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FROM ADOPTION TO TRANSFORMATION: ORGANIZATIONAL OUTCOMES OF ARTIFICIAL INTELLIGENCE INTEGRATION WITHIN TEXTILE SMES IN PAKISTAN

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ABSTRACT

Purpose: The purpose of this study is to examine the organizational outcomes achieved by Small and Medium Enterprises (SMEs) in Pakistan's textile industry after adopting Artificial Intelligence (AI) technology. This study uses the Resource-Based View (RBV) and Dynamic Capabilities (DC) theories to understand how AI adoption will impact process efficiency, customer and market responsiveness, innovation, costs, and strategic growth. **Design/Methodology/Approach:** This study employed a qualitative multi-case design. Eleven SMEs from the textile industry in Punjab, Pakistan, were interviewed. The SMEs were then categorized by AI maturity level (Nascent, Intermediate, and Advanced). Thematic Analysis was conducted in NVivo 12 using the six steps outlined by Braun and Clarke (2006). **Findings:** Overall, 5 outcome categories were identified: Process Efficiency, Customer & Market Responsiveness, Innovation & Improvement, Cost Reduction & Improvements, and Strategic Growth. The range of outcomes seen differed across the AI maturity levels. Those with a higher maturity level experienced larger organizational change. **Originality/Value:** This study provides detailed qualitative insights into the outcomes of AI adoption in Pakistan's textile SMEs. Using RBV and Dynamic Capabilities theories, this study demonstrates how organizational AI maturity influences outcomes.

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Introduction

Artificial Intelligence (AI) has moved from being an emerging digital technology to a strategic organizational resource. Recent advancements in AI have enabled its application across many

areas of organizations (Lodhi et al., 2026). AI can be used to increase productivity, process efficiency, decision-making, and innovation. Recent reviews have shown that outcomes from AI adoption in SMEs depend on the conditions under which the technology is implemented and the organization's capabilities (Aish & Noor, 2025; Badghish & Soomro, 2024; Lodhi et al., 2026). This is especially important in developing countries, as AI can be used to improve productivity, increase competitiveness, and enhance knowledge and capabilities within organizations (Badghish & Soomro, 2024). AI can be used to improve strategically important industries such as healthcare, education, agriculture, manufacturing, the automobile industry, and the textile industry. AI can be used to improve human capabilities and utilize resources more efficiently within resource-restricted organizations (Lodhi et al., 2026; McCarthy, 2022). Within this environment, AI may not be used to develop complex technology ecosystems but rather to improve existing technology (Aish & Noor, 2025; Ashoer et al., 2025; Vrontis et al., 2022). This is especially important for SMEs, as they play a significant role in developing countries but often face challenges due to limited budgets, low-technology, and low-capability staff (Aish & Noor, 2025; Halepoto et al., 2022; Lodhi et al., 2026). AI can help reduce costs, automate repetitive tasks, improve managerial decision-making, and expand customer and market reach (Khanfar et al., 2025; Lasmiatun & Manteghi, 2025; Marwan, 2020; Vrontis et al., 2022). However, this will depend on the ability of the organisation to incorporate AI into their processes, routines, knowledge and human capabilities (Ashoer et al., 2025; Badghish & Soomro, 2024; Spector, 2006).

There is research available looking at the factors influencing AI within SMEs. This includes technological, organizational, and environmental factors such as infrastructure, knowledge, budget, leadership, staff capabilities, and external support (Lasmiatun & Manteghi, 2025; Lodhi et al., 2026; Sotamaa et al., 2025). Recently, research has shown a positive correlation between AI adoption and organizational or sustainable performance (Aish & Noor, 2025; Pillai et al., 2024). This is due to the complementary capabilities and conditions within the organization (Global, 2020; Rahman et al., 2026; Sotamaa et al., 2025)(Abdul Wahab & Radmehr, 2024; Soomro et al., 2025). However, most of this research looks at factors influencing adoption or correlations between adoption and performance. Less research has examined how organizations translate AI use into outcomes.

A key gap in research concerns how AI adoption leads to organizational transformation. AI adoption is just the first step in using AI. Only when AI is embedded within processes, decision-making, staff practices, and strategic activities can organizational transformation occur. If an organization adopts AI but lacks the capabilities to utilize it, there will be no real change (Badghish & Soomro, 2024; Lodhi et al., 2026; Shabbir & Anwer, 2018; Vishwakarma & Singh, 2023). However, if AI is consistently incorporated, it can help improve processes, decision-making, customer responsiveness, innovation, resource utilization, and strategic capabilities within the organization (Aish & Noor, 2025; Bhargava et al., 2021; Jain et al., 2021; Pereira et al., 2022; Pillai et al., 2024; Vrontis et al., 2022). This shows that AI adoption within organizations is a complex topic to understand, and that how organizations interpret, incorporate, adapt, and gain value from AI needs to be understood (Ashoer et al., 2025; Lu, 2019; Spector, 2006).

This is especially relevant within the textile industry, as there are many interdependencies among purchasing, planning, quality, stock, forecasting, and the supply chain (Garg et al., 2021; Khanfar et al., 2025; McCarthy, 2022; Sotamaa et al., 2025). AI can be used to improve planning, quality assurance, predictive maintenance, and optimize processes, but it will depend on data, infrastructure, staff capabilities, and organizational readiness (Pereira et al., 2022; Pillai et al., 2024; Rahman et al., 2026; Sotamaa et al., 2025; Spector, 2006; Teece, 2023; Vrontis et al., 2022). The textile industry faces challenges in improving productivity and quality whilst meeting buyer demands and international competition. Despite growing interest in AI technology, there is limited understanding of how AI integration can affect organizations in emerging economies (Halepoto et al., 2022; Jain et al., 2021; Teece, 2023; Wamba-Taguimdje et al., 2020).

