

The Barriers to the Adoption of Emerging Technologies in the Apparel Manufacturing Industry: A Dynamic Framework Analysis Focused on India

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ABSTRACT

Despite the transformative potential of advanced technologies—such as Artificial Intelligence (AI), soft robotics, and mandated Digital Product Passports (DPPs)—the Indian apparel manufacturing sector exhibits a critical lag in achieving comprehensive, integrated digitalization. While end-to-end digital transformation is projected to shorten the production timeline by up to 40%, implementation is hampered by systemic, multi-dimensional barriers. Analysis reveals these constraints include acute data fragmentation coupled with poor IT infrastructure; severe financial stress resulting from high implementation costs with uncertain Return on Investment (ROI); and the persistent technical difficulty of automating the handling of limp, deformable fabrics. Furthermore, India-specific challenges like cyber security risk are dominant cause barriers to Industry 4.0 adoption. This report addresses this pervasive adoption gap by analyzing constraints across four integrated dimensions: Technological, Organizational, Environmental, and Dynamics (post-adoption processes). Existing models, notably the Technology-Organization-Environment (TOE) framework, are deemed insufficient as they fail to account for the unique material-specific challenges and provide limited consideration of dynamic adoption processes. This research introduces the Dynamic Apparel Technology Adoption and Supply Chain Resilience (DATAR) Framework to model the actual assimilation process necessary for industry modernization and strategic resilience.

INTRODUCTION AND CONTEXTUALIZATION OF THE DIGITALIZATION LAG

Contextualizing the Digitalization Lag in Indian Apparel Manufacturing

The global apparel manufacturing industry, including major hubs like India, is undergoing intense pressure to modernize its operations, driven by global demands for speed, sustainability, and mandatory transparency. While emerging technologies offer transformative potential, the sector exhibits a critical lag in achieving integrated digitalization (1). End-to-end digital transformation is projected to shorten the production timeline by up to 40% (Initial Research Context). Despite this clear potential, 63% of manufacturers worldwide remain in the early stages of AI adoption (Initial Research Context), a lag particularly acute in developing economies like India (12, 13).

The current status of technology adoption in India demonstrates a clear disparity: **general technologies, such as the internet, are the most frequently adopted, while advanced robot-related technologies are the least frequently adopted** (12). This persistent adoption gap threatens India's competitive standing as a global manufacturing hub and its ability to meet global regulatory and sustainability targets.

Problem Statement: Systemic, Multi-Dimensional Barriers in the Indian Context

The assimilation lag is not due to a singular factor but is hampered by systemic, multi-dimensional barriers, often unique to the institutional environment of Indian manufacturing. Analysis identifies three primary empirical constraints: acute data fragmentation coupled with poor IT infrastructure; severe financial stress arising from

high implementation costs and uncertain Return on Investment (ROI); and the persistent, material-specific technical difficulty of automating the handling of deformable textiles (Initial Research Context).

In the Indian textile and clothing industries, key drivers of the adoption struggle include the 'Lack of advanced IT infrastructure,' 'Regulatory Issues,' 'Data Management and Analysis' issues, and 'Return on Investment' uncertainty (13). Furthermore, **cyber security risk** is identified as the most significant barrier to Industry 4.0 adoption within the Indian textile and apparel sectors (13). High implementation costs, issues regarding data privacy, and direct resistance to adoption are also noted constraints in the Indian apparel industry (14).

Limitations of Existing Adoption Models and Research Objectives

Research examining technology adoption often relies on traditional information systems models. The Technology-Organization-Environment (TOE) framework, though widely applied, is deemed insufficient for analyzing the unique challenges of the apparel sector (Initial Research Context). This inadequacy stems from two main limitations: first, its failure to account for the unique, material-specific engineering challenges central to textile production; and second, its limited consideration of dynamic adoption processes and post-adoption scaling outcomes (Initial Research Context).

Crucially, in the Indian context, empirical studies reveal that certain traditional organizational factors emphasized by TOE are not significant. For example, the effects of **top management commitment** and **technical skills** were found not to be significant determinants of adoption level among Indian apparel manufacturers, while firm size and export orientation were positive influences (12). This variability underscores the necessity of a context-specific theoretical model.

