

AI in the Textile Value Chain

A Strategic Guide to Artificial Intelligence for the Global Textile Industry



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Preface

This white paper grew out of the ITMF & ITA Webinar Series “AI in the Textile Value Chain” (2024–2026), which brought together global experts from academia, industry, and policy to explore how Artificial Intelligence is transforming textiles. Across ten sessions [1], speakers addressed topics from fundamental concepts and regulation to concrete applications in production, supply chains, design, and business models. The insights gained highlighted both the potential and the challenges of AI and underscored the need for a structured overview that connects theory with practice. This volume responds to that need, offering a comprehensive guide for industry leaders, policymakers, and educators seeking to understand and adopt AI across the textile value chain.

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Executive Summary

This white paper examines how Artificial Intelligence can help the textile industry respond to increasing structural pressures across the value chain while recognising its uncertain long-term effects on work, decision-making, and organisational structures. This summary distils the key findings for each stakeholder group.

For Industry Leaders and Decision-Makers

For executives and senior managers, the central learning is that AI is best understood as a capability for managing complexity, not as a shortcut to productivity gains. Value emerges when AI is applied incrementally to well-defined problems, particularly quality management, planning, and coordination. Successful adoption depends less on choosing the “right” algorithm than on investing in data foundations, skills, governance, and trust. Leaders must also determine which decisions should remain human-led, which can be supported or delegated, and which may eventually be automated within clearly defined boundaries. Speed of adoption matters less than coherence between strategy, organisation, technology, and responsibility.

For Operational and Technical Teams

For engineers, IT specialists, and operational managers, AI relies on an existing digital and organisational foundation: data quality, system integration, and understandable outputs are prerequisites for meaningful use. Current evidence is strongest for decision support and bounded automation, but the appropriate level of autonomy depends on the task, its risks, the maturity of the system, and the consequences of failure. Human expertise is currently essential for defining objectives, interpreting unusual situations, managing exceptions, and ensuring accountability. Over time, operational roles may shift increasingly toward supervision, orchestration, and intervention. Human oversight must therefore be designed as a substantive capability, with sufficient competence, information, time, and authority to challenge or override the system, rather than as a nominal approval step.

For the Workforce and Skills Development Stakeholders

For employees, training providers, and HR functions, AI adoption is redistributing tasks and decision responsibilities and may redesign, consolidate, or replace some roles. Routine analytical, administrative, and coordination activities are increasingly supported or performed by AI, while human work may shift toward judgement, orchestration, exception handling, and interpersonal responsibilities. This raises demand for digital literacy, data awareness, and the ability to critically evaluate AI-supported outputs. Acceptance depends on transparency, participation, and opportunities for upskilling. Preserving critical thinking is

particularly important: human oversight has little value if employees gradually lose the knowledge or confidence required to question the system.

For Industry Associations and Collaborative Platforms

For associations and networks, the white paper highlights the importance of **collective capability-building**. Challenges such as data standards, interoperability, skills development, and shared learning cannot be addressed effectively by individual companies alone. Associations are well positioned to facilitate exchange, reduce duplication, and create shared reference points, enabling learning, coordination, and trust across a diverse industry landscape.

For Policymakers and Regulators

For policymakers and regulatory bodies, regulation shapes AI adoption as much as technology does. Clear, proportionate frameworks build trust and provide orientation, particularly for SMEs. Effective regulation supports explainability, accountability, risk management, and meaningful human control where it is required, without imposing ceremonial oversight that adds cost but little protection. Ongoing dialogue between regulators, industry, and research remains essential to align regulatory intent with operational realities and changing technological capabilities.

For Researchers and Knowledge Institutions

For academic and applied research stakeholders, AI in the textile industry is an **organisational and socio-technical challenge** as much as a technical one. Research that integrates technology, human factors, governance, and economics is particularly valuable. Long-term impact depends on translating insights into usable frameworks, tools, and educational formats. Important research questions concern how decision rights will be distributed between humans and AI over time, whether human orchestration will remain substantively necessary in operations, and how organisations can balance efficiency with accountability, resilience, and human agency.

Shared Conclusion: Managing a Transition with an Open Endpoint

Across all groups, a common conclusion emerges: the impact of AI on the textile industry will depend less on technological breakthroughs than on coherence: between data and systems, between human capabilities and machine autonomy, and between individual initiatives and collective action.

In the present transition phase, human expertise remains necessary for guidance, alignment, contextual interpretation, exception handling, and accountability. This should not, however, be interpreted as proof that every decision must remain human-led in the long term. As AI systems become more capable, some cognitive and operational activities may move from support to delegation and, within bounded contexts, to autonomous execution. Human roles

may consequently shift toward setting objectives, orchestrating systems, governing exceptions, and accepting responsibility.

The long-term distribution of decision-making between humans and AI remains uncertain. It will be shaped not only by technical performance, but also by risk, regulation, trust, organisational design, and the value society places on human agency. The strategic challenge is therefore not simply to preserve human involvement or to maximise automation, but to determine where human contribution remains substantively valuable and where greater machine autonomy is responsible and advantageous.

Introduction

Artificial Intelligence has become a strategically relevant topic for the textile industry. Not because it promises disruption for its own sake, but because it intersects with structural pressures that established approaches can no longer address: demographic change, skills shortages, market volatility, and rising expectations regarding quality, transparency, and sustainability. The key question is no longer whether AI will matter, but how it can be integrated responsibly and effectively — and how decision-making responsibilities should be distributed between humans and AI as capabilities evolve.

This white paper is the result of a joint initiative between the International Textile Manufacturers Federation (ITMF) and the Institut für Textiltechnik of RWTH Aachen University (ITA). ITMF contributes its role as a global industry platform; ITA brings research-based expertise and methodological perspective. Together, both organisations connect academic insight with practical industry experience.

The paper builds on the webinar series *AI in the Textile Value Chain* (2024–2026) [1], which brought together experts from industry, academia and policy to discuss technological foundations, practical applications, and regulatory implications. These perspectives were complemented by the World Café session *Strike First – AI Advantage in Textiles & Apparel* at the ITMF & IAF Conference 2025 in Yogyakarta [2], where practitioners, researchers, and industry representatives reflected collectively on current experiences, challenges, and future expectations.

Its purpose is to clarify where AI already creates value, where its limits remain, and which organisational, technical, and governance conditions shape meaningful adoption. It also examines how AI may redistribute cognitive tasks and decision responsibilities within textile organisations. Throughout, AI is treated neither as a threat nor as a panacea, but as a capability whose role may range from decision support and partial task delegation to autonomous action. Its value depends on coherence between technology, people, data, and governance, and on matching the level of machine autonomy and human involvement to the characteristics and risks of each application.

In the current transition phase, human expertise remains important for guidance, contextual interpretation, exception handling, and accountability. Whether substantive human involvement will remain necessary at all organisational levels in the long term is an open question that this paper does not claim to resolve.

Thank you to all our speakers!

