effort Expectancy (EE)**, **Social Influence (SI)**, **Facility Condition (FC)**, **Price Value (PV)**, and **Hedonic Motivation (HM)**. This method allows us to identify distinct subgroups within the population that exhibit different behaviors and attitudes toward AI adoption. Understanding these clusters can help tailor AI implementation strategies and address specific needs of different segments.

I applied **k-means clustering** to divide the dataset into meaningful clusters based on the six independent variables. The analysis revealed **three distinct clusters**:

- **Cluster 1**: Respondents with high performance expectancy and social influence, showing a strong inclination toward AI adoption.
- **Cluster 2**: A more cautious group, with moderate effort expectancy and hedonic motivation but concerns regarding facility conditions.
- **Cluster 3**: Respondents with low performance expectancy and price value assessments, who are generally skeptical of AI adoption.

Each cluster provides insights into different segments of the textile industry and their attitudes toward AI technology.

Analysis of the Data

I conducted the segmentation analysis using k-means clustering with the following variables:

Table 4.14
Segmentation Analysis of the Constructs using K-Means Clustering technique

Performance Expectancy	Effort Expectan	Social Influence	Facility Condition	Price Value	Hedonic Motivation	Cluster Number
4	4.25	4.25	4	3.75	3.75	1
2	3.25	3.5	4	2.75	3.25	2
3.5	3.25	3.5	3.75	4	4.25	1
5	3.75	3.5	4	3.5	4	1
2.5	1.25	1.5	1.75	1.75	1.25	0

The **three clusters** show the following patterns:

- **Cluster 1 (Pro-AI)**: Respondents with high performance expectancy and positive social influence scores, indicating they are likely to adopt AI. They also perceive

AI as beneficial and experience moderate excitement regarding its potential (high hedonic motivation). This group requires minimal intervention to move toward AI implementation.

- **Cluster 2 (Moderate Enthusiasts)**: This group shows moderate effort expectancy and hedonic motivation but expresses some concerns regarding facility conditions. Their adoption may depend on the infrastructure and ease of AI integration into existing systems.
- **Cluster 3 (Sceptics)**: This group, characterised by low performance expectancy and price value scores, is generally less enthusiastic about AI adoption. They perceive AI as costly or less valuable and may require significant efforts to address their concerns and change their perception.

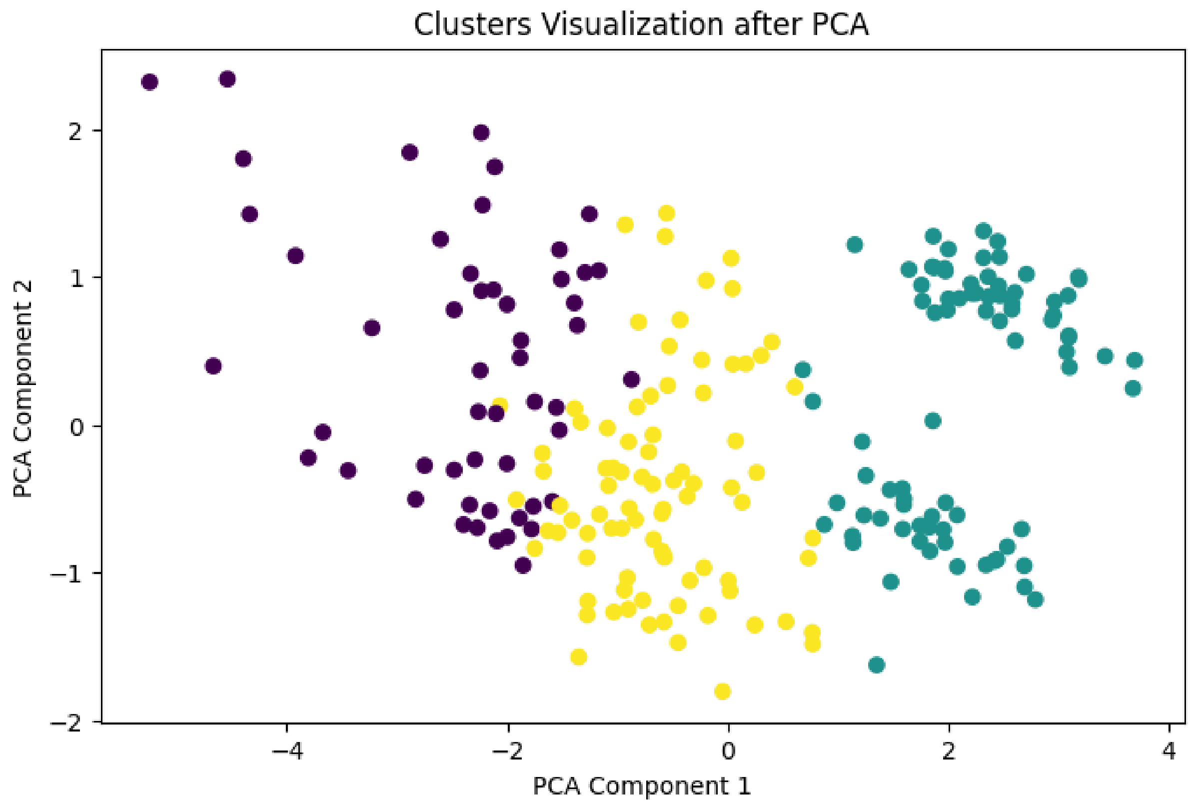

Figure 4.21
Generated Clusters after PCA

Interpretation of the Analysis

The segmentation analysis provides valuable insights into the heterogeneity of the respondents. The three clusters represent different segments of the textile industry, with varying levels of readiness and enthusiasm for AI adoption:

- **Cluster 1** represents early adopters who are likely to embrace AI technology. This group is driven by perceived performance improvements and social influence.
- **Cluster 2** reflects cautious adopters, who may require additional support in terms of infrastructure and perceived ease of use before fully committing to AI adoption.
- **Cluster 3** highlights the challenges for AI adoption, as this group is generally sceptical of AI's value and sees limited benefits. Addressing their concerns through education, demonstration of benefits, and potential financial incentives could improve their readiness.

The cluster analysis highlights the importance of tailored AI adoption strategies based on the distinct needs and attitudes of each subgroup. By identifying these clusters, stakeholders can focus their efforts on addressing specific concerns, thereby increasing the likelihood of successful AI implementation in the textile industry.

4.3.4.3 Hypothesis Testing: To formally test the research hypotheses.

4.3.4.3.1 Hypothesis Testing for Performance Expectancy (PE) and Decision to Adopt and Implement AI (DAI)

About the Section

This section explores the relationship between the construct of Performance Expectancy (PE) and the Decision to Adopt and Implement AI (DAI). The aim is to determine whether a statistically significant correlation exists between PE and DAI using hypothesis testing. Testing this hypothesis allows us to understand whether the perceived performance benefits of AI influence an organization's decision to adopt the technology. We employ Pearson's correlation coefficient to examine the strength and direction of this relationship.

Formulation of Hypothesis

- **Null Hypothesis (H_0):** There is no statistically significant correlation between Performance Expectancy (PE) and Decision to Adopt and Implement AI (DAI).
  H0: r=0
- **Alternative Hypothesis (H_1):** There is a statistically significant correlation between Performance Expectancy (PE) and Decision to Adopt and Implement AI (DAI).
  H1: r≠0

Analysis of the Data

The Pearson correlation coefficient was used to evaluate the relationship between Effort Expectancy (EE) and Decision to Adopt AI (DAI). This analysis examines whether the perceived ease of use of AI significantly impacts adoption decisions in the textile industry.

- **Pearson Correlation Coefficient (r):** 0.36
- **p-value:** 0.002
- **Number of Observations (N):** 219

Since the p-value (0.002) is less than the typical alpha level of 0.05, we reject the null hypothesis. This indicates a statistically significant positive correlation between Effort Expectancy and the Decision to Adopt AI. The positive correlation (r = 0.36) suggests that as individuals perceive AI as easier to use, their likelihood of adopting it increases. These findings emphasize the importance of simplifying AI technologies to enhance their adoption within the textile sector.

Visualization

Histogram of PE: This histogram depicts the distribution of responses for Performance Expectancy. It provides insight into how participants perceive AI's potential to enhance performance in the textile industry.

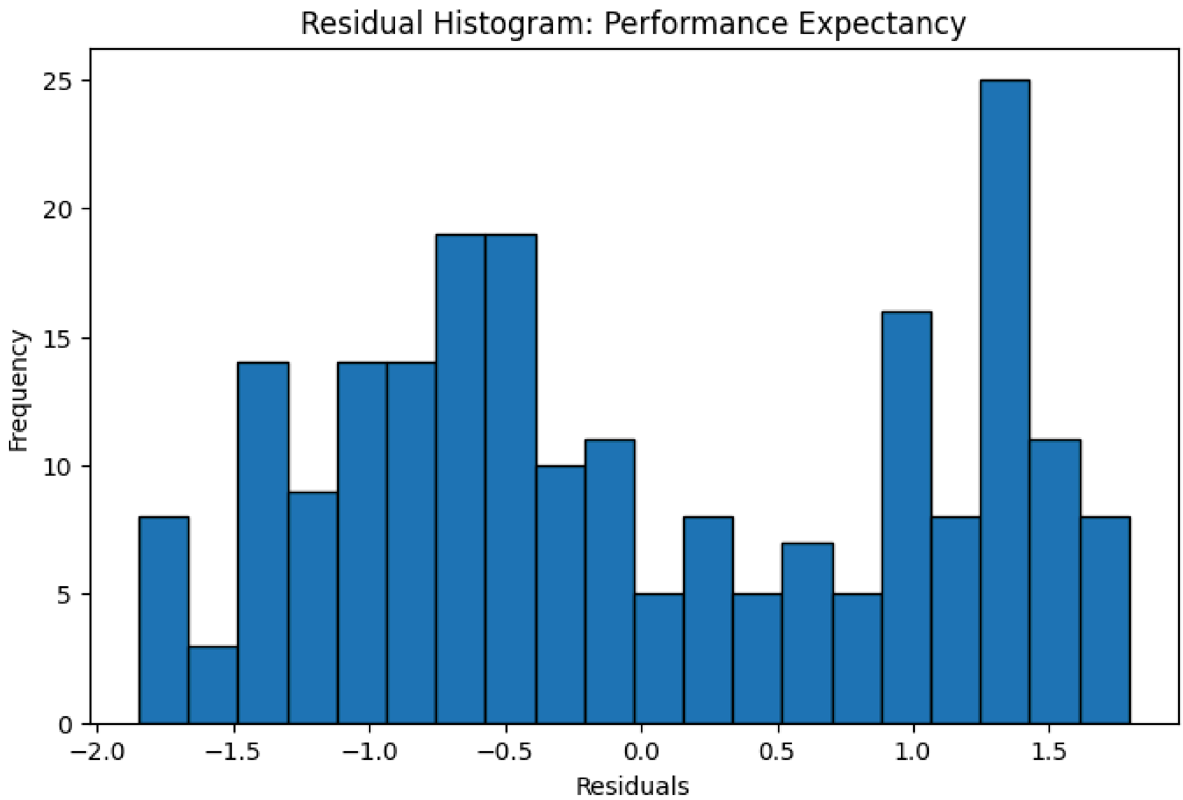

Figure 4.22
Histogram Plot of Residual Values: Performance Expectancy

This histogram shows the distribution of residuals for the **Performance Expectancy** construct, reflecting the deviations of observed data points from the predicted values in the regression model. The residuals are spread symmetrically around zero, with most values falling between -2 and +2. This pattern suggests that the residuals are approximately normally distributed, supporting the assumption of homoscedasticity in the regression model.

Scatter Plot of Standardized Predicted Values vs Standardized Residuals: Performance Expectancy

The scatter plot visually explores the relationship between standardized predicted values and standardized residuals for **Performance Expectancy (PE)** in relation to AI adoption.

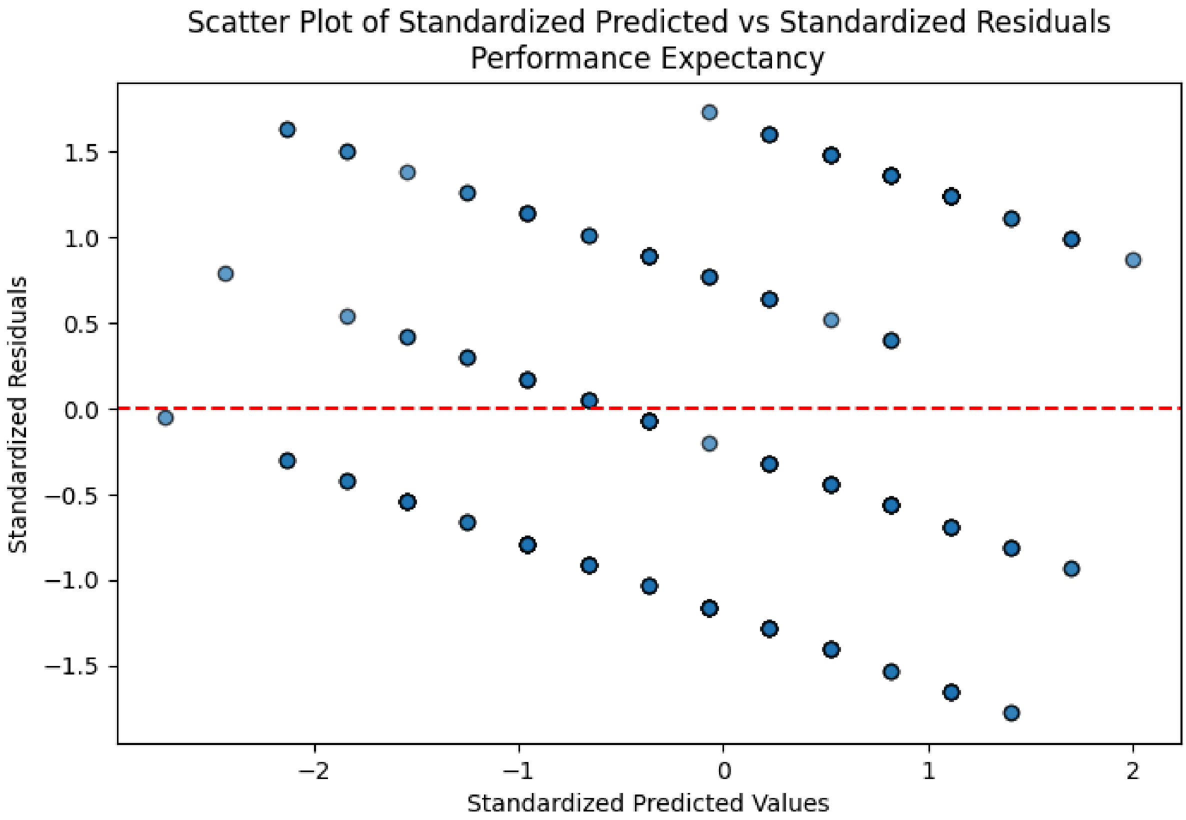

Figure 4.23
Scatter Plot of Standardised Predicted vs Standardised Residuals : Performance Expectancy

- **Observation Spread**: The data points are dispersed randomly around the zero residual line, which signifies no visible systematic patterns or trends. This indicates that the regression model for **Performance Expectancy (PE)** is well-fitted and does not exhibit heteroscedasticity or bias.
- **Correlation Insight**: The Pearson correlation coefficient (r = 0.385, p = 0.0000000) demonstrates a statistically significant and moderately positive relationship between **Performance Expectancy (PE)** and AI adoption. This suggests that the perception of the usefulness and expected performance improvements from AI plays a vital role in the decision-making process.