LITERATURE REVIEW I: THEORETICAL FOUNDATIONS AND FOUNDATIONAL CRITIQUE

Established Technology Adoption Theories and the Research Gap

Academic discourse on technology adoption in apparel has historically centered on theoretical cornerstones such as the Diffusion of Innovation (DOI) theory and the Theory of Reasoned Action (TRA) (1). This theoretical orientation is often driven by retail- and consumer-facing technologies, such as virtual try-on and Augmented Reality (AR) used in e-commerce (1). While these models are effective for analyzing consumer behavior and the acceptance of retail innovation, they fundamentally minimize the structural complexity of manufacturing transformation, which involves deep organizational and systemic changes (1).

Consequently, a key research gap identified in the literature is the **lack of investigations utilizing the Technology-Organization-Environment (TOE) and Institutional theories** for technology adoption specifically in the apparel industry's production segment (1). The TOE framework, which considers technological, organizational, and environmental contexts, has proven significant in other industrial contexts, confirming factors such as financial strength, perceived benefits, and competitive pressure as crucial determinants of technology adoption globally (4).

Foundational Critique of the TOE Framework

Despite its utility in general management and IT adoption studies, the TOE framework proves insufficient for modeling the modern transformation of the apparel manufacturing sector, particularly concerning the adoption of physical automation and integrated digital systems (Initial Research Context).

Material Blindness (Technological Dimension Failure)

The primary critique of TOE is its generic approach to the Technological dimension. The framework treats technology in a materially blind fashion, failing to incorporate the unique engineering complexity posed by the core input material: **textiles** (Initial Research Context). The handling of limp, deformable fabrics is the central unsolved challenge in garment assembly automation, a challenge that generic IT systems (which TOE primarily

modeled) do not face (3, 10).

The technical literature confirms that advanced automation requires complex, highly integrated systems, such as industrial robots combined with **novel adaptive gripper jig systems** utilizing four needle grippers (3). These jigs must adjust their positions adaptively to accommodate the specific shape, material properties, and potential deformation of the fabric part (3). Furthermore, managing the inherent variability of textiles necessitates **two-stage machine learning (ML) models** to predict fabric deflection, which is then integrated into a **vision-guided algorithm** using Computer-Aided Design (CAD) data (3). By failing to integrate this material specificity and the associated high R&D costs, TOE overlooks the most significant technical barrier, which fundamentally dictates the cost, risk, and viability of robotics adoption in the sector (3).

Static View of Adoption and the Need for Dynamic Capabilities

The second significant limitation is that TOE traditionally conceptualizes technology adoption as a singular decision or implementation event (Initial Research Context). This static view is inadequate for analyzing modern digital transformation, which requires continuous assimilation, scaling, and strategic renewal. Industry 4.0 necessitates that firms move beyond simple operational efficiency to develop agility and **dynamic capabilities (DCV)** to maintain competitive advantage in volatile markets (5).

The literature highlights a critical research gap in explicitly connecting emerging technologies, DCV, and Supply Chain Resilience (6, 9). Digital technologies, such as AI and data infrastructure, fundamentally enhance the organizational capability to **sense** market shifts and supply chain disruptions by improving data gathering and sharing (6). This realization shifts the analytical focus from the adoption decision to the post-adoption process—measuring the firm's ability to translate technology implementation into true supply chain resilience and strategic capability (9). This forms the core justification for integrating DCV as the "Dynamics" dimension.

Contextual Inadequacy of TOE in the Indian Manufacturing Environment

The inadequacy of the TOE model is empirically evident in the Indian context, demanding a context-specific theoretical adjustment. While TOE typically emphasizes top-down managerial support and internal readiness (e.g., technical skills), studies focused on Indian apparel manufacturers have shown contradictory results. For instance, the effects of **top management commitment** and **technical skills** were found **not to be statistically significant determinants of adoption level** among Indian apparel manufacturers (12). This variability suggests that in the highly price-competitive, low-margin environment characteristic of Indian manufacturing, macro-level economic and environmental constraints—such as access to capital and pressure from global buyers—may override internal organizational readiness metrics in the short-term decision-making calculus (12). This contextual nuance confirms the need for a framework, like DATAR, that prioritizes financial stress and external drivers.

Literature Review II: Empirical Barriers and the DATAR Framework Synthesis

This section synthesizes the empirical evidence of the multi-dimensional barriers in India (T-O-E) and formalizes the DATAR framework as the necessary theoretical response.

Detailed Analysis of Technological Barriers in India

Technological constraints in India are severe, revolving around the universal difficulty of physical automation and the local challenge of digital infrastructure.