We extend our sincere thanks to the following individuals for sharing their knowledge and insights in the webinar series:

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- Mr. Volkan Seyok, Karsu Textile, Türkiye
- Mr. Jonas Wand, Foursource, Germany
- Mr. Friedrich Weninger, MIR Insight, Norway
- Mr. Kai Zenner, European Parliament

All presentations and webinar recordings are available for ITMF members at: <https://www.itmf.org/virtual-forum> [1]

1 – Structural Pressures Driving AI Adoption in the Textile Industry

Discussions about Artificial Intelligence in the textile industry often focus on technology, while the more decisive forces shaping the sector are structural. This chapter asks **why AI has become unavoidable** for the textile industry, regardless of what AI itself can do.

1.1 Structural Pressures on the Textile Industry

The textile industry is undergoing structural pressure that extends beyond cyclical market fluctuations. Long-term demographic trends, intensifying global competition, and rising expectations around sustainability and responsiveness are reshaping operating conditions across regions and value-chain segments (Figure 1).

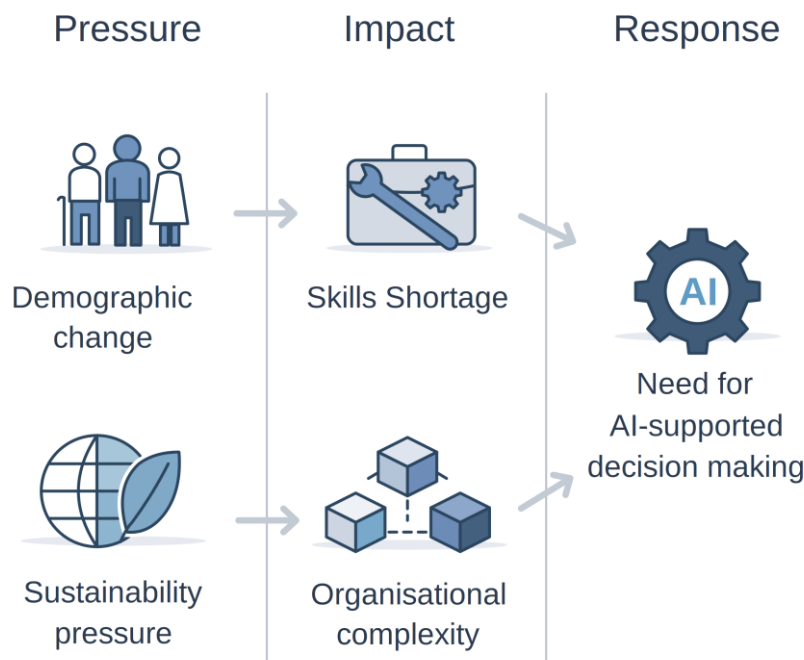


Figure 1: Structural pressures, organisational impacts, and the resulting need for AI-supported decision-making in the textile industry

In many OECD countries, population ageing and declining fertility are reducing the working-age population, putting pressure on labour supply [3]. Entry rates into technical and engineering professions are insufficient to offset retirement and attrition — affecting shop-floor labour, engineering, management, and specialist roles alike. The EU textile and clothing industry faces an ageing workforce alongside declining graduate numbers in relevant manufacturing disciplines. The share of employees over 50 rose from 29.3% in 2014 to 44.8% in 2024, while the number of bachelor's and master's graduates in textile, clothing, leather and footwear manufacturing and processing programmes fell from 3,851 in 2013 to

1,686 in 2024 [4, p. 13]. These trends suggest increasing challenges in workforce renewal. Career-attractiveness challenges compound demographic pressures. The TCLF Skills Alliance reports limited interest in manufacturing careers among digitally skilled young labour-market entrants [5, p. 2]. This suggests that workforce renewal is constrained by both demographic change and difficulties attracting talent. The constraint is therefore both demographic and structural in terms of talent attraction.

Competitive pressure intensifies in parallel. Textile value chains operate in a context of weak demand, geopolitical tension, and cost pressure [4], [6]. Margins remain thin [7] while requirements for quality, traceability, and flexibility rise. Traditional productivity gains through scale, relocation, or incremental automation are no longer sufficient [7, pp. 18–19].

1.2 Limits of Traditional Digitalisation Approaches

Decades of investment in automation, enterprise software, and data collection have improved efficiency — but show clear limits under current conditions:

- **Siloed initiatives.** Data is collected but not systematically integrated. Information is available, yet decisions are still made in silos.
- **Repetitive-task focus.** Conventional automation does not address the scarcity of qualified personnel in planning, quality, engineering, sales, and coordination.
- **Added complexity.** Digital tools that require expert configuration and maintenance can exacerbate skills shortages rather than alleviate them, particularly in SMEs.

1.3 Artificial Intelligence as a Response to Structural Constraints

Unlike rule-based automation (see Chapter 3), AI systems can process heterogeneous data, recognise patterns, and support decision-making under uncertainty — exactly the conditions that define textile value chains. AI augments human capabilities by:

- reducing cognitive load from repetitive analysis and documentation,
- supporting consistent decisions in quality and planning,
- preserving and scaling expert knowledge,
- enabling faster response to changing market and production conditions.

In the current transition phase, AI is most plausibly understood as a complement to human expertise. Human involvement remains important for defining objectives, interpreting context, handling exceptions, aligning outputs with organisational priorities, and accepting accountability. This should not, however, be interpreted as a permanent division of labour between humans and machines. As AI capabilities develop, routine cognitive tasks and bounded operational

decisions may increasingly be delegated to AI systems, while human roles shift toward supervision, orchestration, governance, and intervention.

The long-term allocation of decision-making between humans and AI remains uncertain. Within hierarchical organisations, one possible development is that strategic decision rights become concentrated at senior levels while AI agents perform a growing share of lower-level analytical and coordination tasks. Operational employees may increasingly act as orchestrators of interconnected systems rather than executing each task themselves. However, it remains open whether substantive human decision-making will continue to be necessary at the strategic level and whether human orchestration will remain necessary in operations. The answer will depend not only on technical capability, but also on risk, regulation, trust, accountability, organisational design, and the value placed on human agency.

1.4 Workforce, Skills, and Attractiveness

Skills shortages extend beyond production labour to digital capabilities [5, p. 2]. The industry also struggles to attract younger talent, as manufacturing and shop-floor occupations in particular are perceived as unattractive from a career perspective [5, p. 3]. **Skills shortages also extend to tacit process knowledge** — the operator-level experience of how a machine actually behaves under specific conditions, which retires with experienced staff and is rarely captured in formal documentation [8]. This dimension is increasingly visible across process-heavy segments, where set-point adjustments still depend on operator intuition.

AI-supported tools can improve working conditions by reducing monotonous tasks, enabling hybrid work models, supporting knowledge transfer, and increasing decision transparency. These benefits are not automatic.

Without deliberate design, habitual reliance on AI outputs may reduce engagement in critical thinking [9] and create a risk of skill decay [10]. Participation, transparency, and training are therefore prerequisites for sustainable adoption. Organisations should also recognise that employees and society may value meaningful human agency even where a more automated system would appear more efficient. The appropriate balance between efficiency and human involvement is therefore not purely a technical question.

