RESEARCH PAPER

Vulnerability among Textile MSMEs in Haryana: The Impact of Technological Constraints on Performance

Sakshi Sharma[1*], Dr. Faraz Ahmad[2]

[1*] Research Scholar Amity School of Economics, Amity University Haryana, Amity Education Valley, Panchgaon, Manesar, Gurugram (Gurgaon), Haryana – 122413 Email: sakshisharma.econ@gmail.com
Orcid id: 0009-0006-3444-8999
[2]Assistant Professor Amity School of Economics, Amity University Haryana, Amity Education Valley, Panchgaon, Manesar, Gurugram (Gurgaon), Haryana – 122413 Email: ahmad_faraz@rediffmail.com
Orcid Id: 0000-0002-7092-1484

Abstract

Purpose

This study investigates the determinants of technology adoption and its impact on enterprise performance in labour-intensive textile units. Grounded in the Technology-Organisation-Environment (TOE) framework and integrated with the Stimulus-Organism-Response (SOR) model, the research examines how technological context, organisational readiness, and environmental pressures influence adoption intensity, which in turn influences enterprise performance.

Design/Methodology/Approach

Primary data were collected from 350 textile units in Haryana, India, using a structured questionnaire. Structural Equation Modelling (SEM) was employed to test the measurement and structural models. Confirmatory Factor Analysis (CFA) established reliability and validity. Quantitative findings were supplemented with qualitative interviews to capture contextual and behavioural insights.

Findings

Technological context, organisational readiness, and external environment significantly influence adoption intensity, with organisational readiness emerging as the strongest predictor. Adoption intensity exerts a strong positive effect on enterprise performance outcomes, including productivity, quality consistency, delivery efficiency, and competitiveness. Qualitative evidence highlights financial constraints, skill gaps, and managerial conservatism as key barriers.

Research Limitations/Implications

The study is limited to textile MSMEs in one Indian state and uses cross-sectional data. Future research may incorporate longitudinal and multi-regional designs and examine behavioural moderating variables.

Originality/Value

The study extends the TOE framework by demonstrating that internal organisational capacity is the primary driver of adoption intensity in structurally rigid, labour-intensive manufacturing settings.

Keywords: Textiles, Technology Adoption, TOE framework, Modernisation, Industry Upgrade, Vulnerability, Enterprise Performance

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1. Introduction

The world manufacturing industry is rapidly changing, driven by automation, digitalisation, and Industry 4.0 technologies; however, the change is not evenly distributed across industries, as the textile and apparel industry is one of the most labour-intensive in the world. Whilst the most popular companies use sophisticated automation, cyber-physical systems, and data-driven production models to achieve greater efficiency, quality, and responsiveness, numerous small- and medium-sized textile companies are constrained by technological obsolescence and a lack of automation (Butollo et al., 2021; Rai et al., 2021). Technological obsolescence occurs when old equipment and old systems go unnoticed due to a lack of competitiveness against newer alternatives and faded effectiveness in carrying out tasks, displaying talent, and responding to the market (Moeuf et al., 2018; Bhatia et al., 2023). Meanwhile, automation deficits will indicate the inefficient use of process automation, restricting cost efficiency, quality consistency, and timely delivery (Fatorachian & Kazemi, 2018; Marzi et al., 2018). These fixed costs increase performance gaps, especially in emerging economies where the conservativeness in investment patterns and constraints on the availability of resources hinder diffusion of technology (Jahan et al., 2022; Pu et al., 2023). Even though advanced manufacturing technologies suggest quantifiable improvements in productivity and environmental performance, the adoption occurs not only concerning technological preparation but also concerning organisational performance and environmental pressures; therefore, frameworks including Technology-Organisation-Environment (TOE) and Stimulus-Organism-Response (SOR) play an important role in explaining the uneven modernisation patterns found in textile manufacturing.