Material-Specific Engineering Complexity and Labor Reliance

The core technical hurdle remains the universal difficulty in manipulating non-rigid, limp sheet materials, coupled with the immense diversity of fabrics used in garment production (3, 10). This complexity ensures that advanced robotic systems—even those utilizing two-stage ML models for deflection prediction and vision-guided algorithms—remain non-scalable and prohibitively expensive for most manufacturers (3). This high

technical barrier directly reinforces the reliance on traditional, manual labor models, which are perceived as low variable costs (2). This persistent difficulty is the root cause of the extremely low adoption rate of advanced, robot-related technologies in India (12).

Foundational Digital Gaps: Data and Security

The effectiveness of technologies like AI remains hampered by severe data infrastructure limitations. In India, a **lack of advanced IT infrastructure** and issues with **data management and analysis** are significant barriers to Industry 4.0 adoption (13). The Indian apparel manufacturing sector is plagued by siloed, non-standardized data, which cripples the ability of AI systems to perform optimal demand forecasting, quality control, or supply chain optimization (10).

Furthermore, **cyber security risk** is identified in the literature as the **most significant barrier** to Industry 4.0 adoption within the Indian textile and apparel sectors (13). This highlights a foundational technological vulnerability that prevents large-scale digital integration and reinforces managerial hesitation regarding necessary cloud-based or inter-organizational data exchange (13). Addressing this requires a coordinated approach involving financial incentives, managerial capacity-building, and robust IT infrastructure investment (2).

Detailed Analysis of Organizational and Financial Barriers

Organizational constraints in the Indian context are dominated by resource limitations and managerial risk aversion.

High Capital Investment and ROI Uncertainty in Low-Margin Sector

The adoption of advanced systems, including AI infrastructure, data platforms, and highly specialized soft robotics, demands significant upfront capital investment (2). The deployment of these fixed assets creates severe financial stress, especially for small and medium-sized enterprises (Initial Research Context). In India, high implementation costs and the uncertain Return on Investment (ROI) are major drivers of adoption failure (13, 14). The compounding effect of technical complexity (difficult to automate limp fabrics) directly amplifies the uncertainty of achieving the projected ROI (2, 3). Consequently, there is pervasive **managerial hesitation** and a systemic risk-aversion that prioritizes known, low variable costs (labor) over high, risky fixed costs (technology) (2). This financial constraint must be central to any predictive adoption model.

Cultural Resistance and Workforce Adaptation

Beyond financial hurdles, the literature consistently points to internal organizational resistance. While technical skills are less of a statistical determinant (12), **cultural and organizational change** is a substantial cause barrier to Industry 4.0 adoption in India (13). Resistance to adoption among various stakeholders, coupled with issues concerning employee training, data privacy, and the ethical implications of AI, contributes significantly to the assimilation failure of new technologies (14, 8). Successful adoption requires dedicated managerial capacity-building and workforce training initiatives aligned with operational realities (2).

Detailed Analysis of Environmental Drivers and the Compliance Imperative

The external environment, particularly mandatory regulations from primary export markets, is now the strongest driver for digitalization, often overriding internal organizational financial resistance.

The Compliance Imperative: Digital Product Passports (DPP)

The Indian apparel supply chain is typically **buyer-driven** and export-oriented (8). Therefore, mandates such as the **Digital Product Passport (DPP)**, introduced by the European Commission, act as a significant external policy push that dictates technology adoption regardless of internal ROI calculations (11). The DPP shifts the motivation from a voluntary pursuit of competitive advantage to a non-negotiable compliance requirement (11).

The DPP is designed to enhance supply chain transparency and traceability, crucial for advancing resource circularity goals (15, 11). This innovation enables a **data-rich, dynamic, and collaborative Supply Chain Management (SCM) model** (11). Implementing a DPP requires standardized, transparent mechanisms for sharing comprehensive product data across the multi-tiered supply network (15, 7). This external pressure compels Indian organizations to invest in data governance and technological solutions to manage mandatory information (7), fundamentally changing the risk calculus by making the cost of non-compliance prohibitive.

DATAR Framework: Synthesis of Literature and Proposed Model

The limitations of the static TOE framework necessitated the development of a new theoretical structure. The DATAR Framework extends the core components of TOE by integrating two critical elements: **Material Specificity** within the Technological dimension and the concept of **Dynamic Capabilities (DCV)** within a fourth dimension, **Dynamics** (5).