1.5 The Risk of Inaction

Companies that fail to address labour scarcity, decision complexity, and data fragmentation risk a gradual erosion of competitiveness rather than abrupt disruption. AI adoption in the textile industry is therefore less about first-mover advantage than about **avoiding long-term disadvantage**.

Summary

The growing relevance of AI in the textile industry is driven by structural pressures rather than technological enthusiasm: demographic decline, persistent skills shortages, and rising complexity across global value chains. Earlier digitalisation efforts have delivered efficiency gains but have not resolved the scarcity of qualified personnel or the fragmentation of decision processes — and in some cases have added complexity. Against this backdrop, AI represents a qualitatively different response, with the potential to augment human capabilities, improve decision quality, reduce cognitive burden, and increasingly perform bounded cognitive and operational tasks. During the present transition, human expertise remains necessary for guidance, alignment, exception handling, and accountability. The longer-term balance between augmentation, delegation, substitution, and human orchestration remains uncertain and will differ across organisational and operational contexts.

Key takeaway: AI is becoming relevant in the textile industry not because of technological hype, but because structural pressures such as labour scarcity, rising complexity, and global competition are making traditional approaches insufficient.

2 – Digitalisation in the Textile Industry: Progress and Fragmentation

Before assessing what AI can contribute, it is necessary to examine the industry's current digital foundations. The ILO identifies differences in the uptake of digital technologies across textiles according to company size, country, and value-chain segment [11, pp. 16–17, 24–25] — and AI builds on these foundations rather than replacing them.

2.1 Digitalisation as a Longstanding but Uneven Trajectory

Digitalisation is not a new phenomenon in the textile industry. Over several decades, companies have introduced automation technologies, ERP systems, and digital monitoring tools to improve efficiency, quality, and cost control. These efforts have delivered tangible benefits, particularly in standardised, high-volume processes.

Progress has, however, been uneven. Capital-intensive production steps such as spinning, weaving, and finishing generally show higher automation levels than labour-intensive garment assembly [12, pp. 8–9], [13]. Large enterprises and global suppliers often operate with advanced digital infrastructures, while SMEs frequently rely on partial or legacy systems. Across the economic activities covered by Eurostat's enterprise ICT survey in the EU in 2025, for example, 89% of large enterprises used ERP software against 41% of small enterprises [14], and 55% of large versus 17% of small enterprises used at least one AI technology [15]. As a result, the textile industry cannot be described as digitally immature — but neither can it be considered digitally integrated. **These differences suggest that digitalisation can exist in fragments rather than as a coherent, end-to-end transformation.**

2.2 Fragmentation of Systems and Decision-Making

A defining characteristic of digitalisation in textiles is fragmentation. Data is generated across machines, quality systems, logistics platforms, and enterprise software, yet these streams are rarely fully interoperable (Figure 2).

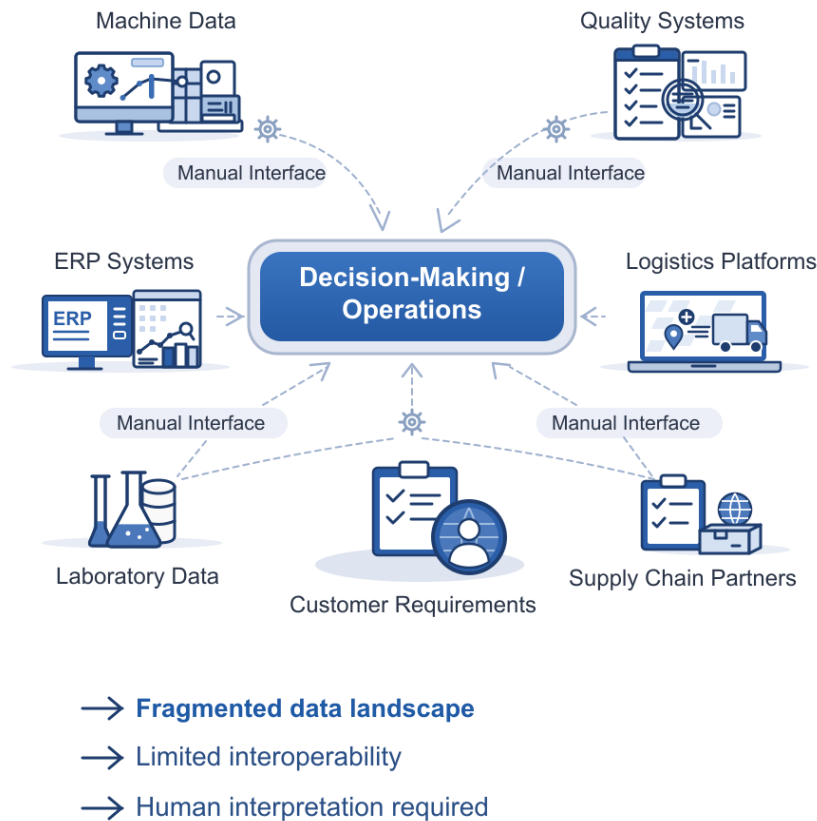


Figure 2: Fragmented digital system landscape in the textile industry: data is generated across multiple systems but rarely integrated into coherent decision support

This fragmentation has several consequences:

- Decision-making remains distributed across organisational silos.
- Information is duplicated, manually transferred, or reinterpreted.
- Opportunities for cross-functional optimisation remain limited.

In many cases, digital systems are used primarily for documentation and reporting rather than for active decision support. Data is collected after the fact, not integrated in real time — limiting the industry's ability to respond to demand variability, quality deviations, or supply-chain disruptions.

2.3 Focus on Physical Automation and Its Limits

Traditional digitalisation in textiles has focused largely on automating physical processes. Robotics, control systems, and sensor-based monitoring have improved productivity and consistency in production, and these advances continue to deliver value.

But a growing share of organisational workload lies outside purely physical processes. Planning, quality assurance, compliance, coordination, and customer interaction involve complex judgement, interpretation, and communication. These activities are labour-intensive and increasingly constrained by skills shortages, and conventional automation provides limited support for them: rule-based

systems struggle with variability and exceptions, while human experts are required to bridge gaps between data sources, systems, and organisational units.

2.4 Digital Complexity and Skills Constraints

As digital systems proliferate, complexity increases. Many textile companies operate heterogeneous landscapes of machines, software tools, and interfaces, and maintaining them requires specialised expertise that is often scarce.

This creates a paradox: **digitalisation intended to increase efficiency can become a source of inefficiency** when systems are difficult to integrate, maintain, or interpret. Smaller organisations may be particularly affected, as they are less likely to employ ICT specialists [16]. The skills challenge is not limited to operating digital tools, but extends to understanding data, managing interfaces, and translating digital outputs into actionable decisions.