*Author for Correspondence: sakshisharma.econ@gmail.com

1.1. Technology gaps in India's textile sector

India is ranked in sixth position among the world's textile exporters after China, Bangladesh, Vietnam, Turkey, and the European Union (Government of India, 2025); however, the sphere of its industry is marked by high levels of structural dualism. The industry consists of traditional handloom work, modern composite mills, and clustered micro, small, and medium industries, which led to a great disparity in the level of technological complexity and operational preparedness. As big businesses are progressively moving towards sensor-driven production, automated cutting, and digital traceability solutions, many MSMEs still use outdated machines and manual quality control, and their operations are usually batch-based (Tao et al., 2021). Though such variety presents the socio-economic significance and labor concentration in the sector, at the same time, it yields disproportionate technological capacities due to insufficient financial resources, talent gaps, lack of coherent value chains, and insufficient institutional provisions (Saha et al., 2021). Decades-old spinning, weaving, and processing machinery leads to high levels of energy usage, increases in maintenance expenses, decreased flexibility, and limited market operation in high-outcome markets as evidence of obsolescence (Iyer, 2018; Vijayan et al., 2016). Besides old stock equipment, there is also the problem of the lack of automation in between the digital and the smart manufacturing systems, especially in smaller companies that are still largely labour-based (Habib et al., 2024; Chourasiya and Pandey, 2025). Evidence of uneven technology development in regional groups of textile industries, including Tirupur, Ludhiana, Surat, Coimbatore, and Bhiwandi, also demonstrates the impact of institutional ecosystem differences on uneven development (Mankirat, 2024). Although a series of government-led schemes, such as the Technology Upgradation Fund Scheme (TUFS), Make in India, and Production-Linked Incentive (PLI) scheme, are supposed to enhance and speed up technological renewal, structural rigidity and absorptive constraints have limited their effectiveness and left the industry technologically fragmented and competitively vulnerable (Goyal et al., 2018).

Technology adoption in the Indian textile industry is constrained by skill gaps, financial limitations, and growing sustainability pressures (Birajdar & Vasudevan, 2022). This study applies the Technology–Organisation–Environment (TOE) framework to identify adoption determinants and integrates the Stimulus–Organism–Response (SOR) model to examine how adoption influences enterprise performance using Structural Equation Modelling (SEM). By focusing on a labour-intensive sector facing structural inertia and modernisation pressures, the study explains the uneven yet critical nature of technological transition. The remainder of the paper proceeds with the literature review, theoretical framework, methodology, results and discussion, implications, limitations, and conclusion.

2. Review of Literature

2.1 Factors that determine technology adoption in firms

An honourable amount of academic literature indicates that technological, organisational, and environmental factors jointly determine the uptake of technology at the firm level. According to the previous research, relative advantage, complexity, compatibility, organisational preparedness, managerial support, competitive intensity, regulatory environment, and network relations are potent predictors of adoption choices (Huang et al., 2025). Equally, a study on SMEs in the textile and garment industry identifies performance expectancy, effort expectancy, trust, government support, and market competition to be key drivers of the adoption of digital technology (Susanty et al., 2025). It has also been demonstrated that organisational capabilities, such as human resources, financial power, managerial productivity, and structural preparedness, also make a decisive contribution to the outcomes of adoptions (Chen and Chen, 2024; Chourasiya and Malviya, 2025). The enabling factors in automation and digital transformation in the Indian environment are found to be technology readiness, the ability to invest, scalability, market need, and government support (Hossain et al., 2024; R and G, 2025). Taken together, the available sources accumulate in the concepts of cost, availability of resources, managerial commitment, size of the firm, resource pressures, institutional support, and linkages of the supply chain as core variables influencing technology adoption (Ishmael et al., 2017; Hoque et al., 2023; Mim et al., 2024). Nevertheless, most of the literature has focused on cost efficiency, productivity improvement, and sustainability, but very little has been done on the relationship between technological obsolescence, deficits in automation, and the performance of companies. This paper fills this gap by considering the issue of structural technological constraints and their impact on adoption behaviour and the resultant performance outcomes.