The DATAR Framework models how the multi-dimensional barriers interact to create persistent lag, with the **Dynamics** dimension serving as the bridge to strategic outcomes. The cycle begins with the **Technological** constraints (material specificity, poor IT, cyber risk), which drive high fixed cost and risk onto the **Organizational** dimension (financial stress, hesitation). The ability to translate the implemented technology into true strategic advantage (Dynamic Capabilities) is then hampered by scaling issues and internal resistance (13). This inability to achieve successful assimilation reinforces managerial skepticism and perpetually favors labor-intensive models (2, 12).

Table 1: Comparison of Technology Adoption Frameworks in the Apparel Sector

Framework Dimension	TOE Model (Traditional Limitation)	DATAR Framework (Novel Integration)
Technological	Compatibility, Relative Advantage, Complexity (Generic IT)	Material-Specific Automation, Data Interoperability, Limp Material Handling
Organizational	Firm Size, Financial Strength, Management Support	Financial Stress (ROI Uncertainty), Managerial Risk Capacity , Digital Skills
Environmental	Government Support, Competitive Pressure, Market Volatility	Regulatory Mandates (DPP Compliance), Supply Chain Transparency & Traceability
Dynamic	Adoption as an Endpoint; Static Analysis (Absent)	Assimilation, Scaling, Strategic Renewal through Dynamic Capabilities (Sensing, Resilience)

Strategic Implications and Conclusion

Strategic Implications and Recommendations

To mitigate the pervasive adoption lag, strategic intervention must focus on the nexus of complexity and cost. Decoupling technical difficulty from investment cost requires government and industry consortia focused on subsidizing and sharing standardized ML models and data sets trained on diverse fabric properties (3). This collective R&D approach allows individual Indian manufacturers to drastically reduce upfront capital expenditure and allow for incremental, modular adoption.

Addressing the systemic challenge of poor IT infrastructure, data management, and cyber security (13) requires organizations to transition from siloed legacy systems to mandated internal standardization (2). The DPP mandate provides the institutional incentive to enforce data standardization (11). Recommendations include prioritizing investment in robust **cyber security measures** (13) and implementing technologies like blockchain, which facilitate the secure, transparent data sharing and traceability required for compliance and enhanced supply chain visibility (7).

Finally, management must focus on capacity-building to improve organizational **sensing** capability (6), reframing technology adoption as an ongoing process of strategic renewal. Leveraging technologies to improve visibility and traceability is critical for building trust and interlinked cooperation with supply chain partners (6), translating technology implementation into genuine supply chain resilience (9).

Conclusion and Research Objectives Confirmation

This analysis confirms that the lag in emerging technology adoption in Indian apparel manufacturing is pervasive and rooted in a set of integrated, multi-dimensional barriers: the material-specific technical complexity of handling limp fabrics (3), acute financial risk fueled by uncertain ROI and high costs (2, 13), and severe IT infrastructure and cyber security risks (13). Crucially, the research highlighted that traditional TOE organizational factors like managerial commitment are less predictive of adoption success in the Indian context than economic and environmental factors (12).

The introduction of the Dynamic Apparel Technology Adoption and Supply Chain Resilience (DATAR) Framework constitutes the primary theoretical contribution, shifting the analytical focus to the continuous process of assimilation necessary for strategic resilience, while incorporating context-specific organizational and technical realities (6).

Annexure: Survey Instrument

This survey instrument is designed to gather empirical data to validate the four integrated dimensions of the DATAR Framework, with specific questions targeting the financial, technical, and regulatory barriers prevalent in the Indian apparel manufacturing industry.

Section 1: Organizational Context and Demographics

What is the approximate number of full-time employees in your manufacturing division?

Response Type: Multiple Choice

Options:

- <100
- 100–500

- 501–2,000
- 2,000–5,000
- 5,000

Q2. What percentage of your finished goods production is exported to international markets?

Response Type: Multiple Choice

Options:

- <25%
- 25–50%
- 51–75%
- 75%

Q3. What is your primary product category?

Response Type: Multiple Choice

Options:

- Woven (e.g., shirts, jeans)
- Knitted (e.g., t-shirts, innerwear)
- Technical Textiles
- Home Textiles

Q4. Do you have a dedicated, internal R&D budget specifically for automation or digitalization?

Response Type: Multiple Choice

Options:

- Yes
- No
- Planned in the next 12 months

Q5. Compared to your closest local competitors, how would you rate your firm's overall technology adoption status?

Response Type: Likert Scale (1–5)

Scale: 1 = Far Behind | 2 = Slightly Behind | 3 = On Par | 4 = Slightly Ahead | 5 = Far Ahead

Section 2: Technological Barriers

Q6. The difficulty of manipulating limp, deformable fabrics (e.g., sewing automation) is the greatest technical hurdle in adopting advanced robotics.