Pakistan has a significant context in this research. The textile industry plays a key role in Pakistan's industrial and export economy. It contributes around 8.5% of GDP, over 60% of export revenue, and employs around 25 million people (Pakistan Bureau of Statistics, 2023; Pakistan Economic Survey, 2022). Therefore, incorporating technology into the textile industry can have an impact on the entire industry (Pereira et al., 2022; Venero & Paz, 2026). AI can provide opportunities for Pakistani textile SMEs to reduce production inefficiencies, improve quality, enhance forecasting and planning, improve customer and market responsiveness, and strengthen innovation capabilities (Ashoer et al., 2025; Halepoto et al., 2022). However, organizations will face challenges when incorporating AI due to resource constraints, limited technology, a lack of skilled staff, and limited staff adaptability and organizational capabilities. This makes Pakistan's textile SMEs a valuable context for examining how AI can move from a technology to an organizational change (Khan et al., 2024; Sotamaa et al., 2025; ul Amin et al., 2025).

There is some research examining AI adoption in Pakistani SMEs and its relationship to organizational and sustainable performance (Halepoto et al., 2022; ul Amin et al., 2025; Wamba-Taguimdje et al., 2020). However, the quantitative nature means there isn't much detail on how organizational stakeholders experience AI integration, how processes have evolved, and how organizations have turned their investment into resources and capabilities. A qualitative approach can help understand these processes (Khan et al., 2024; Rahman et al., 2026; Sotamaa et al., 2025).

This study aims to address this by examining how AI integration leads to organizational outcomes. AI adoption was viewed as an ongoing process within organizations. This study explores how organizational outcomes are impacted by AI integration. This includes process performance, responsiveness to customers and market, innovation and improvements, financial outcomes, and strategic performance. This study also examines how organizational AI maturity can affect how organizations translate their investment into organizational outcomes. This helps explain why organizations may achieve different outcomes with the same technology.

The Resource-Based View (RBV) and Dynamic Capabilities (DC) were used to understand the processes. RBV focuses on how AI can be combined with complementary resources such as staff capabilities, knowledge, data, infrastructure, and managerial capabilities. DC focuses on how organizations can sense, seize, and reconfigure resources and processes (Teece et al., 1997). Recent

research has shown that dynamic capabilities and organizational readiness can help explain whether AI adoption will lead to improved performance (Halepoto et al., 2022; Lasmiatun & Manteghi, 2025; Marwan, 2020). Overall, this study aims to answer the following research question: How does AI integration lead to outcomes and organizational transformation within Pakistani textile SMEs?

This study contributes to the emerging area of AI, SMEs, and organizational transformation. Firstly, this study focuses on how AI integration leads to organizational outcomes rather than adoption. There is extensive research on the factors influencing AI adoption. However, there is limited research on what happens after adoption and how organizations translate their investment into organizational outcomes. By identifying the differences among adoption, integration, and organizational transformation, this study shows that AI adoption is just the first step in organizational change. Organizational transformation will occur when AI is embedded within processes, decision-making, staff practices, and strategic activities. This provides a more detailed understanding of how value is created from AI.

Secondly, this study provides insight into how organizational AI maturity can influence AI outcomes. This shows that AI adoption will not necessarily lead to improved organizational performance. The outcomes will depend on how well an organization integrates AI with its technology, staff capabilities, knowledge, managerial capabilities, and processes. AI maturity is an important factor in turning investment into value. Organizations at a lower maturity level will see greater improvements in their processes, such as automation, efficiency, and cost reductions. However, those with a higher maturity level will start to gain value from AI in terms of customer responsiveness, innovation, financial improvements, and strategic decision-making. This provides a more detailed understanding of why organizations may see different outcomes from the same AI technology.

Thirdly, this study extends the RBV. AI was viewed as a resource within the organization. Whilst AI technology can be adopted by competing organizations, its value will depend on how well it is combined with complementary resources. This includes staff capabilities, knowledge, data, digital infrastructure, managerial capabilities, and organizational learning. This study provides an AI-enabled resource view.

Fourthly, this study contributes to the DC theory. This study shows how AI can serve as a resource and help develop organizational capabilities. AI-supported analytics can help improve sensing capabilities, and AI-supported decision-making can help increase responsiveness. Consistently using AI can help with organizational reconfiguration by changing processes, staff roles, and knowledge. Combining RBV and DC provides a theory-driven understanding of how AI resources can be transformed into adaptable, innovative capabilities.

Finally, this study provides a context and methodology for understanding AI integration within textile SMEs in Pakistan. The textile industry is economically important but can face challenges due to limited resources, technology, and skills, as well as international competition. Using a qualitative approach provides insight into how managers and staff feel about AI integration and

the organizational outcomes resulting from changes to daily processes. Overall, this study contributes to the literature by showing that AI adoption does not automatically lead to organizational transformation. This will only happen if organizations have the maturity, complementary resources, and dynamic capabilities to integrate and utilize AI effectively.

Overall, this study helps move the debate on AI adoption beyond the question of why firms adopt AI and provides insight into how such adoption leads to organizational transformation. This study provides theory-driven and context-specific insights into how AI can create value within resource-restricted organizations through Pakistani textile SMEs.