2.2 Technological Obsolescence, Automation Deficits, and Performance Gaps in Manufacturing

Current literature discusses the topic of technological obsolescence and the lack of automation, which has a negative impact on performance in the manufacturing industry in its pure form. Sierra-Fontalvo et al. (2023) define technological obsolescence as when the newer technology or equipment makes the already existing systems ineffective, less efficient, and unattractive. The toleration of this obsolescence in the long run may lead to a decline in productivity, high cost of manufacturing, and under competitiveness, and so to poor underperformance among the firms, as Amankwah-Amoah (2017) points out. Bernardino et al. (2025) also show that the textile industry is technologically obsolete, not only in the green sense, but also in the psychological one, when a new piece of equipment and the development of fast fashion, on the one hand, lead to the fact that older products, which are manufactured on outdated technologies, are forgotten. According to Ates and Acur (2022), companies that implement strong adaptive practices learn to reduce the risks of becoming obsolete and, at the same time, continually remain on their feet among changing circumstances. Automation deficits, which can be explained as the terms established by Doran et al. (2025), are gaps or deficits in the adoption, implementation, and utilisation of automation technologies in a given sector or industry. In the textile sector, these deficits are still present mainly because of economic, sectoral, and structural obstacles like expensive start-up expenses, skills shortages, and resistance to change (R & G, 2025). Another point Lopera and Velez-Ocampo (2021) make is that although automation can limit the generation of jobs in the labour market, anti-automation may limit productivity and place a person at risk of being outcompeted. According to Hwang and Kim (2022), the performance gap, which is caused by technology, is the inability to correctly use and integrate new technology, leading to lower productivity, efficiency, competitiveness, and missed opportunities compared to innovative companies in the field. The unsatisfactory performance is often maintained by a lack of financial resources, skills and capacity, organisational readiness, complexities and integration issues, and external impediments (Cotrino et al., 2020; Ghobakhloo et al., 2022; Roman and Rusu, 2022; Shah et al., 2024; Jamil et al., 2025). Further, the literature separates the contributions of technological obsolescence and deficiency of automation in the explanation of the performance gap, which indicates evidence of their undermining effect on the performance of the textile sector and manufacturing industry firms. Lastly, available literature is most likely to be narrow and concentrated around specific technological aspects (i.e., ICT, digitalisation, or automation) instead of using a more integrative approach (considering all the applicable technology aspects).

2.3 Technology Adoption in the Textile Industry: Global Evidence, Indian Context, and Structural Barriers

The extensive research on technology adoption in the textile industry shows that its diffusion does not occur evenly in terms of geographic location and scale of firms, and has significant differences in developed and developing economies, or large firms versus micro, small, and medium enterprises. Typically, the identified barriers include financial limits, lack of skills, organisational inflexibility, lack of infrastructure, and regulatory burdens (Khin and Kee, 2022; Mahmood et al., 2025). At the same time, the data of the international empirical research supports the idea that technological modernization promotes the improvement of sustainability performance, supply-chain integration, strategic agility, innovation potential, and operational efficiency (Ahmad et al., 2020; Zhang et al., 2023; Oliveira Neto et al., 2023). Similar limitations persist in the Indian context, including high implementation costs, managerial commitment levels, workforce upskilling issues, institutional inefficiencies, and lack of infrastructural protection, thus affecting the platform's ability to modernize (Chaudhary et al., 2020; Kaur et al., 2024). Whereas adoption can bring about visible productivity and competitiveness increase, structural inflexibility hinders extensive change. All of the literature taken together influences the point that the issue of technological obsolescence and lack of automation continue to contribute to performance gaps in this labour-intensive but somewhat capital-intensive sector, and thus poses the need for a more comprehensive analysis of the structural factors hindering it.

3. Theoretical and Conceptual Model

The suggested model is based on the Technology-Organisation-Environment (TOE) paradigm (Tornatzky & Fleischer, 1990), modified to consider the aspect of structural limitations peculiar to textile production. The model assumes the involvement of technological conditions, organisational capacities, and environmental pressures in adopting technology.

3.1 Technological Context

The technological environment brings forth the attributes of current and new systems of production, which determine the adoption. The three issues that are notable in terms of textile manufacturing include technological obsolescence, shortage of automation, and change resistance (Moeuf et al., 2018). Obsolescence is becoming a problem when old machines no longer find company in terms of competitive relevance and thus reduce their operational efficiency, flexibility, and responsiveness (Bhatia & Kumar, 2023). The shortage of automation - reduced integration and use of automated and digital systems - hinders the achievement of quality consistency, speed in production, and cost-effectiveness (Fatorachian & Kazemi, 2018). The companies that apply programmable, sensor-based, and automated technologies are more competitive than the firms that rely on legacy systems (Marzi et al., 2018). In turn, these technological environments should determine the preference of firms to use modern systems.

H1: Technological factors have a significant impact on the adoption intensity of technology in textile firms.

3.2 Organisational Readiness

Organisational readiness embodies internal preparedness, such as monetary strength, managerial dedication, workforce expertise, and organisational flexibility. Textile MSMEs frequently face the threat of capital limitation, the lack of skills, and the disjointed coordination systems that restrict absorptive capacity (Saha et al., 2021). Restricted involvement of the managerial staff and aversion to risks postpone the investment in modern technologies, as well as strengthening the adherence to old production habits. On the other hand, financially stable companies possess quality human capital and have positive leaders who can easily undertake a technological upgrade and embrace new systems with ease (Chen and Chen, 2024). The organisational preparedness is therefore a decisive factor when it comes to the results of the adoption.