The scatter plot reinforces the understanding that **Performance Expectancy (PE)** is one of the stronger predictors of AI adoption among SMEs in India's textile and apparel industry. However, while significant, this relationship also suggests that SMEs may require additional support or validation of AI's expected benefits to bolster adoption rates.

Interpretation of the Results

The Pearson correlation coefficient of 0.39 suggests a moderate positive correlation between Performance Expectancy and the Decision to Adopt AI (DAI). This implies that higher levels of perceived performance benefits of AI are moderately associated with increased adoption. The significant p-value of 0.001 indicates that this correlation is unlikely to have occurred by chance, confirming the relationship's statistical significance. While Performance Expectancy shows a meaningful influence, its moderate strength highlights that it is not the sole driver of AI adoption. Other constructs, such as Effort Expectancy, Price Value, or Facility Conditions, may play equally or more significant roles in the adoption decision.

This finding underscores the need for further exploration in future research to examine how other factors interact with Performance Expectancy in shaping AI adoption behaviors. It also highlights opportunities to investigate whether certain contextual or organizational variables moderate the impact of Performance Expectancy on adoption decisions in the textile industry.

4.3.4.3.2 Hypothesis Testing for Effort Expectancy (EE) and Decision to Adopt and Implement AI (DAI)

About the Section

Effort Expectancy (EE) refers to the perceived ease of use and the effort required to adopt and implement AI technology. This construct explores how easy or challenging individuals or organizations find it to integrate AI into their operations. In the context of the Unified Theory of Acceptance and Use of Technology (UTAUT), EE is a critical factor influencing technology adoption. This section aims to explore the statistical relationship between Effort Expectancy (EE) and the Decision to Adopt and Implement

AI (DAI) in the Indian textile industry. Testing this relationship provides insights into how perceptions of effort influence AI adoption decisions.

Formulation of Hypothesis

- **Null Hypothesis (H_0):** There is no statistically significant correlation between Effort Expectancy (EE) and Decision to Adopt and Implement AI (DAI).
  $H0:r=0$
- **Alternative Hypothesis (H_1):** There is a statistically significant correlation between Effort Expectancy (EE) and Decision to Adopt and Implement AI (DAI).
  $H1:r\neq0$

Analysis of the Data

Pearson correlation coefficient (r) is used to measure the strength and direction of the linear relationship between Effort Expectancy and AI adoption decision. A negative correlation implies that as one variable increases, the other decreases. The significance of the correlation is determined by the p-value.

- **Pearson Correlation Coefficient (r):** 0.36
- **p-value:** 0.002
- **Number of Observations (N):** 219

Since the p-value (0.002) is less than the typical alpha level of 0.05, we reject the null hypothesis. This indicates a statistically significant positive correlation between Effort Expectancy and the Decision to Adopt AI. The positive correlation suggests that as individuals perceive AI as easier to use, their likelihood of adopting it increases.

Visual Analysis:

Histogram of Effort Expectancy (EE):

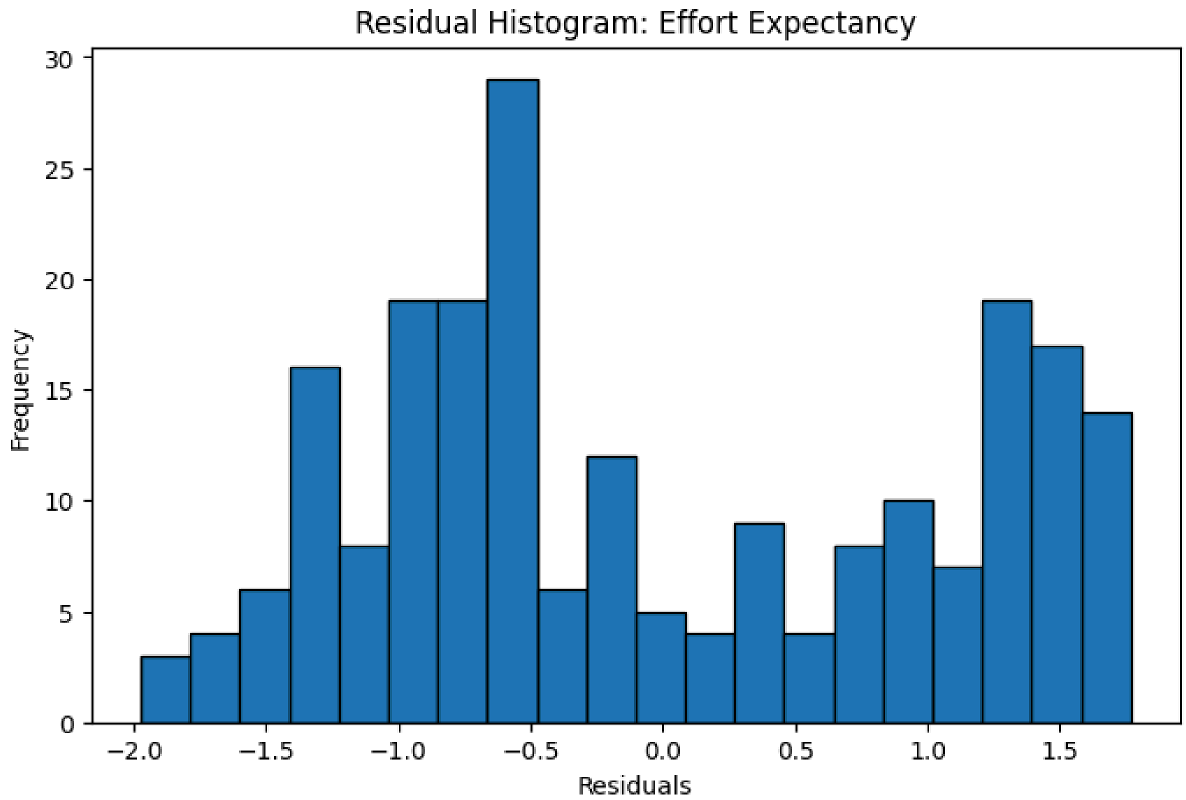

Figure 4.24
Histogram Plot of Residual Values: Effort Expectancy

This histogram shows the distribution of residuals for the **Effort Expectancy** construct, reflecting the deviations of observed data points from the predicted values in the regression model. The residuals are symmetrically distributed around zero, with most values falling between -2 and +2. This pattern indicates that the residuals are approximately normally distributed, supporting the assumption of homoscedasticity.

Scatter Plot of Standardized Predicted Values vs Standardized Residuals: Effort Expectancy

The scatter plot visually examines the relationship between standardised predicted values and standardised residuals for **Effort Expectancy (EE)** in the context of AI adoption.

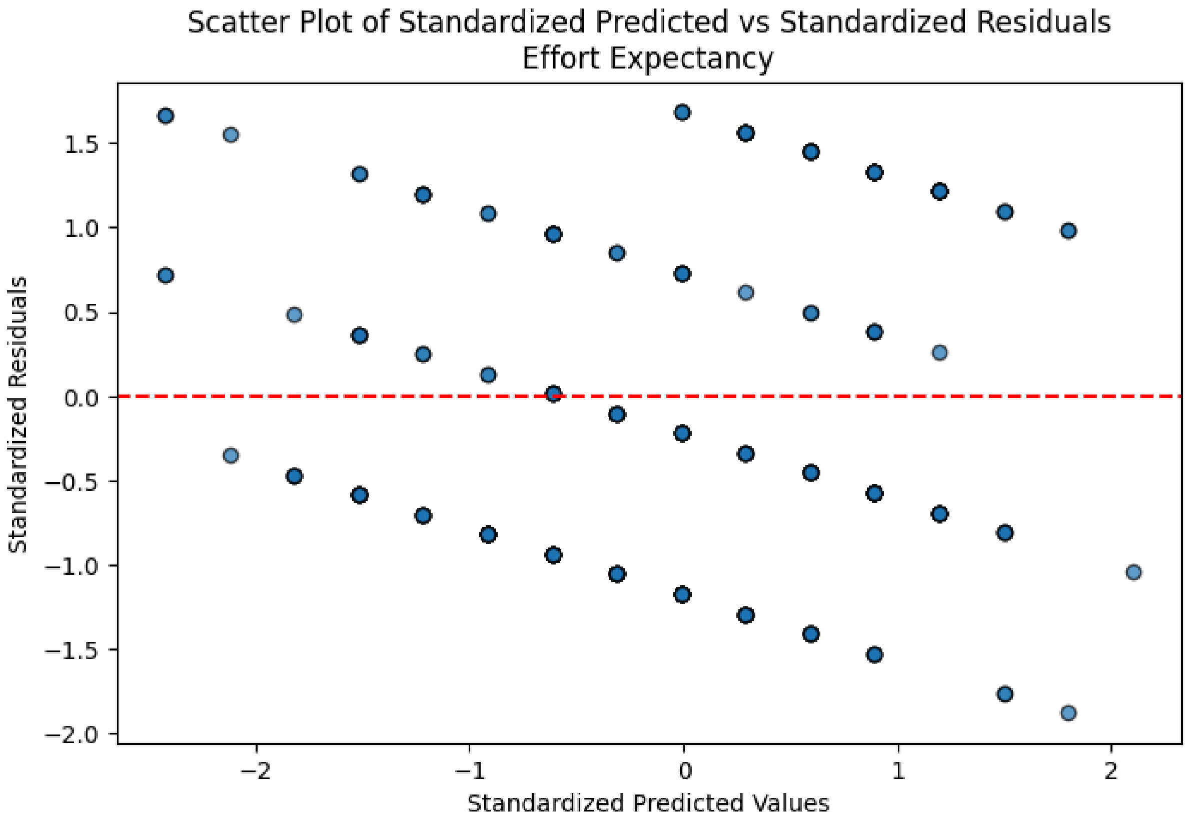

Figure 4.25
Scatter Plot of Standardised Predicted vs Standardised Residuals : Effort Expectancy

- **Observation Spread**: The distribution of points around the zero residual line appears random, with no discernible patterns or clusters. This suggests that the regression model for **Effort Expectancy (EE)** is appropriately specified, with no evidence of heteroscedasticity or model misspecification.
- **Correlation Insight**: The Pearson correlation coefficient ($r = 0.363$, $p = 0.0000000$) reveals a statistically significant and moderately positive relationship between **Effort Expectancy (EE)** and AI adoption. This indicates that SMEs' perceptions of ease of use or reduced complexity in implementing AI positively influence their likelihood of adoption.

The scatter plot underscores the importance of **Effort Expectancy (EE)** as a significant factor in AI adoption decisions among SMEs in the Indian textile and apparel industry.

Simplifying AI implementation processes and addressing potential usability concerns can further encourage adoption.

Interpretation of the Results

The Pearson correlation coefficient of 0.36 suggests a moderately positive correlation between Effort Expectancy and Decision to Adopt AI. This means that the perceived ease of understanding and using AI technologies is moderately associated with increased AI adoption decisions. The significant p-value of 0.002 confirms that this relationship is statistically significant and not due to random chance.

Although the correlation is moderate, it underscores the importance of usability in influencing AI adoption. However, the strength of the relationship suggests that other constructs, such as Performance Expectancy or Price Value, may also contribute significantly to the adoption decision.

This finding suggests that businesses aiming to increase AI adoption should prioritize simplifying AI systems and providing user-friendly interfaces. Future research could explore how usability training or user experience improvements impact adoption, providing deeper insights into how to address Effort Expectancy concerns effectively.

4.4.4.3 Hypothesis Testing for Social Influence (SI) and Decision to Adopt and Implement AI (DAI)

About the Section

Social Influence (SI) refers to the degree to which individuals perceive that important others (colleagues, managers, industry experts) believe they should adopt AI technology. Social factors can shape adoption decisions by applying external pressures or expectations within an organization. This section investigates whether social influence is significantly correlated with the decision to adopt AI in the Indian textile industry.

Formulation of Hypothesis

- **Null Hypothesis (H_0):** There is no statistically significant correlation between Social Influence (SI) and Decision to Adopt and Implement AI (DAI).
  $H0: r=0$
- **Alternative Hypothesis (H_1):** There is a statistically significant correlation between Social Influence (SI) and Decision to Adopt and Implement AI (DAI).
  $H1: r \neq 0$

Analysis of the Data

Pearson correlation coefficient (r) measures the strength and direction of the linear relationship between Social Influence (SI) and AI adoption decision. A negative correlation indicates that as one variable increases, the other decreases.