Theoretical Background and Literature Review

Resource-Based View and AI as a Resource

The Resource-Based View (RBV) posits that organizations can gain a competitive advantage by leveraging valuable resources (Barney, 1991; Peteraf, 1993). However, AI tools may be widely available within SMEs; therefore, they may not be rare or difficult to imitate. The value may depend on complementary resources such as data management, analytical capabilities, staff capabilities, and process improvement. Recent research has shown that AI adoption within SMEs heavily relies on resources, knowledge, and implementation capabilities (Badghish & Soomro, 2024; Shabbir & Anwer, 2018).

Dynamic Capabilities and AI as a Capability

Dynamic Capabilities focus on how organizations can sense opportunities and threats, seize opportunities, and reconfigure resources (Eisenhardt & Martin, 2000; Teece et al., 1997). AI can be used to improve sensing capabilities through AI-supported analytics. Decision-making can be improved through decision support systems. Processes can be improved through changing workflows. Recent research has shown that dynamic capabilities and organizational agility can help understand the relationship between AI assimilation and performance in SMEs (Aish & Noor, 2025; Lodhi et al., 2026; Lu, 2019; Teece, 2023; Vrontis et al., 2022).

AI adoption in SMEs

The application of Artificial Intelligence (AI) has become an interesting field of study due to the opportunities it offers for improving organizations. However, various technological, organizational, and environmental factors influence the adoption of AI among Small and Medium Enterprises (SMEs). A systematic review of 106 peer-reviewed articles was conducted by Khanfar et al. (2025), who found that infrastructure, finance, culture, knowledge, competition, and regulation were important factors to consider when implementing AI in SMEs. Badghish and Soomro (2024) also identified some of the challenges in implementing AI, such as a lack of knowledge, resources, and technology. Research has also shown that the application of AI differs between SMEs and larger organizations due to differences in finances, technology, management support, and staff capabilities (Sharif et al., 2025). This shows that applying AI is not simply about having access to the technology but also about ensuring the capability to implement it within their organization

(Aiudi et al., 2026; Fitriastuti, 2026). More research is required to understand how the application of AI can lead to particular outcomes within SMEs with limited resources (Halepoto et al., 2022; Lodhi et al., 2026).

AI Adoption by SMEs in Pakistan

The adoption of artificial intelligence (AI) in small- and medium-sized enterprises (SMEs) in Pakistan is a relatively new research topic (Pillai et al., 2024; Spector, 2006; ul Amin et al., 2025; Wamba-Taguimdje et al., 2020). However, recent studies have suggested that Pakistani SMEs encounter a number of issues when adopting AI technologies in their businesses. These include limitations regarding technical knowledge, lack of resources, and resistance towards technology (Lodhi et al., 2026; Shabbir & Anwer, 2018). However, it can improve business efficiencies, increase productivity, and support customer engagement (Emon, 2026; Pereira et al., 2022).

Research conducted by Khanfar et al. (2025) found that top management support, employee ability, perceived relative advantage, customer pressure, and supplier support positively impact AI adoption within SMEs. This has been associated with improvements in economic, social, and environmental performance (Aiudi et al., 2026; Pereira et al., 2022).

Recent research on the textile industry in Pakistan highlights the importance of perceived usefulness, resource availability, management support, and competitive pressure in adopting AI to drive open innovation within export-oriented SMEs (Sharif et al., 2025). Further research is required to understand how Pakistani SMEs utilize AI adoption to gain sustainable results within their organization, especially within traditional manufacturing industries where there may be limited resources (Aish & Noor, 2025; Lodhi et al., 2026; McCarthy, 2022; Pillai et al., 2024; Sharif et al., 2025).

AI Adoption Outcomes and Maturity

Increasing research is examining the outcomes of AI. Halepoto et al. (2022) show the importance of ensuring AI is aligned with business processes. Studies have shown AI assimilation can lead to improved performance within SMEs through capabilities such as absorptive capability and customer agility (Halepoto et al., 2022; Lodhi et al., 2026). Recent reviews have shown that challenges with AI adoption within SMEs include knowledge, infrastructure, cost, and organizational readiness (Halepoto et al., 2022; Jain et al., 2021; Khanfar et al., 2025). AI can be used in manufacturing to improve quality assurance, maintenance, planning, and optimizing processes (Gao et al., 2024; Heimberger et al., 2026). Evidence shows that AI adoption can improve sustainable performance in manufacturing SMEs in Pakistan (Marwan, 2020; Rahman et al., 2026; Sotamaa et al., 2025). This provides the foundations for understanding how AI maturity can impact outcomes from textile SMEs (McCarthy, 2022).