H2: Organisational readiness has a significant impact on the adoption intensity of technology in textile firms.

3.3 External Environmental

The environmental aspect comprises external market and institutional pressures that condition adoption incentives. Regulatory frameworks, government incentives, intensity of competition, and a changing market demand are all pressures on the firms to modernise (Tao et al., 2021). The policy tools like TUFS and PLI are expected to enhance the process of technological modernization in India, whereas the global competition standards and sustainability standards increase the price of technological inertia (Government of India, 2025). The effectiveness of these interventions can, however, be moderated by bureaucratic complexity and skewed institutional support. Environmental pressures thus play the role of a driver as well as a restraint of decisions to adopt.

H3: The external environment has a significant impact on the adoption of technology in textile firms.

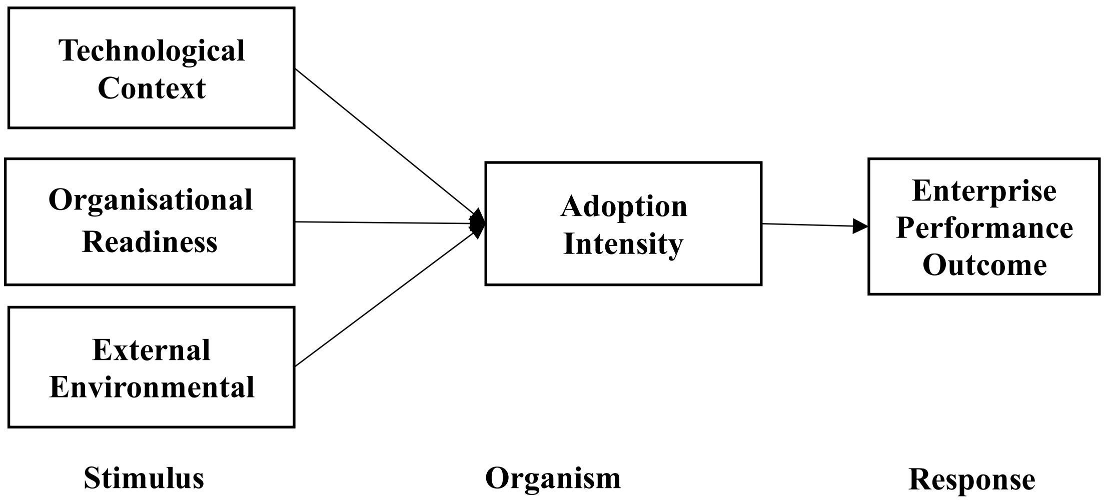
3.4 Adoption Intensity and Enterprise Performance Outcome

The adoption of technology goes beyond operational adjustment, and it has a direct impact on performance. The practice demonstrated by empirical research alters the findings that automation and digital integration contribute to increased productivity, consistency, and uniformity of quality, delivery reliability, and decreased costs (Rai et al., 2021; Rana et al., 2024). Conversely, continuous use of outdated technologies increases the disparity of performance in terms of inefficiency, inconsistency, and decreased market responsiveness (Hwang & Kim, 2022). The adoption, therefore, functions under a strategic mode that companies reduce the differentials of competitiveness and enhance the long-term sustainability.

H4: Adoption of technology significantly impacts the enterprise performance.

The conceptual model presented in Figure 1 below is drawn based upon the Stimulus-Organism-Response (SOR) framework by Mehrabian & Russel (1974), explaining how technology, organisation, and environment-related factors stimulate technology adoption, further leading to a response in firm performance.

Figure 1: Conceptual Model



Source: Author's work

4. Methodology

4.1 Measurements

The study utilized a structured questionnaire to operationalize latent constructs derived from established literature, ensuring both measurement validity and cross-study comparability. All items were assessed using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree), a widely accepted measurement approach in social science research (Likert, 1932; Kothari, 2004; DeVellis, 2012).