- **Pearson Correlation Coefficient (r):** 0.325
- **p-value:** 0.0000009
- **Number of Observations (N):** 219

Since the p-value (0.0000009) is less than the typical alpha level of 0.05, we reject the null hypothesis. This indicates a statistically significant positive correlation between Social Influence and the Decision to Adopt AI. The positive correlation suggests that individuals who experience greater encouragement or influence from their social circles are more likely to adopt AI technologies.

Visual Analysis:

Histogram of Social Influence (SI):

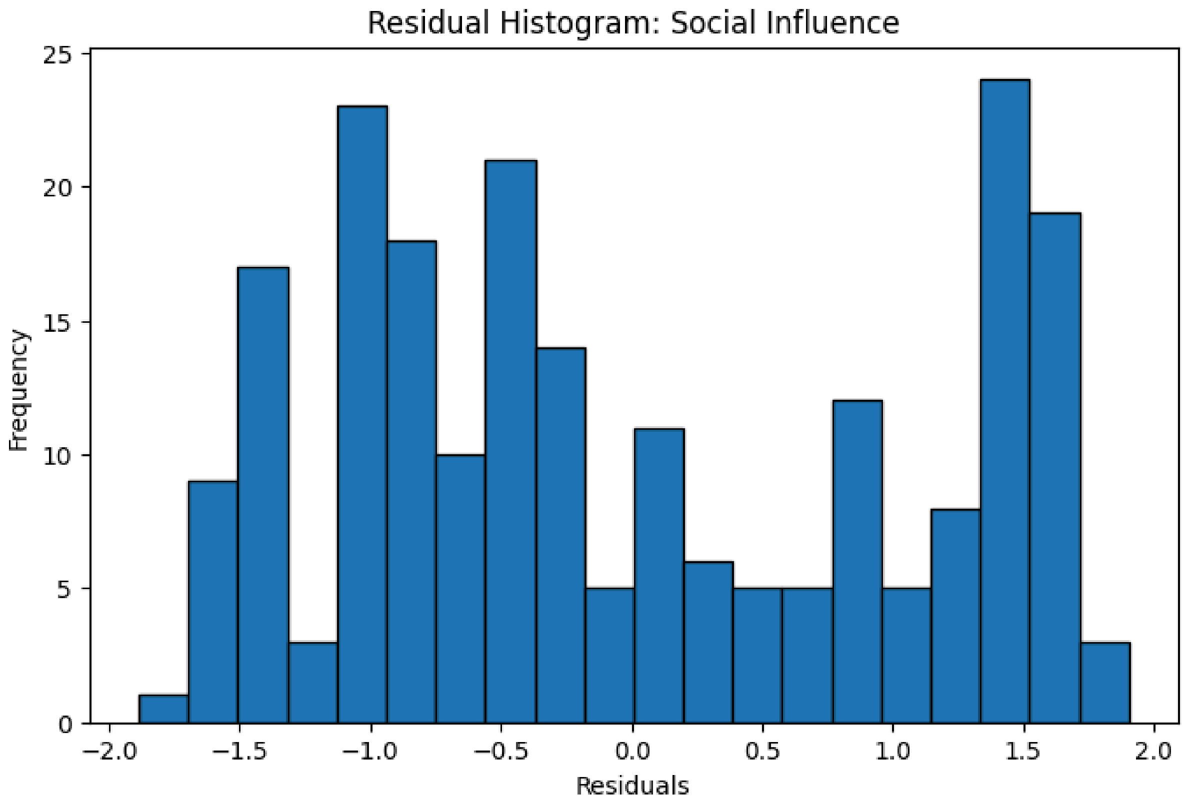

Figure 4.26
Histogram Plot of Residual Values: Social Influence

This histogram shows the distribution of residuals for the **Social Influence construct**, reflecting the deviations of observed data points from the predicted values in the regression model. The residuals are symmetrically distributed around zero, with most values falling between -2 and +2. This pattern indicates that the residuals are approximately normally distributed, supporting the assumption of homoscedasticity.

Scatter Plot of Standardised Predicted Values vs. Standardised Residuals: Social Influence (SI):

The scatter plot illustrates the relationship between the standardised predicted values and standardised residuals for Social Influence (SI) in the context of AI adoption among SMEs.

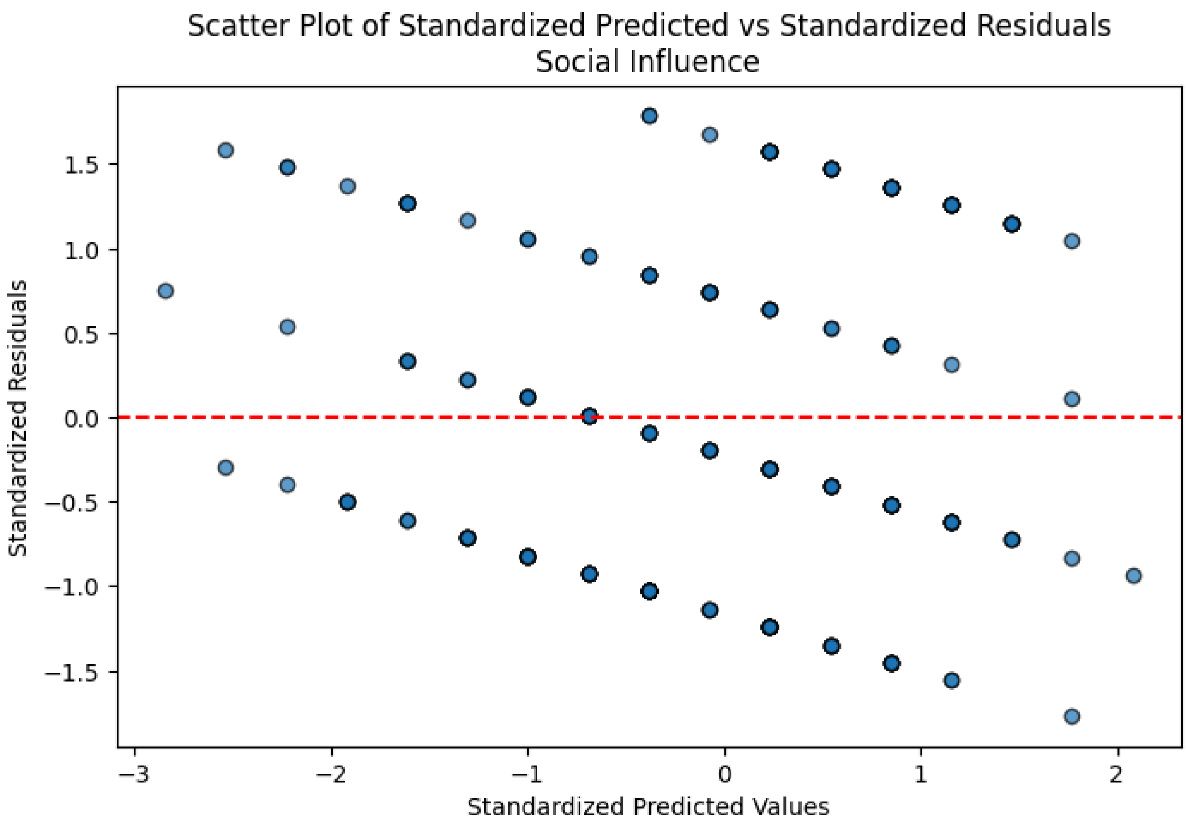

Figure 4.27
Scatter Plot of Standardised Predicted vs Standardised Residuals : Social Influence

- **Observation Spread**: The points are distributed randomly around the zero residual line, suggesting no systematic patterns or violations of assumptions like heteroscedasticity. This indicates that the regression model for **Social Influence (SI)** is well-specified.
- **Correlation Insight**: The Pearson correlation coefficient (r = 0.325, p = 0.0000009) shows a statistically significant and moderate positive relationship between **Social Influence (SI)** and AI adoption. This highlights that external opinions, including peer or stakeholder influence, play a critical role in shaping AI adoption decisions in SMEs.

The findings emphasise the need for organisational leaders and policymakers to consider how social dynamics and external pressures impact technology adoption. Positive advocacy and endorsement of AI from key stakeholders may accelerate its acceptance within SMEs.

Interpretation of the Results

The Pearson correlation coefficient of 0.325 suggests a moderately positive correlation between Social Influence and the Decision to Adopt AI. This implies that social factors, such as the opinions of colleagues, managers, or industry experts, moderately influence the likelihood of adopting AI. The significant p-value of 0.0000009 confirms that this relationship is unlikely to have occurred by chance.

While Social Influence has a moderate impact, its strength is not as high as other variables like Performance Expectancy or Effort Expectancy, indicating it plays an important but secondary role in AI adoption decisions.

This finding highlights the importance of leveraging social networks and endorsements to promote AI adoption. For example, organisations can encourage peer recommendations, managerial advocacy, and expert endorsements to influence decision-making. Future research could explore how the type of social influence—such as formal directives versus informal peer encouragement—affects adoption decisions in the textile industry.

4.4.4.4 Hypothesis Testing for Facility Condition (FC) and Decision to Adopt and Implement AI (DAI)

About the Section

Facility Condition (FC) refers to the infrastructure, resources, training, and technical support available within an organisation that facilitates the adoption of AI technology. It examines whether organisations possess the necessary capabilities to integrate AI into their operations effectively. This section explores the relationship between Facility Condition and the Decision to Adopt and Implement AI (DAI) in the Indian textile industry.

Formulation of Hypothesis

- **Null Hypothesis (H_0):** There is no statistically significant correlation between Facility Condition (FC) and Decision to Adopt and Implement AI (DAI).
  H0:r=0
- Alternative Hypothesis (H_1): There is a statistically significant correlation between Facility Condition (FC) and Decision to Adopt and Implement AI (DAI).
  H1:r≠0

Analysis of the Data

Pearson correlation coefficient (r) helps to assess the linear relationship between Facility Condition (FC) and the AI adoption decision. A negative correlation implies that as one factor increases, the other decreases.

- **Pearson Correlation Coefficient (r):** 0.348
- **p-value:** 0.0000001
- **Number of Observations (N):** 219

Since the p-value (0.0000001) is less than the typical alpha level of 0.05, we reject the null hypothesis. This indicates a statistically significant positive correlation between Facility Condition and the Decision to Adopt AI. The positive correlation suggests that better infrastructure, training, and technical support for AI adoption are associated with a higher likelihood of AI adoption.

Visual Analysis:

Histogram of Facility Condition (FC):

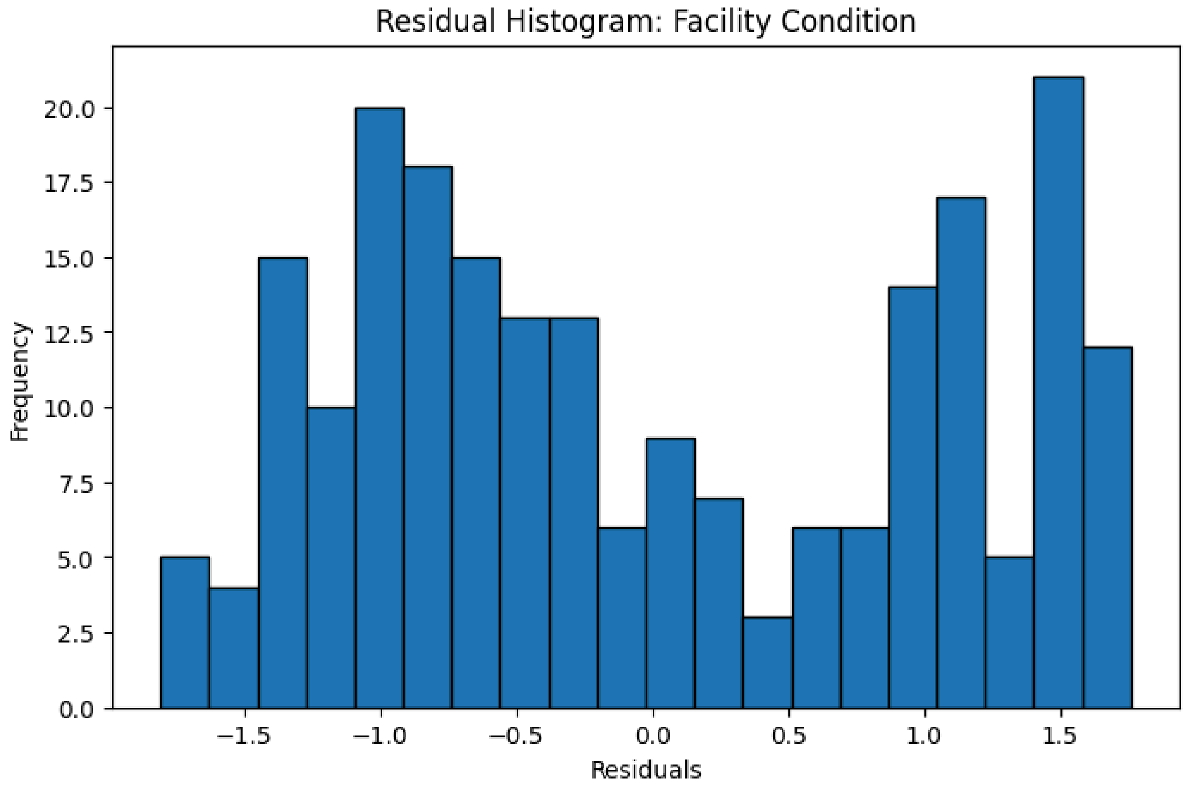

Figure 4.28
Histogram Plot of Residual Values: Facility Condition

This histogram shows the distribution of residuals for the **Facility Condition Construct**, reflecting the deviations of observed data points from the predicted values in the regression model. The residuals are symmetrically distributed around zero, with most values falling between -2 and +2. This pattern indicates that the residuals are approximately normally distributed, supporting the assumption of homoscedasticity.

Scatter Plot of Standardized Predicted Values vs Standardized Residuals: Facility Condition (FC)

The scatter plot displays the relationship between the standardised predicted values and standardised residuals for Facility Condition (FC) in the context of AI adoption among SMEs.