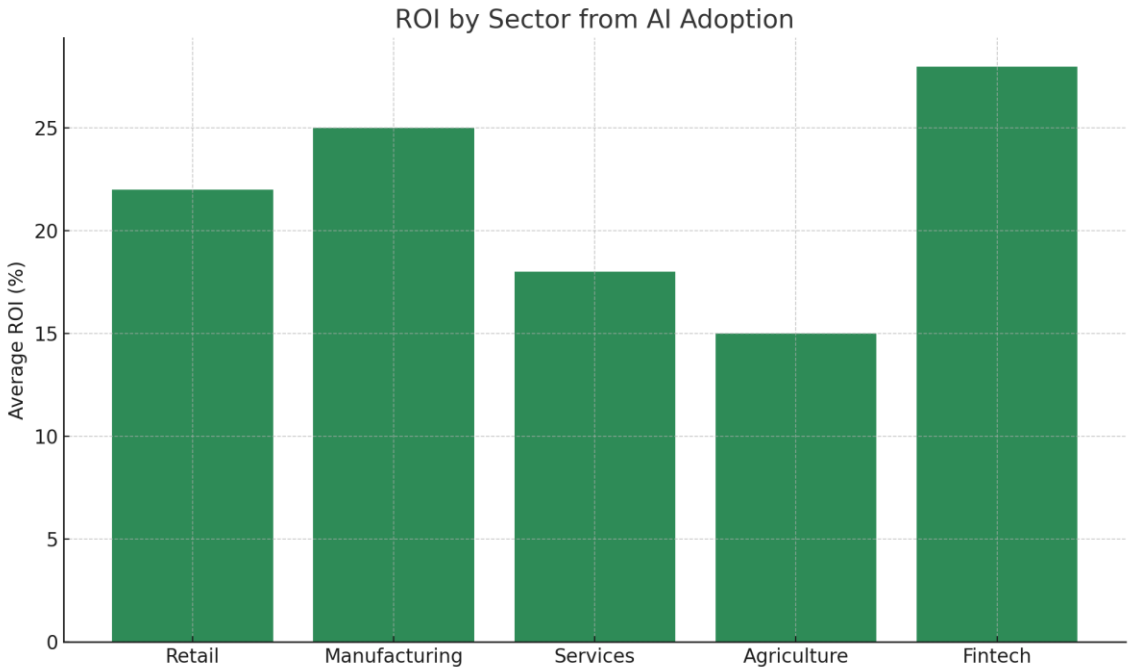


Figure 2. Average Return on Investment (%) by Sector from AI Adoption. The manufacturing sector (directly relevant to textile SMEs) records an average ROI of 25%—source: Adapted from thesis findings.

Figure 2 shows the average returns on investment (%) by sector. The manufacturing sector (directly relevant to textile SMEs) has an average 25% ROI. This has been adapted from findings within the thesis.

Research Methodology

Research Design

This study adopts a qualitative multi-case design methodology based upon an interpretive and constructivist philosophical underpinning (Kothari, 2004). There are multiple cases within the study, allowing Analysis across different maturity levels. This will help identify any patterns related to AI maturity levels that might not be apparent if only one organization were studied. The organizations selected met the following criteria: they had to be from the textile industry, be SMEs, and have actively used AI. This meant that they had at least one AI application in place or had trialed it. Table 1 shows the maturity levels. Table 1. AI Maturity Classification of Participant Firms.

Table 1:

Source: Primary fieldwork, June–September 2026.

Maturity Level	N	AI Applications	Duration of Use	Primary Outcome	Magnitude
Nascent	5	1 pilot app	<1 year	Operational efficiency gains only	Narrow / Incremental
Intermediate	4	2–3 applications	6–18 months	Operational + Market responsiveness	Moderate / Expanding
Advanced	2	3+ integrated apps	>18 months	Full spectrum incl. strategic growth	Broad / Transformative

Sample

Table 2 provides the details of the complete sample of participants. There were 11 participants from 11 SMEs in Pakistan's textile industry. Four were SME owners, three were operations managers, two were IT managers, and two were production supervisors. The diversity of participants offers multiple perspectives on the impact of AI. SME owners provided information on strategic decisions, investment, and how they see AI impacting their business. Operations managers and production supervisors provided insight into how AI impacts processes and production. IT managers provided insight into AI implementation and infrastructure. The companies were from Faisalabad, Lahore, Multan, and Sheikhupura, meaning they were based in key textile businesses within Punjab (Pakistan). Having participants from different companies and positions allows a range of experience with AI. This means comparisons can be made between cases to gain a better understanding of how different organizations may have varying impacts with AI.

Table 2. Study Participants Profile and Firm Characteristics

Source: Primary fieldwork, June–September 2026

Code	City	Company	Role	Employees	AI Maturity
1	Faisalabad	Rashid Textile Mills Ltd	SME Owner	80–100	Nascent
2	Faisalabad	Maheen Textile Mills Ltd	Operations Manager	60–80	Nascent
3	Faisalabad	Gohar Textile Mills	IT Manager	45–60	Intermediate
4	Faisalabad	Awan Textile Mills	Production Supervisor	100–130	Nascent
5	Faisalabad	Sargodha Cloth Processing Industries	SME Owner	70–90	Nascent
6	Lahore	Style Textile (Pvt) Ltd	IT Manager	150–200	Advanced
7	Lahore	Denim Plus (Pvt) Ltd	Operations Manager	130–180	Intermediate

8	Lahore	Moiz Textile Mills Ltd	SME Owner	90–120	Intermediate
9	Multan	Mahmood Textile Mills Limited	SME Owner	180–230	Advanced
10	Multan	Allawasaya Textile & Finishing Mills	Production Supervisor	120–160	Intermediate
11	Sheikhupura	Ayesha Spinning Mills Ltd	Operations Manager	100–140	Nascent

Data Collection and Analysis

Semi-structured interviews were conducted between June and September 2026 to identify the organizational outcomes of AI implementation in textile SMEs. Questions were aimed at understanding how AI was impacting product/service quality, increasing productivity, improving efficiency, and reducing costs. Interviewees were also asked about how their relationships with customers had changed, improvements in market responsiveness, increased innovation capability, and changes in strategic direction. This allowed the researcher to use a flexible yet consistent method for gathering data. The data collected was analyzed using the six-stage thematic analysis process proposed by Braun and Clarke (2006). This included: becoming familiar with the data, coding, developing themes, reviewing themes, defining and naming themes, and reporting. This gave five superordinate themes.