The analytical framework comprised five principal constructs: Technological Context (TC), Organisational Readiness (OR), External Environment (EE), Adoption Intensity (AI), and Enterprise Performance Outcomes (EPO). These constructs were adapted from prior empirical and theoretical studies grounded in the Technology–Organisation–Environment framework and related adoption-performance literature (Tornatzky & Fleischer, 1990; Venkatesh et al., 2003; Moeuf et al., 2018; Tao et al., 2021; Rana et al., 2024; among others). A pilot survey involving 50 respondents was conducted to assess clarity, reliability, and instrument consistency. The reliability analysis indicated that Cronbach's alpha values for all constructs exceeded the recommended threshold of 0.70 (Nunnally, 1978). Content validity was further ensured through expert evaluation using Lawshe's (1975) content validity approach.

4.2 Data

The primary survey covered textile unit owners, operations managers, and production heads in Haryana. A proportionate stratified sampling method ensured representation across value chain segments (Kothari, 2004). Using Cochran's (1963) formula, a statistically robust sample size of 350 respondents was determined. Data were collected through online surveys and factory-visit interviews, with outliers screened to maintain data quality.

4.3 Normality

Normality was assessed using skewness and kurtosis statistics (Kline, 2011). All values fell within the acceptable ±2 threshold, confirming univariate normality.

Table 1: Normality of Data

Factors	Mean	Std. Deviation	Skewness	Kurtosis
TC1	3.73	0.89	-0.279	0.478
TC2	3.67	0.92	-0.119	-0.183
TC3	3.79	0.87	-0.339	0.268
OR1	3.68	0.82	0.052	-0.138
OR2	3.57	0.86	0.184	0.332
OR3	3.72	0.862	0.062	0.188
OR4	3.61	0.83	-0.072	0.192
OR5	3.72	0.91	-0.098	-0.063
EE1	3.59	0.89	-0.187	0.283
EE2	3.59	0.86	0.122	-0.064
EE3	3.73	0.87	-0.15	-0.114
EE4	3.67	0.91	-0.219	0.369
AI1	3.63	0.93	0.162	0.149
AI2	3.70	0.88	0.041	-0.071
AI3	3.77	0.87	0.086	0.293
EPO1	3.76	0.87	-0.132	0.202
EPO2	3.67	0.91	-0.172	-0.041
EPO3	3.71	0.88	0.111	0.332
EPO4	3.77	0.86	0.061	-0.152
EPO5	3.69	0.92	-0.213	0.312

4.4 Reliability and Validity

Construct reliability and validity were assessed using Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). As reported in Table 2, all Alpha and CR values exceeded 0.70, while AVE values were above 0.50, confirming convergent validity. Discriminant validity was established using the Fornell–Larcker criterion (1981) (Table 3), and VIF scores indicated no multicollinearity concerns.

Table 2: Reliability of Constructs

Constructs	No. of items	Standardized loadings	Cronbach's A-alpha	Composite Reliability (CR)
TC	TC1	0.784	0.842	0.879
	TC2	0.819		
	TC3	0.832		
OR	OR1	0.765	0.882	0.908
	OR2	0.801		
	OR3	0.815		
	OR4	0.783		
	OR5	0.827		
EE	EE1	0.789	0.864	0.899
	EE2	0.843		
	EE3	0.821		
	EE4	0.845		
AI	AI1	0.801	0.853	0.891
	AI2	0.832		
	AI3	0.809		
EPO	EPO1	0.843	0.900	0.946
	EPO2	0.818		
	EPO3	0.829		
	EPO4	0.858		
	EPO5	0.851		

Table 3: Discriminant Validity

	TC	OR	EE	AI	EPO
TC	0.812				
OR	0.423*	0.798			
EE	0.381*	0.439*	0.825		
AI	0.509*	0.561*	0.479*	0.814	
EPO	0.467*	0.492*	0.415*	0.623*	0.840

Note: Diagonal values represent the square root of Average Variance Extracted (√AVE). Each √AVE exceeded the inter-construct correlations, confirming discriminant validity among all constructs.

4.5 Structural Equation Modelling

Structural Equation Modelling (SEM) was employed as it integrates factor and path analysis, enabling examination of complex relationships among multiple latent constructs (Bollen, 1989; Hair et al., 2019). The analysis proceeded with Confirmatory Factor Analysis (CFA) for model validation, followed by structural modelling for hypothesis testing (Anderson & Gerbing, 1988).