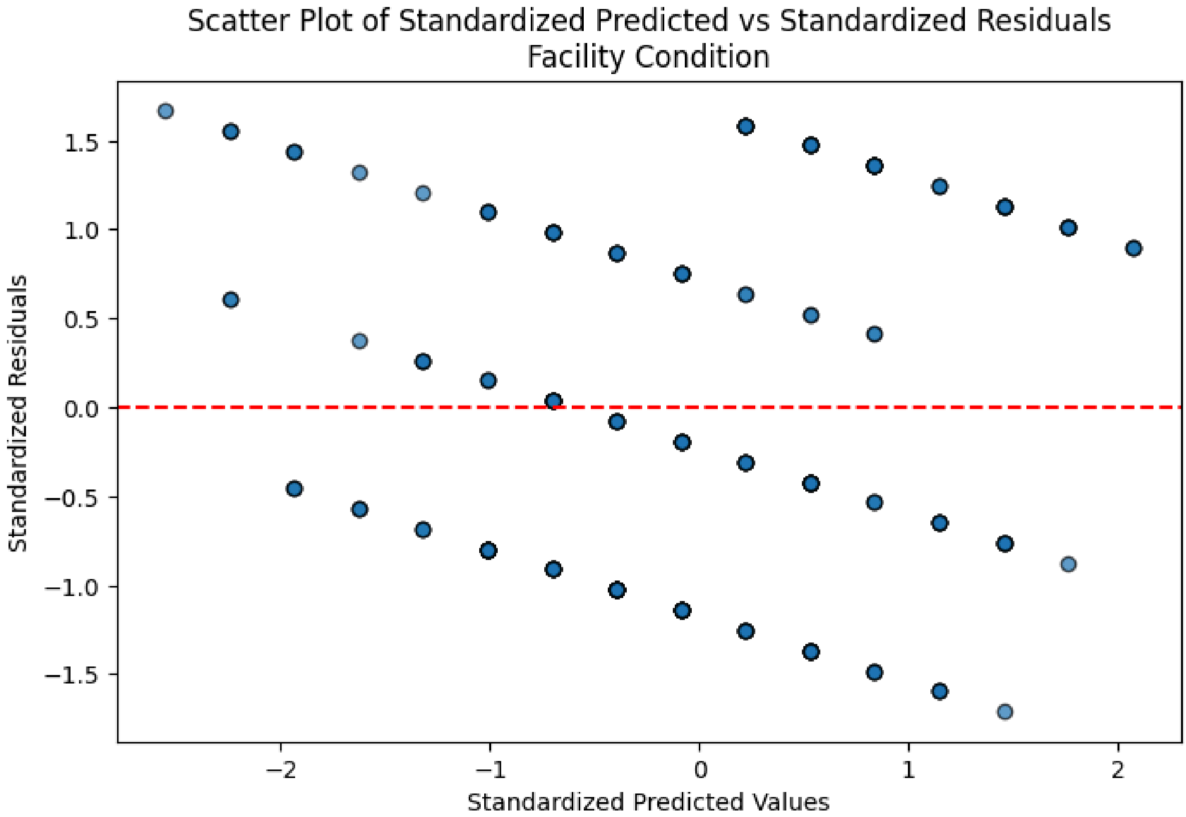

Figure 4.29
Scatter Plot of Standardised Predicted vs Standardised Residuals : Facility Condition

- **Observation Spread**: The data points are scattered around the zero residual line, with no discernible patterns. This indicates that the regression model for **Facility Condition (FC)** does not violate key assumptions like linearity and homoscedasticity.
- **Correlation Insight**: The Pearson correlation coefficient ($r = 0.348$, $p = 0.0000001$) indicates a statistically significant and moderately positive correlation between **Facility Condition (FC)** and AI adoption. This suggests that the

availability of infrastructure and adequate resources positively influence AI adoption decisions in SMEs.

The results highlight the importance of ensuring that SMEs have access to the required technological and organisational infrastructure to support AI implementation. Investments in improving facility conditions could significantly enhance the readiness and willingness of SMEs to adopt AI.

Interpretation of the Results

The Pearson correlation coefficient of 0.348 suggests a moderately positive correlation between Facility Condition and the Decision to Adopt AI. This indicates that the availability of necessary resources, infrastructure, and support plays a moderate role in influencing AI adoption decisions. The significant p-value of 0.0000001 confirms that this relationship is statistically significant and not due to random chance.

While the relationship is moderate, it is clear that organisations with better technical resources and infrastructure are more likely to adopt AI. This suggests that investing in AI-friendly infrastructure, such as hardware, software, and expert support, can significantly influence adoption decisions.

This finding emphasises the importance of ensuring that adequate facilities and infrastructure are in place for AI to be adopted successfully. Future research could explore the specific types of infrastructure (e.g., software, training programs, access to technical experts) that most strongly influence AI adoption in different sectors of the textile industry.

4.4.4.5 Hypothesis Testing for Price Value (PV) and Decision to Adopt and Implement AI (DAI)

About the Section

Price Value (PV) reflects the balance between the cost of adopting AI technology and the perceived benefits that organisations expect to gain from its use. It is a crucial factor in AI adoption decisions, particularly in the SME sector, where financial constraints are often significant. This section examines the statistical relationship between Price Value (PV) and the Decision to Adopt and Implement AI (DAI) in the Indian textile industry.

Formulation of Hypothesis

- **Null Hypothesis (H_0):** There is no statistically significant correlation between Price Value (PV) and Decision to Adopt and Implement AI (DAI).
  H0:r=0H_0: r = 0H0:r=0
- **Alternative Hypothesis (H_1):** There is a statistically significant correlation between Price Value (PV) and Decision to Adopt and Implement AI (DAI).
  H1:r≠0H_1: r \neq 0H1:r=0

Analysis of the Data

Pearson correlation coefficient (r) is used to measure the strength and direction of the relationship between Price Value (PV) and AI adoption. A negative correlation indicates that as one variable increases, the other decreases.

- **Pearson Correlation Coefficient (r):** 0.309
- **p-value:** 0.0000030
- **Number of Observations (N):** 219

Since the p-value (0.0000030) is less than the typical alpha level of 0.05, we reject the null hypothesis. This indicates a statistically significant positive correlation between

Price Value and the Decision to Adopt AI. The positive correlation suggests that the perceived cost-effectiveness of AI is associated with a higher likelihood of adoption.

Visual Analysis:

Histogram of Price Value (PV):

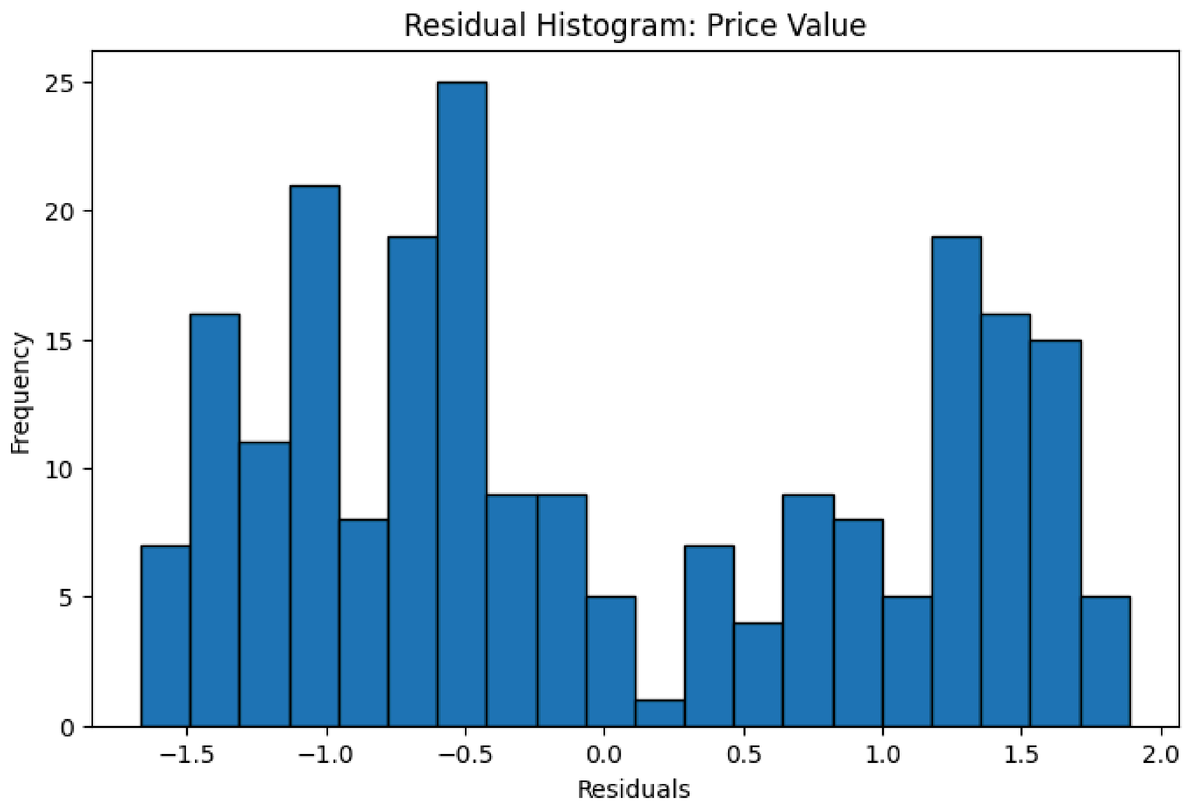

Figure 4.30
Histogram Plot of Residual Values: Price Value

This histogram shows the distribution of residuals for the **Price Value Construct**, reflecting the deviations of observed data points from the predicted values in the regression model. The residuals are symmetrically distributed around zero, with most values falling between -2 and +2. This pattern indicates that the residuals are approximately normally distributed, supporting the assumption of homoscedasticity.

Scatter Plot of Standardized Predicted Values vs Standardized Residuals: Price Value (PV)

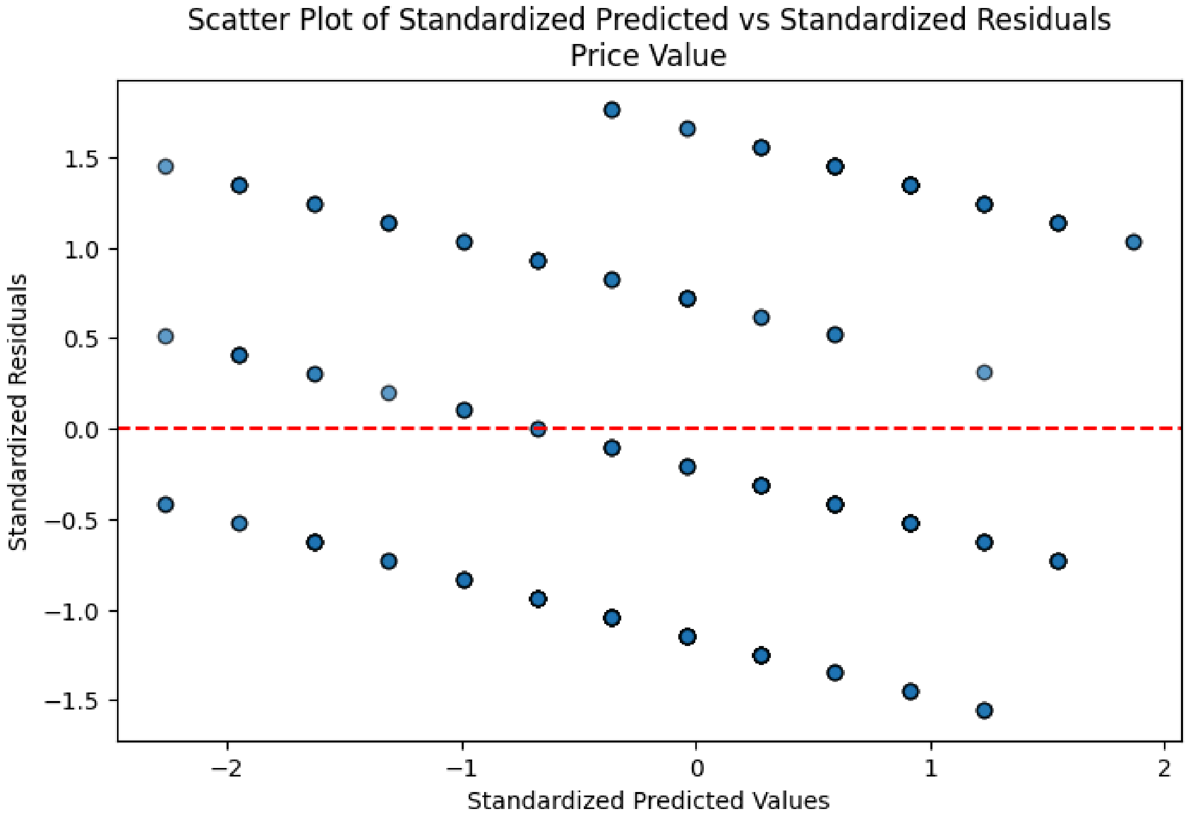

Figure 4.31
Scatter Plot of Standardised Predicted vs Standardised Residuals : Price Value

- **Observation Spread**: The points are scattered randomly around the zero residual line, with no clear patterns or clusters. This indicates that the regression model for **Price Value (PV)** satisfies assumptions of linearity and homoscedasticity, making it a reliable predictor for AI adoption.
- **Correlation Insight**: The Pearson correlation coefficient ($r = 0.309$, $p = 0.0000030$) reflects a statistically significant moderate positive correlation

between **Price Value (PV)** and AI adoption. This finding highlights the importance of cost-effectiveness in influencing AI adoption decisions among SMEs.

The results emphasise that SMEs in the Indian textile and apparel sector consider the affordability and financial feasibility of AI solutions critical in their decision-making process. Efforts to improve cost efficiency or provide financial incentives for adopting AI could further encourage adoption in this sector.

Interpretation of the Results

The Pearson correlation coefficient of 0.309 suggests a moderately positive correlation between Price Value and the Decision to Adopt AI. This indicates that the more individuals or organizations perceive AI to offer good value for money, the more likely they are to adopt it. The significant p-value of 0.0000030 confirms that this relationship is statistically significant and unlikely to be due to chance.