Findings

Five main themes were found from the thematic Analysis. Each theme includes many sub-themes to show the variety of outcomes from AI adoption. Table 3 shows a detailed summary of the outcomes.

Table 3. Summary of AI Adoption Outcomes by Theme, Mechanism, and Maturity Level

Source: NVivo 12 Thematic Analysis; N=11 interviews across three AI maturity levels.

Outcome Theme	Key Mechanisms	Maturity Level	Illustrative Evidence	Theoretical Link
Operational Efficiency	AI visual inspection; predictive maintenance; scheduling	Nascent–Advanced	Defect rate: 70%→>95%; idle time down ~20%	RBV: Productive Resource
Customer & Market Responsiveness	Demand forecasting, real-time order tracking, buyer analytics	Intermediate–Advanced	Safety stock down 30%; 2 export buyers retained	DC: Sensing Capability
Innovation & Continuous Improvement	AI-assisted design tools; predictive maintenance culture spread	Advanced	Trend analytics adopted; proactive culture beyond AI machines	DC: Learning Capability

Cost Savings	Labor recomposition; waste reduction; material optimization	Nascent–Advanced	Cutting waste down ~15%; gross margin improvement reported	RBV: Cost Resource
Strategic Growth	International certification; organizational AI capability development	Advanced only	Qualified for 2 buyer certifications; AI capability is now a strategic asset	DC: Transforming Capability

Figure 3 presents the NVivo thematic tree map for the outcomes cluster. Strategic Growth dominates, followed by Innovation & Continuous Improvement and Improved Operations & Efficiency—confirming participants' primary framing of AI value in terms of long-term strategic and innovation consequences rather than immediate operational gains.

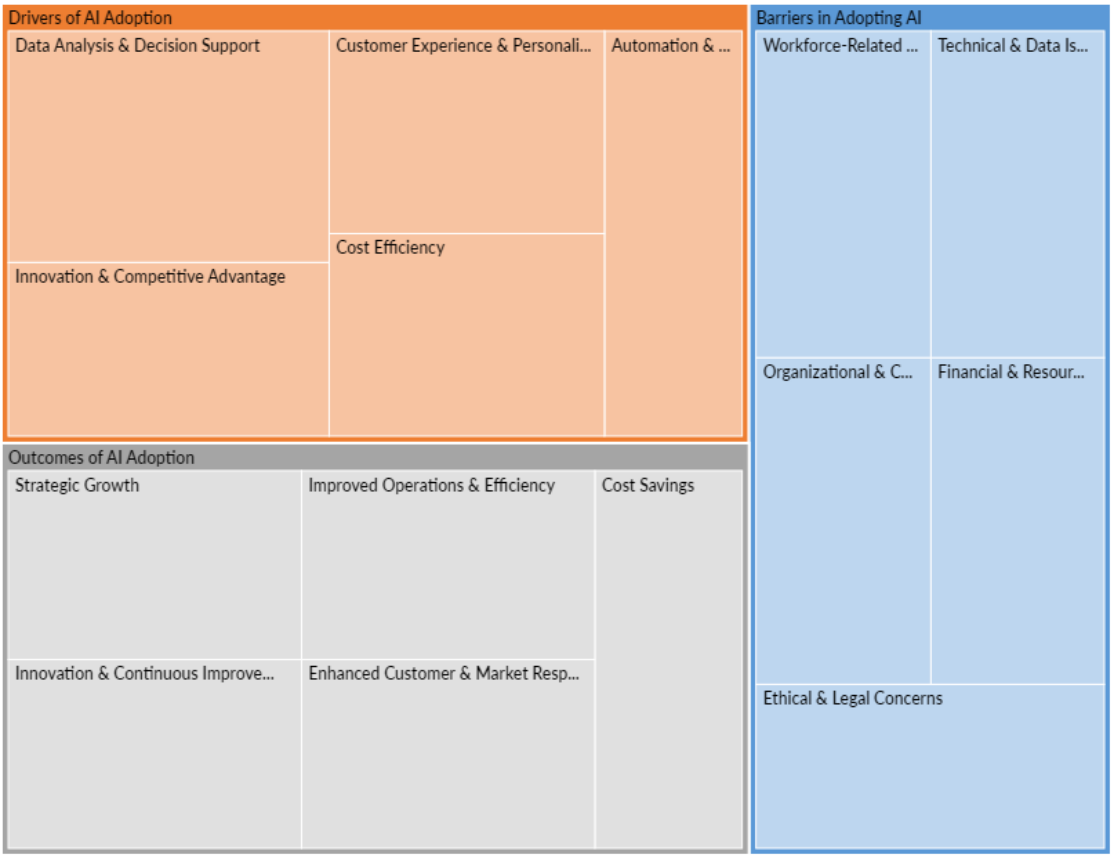


Figure 3. NVivo Thematic Tree Map: AI Adoption Outcomes Categorization (Grey boxes = Outcomes cluster). Box size proportional to coding frequency. Source: NVivo 12 analysis output.

Figure 4 presents the full NVivo coding frequency bar chart across all fifteen themes. The comparative positioning of outcome themes relative to driver and barrier themes confirms that participants devoted greater cumulative interview content to AI outcomes (particularly Strategic Growth and Innovation) than to any individual driver or barrier category.