4.5.1 Measurement Model: CFA

The measurement model was evaluated using Confirmatory Factor Analysis (CFA) to ensure adequacy and statistical robustness. All five latent constructs were operationalised through validated scales. Standardised factor loadings exceeded the recommended 0.70 threshold, supporting convergent validity (Hair et al., 2019). Composite Reliability values were above 0.70, indicating strong internal consistency (Fornell & Larcker, 1981), while AVE values surpassed 0.50, confirming that each construct explained a substantial share of variance in its indicators. Discriminant validity was established using the Fornell-Larcker criterion, where the square root of AVE for each construct exceeded inter-construct correlations. Additionally, HTMT ratios were below 0.85 (Henseler et al., 2016), further confirming discriminant validity among the five constructs: TC, OR, EE, AI, and EPO. Model fit indices indicated an acceptable fit: χ^2/df was below 3.0, CFI and TLI exceeded 0.90, and RMSEA and SRMR were below 0.08 (Hu & Bentler, 1999). Collectively, these results demonstrate that the measurement model was statistically sound and suitable for subsequent structural analysis.

4.5.2 Structural Model

Path analysis results in Table 4 indicate that Technological Context, Organisational Readiness, and External Environment exert significant positive effects on Adoption Intensity, which in turn positively influences Enterprise Performance Outcomes in textile firms.

Table 4: Path Coefficients

Hypotheses	Path	Standardized direct Effect	Critical Ratio	Result
H1	TC → AI	0.273	4.83*	Accepted
H2	OR → AI	0.418	7.61*	Accepted
H3	EE → AI	0.236	3.42*	Accepted
H4	AI → EPO	0.547	9.17*	Accepted

4.6 Qualitative Study

Qualitative interviews with owners and managers complemented the survey by exploring contextual barriers to technology adoption. The findings reinforced the role of technological, organisational, and environmental determinants in shaping firm performance and provided deeper insight into cultural and operational constraints within textile units.

4.6.1. Qualitative analysis

Semi-structured interviews explored technology adoption practices, guided by the quantitative constructs and additional questions on operational context and managerial perceptions. A recurring theme was participant attitude: while respondents acknowledged the importance of technology adoption, many preferred labour-intensive processes. Field observations further indicated the possible presence of disguised unemployment within textile units.

Table 5 below shows the demographic profile of workers.

Table 5: Demographic Profile of Respondents

Participants ID	Age	Experience (in Years)	Firm Type	Firm Category
P1	48	21	Small	Knitting
P2	41	14	Micro	Spinning
P3	31	8	Micro	Garmenting
P4	27	1	Micro	Garmenting
P5	32	6	Micro	Dyeing & Finishing
P6	51	29	Small	Spinning
P7	45	17	Small	Weaving

P8	39	15	Micro	Spinning
P9	37	16	Micro	Garmenting
P10	41	13	Small	Dyeing & Finishing
P11	29	6	Micro	Spinning
P12	40	12	Micro	Weaving
P13	33	12	Micro	Knitting
P14	54	26	Small	Dyeing & Finishing
P15	32	7	Micro	Garmenting
P16	35	15	Small	Garmenting
P17	42	18	Micro	Knitting
P18	28	2	Micro	Spinning
P19	37	13	Micro	Spinning
P20	31	9	Micro	Weaving
P21	47	5	Micro	Dyeing & Finishing
P22	53	27	Small	Knitting
P23	29	4	Micro	Garmenting
P24	56	32	Small	Dyeing & Finishing
P25	40	10	Micro	Weaving
P26	49	15	Small	Spinning
P27	55	10	Micro	Knitting
P28	47	12	Small	Knitting
P29	30	8	Micro	Spinning
P30	23	1	Micro	Garmenting

The interviews revealed that the biggest obstacle to adopting new technologies was simply a lack of financial resources. However, beyond structural constraints, the mindset of the adopters also played a crucial role. Although most owners and managers clearly understood the benefits of modern technologies, many still felt more comfortable relying on familiar, traditional production methods. The following excerpts from respondents reflect these sentiments.