A frequently underappreciated dimension is the **gap between data that companies believe is structured and data that is structured in a usable sense**. A tech pack that specifies “fabric as original” or “sample as original” may sit neatly inside a document management system, yet contain none of the parameters required for automated processing [17]. Finished garments are the sum of yarn, components, fabric, and process treatments; only when the full chain is documented at that level does a company genuinely hold structured data. Most companies are not yet there, and this hidden delta is the practical obstacle most organisations encounter when assessing AI readiness.

2.5 Positioning Artificial Intelligence Within the Digital Landscape

AI is neither a clean break from existing digitalisation nor a simple extension of current automation. It occupies a specific position within an already complex digital landscape.

AI builds on existing digital foundations: **data availability, sensor infrastructure, and enterprise systems are prerequisites**. At the same time, AI introduces new capabilities — pattern recognition, probabilistic reasoning, and adaptive decision support across fragmented data environments (see Chapter 3 for definitions). Where digital foundations are weak or fragmented, AI deployment is constrained. Where digital maturity is higher, AI can act as a connective layer that reduces fragmentation and enables more integrated decision processes — ranging from improved human decision support to the bounded delegation or automation of specific tasks.

2.6 Data Spaces and Cross-Company Exchange

The fragmentation described above is not only internal to companies but extends across the value chain. Decisions about sustainability, Scope 3 emissions [18],

traceability, and quality often require data held by different organisations, which may not be exchanged through interoperable channels.

Two broad models address this. The traditional approach is **platform-based**, with a central operator mediating data flows between participants. This can deliver integration but create dependency: the platform operator can control the rules of access and data exchange. The alternative model, known as **data spaces**, does not require central storage of the data and leaves control over its use with the data provider (data sovereignty). Participants exchange data directly under shared governance, supported by common services (identity, security, data-model standards) provided by trusted intermediaries rather than by a single dominant platform [19].

The **Digital Product Passport (DPP)** [20] and the related **Asset Administration Shell** [21] can provide a common reference for product information across such exchanges. They can allow authorised actors along the value chain to attach quality, sustainability, and process information to a product, raw material, or component in an interoperable form, subject to defined access rights. Projects such as OKEANOS [22] in Germany aim to show how this infrastructure can be assembled in practice.

Data spaces may be particularly relevant to the EU textile and clothing industry, where micro, small, and medium enterprises account for 99.7% of companies [4, p. 10]. Governance, interoperability standards, and decentralised ownership of data align well with that structure. Without such infrastructure, end-to-end use cases — Scope 3 reporting, lifecycle traceability, integrated quality data — remain difficult to scale.

Summary

Digitalisation in the textile industry is **neither absent nor complete**, but characterised by fragmentation, uneven maturity, and growing complexity. Earlier waves of investment have optimised individual processes — particularly physical production — while leaving coordination-intensive and knowledge-based activities only partially supported. Data is abundant, yet decision processes remain siloed and slow. AI does not emerge in a digital vacuum, nor does it remove the need for robust digital foundations; its potential lies in addressing fragmentation and variability, reducing the burden placed on scarce human expertise, and enabling the gradual redistribution of analytical, coordination, and operational tasks between humans and AI systems.

Key takeaway: The textile industry is not under-digitalised, but digitally fragmented. AI only creates real value when data, systems, and skills are connected well enough to turn isolated digital activity into scalable end-to-end improvement.

3 – What is Artificial Intelligence?

What distinguishes AI from earlier digital technologies, and why does that distinction matter for the textile value chain?

3.1 Artificial Intelligence Beyond Automation

Artificial Intelligence differs fundamentally from earlier generations of digital technologies used in the textile industry. While traditional automation relies on predefined rules and deterministic logic, AI systems infer outputs from inputs using approaches such as machine learning or knowledge-based reasoning [23], [24]. Figure 3 contrasts both approaches.

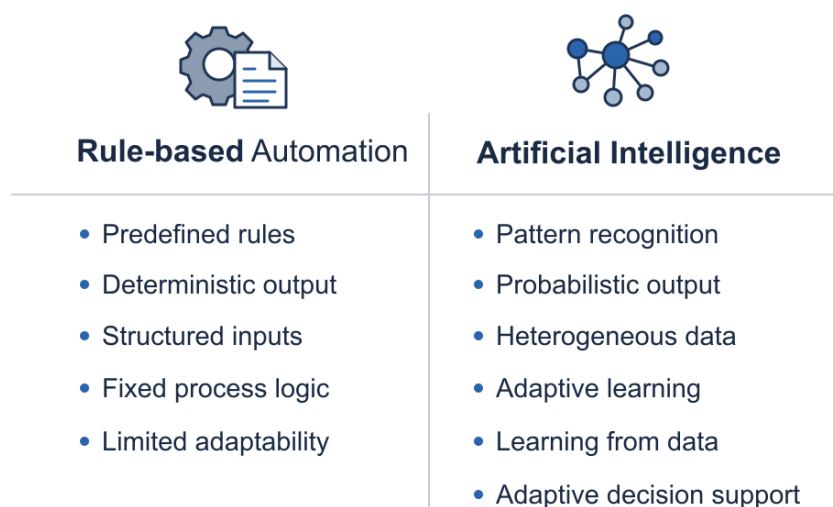


Figure 3: Artificial Intelligence beyond automation

This distinction is central to AI's relevance for textile value chains. Many operational and managerial challenges are characterised by variability, incomplete information, and trade-offs between competing objectives — conditions that limit rule-based systems but align with AI-based approaches. AI is therefore best understood not as an extension of mechanical automation, but as a complementary capability for decision-making in complex, dynamic environments.

3.2 Forms of AI Relevant to the Textile Industry

AI in the textile industry appears in several distinct but related forms. A useful taxonomy distinguishes them by the kind of judgement they support (Figure 4):

- **Discriminative AI** — recognises and classifies. Machine-learning models for prediction and demand forecasting; computer vision for fabric and yarn inspection, defect detection, and visual classification.

- **Generative AI** — produces new content [23]. Language models for documentation, knowledge retrieval, internal assistants; image and design models for marketing and early-stage product development.
- **Assistive AI** — observes a process and prompts a human action. AI-supported decision support that flags anomalies, surfaces relevant information, and proposes interventions for human approval.
- **Prescriptive AI** — recommends specific actions and set-points [25]. Optimisation and decision-support systems for planning, scheduling, resource allocation, and production tuning, including **causal AI** approaches that move from prediction to intervention by modelling cause-and-effect rather than correlation [26].
- **Agentic AI** — executes multi-step workflows toward a defined goal [27]. Multiple specialised agents can be orchestrated to deliver an end-to-end outcome with a defined degree of human supervision (e.g. across sourcing, RFQ, supplier qualification, order follow-up).
- **Autonomous AI** — controls a process directly. Fully closed-loop operation in which the system itself adjusts parameters in real time without human intervention.

These families are not mutually exclusive: most industrial deployments combine several, embedded in existing digital infrastructures and workflows. The relevant question is rarely “which one” but “which combination, for which task, under which level of human oversight.”