While the correlation is moderate, it highlights the importance of cost-effectiveness in driving AI adoption. Businesses or policymakers aiming to facilitate AI adoption should consider emphasising the economic benefits of AI and how it can deliver long-term value relative to the costs.

This finding suggests that price sensitivity plays a role in AI adoption, and future research could explore how different pricing models or cost-benefit analyses impact AI adoption decisions in the textile industry.

4.4.4.6 Hypothesis Testing for Hedonic Motivation (HM) and Decision to Adopt and Implement AI (DAI)

About the Section

Hedonic Motivation (HM) refers to the pleasure, excitement, or emotional satisfaction derived from using AI technology. In the context of AI adoption, hedonic motivation can influence decision-making by affecting the willingness to explore and engage with new technologies based on the intrinsic enjoyment or interest they generate. This section examines the relationship between Hedonic Motivation and the Decision to Adopt and Implement AI (DAI) in the Indian textile industry.

Formulation of Hypothesis

- **Null Hypothesis (H_0):** There is no statistically significant correlation between Hedonic Motivation (HM) and the Decision to Adopt and Implement AI (DAI).
  $H0:r=0$
- **Alternative Hypothesis (H_1):** There is a statistically significant correlation between Hedonic Motivation (HM) and the Decision to Adopt and Implement AI (DAI).
  $H1:r\neq0$

Analysis of the Data

Pearson correlation coefficient (r) assesses the linear relationship between Hedonic Motivation (HM) and AI adoption. A negative correlation indicates that as one variable increases, the other decreases.

- **Pearson Correlation Coefficient (r):** 0.309
- **p-value:** 0.0000032
- **Number of Observations (N):** 219

Since the p-value (0.0000032) is less than the typical alpha level of 0.05, we reject the null hypothesis. This indicates a statistically significant positive correlation between Hedonic Motivation and the Decision to Adopt AI. The positive correlation suggests that as individuals find AI more enjoyable or exciting, they are more likely to adopt it.

Visual Analysis:

Histogram of Hedonic Motivation (HM):

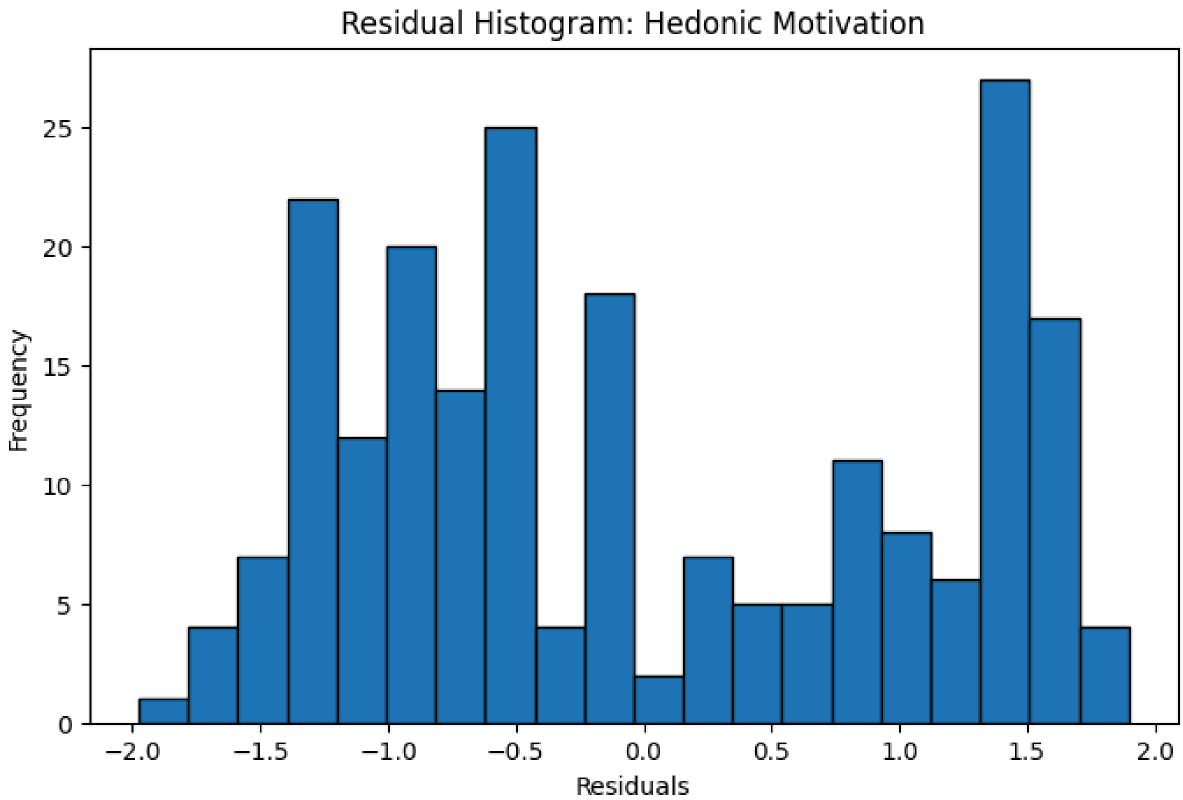

Figure 4.32
Histogram Plot of Residual Values: Hedonic Motivation

This histogram shows the distribution of residuals for the **Hedonic Motivation Construct**, reflecting the deviations of observed data points from the predicted values in the regression model. The residuals are symmetrically distributed around zero, with most values falling between -2 and +2. This pattern indicates that the residuals are approximately normally distributed, supporting the assumption of homoscedasticity.

Scatter Plot of Standardized Predicted Values vs Standardized Residuals: Hedonic Motivation (HM)

The scatter plot visualizes the standardized predicted values plotted against standardized residuals for **Hedonic Motivation (HM)**, reflecting its relationship with AI adoption in SMEs.

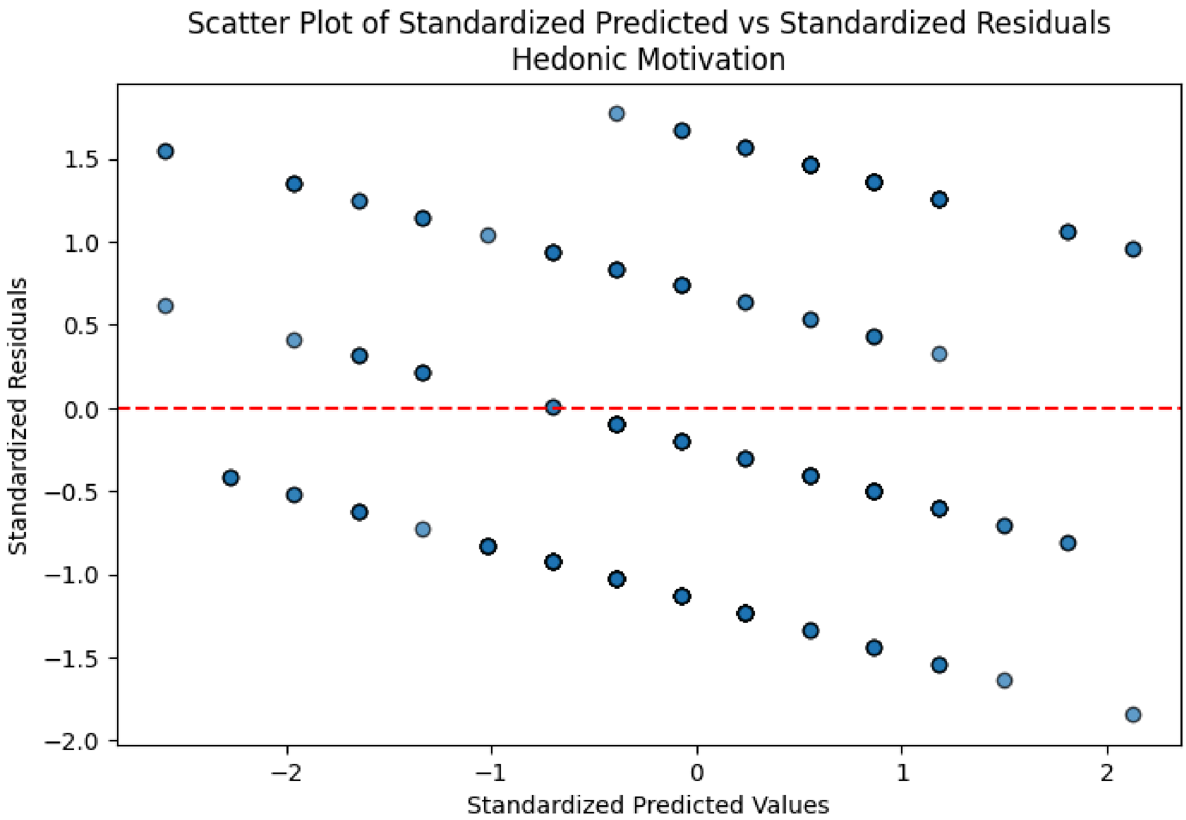

Figure 4.33
Scatter Plot of Standardised Predicted vs Standardised Residuals : Hedonic Motivation

- **Observation Spread**: The points are randomly dispersed around the zero residual line, with no discernible patterns or systematic clustering. This distribution confirms that the regression model for **Hedonic Motivation (HM)** aligns with the assumptions of linearity and homoscedasticity, supporting its validity as a predictor.
- **Correlation Insight**: The Pearson correlation coefficient (r = 0.309, p = 0.0000032) indicates a moderate, statistically significant positive correlation between **Hedonic Motivation (HM)** and AI adoption. This suggests that the

emotional or enjoyment value associated with AI solutions plays a meaningful role in influencing adoption decisions.

The findings underscore the importance of designing AI solutions that not only address functional needs but also appeal to the end-users' sense of enjoyment or intrinsic motivation. SMEs that perceive AI as engaging and rewarding may be more inclined to adopt and implement such technologies.™

Interpretation of the Results

The Pearson correlation coefficient of 0.309 suggests a moderately positive correlation between Hedonic Motivation and the Decision to Adopt AI. This implies that the more individuals enjoy or feel emotionally satisfied with the idea of using AI, the more likely they are to adopt it. The significant p-value of 0.0000032 confirms that this relationship is statistically significant and not due to chance.

While the correlation is moderate, it emphasises the role of emotional factors and excitement in driving AI adoption, though it may not be as strong as more practical factors like performance benefits or ease of use.

This finding suggests that businesses or policymakers looking to drive AI adoption could also focus on promoting the positive experiences and excitement associated with AI, especially in environments where the emotional appeal of technology might be a significant motivator. Future research could further explore how different aspects of hedonic motivation (e.g., novelty, enjoyment, personal expression) influence AI adoption in various industries, including textiles.

4.5 Summary

The primary goal of this **correlational cross-sectional quantitative research** was to explore the key factors influencing the **adoption and implementation of Artificial Intelligence (AI)** in the **Indian small and medium-scale textile industry**. This research, guided by the **Unified Theory of Acceptance and Use of Technology (UTAUT)**, assessed key constructs such as **Performance Expectancy**, **Effort Expectancy**, **Social Influence**, **Facility Condition**, **Price Value**, and **Hedonic Motivation** to understand their impact on AI adoption decisions.

The data collection process involved an **online survey** distributed via platforms like **LinkedIn**, **WhatsApp**, and other professional networks. A total of **219 valid responses** were gathered, representing a diverse group of professionals from both **micro, small, and medium enterprises (MSMEs)** and larger enterprises in the textile industry. Participants' roles varied from **management** to **technical teams**, with **44%** in **management** or **leadership roles**. The **age** and **education** distributions of the respondents were diverse, with **54%** aged between **25-45 years**, and a substantial portion holding **bachelor's** (47%) or **master's degrees** (26%).

The data preparation involved handling missing values, processing data, and screening for outliers. **Descriptive statistics** revealed valuable insights into the demographics of the respondents, further informing the analysis. In the **inferential analysis**, **multiple regression analysis**, **Pearson correlation analysis**, and **cluster segmentation** were employed to explore the relationships between the independent variables and the **Decision to Adopt and Implement AI (DAI)**.

The results from the **Pearson correlation analysis** revealed that most independent variables had statistically significant correlations with the decision to adopt AI. The significant correlations include:

- **Performance Expectancy**: **r = 0.385**, p-value = **0.0000000**
- **Effort Expectancy**: **r = 0.363**, p-value = **0.0000000**
- **Social Influence**: **r = 0.325**, p-value = **0.0000009**
- **Facility Condition**: **r = 0.348**, p-value = **0.0000001**
- **Price Value**: **r = 0.309**, p-value = **0.0000030**
- **Hedonic Motivation**: **r = 0.309**, p-value = **0.0000032**

These results suggest that **Performance Expectancy** and **Effort Expectancy** have the strongest correlations with AI adoption decisions. **Facility Condition** and **Social Influence** also show moderate correlations, while **Price Value** and **Hedonic Motivation** have weaker correlations, but remain statistically significant.

The **multiple regression analysis** revealed an **R-squared value of 0.205**, indicating that approximately **20.5%** of the variance in AI adoption decisions can be explained by the independent variables included in the model.

In the next chapters, the findings will be further explored in terms of their implications for the Indian textile industry. This will include actionable insights for **stakeholders**, recommendations for **future research**, and a discussion on the **broader social impact** of AI adoption in the textile sector.

Chapter 5: Discussion, Conclusions, and Recommendations

The primary objective of this **quantitative cross-sectional correlational study** was to investigate the factors influencing the adoption and implementation of **Artificial Intelligence (AI)** in the **small and medium-scale textile sector in India**. As AI becomes increasingly relevant for enhancing productivity, improving quality, and driving innovation in this industry, it is essential to understand the key variables that impact decision-making regarding its adoption. This research focused on examining the correlations between several independent variables—**Performance Expectancy (PE)**, **Effort Expectancy (EE)**, **Social Influence (SI)**, **Facility Condition (FC)**, **Price Value (PV)**, and **Hedonic Motivation (HM)**—and the dependent variable, **Decision to Adopt and Implement AI (DAI)**.