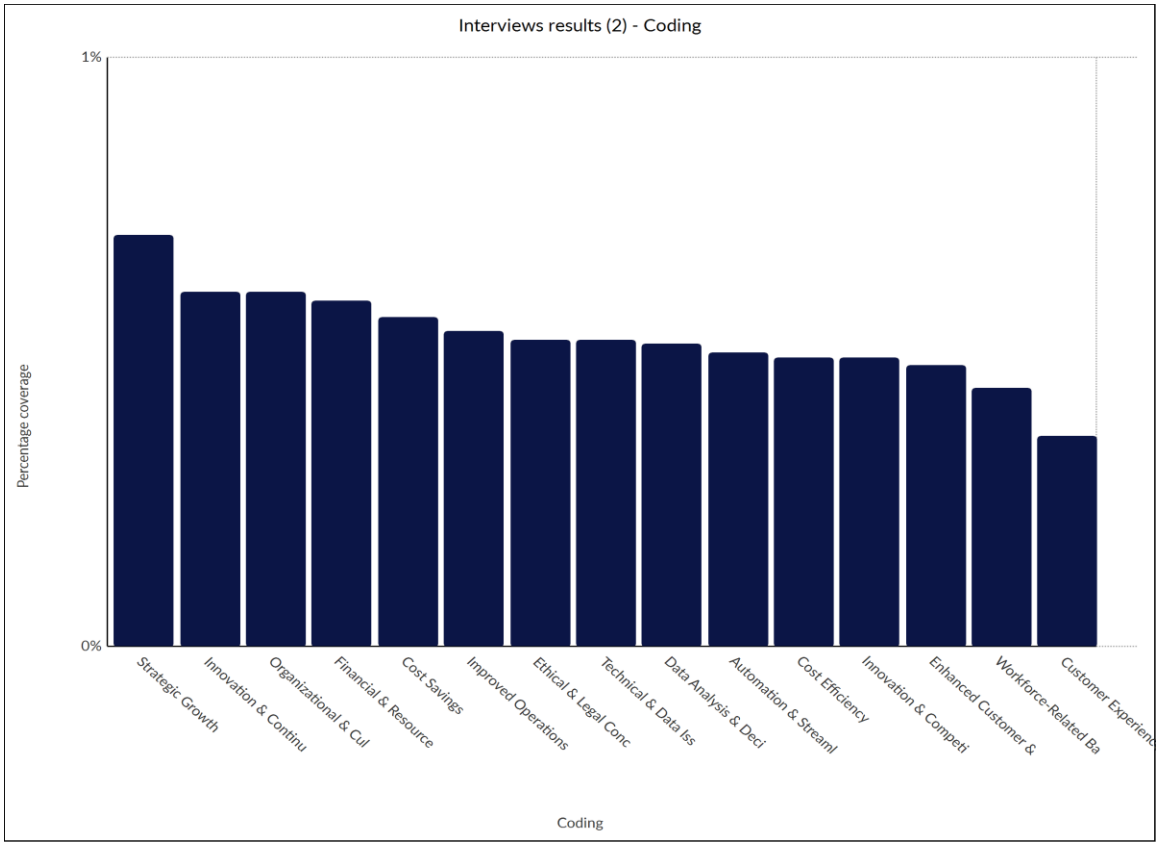


Figure 4. NVivo Interview Coding Analysis: Percentage Coverage Across All Fifteen Themes. Source: NVivo 12 thematic analysis output.

Improved Efficiency and Control

Quality Control & Reduced Defects

Quality improvement was the most consistent and verifiable outcome across the maturity spectrum. Many respondents commented on the improvement in production quality due to the implementation of AI. This is because an AI system serves as a productive resource, enabling organisations to improve outcomes in line with the RBV. Several respondents commented on how much their defect rate fell after they began using an AI inspection system. For example;

"Before we had AI inspection systems, we had quality control staff at the end of the production line who found maybe 70% of defects. Since we implemented the AI, our quality control has found over

95% of defects. We have had over a third fewer returns from our customers in the last 8 months." Participant 7, Operations Manager, Lahore

"Our AI camera never gets tired, never has bad days, and will never miss any defects due to distraction. It is so consistent. Since we implemented our AI, we have had zero quality complaints from our key buyer, which we never had before." Participant 9, SME Owner, Multan

This shows how AI can improve the organisation's quality by eliminating inconsistencies during the shift. As shown above, the AI will never get tired, meaning that defects will never be missed.

Optimal Production Scheduling

AI-enabled scheduling systems helped intermediate and advanced adopters increase their output. This is because the AI is acting as a dynamic capability, helping to organise resources more effectively than a person could with limited information-processing capabilities.

"My AI scheduling system has reduced downtime on our machines by around 20%. We are getting more outputs per shift without hiring additional staff or machines. Our orders are scheduled intelligently, and we are not losing any time due to manual ordering." Participant 7, Operations Manager, Lahore

"We used to have issues with bottlenecks in our production. By using our AI scheduling system, we can clearly see where the issues are coming from. We can easily fix the issue because we can see where the bottleneck is." Participant 6, IT Manager, Lahore

Improved Customer and Market Responsiveness

Demand Forecasting & Reduced Lead Times

Intermediate and advanced adopters saw improvements in AI-driven demand forecasting. This allowed them to plan their raw material purchases more effectively, schedule their production more accurately, and reduce overstock. This shows how AI is adding value to the organisation across multiple areas, as it is improving the organisation's information-processing capabilities. This fits with the RBV theory, as it provides an organisation with a valuable and productive resource.