Figure 4: Main forms of Artificial Intelligence currently applied in the textile industry

3.3 Human–AI Decision-Making: A Transition with an Open Endpoint

AI can improve decision-making without implying that humans must always make every decision. The apparent tension between “AI supports decision-making” and “AI does not replace human decision-making” arises partly because decision-making is often treated as a single activity. In practice, it consists of several functions: defining objectives, gathering and interpreting information, generating options, predicting consequences, evaluating trade-offs, selecting an action, executing it, monitoring the outcome, and accepting responsibility [28].

These functions can be distributed differently between humans and AI systems. AI may provide information for a human decision, recommend an action, execute a decision within predefined boundaries, or control a bounded process autonomously [27], [28]. The appropriate allocation depends on the task, the consequences of failure, the reversibility of the decision, the maturity of the system, and the organisational and regulatory context.

In the current transition phase, human expertise remains important for setting objectives, providing contextual guidance, handling exceptions, aligning outputs with organisational priorities, and ensuring accountability. This should not, however, be interpreted as a permanent or universal division of labour. As AI systems become more capable, routine cognitive and operational tasks may increasingly be delegated to AI agents. Human roles may consequently shift toward supervision, orchestration, governance, and intervention.

The long-term endpoint remains uncertain. Within hierarchical organisations, one possible development is that strategic decision rights become concentrated at senior levels while AI agents perform a growing share of lower-level analysis, coordination, and execution. Humans remaining in operational roles may act primarily as orchestrators of interconnected systems. However, it is not yet clear whether substantive human decision-making will remain necessary at the strategic level or whether human orchestration will remain necessary in operations.

These questions will not be determined by technical capability alone. Trust, acceptance, regulation, accountability, organisational design, and the value placed on human agency will influence how far autonomy develops. Organisations and societies may sometimes prefer a less efficient arrangement that preserves meaningful human participation. The relevant trade-off is therefore not simply between human and machine performance, but between efficiency, resilience, accountability, legitimacy, and human agency.

3.4 Data as a Prerequisite and Constraint

AI systems depend on data availability, quality, and structure. In textiles, data is generated across machines, laboratories, enterprise systems, and supply-chain

interfaces — but is frequently fragmented, inconsistently formatted, and difficult to integrate. Figure 5 shows a simplified architecture of AI-enabled decision support.

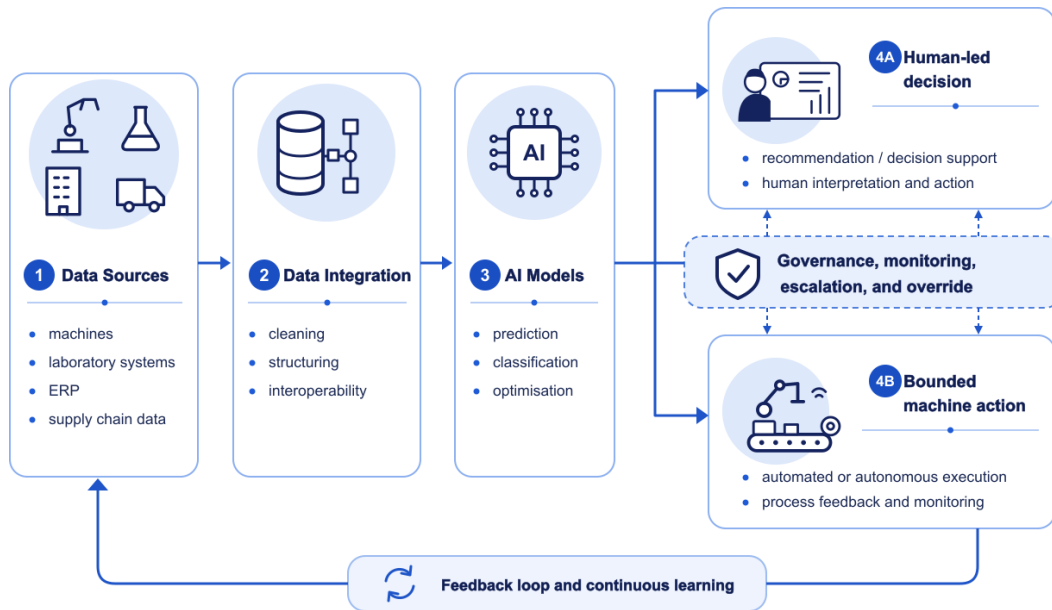


Figure 5: Simplified architecture of AI-enabled decision support in industrial environments

The effectiveness of AI is therefore constrained not by algorithms alone, but by the underlying data landscape. Poor data quality limits model performance [29]; lack of interoperability restricts the scope of AI applications. Data preparation, governance, and integration are not peripheral activities but **core enablers** of AI use. Without sustained investment in these areas, AI remains confined to isolated pilots rather than scalable solutions.

3.5 Infrastructure and Deployment Choices

AI deployment involves strategic choices regarding infrastructure: cloud-based services, on-premise systems, or hybrid approaches. Each option entails trade-offs between scalability, cost, control, and data sovereignty.

In industrial contexts — particularly where sensitive production data and intellectual property are involved — concerns about data protection play a decisive role. On-premise or locally operated AI systems are increasingly considered viable, especially for bounded applications such as internal knowledge systems or production monitoring. These choices influence not only technical performance but also organisational trust, regulatory compliance, and long-term flexibility.

A practical pattern increasingly visible in industrial deployments is the use of **locally hosted, compressed language models** as an alternative to cloud-based foundation models. Large language models can be distilled and quantised into smaller footprints that may enable deployment on factory servers [30] — exchanging some general capability for local control over data and independence

from external providers [31], [32]. Connected via standardised interfaces such as the Model Context Protocol (MCP) [33] to existing process and energy databases, these local models can translate natural-language questions into queries against trusted plant data without exposing that data to external providers, provided inference and data processing remain local. The same pattern underlies the “sector-specific AI tool” or “Textile GPT” idea discussed in Chapter 5: a controlled environment that consolidates trusted knowledge while respecting data sovereignty.

3.6 Explainability, Transparency, and Trust

Trust in AI systems depends on more than accuracy. Users must understand, at a functional level, how outputs are generated and what their limitations are [34, Sec. 3.5] — particularly in production and quality-related applications, where errors can have direct operational and financial consequences. Explainability does not necessarily imply full transparency of internal model mechanics; practical explainability can include [35]:

- showing which inputs influenced an output,
- providing visual or contextual cues,
- documenting model scope and limitations.

Explainability is also important for preserving human critical thinking. As users become accustomed to AI-generated recommendations, there is a risk that outputs are accepted routinely rather than evaluated independently [24, Art. 14(4)(b)], [28]. Over time, this may weaken the expertise required to recognise errors, challenge assumptions, or intervene when the system operates outside its intended scope [10], [28]. Human oversight is therefore meaningful only when users retain sufficient knowledge, information, time, and authority to question or override the system.

3.7 Governance and Responsibility

As AI systems move closer to core decision processes, governance becomes central. It encompasses:

- definition of permissible use cases,
- access control and authorisation,
- monitoring of system performance,
- procedures for escalation and override.