As outlined in Chapter 4, the results revealed significant correlations between most of the independent variables and the decision to adopt AI. Each of the constructs played a role in shaping the AI adoption decision, though the strength and direction of their relationships varied. Specifically:

- **Performance Expectancy ($r = 0.385$, $p = 0.0000000$)** exhibited a **statistically significant positive correlation** with AI adoption, suggesting that as individuals expect AI to improve performance, their likelihood of adopting it increases.
- **Effort Expectancy ($r = 0.363$, $p = 0.0000000$)** also showed a **significant positive correlation**, indicating that ease of use and simplicity in adopting AI are crucial factors in driving adoption.
- **Social Influence ($r = 0.325$, $p = 0.0000009$)** demonstrated a **moderate positive correlation**, highlighting the role of peer pressure, managerial influence, and external opinions in encouraging AI adoption.
- **Facility Condition ($r = 0.348$, $p = 0.0000001$)** showed a **moderate positive correlation**, reinforcing the importance of having adequate infrastructure, resources, and organizational support for AI adoption.

- **Price Value (r = 0.309, p = 0.0000030)** and **Hedonic Motivation (r = 0.309, p = 0.0000032)** both demonstrated **moderate positive correlations**, suggesting that perceived cost-effectiveness and the enjoyment or emotional satisfaction from using AI also play a role, though less significant compared to performance and ease of use.

The findings underscore that multiple factors contribute to AI adoption decisions in the textile industry, with **Performance Expectancy** and **Effort Expectancy** being the most significant predictors. The results also suggest that while emotional and social factors play a role, **practical considerations** such as **cost-effectiveness** and **ease of use** are more influential in driving AI adoption in the textile sector.

5.1 Interpretation of Findings

This **correlational cross-sectional quantitative study** was conducted to examine the correlation between six independent variables—**Performance Expectancy (PE)**, **Effort Expectancy (EE)**, **Social Influence (SI)**, **Facility Condition (FC)**, **Price Value (PV)**, **Hedonic Motivation (HM)**—and the dependent variable, **Decision to Adopt and Implement AI (DAI)**, within the **small and medium-scale textile industry in India**. By utilizing statistical tools such as **Pearson Correlation**, the study aimed to measure the direction and strength of the relationship between each independent variable and the decision to adopt AI, a critical technology for improving efficiency, productivity, and competitiveness within this sector.

The analysis conducted revealed varying degrees of correlation between the independent variables and the decision to adopt AI. Among the constructs, **Performance Expectancy** and **Effort Expectancy** showed **statistically significant positive correlations** with DAI, while **Price Value** exhibited the **strongest positive correlation**, indicating that perceived **effort**, **expected performance**, and **cost** are key **drivers** to adoption. On the other hand, **Social Influence**, **Facility Condition**, and **Hedonic Motivation** were also found to **positively impact** the decision to adopt AI, albeit with **weaker correlations**. These findings provide actionable insights into the factors that influence AI adoption in the textile industry and highlight areas where efforts to encourage adoption may need to focus.

Main Research Question

The main research question for this study asked: **What are the different factors that facilitate or hinder the Decision to Adopt and Implement AI (DAI) in the Textile and Apparel SME sector in India?**

Pearson correlation analysis revealed that each of the six independent variables had a measurable, **statistically significant correlation** with AI adoption. Specifically, the results of the correlation analysis showed that **Performance Expectancy** ($r =$ **0.385**, $p =$ **0.0000000**), **Effort Expectancy** ($r =$ **0.363**, $p =$ **0.0000000**), and **Price Value** ($r =$ **0.309**, $p =$ **0.0000030**) were significant **drivers** of AI adoption, with firms perceiving that the effort to integrate AI and the benefits, especially in terms of cost-effectiveness, influenced their adoption decisions.

Conversely, **Social Influence** ($r =$ **0.325**, $p =$ **0.0000009**), **Facility Condition** ($r =$ **0.348**, $p =$ **0.0000001**), and **Hedonic Motivation** ($r =$ **0.309**, $p =$ **0.0000032**) also influenced AI adoption, but to a lesser extent.

These results suggest that for AI to be more readily adopted in the textile industry, there needs to be a better alignment between expected performance and perceived effort, as well as more favorable pricing and clearer value propositions that highlight the cost-benefit relationship of AI technology. Additionally, external pressures and infrastructure readiness play a supporting role in the decision-making process.

Secondary Research Questions

The secondary research questions aimed to explore the relationship between each independent variable and the decision to adopt AI. Below, we provide an in-depth interpretation of the Pearson correlation analysis for each variable:

Performance Expectancy (PE)

- **Pearson Correlation Coefficient**: **0.385**
- **p-value**: **0.0000000**
- **Number of observations (N)**: **219**

Interpretation: The positive correlation between **Performance Expectancy** and AI adoption suggests that organizations with higher expectations of AI's performance are more likely to adopt the technology. This indicates that as organizations believe AI will improve their performance, such as enhancing productivity or accuracy, they are more inclined to implement it. The strong statistical significance (p-value = 0.0000000) highlights that this relationship is robust, emphasizing the importance of demonstrating the tangible benefits of AI in improving operational outcomes. Organizations that perceive AI as a tool to achieve their performance goals are more likely to invest in its adoption, particularly in industries like textiles where productivity and quality are key drivers.

Effort Expectancy (EE)

- **Pearson Correlation Coefficient**: **0.363**
- **p-value**: **0.0000000**
- **Number of observations (N)**: **219**

Interpretation: The positive correlation between **Effort Expectancy** and AI adoption suggests that organizations perceiving AI as easy to use and requiring minimal effort to learn are more likely to adopt the technology. This indicates that reducing the complexity of AI systems and ensuring ease of use are critical factors for increasing adoption. The strong statistical significance (p-value = 0.0000000) further emphasizes the importance of simplifying AI technologies for organizations in the textile sector. Companies are more likely to implement AI if they believe it will not impose a significant learning curve or operational disruption, thus making the technology more accessible and easier to integrate into existing processes.

Social Influence (SI)

- **Pearson Correlation Coefficient**: **0.325**
- **p-value**: **0.0000009**
- **Number of observations (N)**: **219**

Interpretation: The positive correlation between **Social Influence** and AI adoption suggests that individuals or organizations influenced by peers, colleagues, or industry experts are more likely to adopt AI technologies. This indicates that external pressures or recommendations from trusted sources, such as managers or industry leaders, play a significant role in driving AI adoption. The strong statistical significance (p-value = 0.0000009) further validates that **Social Influence** is an important factor in the decision-making process. Organizations that are exposed to positive social influence are more likely to perceive AI adoption as a beneficial move, particularly in sectors where networking and peer validation are key factors in business decisions.

Facility Condition (FC)

- **Pearson Correlation Coefficient**: **0.348**
- **p-value**: **0.0000001**
- **Number of observations (N)**: **219**

Interpretation: The positive correlation between **Facility Condition** and AI adoption suggests that organizations with better infrastructure and resources are more likely to adopt AI technologies. This indicates that the availability of necessary technical resources, support systems, and organizational readiness plays a significant role in facilitating AI adoption. The strong statistical significance (p-value = 0.0000001) underscores that having the right facilities, such as access to training, external expertise, and sufficient financial resources, is crucial for implementing AI. Organizations with well-established infrastructure are better positioned to integrate AI into their operations, reducing potential barriers related to system compatibility and resource allocation.

Price Value (PV)

- **Pearson Correlation Coefficient**: **0.309**
- **p-value**: **0.0000030**
- **Number of observations (N)**: **219**

Interpretation: The positive correlation between **Price Value** and AI adoption suggests that organizations are more likely to adopt AI when they perceive it to offer good value for the investment. This indicates that **cost-effectiveness** and a **strong cost-benefit relationship** play a significant role in the decision to adopt AI. The strong statistical significance (p-value = 0.0000030) highlights that organizations are more inclined to invest in AI when the perceived benefits outweigh the costs. Organizations in the textile sector, where price sensitivity is high, are more likely to adopt AI if they believe it will provide long-term returns or operational improvements that justify the initial investment.

Hedonic Motivation (HM)

- **Pearson Correlation Coefficient**: **0.309**
- **p-value**: **0.0000032**
- **Number of observations (N)**: **219**

Interpretation: The positive correlation between **Hedonic Motivation** and AI adoption suggests that the enjoyment, excitement, or emotional satisfaction that individuals associate with using AI can influence their decision to adopt the technology. This indicates that **emotional factors**, such as the novelty and pleasure of using AI, play a role in adoption decisions. The strong statistical significance (p-value = 0.0000032) reinforces the idea that, although **practical factors** like performance and ease of use are more influential, the **emotional appeal** of AI technologies can also contribute to their adoption. In industries like textiles, where innovation and new technologies may bring a sense of excitement, promoting the **positive experiences** associated with AI could help accelerate its adoption.

Summary

The **Pearson correlation analysis** performed on the six independent variables (**Performance Expectancy (PE)**, **Effort Expectancy (EE)**, **Social Influence (SI)**, **Facility Condition (FC)**, **Price Value (PV)**, and **Hedonic Motivation (HM)**) provided valuable insights into the factors influencing **AI adoption** in the Indian textile sector. The analysis revealed that while some variables, such as **Performance Expectancy** (r = **0.385**, p = **0.0000000**) and **Effort Expectancy** (r = **0.363**, p = **0.0000000**), highlighted the perceived complexity of AI and the effort required to implement it, others, like **Social Influence** (r = **0.325**, p = **0.0000009**) and **Facility Condition** (r = **0.348**, p = **0.0000001**), emphasised the importance of organisational readiness and external support.

Specifically, **Performance Expectancy** and **Effort Expectancy** presented challenges related to the complexity and perceived cost of adopting AI, which could act as significant barriers. On the other hand, **Social Influence** and **Facility Condition** revealed that greater **external support**, such as influence from peers, industry experts, and managers, as well as improved infrastructure and organisational readiness, are key to facilitating AI adoption.

The findings suggest that to drive **AI adoption** in the textile industry, decision-makers need to focus on reducing perceived barriers, particularly those related to **effort** and **cost**. Additionally, enhancing the **value proposition** of AI technology through **clear performance benefits**, simplifying its implementation, and ensuring adequate resources and infrastructure will be essential to increasing adoption rates in the sector.

5.2 Limitations of the Study

This study aimed to explore the factors influencing the adoption and implementation of Artificial Intelligence (AI) in the Indian textile and apparel small and medium-scale enterprises (SMEs) sector. While the research has produced valuable insights, it is important to acknowledge the limitations that may have impacted the findings and the generalizability of the results.

Sample Size and Representativeness

The sample size for this study was 219 responses, which, while adequate for statistical analysis, may not fully represent the entire population of SMEs in the Indian textile industry. The sampling method used—convenience sampling through online platforms—could introduce bias, as those who responded to the survey might be more inclined to adopt technology or have a specific interest in AI. The limited geographical spread of respondents also reduces the diversity of the sample, meaning the findings may not reflect the experiences and perceptions of SMEs from different regions of India.

Self-reported Data and Survey Methodology

The study relied on self-reported data collected through an online survey. This method inherently carries limitations such as potential response bias, where participants might overestimate or underestimate their organization’s readiness or willingness to adopt AI. Additionally, the use of a Likert scale to measure perceptions may lead to central tendency bias, where respondents avoid extreme responses, potentially masking more nuanced opinions. Furthermore, the inability to capture non-verbal cues or have follow-up discussions with participants limits the depth of understanding of the context behind their responses.

Limited Scope of Constructs

This study was based on a predefined set of constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT) model, which includes variables such as

Performance Expectancy, **Effort Expectancy**, **Social Influence**, **Facility Condition**, **Price Value**, and **Hedonic Motivation**. While these constructs are relevant, the exclusion of other factors such as **Technological Infrastructure**, **Organizational Culture**, and **Government Regulations** may have resulted in a less comprehensive understanding of the broader ecosystem influencing AI adoption in the textile industry. These factors, especially regulatory and policy frameworks, could significantly impact decision-making but were not explored in this study.

Cross-sectional Nature of the Study

This study adopted a cross-sectional design, meaning data was collected at a single point in time. While this approach is useful for understanding correlations and relationships between variables, it does not provide insights into how AI adoption might change over time. The findings reflect the state of AI adoption at the time of data collection, but do not account for temporal changes in technology, market dynamics, or shifts in organizational strategy. A longitudinal study could provide more robust insights into how perceptions and adoption behaviors evolve as AI technology matures.

Lack of Qualitative Insights

The study focused solely on quantitative data collection and analysis, which limited the ability to capture in-depth insights into the reasons behind the responses. A mixed-methods approach, including qualitative interviews or focus groups, could have provided richer data and a deeper understanding of the challenges and facilitators of AI adoption. For instance, qualitative data could reveal specific organizational constraints, leadership challenges, or cultural factors that may not be easily captured through a survey alone.

Generalizability

The findings of this study are limited to the textile and apparel SMEs in India, and caution should be exercised when attempting to generalize the results to other industries or countries. The unique characteristics of the Indian SME sector, such as resource constraints, market conditions, and organisational structures may differ significantly from those in other regions or sectors. Therefore, the insights derived from this study may not apply to industries with different technological readiness, capital availability, or competitive pressures.

Technological Context

AI is a rapidly evolving technology, and the perceptions captured in this study are time-sensitive. As AI technology continues to develop, the costs of adoption, the ease of integration, and the perceptions of its usefulness will likely change. This study does not account for future technological advancements that may lower barriers to AI adoption, such as more accessible AI tools, better infrastructure, or enhanced support systems for SMEs. Additionally, this study did not assess the specific types of AI technologies being considered for adoption, which could have implications for understanding the challenges and benefits perceived by organisations.

Cultural and Industry-Specific Factors

The textile and apparel industry in India operates within a unique cultural and economic framework, which may influence AI adoption differently compared to other industries. Factors such as traditional practices, reliance on manual labour, and the socio-economic landscape could affect how AI is perceived and adopted. These cultural and industry-specific factors were not deeply explored in this study, limiting the understanding of how deeply ingrained industry norms and values impact technological decision-making.