"We used to have a lot of safety stock for all our products as we couldn't forecast demand very well. With our AI forecasting, we have around 30% less stock and are having fewer stockouts. Our working capital has improved significantly, and we can commit to our buyers' delivery times with much more confidence." Participant 9, SME Owner, Multan

"Our AI looks at the last 3 years of sales and seasonal trends and gives us a demand forecast each month. It is not perfect, but it is much better than guessing. We have reduced the number of emergencies purchases we make, as they always cost us more money. We have reduced by about half." Participant 3, IT Manager, Faisalabad

AI-Enabled Communication with Customers & Buyers

AI-enabled communication tools were used by those with AI incorporated into their production management systems to improve customer experience and improve relationships with buyers. This shows how adopting AI can improve relationships with the organisation by providing an intangible asset: relationship capital. This is done by improving transparency within the organisation.

"Our European buyers now view us differently. We can send them live updates on our production and show them our defect rate so they know we take quality seriously. We have kept 2 buyers who were looking to move to bigger mills." Participant 6, IT Manager, Lahore

"I used to spend 2 hours a week creating order status reports manually for our key buyer. With the AI system, we can automatically create and send these reports. I am using those 2 hours to look for new customers. The AI has given us extra time to grow our sales." Participant 8, SME Owner, Lahore

Innovation

AI-Assisted Design

Advanced adopters highlighted that AI had helped them with their design process. They were using AI design tools to analyse fashion trends, buyer preferences, and social media to inform their designs. This shows how AI is providing them with sensing capabilities, helping them recognise and utilise market signals.

"Our Head Designer used to rely on trade shows and feedback from buyers to know what trends were happening. Now she uses our AI dashboard to track colour trends, fabric preferences, and style changes. This has given her some ideas she wouldn't have thought of before. We have had our best collection in 4 years." Participant 9, SME Owner, Multan

"AI has helped speed up our design process. Previously, it took 3 weeks to design a new design, and we had no idea whether people would like it. We can now test our ideas using market data. We have seen an obvious improvement in our new product's success rate." Participant 6, IT Manager, Lahore

Predictive Maintenance & Proactive Culture

Using predictive maintenance tools provided direct cost savings and also improved innovation within the organisation. This is because it created a proactive culture within the organisation. This is an example of learning-mediated dynamic capabilities, as AI adoption has caused the organisation to develop capabilities beyond just the AI tools being monitored.

"Previously, our engineers would repair our machines when they broke down. Now they are constantly monitoring the machines' performance data. This has created a proactive culture amongst them in how they manage all of our equipment. We haven't had any unexpected shutdowns in the last 6 months." Participant 10, Production Supervisor, Multan

"Now our maintenance team talks about early warning signs for all of our equipment, even the older ones that aren't monitored. The AI project has changed how they think about their job." Participant 9, SME Owner, Multan

Cost Savings & Improved Performance

Improved Labour & Administration

Cost savings were highlighted across all maturity levels. However, rather than replacing labour, AI was often used to free up staff to focus on more valuable work. This is in line with the nuanced findings of Bhargava et al (2021).

"The extra time we have from our administration staff not having to create order reports manually has been used for looking for new customers. The AI has given us extra sales capacity without increasing our staff. We have added 2 new buyers in the last quarter." Participant 7, Operations Manager, Lahore

"We haven't lost any staff due to AI. Instead, we have changed what they do. Those who used to manually count our stock now oversee the AI-driven counting process and address any issues. Their jobs are actually more interesting now." Participant 6, IT Manager, Lahore

Reduced Waste

Advanced adopters reported significant improvements in material efficiency. This is because they had AI tools to optimize their processes. This is a key difference between the advanced and nascent adopters: the advanced adopters had a mature AI and data system, enabling them to quantify the impact. The nascent adopters tended to experience only qualitative improvements.

"Our cutting waste has reduced by around 15% since implementing our AI pattern optimisation. As we spend the most on fabric, this has made a big difference. It has improved our gross margin, and the improvement gets bigger as the AI learns our patterns." Participant 9, SME Owner, Multan

"We used to waste a lot of material as our cutting patterns weren't optimized. The AI calculates the most efficient layout for each order. We have seen a measurable waste reduction. We have also reduced our energy usage as we aren't going through as many correction cycles." Participant 6, IT Manager, Lahore

Facilitated Strategic Growth

Competitive Position & Increased Market Access

Advanced adopters highlighted that they had been able to improve their competitive position. This was done by competing for higher value market segments and gaining certifications from international buyers. This is because they had AI systems that could document their quality. This shows how AI can be used to increase market access by improving its capabilities.

"We have always been a mid-market producer; however, with our AI quality systems, we have gained 2 international buyer certifications. These require us to have documented quality metrics, so it has opened us up to a whole new tier of customers." Participant 9, SME Owner, Multan

"Our competitive position has changed. 2 years ago, we were competing purely on price. Now we are competing on documented quality, reliable delivery, and data transparency. The AI has allowed us to do this. We aren't in the price war anymore." Participant 6, IT Manager, Lahore

AI Capabilities as an Asset

Finally, the organisations had developed AI capabilities as an asset. This includes knowledge of managing data, AI processes, and analyzing and implementing. This falls under the most sustainable source of competitive advantage, as it is a second-order capability. This means it enables the organisation to develop first-order dynamic capabilities effectively.