Under the EU AI Act, obligations concerning AI systems are assigned to providers, deployers, and other human or organisational actors [24, Art. 14(4)(b)]. This does not necessarily mean that a human must substantively make or approve every operational decision. Accountability, operational control, and decision execution should be distinguished: an AI system may execute decisions autonomously within a defined scope, while responsibility for its objectives,

permitted actions, monitoring, and consequences remains assigned through managerial and legal structures. Effective governance therefore integrates AI into existing management and compliance structures rather than treating it as a standalone technical issue.

Summary

AI is a distinct form of digital capability — fundamentally different from the rule-based automation and information systems that shaped earlier waves of digitalisation. Its defining feature is not mechanical efficiency, but the ability to operate under uncertainty, process heterogeneous data, and support decisions. Its value lies not in one fixed relationship to human judgement, but in how it redistributes the different components of decision-making across people and machines. In the current transition phase, AI most often supports human judgement or operates autonomously within bounded contexts. Over time, the balance may shift toward greater delegation and autonomous execution, while human roles increasingly involve objective-setting, orchestration, governance, and exception handling. The long-term need for substantive human involvement remains uncertain.

Key takeaway: AI is not just another step in automation, but a distinct capability for working with uncertainty, complexity, and heterogeneous data. Its role may range from supporting human judgement to executing decisions autonomously. During the current transition, human expertise remains important for guidance, alignment, exception handling, and accountability, but the long-term distribution of decision-making between humans and AI remains open.

4 – Artificial Intelligence in Practice: Insights from the Webinar Series

This chapter draws on the webinar series *AI in the Textile Value Chain* to examine how the concepts of the preceding chapters translate into practice — which AI applications have gained traction along the value chain, and where tensions remain. Figure 6 gives an overview of the applications discussed.

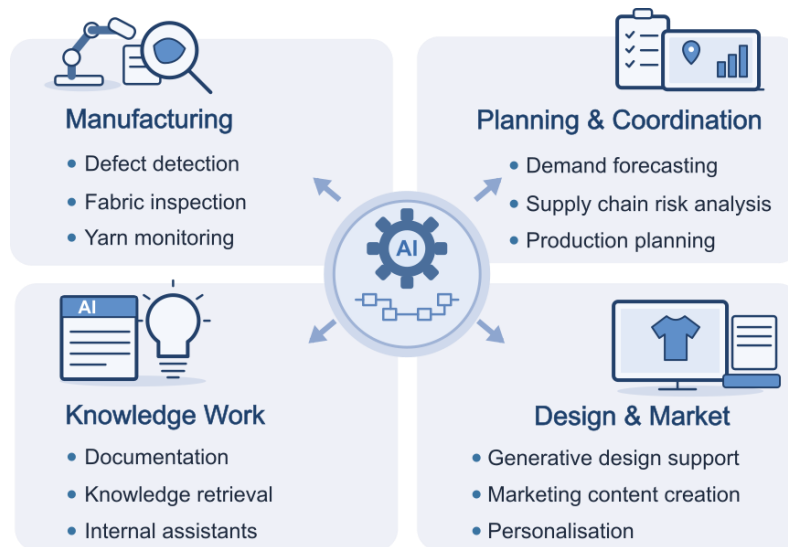


Figure 6: AI applications emerging from the webinar series

4.1 AI as a Strategic Response to Industry Transformation

Across the webinar series, AI is consistently framed as a response to structural transformation rather than as an isolated technological innovation. Speakers emphasise demographic change, skills shortages, and increasing volatility as underlying drivers. From a broader conceptual perspective, AI is positioned within broader frameworks of industrial transformation and Work 4.0 [36], [37]. From an industry perspective, it is discussed as a pragmatic tool to stabilise operations, manage complexity, and maintain competitiveness under constrained conditions.

4.2 Data, Infrastructure, and Integration as Enablers

A central theme across multiple webinars is the **primacy of data**. AI systems rely on data that is accurate, timely, and sufficiently integrated across organisational boundaries. Speakers repeatedly highlight that algorithmic sophistication is secondary to data availability and quality.

Common challenges include fragmented data sources across machines and systems, inconsistent data standards, and limited interoperability along the value chain. Without sustained investment in data infrastructure and governance, AI initiatives remain confined to pilots and fail to scale.

The infrastructure dimension was developed in depth by FOREST and OKEANOS, presented by Dr. Florian Pohlmeier (ITA, RWTH Aachen) [38].

The presentation framed data management as effectively “step zero” — the prerequisite layer that sits below the AI maturity ladder. Two complementary axes were illustrated: at the process level, the FOREST project [39] applies real-time data integration and simulation to energy optimisation in paper production, combining machine data with electricity-market signals [38]; for the demonstrator line, the presentation estimated a savings potential of about €780,000 and 360 t CO₂eq per year [38]. At the value-chain level, the OKEANOS project [22] aims to show how **data spaces** enable cross-company data exchange under shared governance, without a central platform owner. The Digital Product Passport, which can be implemented using Asset Administration Shell standards [21], can act as a common reference for product information across the chain. The takeaway is that AI use cases — particularly those tied to sustainability, Scope 3 reporting, or traceability — depend on infrastructure that no individual company can build alone.

4.3 High-Impact Manufacturing Use Cases

The webinars provide concrete evidence of AI's impact in manufacturing environments, particularly in quality-related applications. Computer-vision systems for fabric and yarn inspection are presented as mature use cases with measurable operational benefits. Successful applications share three characteristics: real-time operation integrated into production flows, explainable outputs that allow human validation, and direct linkage between detected defects and corrective actions.

Illustrative practice from the webinar series. Uster Technologies presented computer-vision-based inspection systems used to identify fabric defects during production, emphasising consistent quality assessment and operator-oriented feedback [40]. Smartex discussed AI-enabled quality monitoring solutions integrated directly into textile manufacturing lines, focusing on early detection of anomalies and reduction of waste through preventive intervention [41]. ARTIFEYE Technologies, together with Karsu Textile, illustrated how AI-based yarn defect detection can be deployed in an operational production environment, highlighting the role of visual explainability in supporting quality decisions on the shop floor [42].

CarboScreen, presented by Dr. Musa Akdere [43], extended the sensor-based monitoring case to high-value, low-volume processes. Originally developed for carbon fibre — where defects are costly, manual inspection is the bottleneck, and stabilisation incidents drive significant downtime — the CarboScan optical sensor system performs three-layer analysis (identification, classification, quantification) of process anomalies. The presentation framed AI-supported monitoring as a journey from a “digital blind” starting point through four digitalisation levels: Digital See, Digital Act, Digital Decide, and Digital Control. The same approach has begun to extend to general textile processes, including weaving, textile printing, and textile sorting in recycling — illustrating how **sensor-**

plus-AI architectures developed for one demanding context can generalise across the value chain.