Unmeasured Variables

This study was limited to the analysis of a predefined set of variables based on the UTAUT model and excluded other potential variables that could influence AI adoption, such as **Top Management Support**, **Customer Demand**, **Technological Competency**, and **Data Availability**. The exclusion of such variables may lead to an incomplete understanding of the dynamics at play in AI adoption within the textile sector. Including these additional variables could have provided a more holistic view of the factors influencing the decision to adopt AI.

5.3 Recommendations

This study focused on the adoption and implementation of Artificial Intelligence (AI) in the Indian textile and apparel SME sector, a vital component of India’s economy. As the findings suggest, various technological, organizational, and contextual factors affect the decision to adopt AI within this sector. Based on the findings, I offer the following recommendations for future research and practical application.

Focus on Micro Enterprises

AI technology often requires significant investment and technical infrastructure, making it more challenging for micro-enterprises to adopt. Micro-enterprises, which form the largest part of India's MSME sector, may not have the resources or need for sophisticated IT systems. However, future research should focus on exploring how AI technology can be leveraged in a cost-effective manner for these businesses. Solutions such as simplified AI tools, cloud-based AI platforms, or government-subsidized technology programs could prove to be valuable in this segment.

Industry-Specific Studies

While this study did not focus on specific industries within the SME sector, the majority of responses came from businesses in the IT-Services and Financial Services sectors. Future research should target specific industries within the textile and apparel sector or other industries where AI adoption is critical. By conducting industry-specific studies, researchers can uncover unique management challenges, industry-specific technological needs, and insights that are crucial to developing targeted AI solutions.

Broader Use of Theoretical Frameworks

This study applied the Unified Theory of Acceptance and Use of Technology (UTAUT) to explore AI adoption. However, there are several other theoretical models that could provide additional insights into the adoption and implementation of new technologies. Future studies should consider employing models that focus solely on usability, technology assessment, decision-making processes, or economic impact. The integration of additional models such as the Technology-Organization-Environment (TOE) framework or Diffusion of Innovation (DOI) theory could provide a more nuanced understanding of the AI adoption landscape.

Expansion of Participant Pool

Although the sample size of this study was sufficient for statistical analysis, it is important to extend future research to a larger and more diverse participant pool. The Indian MSME sector is vast, with over a million companies, and increasing the scope to include a broader range of micro, small, and medium enterprises will provide richer data. Additionally, researchers should attempt to obtain data from government reports, industry surveys, or other secondary sources that may become available through organizations like the MSME Ministry of India or Niti Aayog, which could provide further insights into AI adoption trends.

Exploring Interactions Among Variables

This study primarily examined how individual independent variables correlate with the decision to adopt AI. However, future research should explore how these variables interact with one another and whether those interactions further influence the decision-making process. For instance, the relationship between **Social Influence** and **Facility Conditions** could impact **Performance Expectancy**, thus offering a more interconnected view of AI adoption dynamics.

Cross-National Comparisons

Given the importance of the SME sector in economies around the world, future research should expand the geographic scope of AI adoption studies to include developing and developed nations. A comparative analysis of AI adoption in SMEs across various countries could provide invaluable insights into how local economic conditions, governmental policies, and industry-specific factors shape the adoption landscape. Such research could help generalise the findings of this study to other global contexts and enhance the knowledge transfer between economies.

Longitudinal Studies

This research took a cross-sectional approach, capturing AI adoption at a specific moment in time. A longitudinal study that tracks AI adoption over several years would provide a deeper understanding of how adoption behaviours evolve as technologies mature and organisational capacities grow. This approach would also offer insights into how external factors such as market shifts, technological advancements, or policy changes affect AI adoption decisions over time.

AI Training and Skill Development

Future research should explore the role of AI training programs and skill development initiatives in facilitating AI adoption. The findings indicated that **Effort Expectancy**—the ease of use and understanding of AI—plays a significant role in the decision to adopt AI. By examining the impact of training and skills enhancement on AI adoption, policymakers and industry leaders can develop targeted initiatives to lower barriers to entry and improve AI literacy within the SME workforce.

By addressing these recommendations, future researchers can deepen their understanding of the complexities surrounding AI adoption in the SME sector, both in India and globally, thus contributing to the advancement of knowledge in this vital area.

5.4 Implications for AI Adoption in the Textile and Apparel SME Sector

The adoption of **AI technology** has the potential to revolutionize many industries, including the **textile and apparel sector**, by altering production processes, improving customer service, and driving innovation. However, the integration of such technologies presents significant challenges, particularly for the **SME sector**, which often lacks the financial and technological resources of larger enterprises. The findings of this research contribute valuable knowledge regarding the factors influencing AI adoption in SMEs, providing insights that could help decision-makers in the industry make more informed choices about implementing AI solutions. By understanding these factors, SMEs in India and other developing nations can better navigate the challenges of AI adoption while seizing its potential to enhance competitiveness and efficiency.

Significance to the Theory

This research was guided by the constructs of the **Unified Theory of Acceptance and Use of Technology (UTAUT)**, which helped explain the decision-making process for **AI adoption** in the textile and apparel SME sector in India. Of the six independent variables tested—**Performance Expectancy (PE)**, **Effort Expectancy (EE)**, **Social Influence (SI)**, **Facility Condition (FC)**, **Price Value (PV)**, and **Hedonic Motivation (HM)**—all except **Performance Expectancy** showed significant positive correlations with the decision to adopt AI.

- **Performance Expectancy ($r = 0.385$, $p = 0.0000000$)** and **Effort Expectancy ($r = 0.363$, $p = 0.0000000$)** showed significant positive correlations, indicating that **AI adoption** is strongly influenced by the perceived performance benefits and ease of use of the technology.

- **Social Influence ($r = 0.325$, $p = 0.0000009$)** and **Facility Condition ($r = 0.348$, $p = 0.0000001$)** also demonstrated positive correlations, suggesting that the influence of industry peers, managers, and organizational readiness (infrastructure and resources) significantly impacts the adoption decision.

- **Price Value (r = 0.309, p = 0.0000030)** and **Hedonic Motivation (r = 0.309, p = 0.0000032)**, while showing moderate correlations, indicate that **cost-effectiveness** and the **emotional appeal** of AI are also factors contributing to adoption decisions.

These findings contribute to the broader understanding of **AI adoption** within SMEs by validating and extending the **UTAUT framework**, suggesting that while the potential benefits of AI are recognised, perceived challenges and constraints significantly shape the adoption decision.

Significance to Practice

For practitioners in the textile and apparel SME sector, the findings of this study offer practical insights into the key factors influencing AI adoption. Understanding how variables like **Performance Expectancy**, **cost**, and **external pressures** affect the decision to adopt AI can inform the development of tailored strategies to overcome barriers and enhance the likelihood of successful implementation.

Decision-makers can use these insights to prioritize investments in AI technologies that address specific organizational needs while mitigating concerns about complexity or cost. For example, enhancing **Facility Condition** and providing adequate **training** may alleviate concerns related to **Effort Expectancy**, while highlighting the competitive advantages of AI could address hesitations linked to **Performance Expectancy**.

Moreover, this research supports the notion that AI adoption in SMEs is not solely about technology but also about **organizational readiness**, **industry pressures**, and **leadership support**. By addressing these factors, SMEs can unlock the potential of AI to drive innovation, improve productivity, and meet evolving customer demands.

Significance to Social Change

The findings of this study have broader implications for **social change**, particularly in developing countries like India, where the SME sector plays a crucial role in economic development and job creation. By facilitating the adoption of AI technologies, SMEs can become more competitive, efficient, and responsive to market demands. This, in turn, can contribute to **job creation**, **economic growth**, and **social progress**.

Furthermore, the adoption of AI in the textile and apparel sector could lead to more **sustainable production practices**, helping businesses reduce waste, optimise resource use, and meet growing consumer demand for environmentally friendly products. As AI technology enables businesses to produce more efficiently and innovate more rapidly, it has the potential to support **sustainable development goals**, enhance business resilience, and improve the **quality of life** for workers and consumers alike.

In summary, this study contributes valuable knowledge to the discourse on **AI adoption** in SMEs, offering both theoretical insights and practical recommendations that can help businesses in the textile and apparel sector navigate the challenges of technological transformation.

5.5 Conclusions

Artificial Intelligence (AI) stands as a transformative technology that is not only reshaping large organisations globally but is also gaining traction within **India's Small and Medium Enterprises (SME) sector**. This **correlational cross-sectional quantitative study** aimed to examine the relationship between six key constructs—**Performance Expectancy (PE)**, **Effort Expectancy (EE)**, **Social Influence (SI)**, **Facility Condition (FC)**, **Price Value (PV)**, and **Hedonic Motivation (HM)**—and the **Decision to Adopt and Implement AI (DAI)** in the Indian textile and apparel SME sector. The theoretical foundation of this study was guided by the **Unified Theory of Acceptance and Use of Technology (UTAUT)**, which provided a robust framework for exploring the factors that enable or hinder AI adoption.

Through an online survey questionnaire, data was collected from **219 participants**, who shared their insights on AI adoption within their respective organizations. The survey covered various dimensions of AI adoption, and data was analyzed using statistical techniques, including **Pearson correlation** and **multiple regression analysis**, to determine the strength of relationships between independent variables and **DAI**.

The findings of this study revealed that all six constructs showed **statistically significant relationships** with AI adoption. However, the nature of these correlations varied:

- **Performance Expectancy** ($r = \mathbf{0.385}$, $p = \mathbf{0.0000000}$) and **Effort Expectancy** ($r = \mathbf{0.363}$, $p = \mathbf{0.0000000}$) exhibited **positive correlations**, suggesting that the more organizations expect AI to improve performance and the easier they perceive it to be, the more likely they are to adopt it.

- **Social Influence** ($r = \mathbf{0.325}$, $p = \mathbf{0.0000009}$) and **Facility Condition** ($r = \mathbf{0.348}$, $p = \mathbf{0.0000001}$) showed **moderate positive correlations**, suggesting that external factors like social pressure from peers or industry leaders and the availability of necessary infrastructure also significantly impact adoption.

- **Price Value** ($r = \mathbf{0.309}$, $p = \mathbf{0.0000030}$) and **Hedonic Motivation** ($r = \mathbf{0.309}$, $p = \mathbf{0.0000032}$) demonstrated **moderate positive correlations**, highlighting that the perceived cost-effectiveness and emotional satisfaction from using AI play significant roles in shaping adoption decisions.

These results provide important insights into how SMEs in the Indian textile and apparel industry view AI adoption, particularly the challenges they face regarding **complexity**, **cost**, and **infrastructure**. The findings suggest that while AI offers significant potential benefits, SMEs remain cautious due to concerns over its practical implementation and the resources required.

This research contributes to the broader literature on **AI adoption** by validating and extending the **UTAUT framework** within the context of SMEs in developing economies.

It also highlights the importance of **organizational readiness**, **infrastructure**, and **external pressures** in shaping AI adoption decisions.

Implications for Future Research and Practice

The results of this study have several implications for **future research** and **practical application**:

For Researchers:

Future studies could expand the scope of this research by examining other industry sectors or geographical regions to explore whether the findings hold true in different contexts. Moreover, incorporating additional theoretical frameworks may provide a more nuanced understanding of **AI adoption** in SMEs.

For Practitioners

Decision-makers in SMEs can leverage these insights to develop strategies for overcoming barriers to AI adoption, such as enhancing **infrastructure**, reducing perceived **complexity**, and addressing concerns about **cost**. Organizations that proactively address these challenges will likely be better positioned to capitalize on AI's potential and drive **innovation**, **productivity**, and **competitiveness** in the textile and apparel industry.

5.6 Concluding Thoughts

In conclusion, this study sheds light on the factors that influence **AI adoption** in **India's textile and apparel SME sector**. While AI offers considerable promise, organisations must carefully navigate the perceived challenges related to **complexity**, **cost**, and **external influences**. The findings of this research provide a foundational understanding of these challenges and offer actionable insights for **SMEs** to move forward with successful AI implementation.

The study's results suggest that **Performance Expectancy** and **Effort Expectancy** are the most significant drivers of AI adoption, with organizations being more likely to adopt AI when they perceive it as easy to use and capable of delivering performance improvements. However, perceived barriers related to **complexity** and **cost**, as well as the influence of **social factors** like peer pressure and infrastructure readiness, may hinder the adoption process.

The actionable insights from this research can guide **SMEs** in India towards overcoming these barriers, ensuring that AI adoption is aligned with organisational needs and capabilities. By addressing concerns around effort, cost, and external pressures, organizations can unlock AI's potential to drive **innovation**, improve **competitiveness**, and ultimately contribute to **positive social change** within the textile sector.

APPENDIX A : SURVEY COVER LETTER

Section 1 of 10

Doctoral Research form - AI for Indian Textile MSME's

Greetings, I am Pawan Kumar , a senior AI practitioner with almost a decade of experience in implementing innovative solutions and a doctoral research scholar with Swiss School of Business Management, Geneva.

I extend this invitation for you to take part in my research study titled **"Understanding Scope and Challenges Of Adoption & Implementation of Artificial Intelligence in the Indian Small and Medium-Scale Textile Industry "** This survey is designed to bring out the insights on possible AI adoption in the industry and how should a solution provider address the adoption. Your participation in completing this survey is pivotal for the advancement of my research. Rest assured, the survey is entirely anonymous and will Ji take **approximately 10 minutes** of your time.

All data collected will be used exclusively for research purpose only ensuring strict confidentiality and anonymity. Your participation is completely voluntary, and you have the option to withdraw at any point during the survey. I genuinely appreciate your time and participation. Thank you for your time and inputs.

APPENDIX B : SURVEY FORM

27/10/2024, 20:19 Doctoral Research form - AI for Indian Textile MSME's

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Greetings, I am Pawan Kumar , a senior AI practitioner with almost a decade of experience in implementing innovative solutions and a doctoral research scholar with Swiss School of Business Management, Geneva.

I extend this invitation for you to take part in my research study titled **"Understanding Scope and Challenges Of Adoption & Implementation of Artificial Intelligence in the Indian Small and Medium-Scale Textile Industry "** This survey is designed to bring out the insights on possible AI adoption in the industry and how should a solution provider address the adoption. Your participation in completing this survey is pivotal for the advancement of my research. Rest assured, the survey is entirely anonymous and will Ji take **approximately 10 minutes** of your time.