"We learn from every AI project we do. This means we can develop our next project more quickly and effectively. We have a team that understands what tools to look for, how to incorporate them into our production, and how to manage the change with our staff. This has become a real asset and would be difficult for competitors to replicate quickly." Participant 6, IT Manager, Lahore

"The learning we have had from implementing AI has been just as valuable as the AI itself. Our management team is making decisions differently. They want data, they want to test their assumptions, and they want to measure results. The culture change started with the AI project but has now become part of everything we do." Participant 9, SME Owner, Multan

Discussion

AI as a Resource & Capability

The findings show that AI acted as a productive resource and capability enabler. This is because it fits with the RBV-DC integration presented in this study. It was evident from the findings that AI was providing value to organisations by directly replacing manual processes, augmenting human decision-making, and optimising resources (among nascent and intermediate adopters). AI was also providing value by improving sensing, seizing, and transforming capabilities. This meant they were developing dynamic capabilities to gain sustainable competitive advantages through VRIN-qualifying competencies (advanced adopters). Recent research has found that AI assimilation in SMEs is associated with absorptive capacity, customer agility, and dynamic capabilities (Aish & Noor, 2025; Ashoer et al., 2025; Badghish & Soomro, 2024).

The participants had provided detailed examples of this. Early-stage benefits were observed, including improvements in defect rate and scheduling. Late-stage benefits were observed, such as improved competitive positioning, organisational learning, and second-order AI capabilities. This was in line with DC theory, as it shows how organisations can gain sustainable competitive advantages through learning-mediated capabilities. This is in line with recent reviews showing

that the value of AI in SMEs depends on complementary resources and capabilities (Aish & Noor, 2025; Lodhi et al., 2026).

Maturity Level

The maturity level of the outcomes has implications for organisations. This is because you won't be able to justify investing in AI based on the outcomes from the nascent adopters. The most sustainable competitive advantages come from the strategic and capability development outcomes. These are only seen at higher maturity levels and therefore require a long-term commitment. For SMEs with limited resources, this can create an adoption pitfall. If organisations don't see impressive results from their pilot projects, they may give up on using AI. This is in line with the findings of Aish & Noor (2025), Halepoto et al. (2022), and Lodhi et al. (. This is in line with recent research showing a difference between adoption and assimilation in SMEs. This shows that organisations need to be ready and develop capabilities to see performance benefits (Aish & Noor, 2025; Khanfar et al., 2025; Neale et al., 2011).

Change Management

Across all 5 outcome categories, change management was a key factor in seeing outcomes. Those who had invested in communicating with their staff about how AI would be used within the organisation, providing ways for staff to have their say, and providing training achieved stronger and more widespread outcomes. Participant 6 highlights how staff roles have changed. Those who used to count stock manually now have a greater role in overseeing and addressing issues. This shows how careful change management can turn the threat of staff replacement into an opportunity to enrich them. This created superior outcomes and improved employee relationships. This is in line with research looking at AI in production. This shows that staff, organisational, and infrastructure factors are important (Halepoto et al., 2022; Khanfar et al., 2025)

Conclusion, Implications & Limitations

Conclusion

This study examined the organisational outcomes of AI adoption in Pakistani textile SMEs. It identified 5 main categories of outcomes. These varied depending on the organisation's AI maturity level. This study provides an integrated RBV-DC framework to demonstrate how AI is both a productive resource and a dynamic capability enabler. The participants provided detailed examples of how AI is providing value to organisations from a resource perspective in the early stages. Later, they began to gain value from it from a capabilities perspective.

Implications

Theoretically, this study contributes to the RBV-DC integration in SMEs and provides evidence of AI maturity being a contingency factor. Quality inspection and predictive maintenance should be prioritised in early-stage AI implementations. Policymakers should develop support systems for each maturity level. AI providers should develop modular and affordable solutions for Pakistani

textile SMEs. The findings on organisational learning suggest that the secondary benefits of AI adoption may yield a more sustainable competitive advantage. This is because it changes the organisation's culture, decision-making, and capabilities. This is in line with recent research showing that AI adoption in SMEs is linked to dynamic capabilities and organisational performance (Cimino et al., 2025; Schwaeke et al., 2025; Soomro et al., 2025).

Limitations & Further Research

There are several areas for improvement within the study. Firstly, the qualitative nature of the research and its specific focus on the textile SME sector in Pakistan mean the results cannot be generalised beyond this industry. Longitudinal quantitative studies could be conducted to explore further how the outcomes of AI adoption change over time. This could examine how AI adoption provides benefits such as improved operational efficiency, cost savings, customer responsiveness, innovation, and growth strategies. It could be determined whether there are long-term benefits to using AI (Aish & Noor, 2025; Khanfar et al., 2025).

Secondly, comparative research could be undertaken using mixed methods to understand outcomes of AI adoption across different industries, such as manufacturing, pharmaceuticals, retail, and service sectors. Using both quantitative and qualitative methods is better for understanding the relationship between AI adoption and organisational outcomes. Research could be conducted across countries to understand better how AI adoption varies with institutional, economic, and technological differences (McCarthy, 2022; Pillai et al., 2024).

The findings were largely based on the participants' experiences. This means that there may be bias in the results. Future research could examine organisational, financial, productivity, and operational performance data to determine whether there are real improvements. Triangulation could be used to understand the interview findings alongside objective indicators (Halepoto et al., 2022).

Future research could examine how organisational size, digital maturity, leadership support, employee capabilities, and resources affect the relationship between AI adoption and organisational outcomes. This would help clarify what can be done to ensure organisations gain sustainable value from AI adoption. By overcoming the research's limitations, there will be more evidence to support it, making it more applicable. This will help increase understanding around how organisations can transform using AI (Rahman et al., 2026).

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