Konzek Teknoloji, presented by Mr. Serhat Duman [32], illustrated platform-level integration of MES, energy management, and AI. The Retmes platform combines three native layers — a manufacturing execution system, a power management system that links energy consumption directly to output units (per SKU, per metre, per ton), and an AI layer offering predictive maintenance, anomaly detection, and natural-language analytics. A distinctive architectural choice is that the natural-language layer runs **locally** — compressed open and frontier models hosted on factory servers, connected to plant data through a structured-query bridge so that prompts never leave the customer's environment. The presentation emphasised that data acquisition from closed legacy machinery typically requires hybrid methods (direct PLC integration where possible, retrofit sensors where not, and computer vision on operator screens as a second option) — a pragmatic observation that applies far beyond a single vendor.

4.4 Decision Support Beyond the Shop Floor

Beyond production, the webinar series highlights AI's growing role in decision support functions such as planning, sales, and supply-chain coordination. Predictive analytics, demand forecasting, and risk assessment tools are discussed as means to cope with market volatility and uncertainty. Speakers emphasise that these applications support human judgement by structuring information rather than automating decisions outright — particularly in situations where historical patterns are no longer reliable predictors.

An illustrative example was provided by MIR Insight, which presented AI-based approaches to identifying and forecasting market risk factors relevant to textile value chains [44]. The focus was on combining heterogeneous data sources to support scenario-based planning and risk awareness, with AI used to surface patterns and signals rather than to prescribe decisions.

4.5 Generative AI and Knowledge-Based Work

Other webinars introduce generative AI and language-based models as tools for knowledge-intensive activities — automated documentation, internal knowledge retrieval, and support for design and marketing. These applications address a growing share of work that is administrative, communicative, and interpretive in nature. Speakers caution that generative AI requires careful governance to ensure reliability, traceability, and appropriate use of proprietary data.

Three presentations addressed generative AI in design and marketing. OMNIOUS.AI discussed the use of generative AI to support fashion content creation and go-to-market processes [45], focusing on accelerating content generation while retaining human control. z-emotion addressed the application of AI in fashion design contexts [46], emphasising creative support rather than

automated design. Eekual presented perspectives on re-imagining value chains and personalisation [47], highlighting how AI-enabled tools can support new forms of interaction between design, production, and customers.

4.6 Agentic and Causal AI: Beyond Decision Support

A distinct development in recent webinar contributions is the move beyond stand-alone AI tools toward **multi-step workflows and intervention**. Two presentations illustrated different facets of this shift.

Foursource, presented by Mr. Jonas Wand [17], made the case for agentic AI in fashion sourcing. Sourcing is not a single activity but a chain of interlocking tasks — supplier discovery, RFQ preparation, sample tracking, pricing comparison, compliance, order follow-up — historically held together by email loops and manual reconciliation. The presentation outlined an architecture of specialised agents (supply chain agent, product agent, RFQ agent, order agent), each trained on a narrow task and orchestrated to deliver end-to-end coordination under human supervision. The strategic point was that AI value in fragmented value chains comes less from “smarter models” than from **bringing AI into the actual processes of the industry**, with each agent mirroring an existing role in brand or supplier teams. Practical limits were named with equal honesty: AI cannot yet fix bad data or legacy systems, accountability for agent-mediated decisions remains unresolved, and cultural adoption is at least as binding a constraint as technical capability.

Vernaio, presented by Dr. Christian Paleani [8], illustrated causal AI for production-floor optimisation. Unlike correlation-based models, causal approaches learn cause-and-effect relationships from historical process data and use them to recommend or directly execute set-point changes in live operations. In a referenced deployment on a non-woven production line in the DACH region, the system reduced scrap by 10% by guiding operators through real-time set-point adjustments calibrated against multiple quality KPIs simultaneously. The presentation emphasised that **the move from prediction to intervention** — knowing what to do in a given situation, not just what is likely to happen — is the capability that classical AI tools have generally lacked. Causal methods are still earlier on the hype cycle than generative AI or AI agents [48], but, according to the presenter, already in operation in other process industries [8].

Together, these contributions illustrate that AI in the textile value chain is no longer limited to discrete decision support. It is beginning to **execute multi-step coordination** (agentic) and to **act on processes directly** (causal / autonomous), in both cases under human supervision and within bounded operational scope.

4.7 Organisational Readiness and Skills

Organisational readiness emerges as a decisive factor across the series. Technical feasibility alone does not guarantee successful AI adoption — skills,

culture, and management commitment shape whether AI tools are trusted and effectively integrated into daily work. Several speakers stress the importance of participatory implementation, transparency about system limitations, and continuous training and upskilling.

From an industry perspective, Oerlikon Man-made Fibres illustrated this point by discussing AI from a sales and value-creation viewpoint [49]. The presentation emphasised alignment between AI-supported tools, existing processes, and customer interaction, underlining that organisational capabilities and internal readiness are prerequisites for realising value from AI initiatives.

4.8 Regulation, Trust, and External Constraints

Regulatory developments, particularly the EU AI Act [24], form an important contextual layer. Speakers acknowledge regulation as both a trust-building mechanism and a source of uncertainty. Concerns include blurry boundaries of the high-risk categories, compliance burden for SMEs, and evolving standards and enforcement practices [50], [51]. At the same time, regulation reinforces the need for explainable, well-governed AI systems aligned with societal expectations rather than treated solely as a constraint.

4.9 Cross-Cutting Observations from the Webinar Series

Taken together, the webinar series reveals several cross-cutting observations:

- AI adoption is pragmatic and incremental rather than radical.
- Data and skills are more limiting than algorithms.
- High-value use cases already exist, particularly in quality management and energy optimisation.
- The AI landscape is fragmenting into multiple families — discriminative, generative, assistive, prescriptive (including causal), agentic, autonomous — with very different maturity levels and governance needs.
- Trust, governance, and regulation shape adoption trajectories as much as technical performance.
- Cultural adoption is at least as binding a constraint as technical readiness; one platform provider estimated that fully AI-driven end-to-end sourcing on its own platform is about two to three years away [17].

Summary

The webinar series presents AI as a **pragmatic response to concrete operational and organisational challenges** rather than as a disruptive force. AI delivers its greatest value where it addresses specific pain points — quality variability, decision uncertainty, administrative burden, knowledge fragmentation, and energy or process-set-point optimisation under tight quality constraints — particularly when embedded into existing workflows and designed to support rather than replace human expertise. Where digital foundations, skills, and trust

are strong, AI can act as a stabilising and connective layer; where they are weak, AI remains confined to pilot projects.

Key takeaway: The webinar evidence shows that AI in the textile industry is already moving from concept to practice, but in selective, use-case-driven ways rather than through broad transformation. Real value emerges where companies apply AI to concrete problems and combine it with data readiness, organisational learning, and human oversight.

5 – Industry Perspectives on AI: Insights from the World Café 2025

While the webinar series captures expert perspectives and validated AI applications, it reflects only part of the broader industry reality. The World Café 2025 at the ITMF & IAF Conference in Yogyakarta [2], [52] brought together practitioners, managers, researchers, and association representatives to discuss their experiences with AI — less formal inputs, but very revealing too.