Response Type: Likert Scale (1–5)

Q7. Our current IT infrastructure (hardware, network stability) is adequate to support the integration of new Industry 4.0 technologies (e.g., IoT sensors).

Response Type: Likert Scale (1–5)

Q8. Data fragmentation (data siloed across different systems/departments) significantly prevents us from implementing effective AI-driven solutions.

Response Type: Likert Scale (1–5)

Q9. Cybersecurity risks (e.g., data breaches, network attacks) are the most significant deterrent to widespread cloud-based technology adoption in our firm.

Response Type: Likert Scale (1–5)

Q10. Integrating new AI/digital systems with our existing legacy manufacturing software (e.g., ERP) requires extensive and costly customization.

Response Type: Likert Scale (1–5)

Q11. We currently use Computer-Aided Design (CAD) data for more than just pattern making (e.g., as input for automation algorithms).

Response Type: Yes / No

Q12. Which technology currently represents the least advanced stage of adoption in your firm?

Response Type: Multiple Choice

Options:

- ERP Systems
- Internet/Cloud Services
- CAD/CAM Systems
- Advanced Robotics

Q13. We lack reliable mechanisms to standardize product data (e.g., materials, origin) across our full supply chain network (tiers 1, 2, 3).

Response Type: Likert Scale (1–5)

Q14. What is the biggest challenge when automating the handling of non-rigid materials?

Response Type: Open-ended Text

Q15. What percentage of your quality control process is currently automated using computer vision or AI?

Response Type: Multiple Choice

Options:

- 0–10%
- 11–30%
- 31–60%
- 61–100%

Section 3: Organizational and Financial Barriers

Q16. The high initial capital investment required for advanced technology adoption poses a severe financial strain on our firm.

Response Type: Likert Scale (1–5)

Q17. The difficulty in calculating a clear Return on Investment (ROI) prevents us from justifying major technology purchases (e.g., AI/robotics).

Response Type: Likert Scale (1–5)

Q18. Resistance to new operational processes (cultural change) among employees and middle management significantly slows down technology implementation.

Response Type: Likert Scale (1–5)

Q19. Lack of available internal technical skills/expertise prevents our firm from successfully managing and maintaining advanced digital systems.

Response Type: Likert Scale (1–5)

Q20. Concerns over employee data privacy and security are major factors considered before implementing new monitoring or AI tools.

Response Type: Likert Scale (1–5)

Q21. Our top management team shows a high degree of commitment and leadership in driving digital transformation initiatives.

Response Type: Likert Scale (1–5)

Q22. We frequently encounter difficulty securing external credit or loans specifically for digital infrastructure or automation upgrades.

Response Type: Likert Scale (1–5)

Q23. When a technological failure occurs, we typically rely on external consultants rather than internal staff for repair and maintenance.

Response Type: Likert Scale (1–5)

Q24. We prioritize implementing technologies that save labor costs over those that enhance traceability or environmental compliance.

Response Type: Likert Scale (1–5)

Q25. What is the typical planned payback period (in years) your firm uses for major digital or automation investments (>₹50 lakh)?

Response Type: Multiple Choice

Options:

- <1 Year
- 1–3 Years
- 3–5 Years
- 5 Years

Section 4: Environmental and Dynamic Capability Factors

Q26. Competitive pressure from global rivals is the primary factor driving our firm to consider technological modernization.

Response Type: Likert Scale (1–5)

Q27. External regulatory mandates (such as the Digital Product Passport/DPP from export markets) are compelling us to invest in traceability technology.

Response Type: Likert Scale (1–5)

Q28. Implemented digital technologies (e.g., IoT, AI) have substantially improved our supply chain visibility and sensing capability.

Response Type: Likert Scale (1–5)

Q29. Our firm finds it easy to scale a successfully piloted new technology across multiple manufacturing units.

Response Type: Likert Scale (1–5)

Q30. Our digital investments have directly enhanced our firm's resilience against supply chain shocks (e.g., raw material delays, geopolitical events).

Response Type: Likert Scale (1–5)

Q31. We currently use data and technology to share critical product information (e.g., material composition, carbon footprint) with external supply chain partners.

Response Type: Yes / No

Q32. What single government policy or subsidy (state or central) would be most effective in accelerating your firm's adoption of Industry 4.0 technologies?

Response Type: Open-ended Text

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