"Technical upgrades are seldom required in our textile unit; in fact, the machinery currently in use was installed about a decade ago." (P27, Owner)

"Although new technologies help minimize errors and shorten production time, their associated costs are high." (P17, Manager)

"New technology adoption is challenging and often feels unnecessary, as our labour force is better suited to handle the operations." (P29, Owner)

"Advanced machinery requires workers to develop new skills and undergo additional training to adapt to updated processes." (P19, Owner)

"Buying advanced machinery is not simple for us as it takes a lot of time and formal approvals, especially since most of the high-tech equipment has to be imported from other countries." (P28, Production Head)

"Government schemes and incentives are attractive and could support technology adoption, but they involve oversight and formalities that we would rather avoid." (P21, Owner)

"Although the newer technologies are more efficient than older ones, we seldom feel compelled to adopt them, as the cost of machinery is almost comparable to what we spend on labour." (P22, Manager)

"New technologies don't enter the textile sector very often, so we don't really see much reason to invest heavily in research and development." (P6, Owner)

"Even though new technologies increase upfront costs, they generate sufficient returns over time to justify the investment." (P8, Manager)

"In our kind of work, the human touch really makes a difference in terms of precision and finish. That's why we feel more comfortable relying on skilled workers instead of completely replacing them with machines." (P11, Owner)

5. Results and Discussion

The results show that there is a strong, statistically significant correlation between Adoption Intensity (AI) and Enterprise Performance Outcomes (EPO), and that Technological Context (TC), Organisational Readiness (OR), and External Environment (EE) have a strong influence on AI. The results obtained through the mean values of 3.57 to 3.79 demonstrate that there is moderate concord among the respondents on the technological conditions, organisational preparedness, the environmental pressures, the level of adoption, and performance results. These findings indicate that textile companies are in the transition phase - they realise the need for technology upgrading but have not taken it to high levels. Univariate normality (normality tests, i.e., skewness and kurtosis values within the range of ±2) was confirmed, indicating that structural equation modelling could be used (Kline, 2011). The confirmatory factor analysis (CFA) was used to validate the measurement model. All factor loadings were above 0.70, indicating the indicators' reliability. The Cronbach's Alpha and composite reliability were found to be greater than 0.70, indicating the presence of internal consistency, and the average variance extracted (AVE) was greater than 0.50, indicating the presence of convergent validity. The Fornell-Larcker criterion was used to assess discriminant validity, which indicated the strength of the measure based on the TOE. Model fit indices (χ^2/df < 3; CFI and TLI > 0.90; RMSEA and SRMR < 0.08) did not suggest otherwise, therefore, confirming the robustness of the measurement framework. Structural analysis revealed a positive and significant impact of TC on AI ($\beta = 0.273$, $p = 0.001$), indicating that technological readiness and perceived benefits positively and significantly affect AI. OR turned out to be the most powerful predictor ($\beta = 0.418$, $p < 0.001$), indicating that the key influence on the intensity of adoption is dominated by financial capacity, managerial commitment, workforce competence, and organisational culture. EE also influences AI to a significant degree ($\beta = 0.236$, $p < 0.001$); however, the effect is relatively low, suggesting that policy incentives and competitive pressure are crucial, whereas internal preparedness is more decisive. Lastly, AI showed a positive influence on EPO with a significant value ($\beta = 0.547$, $p < 0.001$). The companies that have a greater rate of adoption have recorded increased productivity, product quality, efficiency of delivery, and competitiveness. Finally, AI demonstrated a strong positive impact on EPO ($\beta = 0.547$, $p < 0.001$). Firms with higher adoption intensity reported improvements in productivity, product quality, delivery efficiency, and overall competitiveness. Altogether, the synthesized evidence has shown that the influence of organisational readiness is the most significant on the intensity of adoption in labour-intensive textile companies, and long-lasting gains in performance are provided by the enhancement in the inner potential and the outer support system.

6. Theoretical and Practical Implications of the Study

It is the study that provides theoretical and empirical information about the adoption of technology in the labour-intensive textile production. Theoretically, the research expands the Technology-Organisation-Environment (TOE) model by proving that Organisational Readiness (OR) is the most significant predictor of Adoption Intensity (AI) when compared to the impact of Technological Context (TC) and External Environment (EE). The results highlight that internal resources such as financial resources, commitment by the managers, employee capabilities, and adaptable organisational culture are the underlying basis of adoption decisions. Furthermore, the study redefines the technological aspect by demonstrating how outdated capital base and routing operations hinder the process of upgrades and empirically proves that higher AI has better Enterprise Performance Outcomes (EPO). This contribution can be enriched with the qualitative evidence that shows the behavioural constraints, including, although not intimately represented in the conventional TOE structure, managerial conservatism, change resistance, and skill deficiencies, have a potent effect on adoption behaviour. These understandings clarify why change in terms of technology in traditional manufacturing environments is likely to be slow and cautious. Theoretically, the analysis has shown that monetary rewards cannot be used alone to ensure effective upgrading. Even with programmes like the TUFS and PLI assistance in providing monetary assistance, a sustainable adoption requires simultaneous investments in skills development, leadership orientation, and organisational restructuring. Planned training of workforce, collaborating with technical education, cluster-based skilling programs, and a regular check of technology are the fundamental steps. Also, administrative processes should be streamlined, and the institutional reach efforts should be increased to increase the effectiveness of the policy. Altogether, the fact that Adoption Intensity (AI) has a strong positive correlation with Enterprise Performance Outcomes (EPO) proves that technological upgrading is a mandatory requirement, not a rather optional upgrade. Integrated, multi-level strategy, strengthening the internal organisational strength, and policy-focused measures are essential to the rapid adoption and the maintenance of the competitiveness of the textile industry.