All data collected will be used exclusively for research purpose only ensuring strict confidentiality and anonymity. Your participation is completely voluntary, and you have the option to withdraw at any point during the survey. I genuinely appreciate your time and participation. Thank you for your time and inputs.

* Indicates required question

About You

1. What best describes your Organisation?

Mark only one oval.

- Micro Enterprise (Part of MSME)
- Small Enterprise (Part of MSME)
- Medium Enterprise (Part of MSME)
- Large Enterprise

https://docs.google.com/forms/d/1i7yM5c-T3gZClDVObwkIcg7yR8IxmNATQ4HaBhJ_Yg0/edit 1/11

27/10/2024, 20:19 Doctoral Research form - AI for Indian Textile MSME's

2. What best describes your title? *

Mark only one oval.

- Management/Leadership
- IT and infrastructure team
- Digital Team
- Security Team
- Plant Head
- Production Team
- Quality Team

3. What best describes your gender?

Mark only one oval.

- Male
- Female
- Prefer not to say
- Other: ____________

4. How Old are you? *

Mark only one oval.

- 18 to 25
- 25 to 35
- 36 to 45
- 46 to 60
- More than 60

https://docs.google.com/forms/d/1i7yM5c-T3gZClDVObwkIcg7yR8IxmNATQ4HaBhJ_Yg0/edit 2/11

5. What is your Educational Level? *

Mark only one oval.

- Secondary School
- Bachelor's Degree
- Master's Degree
- Doctorate Degree
- Other

6. What better describes your geography?

Mark only one oval.

- South India
- North India
- East India
- West India
- Central India

Performance Expectancy

7. AI technology will improve my productivity in the textile industry.

Mark only one oval.

	1	2	3	4	5	
Stro						Strongly Disagree

8. AI technology will enhance the quality of textile products or services.

Mark only one oval.

	1	2	3	4	5	
Stro						Strongly Disagree

9. AI technology will enable faster decision-making in the textile industry.

Mark only one oval.

	1	2	3	4	5	
Stro						Strongly Disagree

10. AI technology will improve the accuracy of tasks in the textile industry.

Mark only one oval.

	1	2	3	4	5	
Stro						Strongly Disagree

Effort Expectancy

11. AI technology is easy to understand and use in the textile industry.

Mark only one oval.

	1	2	3	4	5	
Stro						Strongly Disagree

12. Learning to use AI technology in the textile industry would be easy for me.

Mark only one oval.

	1	2	3	4	5	
Stro						Strongly Disagree

13. AI technology would make my work in the textile industry easier and more efficient.

Mark only one oval.

	1	2	3	4	5	
Stro						Strongly Disagree

14. I believe I could become competent in using AI technology in the textile industry quickly.

Mark only one oval.

	1	2	3	4	5	
Stro						Strongly Disagree

Social Influence

15. Colleagues' opinions significantly influence my decision to adopt AI technology in the textile industry.

Mark only one oval.

	1	2	3	4	5	
Stro						Strongly Disagree

16. Managers' opinions significantly influence my decision to adopt AI technology in the textile industry.

Mark only one oval.

	1	2	3	4	5	
Stro						Strongly Disagree

17. Industry experts' opinions significantly influence my decision to adopt AI technology in the textile industry.

Mark only one oval.

	1	2	3	4	5	
Stro						Strongly Disagree

18. Customers' opinions significantly influence my decision to adopt AI technology in the textile industry.

Mark only one oval.

	1	2	3	4	5	
Stro						Strongly Disagree

Facility Condition

19. My organization provides sufficient training and support for adopting AI technology in the textile industry.

Mark only one oval.

	1	2	3	4	5	
Stro						Strongly Disagree

20. My organization has the necessary infrastructure and technical resources for adopting AI technology in the textile industry.

Mark only one oval.

	1	2	3	4	5	
Stro						Strongly Disagree

21. I have access to external experts or consultants who can assist with AI technology adoption in the textile industry.

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Disagree

22. Financial resources are available to support the adoption of AI technology in the textile industry.

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Disagree

Hedonic Motivations

23. Adopting AI technology in the textile industry would provide me with a sense of excitement and enjoyment.

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Disagree

24. AI technology adoption in the textile industry would satisfy my desire for novelty and variety.

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Disagree

25. AI technology adoption in the textile industry would enhance my personal expression and style.

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Disagree

26. The use of AI technology in the textile industry would evoke positive emotions and pleasure.

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Disagree

Price Value

27. The potential benefits of AI technology outweigh its cost in the textile industry.

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Disagree

28. AI technology provides good value for the investment in the textile industry.

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Disagree

29. The cost of adopting AI technology is justified by the advantages it offers in the textile industry.

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Disagree

30. The return on investment from adopting AI technology in the textile industry makes it worthwhile.

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Disagree

What do you think of AI Adoption

31. In your opinion, how soon organisations in your industry sector will adopt Artificial Intelligence?

Mark only one oval.

- ◯ 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

Thanks

Participants' Rights: As a participant in this research, you have the following rights:

1. Voluntary Participation: Your participation is entirely voluntary, and you have the right to withdraw from the questionnaire at any time without providing a reason.
2. Confidentiality: Your responses will be anonymized, and no personally identifiable information will be associated with your answers.
3. Privacy: We will ensure that your data is stored securely and that only authorized research team members have access to the collected information.
4. Informed Consent: By proceeding with this questionnaire, you are indicating your informed consent to participate in the research. Your consent signifies that you have read and understood this informed consent statement.

If you have any questions or concerns regarding this research or the informed consent statement, please do not hesitate to reach out to

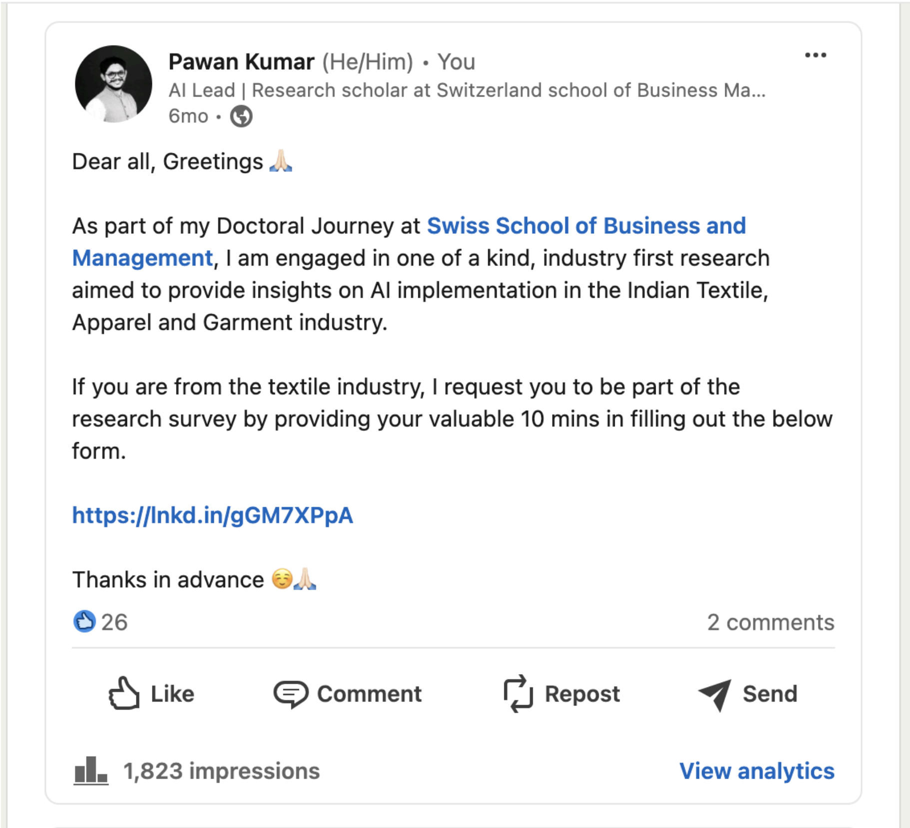
Pawan@ssbm.ch

Or

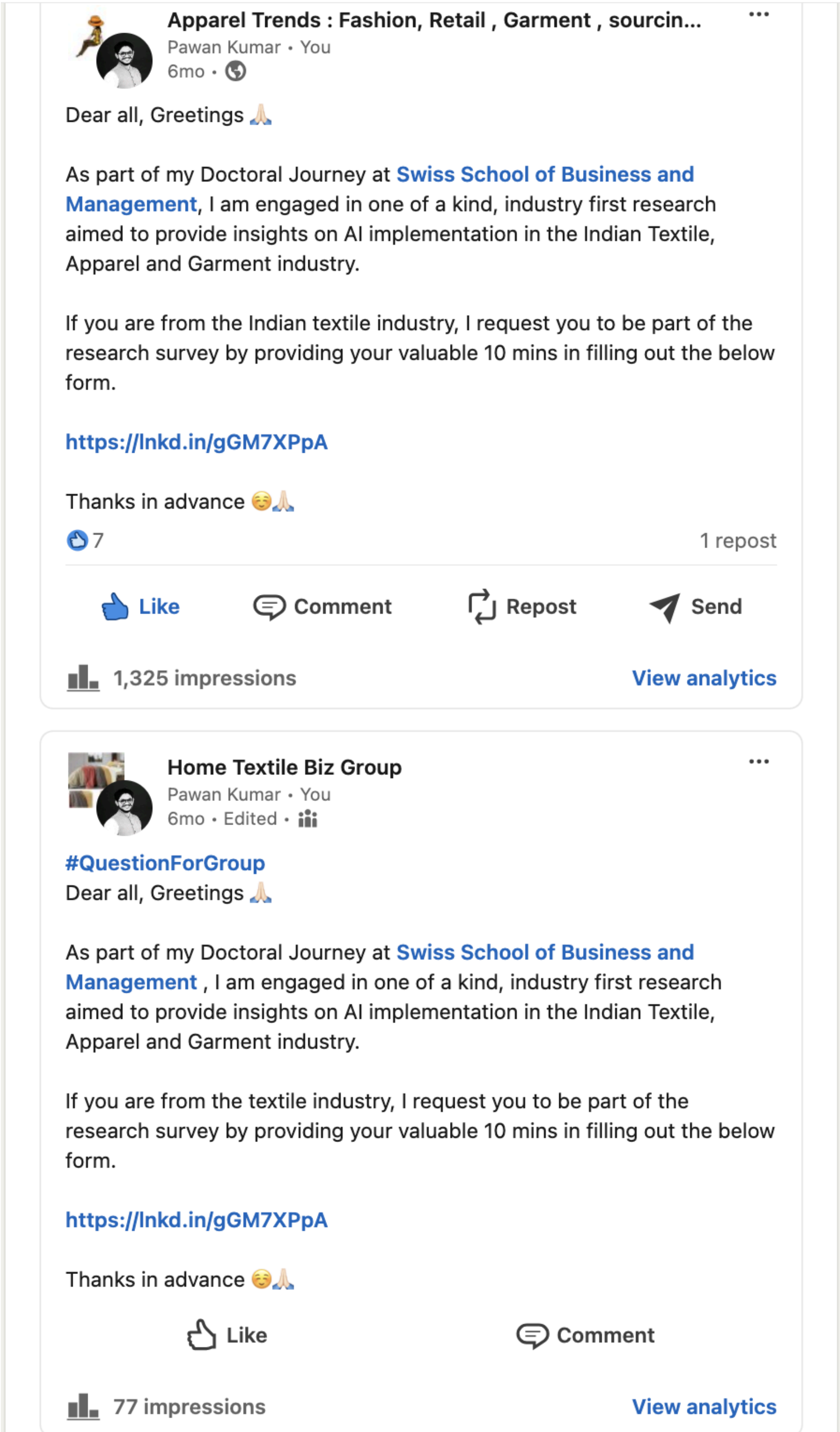
pwnkmr.dst@gmail.com

APPENDIX C : SOCIAL MEDIA POST

Post in Personal Wall



Post in Public Forums



APPENDIX D : PERSONAL EXPERIENCE AND GROWTH FROM THIS STUDY

Starting this DBA journey was nothing short of surreal. After spending more than a decade immersed in professional work, diving back into the world of academia felt like uncharted waters. Juggling the demands of my career and taking on something as vast as this research was no easy task, but it soon became a deeply fulfilling experience, one that not only challenged me but also enriched my understanding of my field.

I've always had a passion for exploring new ideas and constant learning. With my extensive experience in providing AI and ML solutions to various industries, both in India and abroad, the textile industry has always held a special place for me. I’ve had firsthand exposure to the challenges that come with trying to adopt AI in an industry that is steeped in tradition. Seeing the hesitation and mindset of people when it comes to integrating AI into their processes was something that stayed with me. That’s what pushed me towards this research—to understand and help bridge that gap.

Before finalizing my topic, I made it a point to have conversations with people in the industry. Their insights were invaluable in validating the importance of this study, and their support gave me the confidence that my research was on the right track. Over time, I had the opportunity to visit several industries, and these interactions gave me a clearer picture of the practical difficulties and potential AI held for them.

Balancing the pressures of professional life and the demands of writing this thesis was a challenge I hadn’t anticipated. There were times when the rapidly evolving nature of AI research made me feel like I was chasing a moving target. AI is a field that’s constantly shifting, and keeping up with the changes was no small task. But despite these hurdles, I kept pushing forward, driven by the belief that this work would have a meaningful impact.

This journey wasn’t without its moments of confusion and self-doubt, but the unwavering support of my mentor and family made all the difference. My mentor’s guidance was crucial, helping me stay focused and clear-headed even when I felt overwhelmed. And my family, with their endless patience and encouragement, provided the foundation that kept me going.

Reflecting on this entire experience, it's been one of growth—both personally and professionally. The DBA journey has taught me to think differently, to see challenges as opportunities for learning, and to appreciate the depth that comes with thorough research. It wasn't always easy, but it's been incredibly rewarding, and I'll carry the lessons from this experience with me in every future endeavour.

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