7. Limitations and Future Research Directions

The research offers an all-inclusive examination of technology adherence factors and performance at textile companies; some shortfalls put the research results into perspective. To begin with, the empirical domain is limited to textile MSMEs in Haryana. Even though the state is an important textile industry, localism can restrict the extrapolation to places with different industrial or institutional attributes. The study in the future can assume a multi-regional design in order to embrace the concept of heterogeneity in the region. Second, the model analyses on five constructs based on the TOE framework. Although qualitative knowledge has shown behavioral aspects, including managerial attitude and workforce inertia, these aspects were not formulated directly. These variables can have moderating or indirect effects, and they need to be included in the prospective research. Third, a cross-sectional design does not allow tracking of technological transition with time, since adoption is evolutionary in nature. Longitudinal research would have provided a more in-depth picture of how companies advance in the degree of adoption and the results of performance consequent development. In spite of these, the research still offers solid empirical and conceptual support on the use of technology by the textile companies. This can be furthered in the research by future studies, the use of longitudinal designs, the incorporation of behavioral constructs, and a larger geographical scope.

8. Conclusion

This paper has investigated relations between Technological Context (TC), Organisational Readiness (OR), and External Environment (EE), and the relation between Adoption Intensity (AI) and Enterprise Performance Outcomes (EPO) in a labour-intensive textile industry. Based on the Technology-Organisation-Environment (TOE) framework (Tornatzky and Fleischer, 1990), conceptually validated by the S-O-R model (Mehrabian and Russell, 1974), helped the research to capture the dynamics of technological modernisation in textile MSMEs in a developing economy set up. Through Structural Equation Modelling (SEM) and qualitative interviews, the research revealed the importance of the intensity of adoption in ensuring high levels of firm performance, especially those of firms that are limited by technological obsolescence, limited automation, and firm rigidity. The findings suggest that all three TOE dimensions influence AI to a significant degree, though to different degrees. The most significant factor is Organisational Readiness (OR), which was better than technological and environmental factors. The financial resources, management dedication, labour strength, and favourable organisational culture that were assessed internally turned out to be key to the modernisation as far as the contemporary practices were concerned. Technological Context (TC) played a key role as well, with automation pressures and ageing capital stock making firms tend to upgrade. External Environment factors (EE) like incentives provided by the policy, market need, and competitive pressure had a positive effect, although it all depended on the ability of the firms to absorb the effects of the factors. These results confirm the applicability of the TOE model when explaining the adoption behaviour of a resource-limited and culture-conservative manufacturing environment. The existing positive correlation between Adoption Intensity (AI) and Enterprise Performance Outcomes (EPO) points to the fact that active technological modernization is a key to competitiveness. Companies that use old machine equipment are inefficient and slow-paced in manufacturing, and those that are able to adopt modern technologies have improved responsiveness, quality, and market presence. The qualitative information mirrors the conflict between the customary labour-dependence and the need for modernisation of a globally competitive textile sector. The paper demonstrates the importance of the coordinated actions of companies, industry associations, and government. It is essential to bridge the gap between policy design and implementation, simplify bureaucratic procedures, enhance financial and technical capabilities in the institution, and institutionalise the regular audit of technology. Smaller firms can also be further assured against risks of adoption of collaboration platforms and mechanisms through the sharing of resources. Since the textile industry is an important part of an economy, especially in India, the results have broad implications for industrial policy development. The study, in general, makes technological upgrading a strategic necessity and not a discretionary enhancement, and urges multi-level, multi-level intervention to provide sustainable competitiveness and a long-term resilience of the sector.

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