Critical views on AI must be read in context: some reflect experience with earlier models whose performance was still weaker, especially in reasoning-intensive tasks. Part of the scepticism expressed may therefore relate less to AI in principle than to the quality of tools available at the time. This chapter addresses two questions: **what AI has already changed in organisations, operations, and decision-making**, and **what the textile industry must do by 2030** to make AI a useful and trusted technology.

5.1 What AI Has Already Changed in Practice

Participants report that AI has already influenced daily work in several areas of the textile value chain, although adoption remains uneven [52].



Figure 7: Where AI already changes work

Most visible changes occur in the following areas (Figure 7):

- data analysis and reporting,
- demand forecasting and planning,

- administrative and documentation tasks,
- early-stage design and development support.

In these areas, AI functions primarily as an assistant that accelerates existing workflows rather than redefining them. Adoption in core manufacturing processes remains more selective. Where AI is deployed on the shop floor, it is typically focused on **quality inspection**, **defect detection** [52], and **predictive maintenance** — applications valued for their concreteness, explainability, and measurable impact.

5.2 Human–AI Collaboration and Decision-Making

A consistent theme is the emphasis on **human–AI collaboration**. Participants describe AI as a co-pilot, a first-draft generator, or a support tool, with final responsibility and accountability remaining with humans [52]. AI outputs are reviewed, corrected, and contextualised before decisions are made or actions taken.

Reported efficiency gains are substantial in some tasks, particularly knowledge-based and administrative work. These gains depend on clear task definition, appropriate user training, and realistic expectations regarding AI limitations.

5.3 Data as Enabler and Bottleneck

Data quality and availability are identified as the most significant enablers and constraints of AI adoption [52]. Common challenges include fragmented data sources, inconsistent data structures, and limited interoperability between systems and organisations.

Participants emphasise that AI does not compensate for poor data; it **amplifies** existing data issues. Where data governance is weak, AI outputs are unreliable and trust erodes quickly. Data management is therefore widely viewed as a strategic task rather than a technical detail.

5.4 Explicit Red Lines and Conditions for Trust

The discussions surface several non-negotiable conditions for AI use in the industry [52]:

- strict control over access to sensitive business data,
- robust cybersecurity measures,
- transparency regarding AI system scope and limitations,
- preservation of human expertise and accountability.

Participants express concern that uncontrolled or opaque AI deployment could undermine trust among employees, partners, and customers — a trust that, once lost, is difficult to restore. Recent industrial deployments suggest that these conditions are technically achievable — but they require deliberate architectural choices rather than emerging by default.

5.5 Looking Toward 2030: Skills, Standards, and Collective Action

When discussing the future, participants converge on the view that AI's usefulness by 2030 will depend less on technological breakthroughs than on **collective readiness**. Key priorities include [52]:

- broad AI literacy across roles and hierarchy levels,
- modernisation of education and training systems,
- development of pragmatic data and interoperability standards,
- support mechanisms for SMEs navigating AI adoption and regulation.

Several participants stress that isolated company initiatives will not scale. Progress requires shared frameworks, pre-competitive collaboration, and active involvement of associations and research institutions.

5.6 Phased Roadmap and Emerging Concepts

The World Café discussions outline an implicit phased roadmap toward 2030 (Figure 8):

- **Short term:** experimentation, pilots, skills development.
- **Medium term:** broader adoption, partial standardisation, ecosystem building.
- **Long term:** industry-level solutions, shared learning, and harmonised governance.

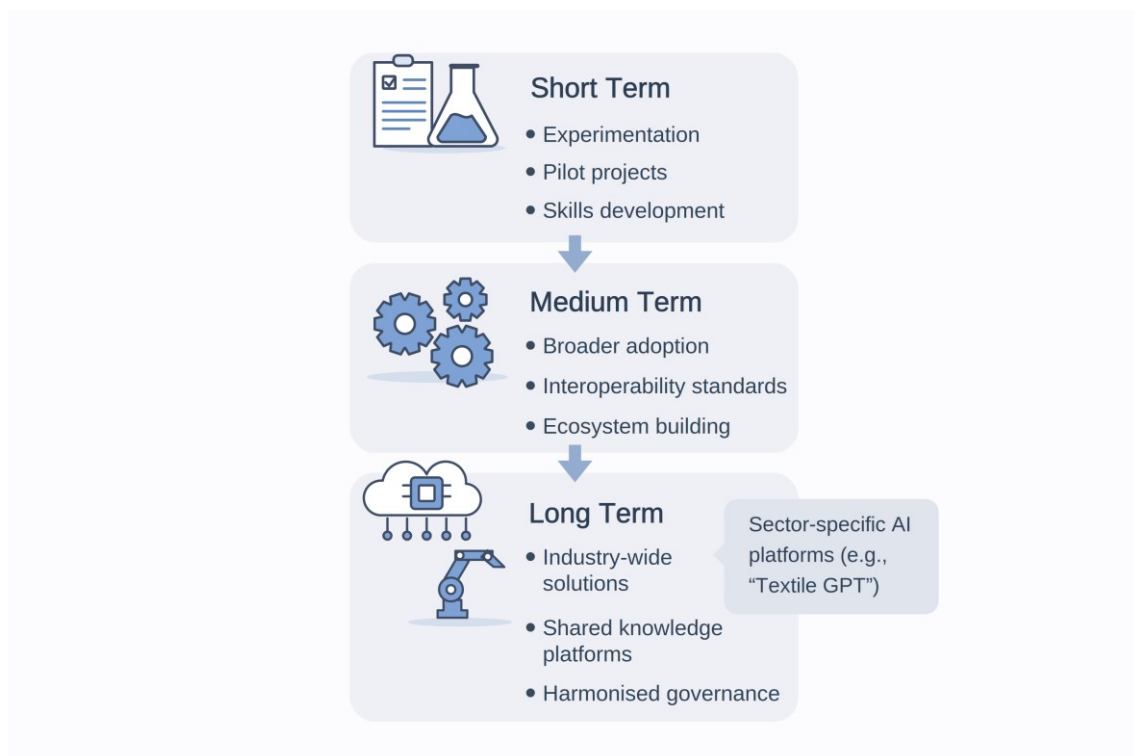


Figure 8: Industry perspectives on the phased development of AI adoption in the textile industry toward 2030

Within this context, the idea of sector-specific AI tools — such as a “Textile GPT” [52] — emerges as a concrete illustration of collaborative infrastructure: controlled environments that consolidate trusted knowledge while respecting data sovereignty.

Architectures emerging since the World Café give this idea concrete shape. Locally hosted language models compressed onto factory servers, connected to plant data through structured-query bridges (see Section 3.5), already operate in production environments [32] and satisfy the data-sovereignty conditions participants identified. Data-space initiatives such as OKEANOS (see Section 2.6) are developing the corresponding cross-company infrastructure for sustainability and traceability use cases. The “Textile GPT” referenced in the World Café discussions therefore appears less as a speculative vision and more as a near-term aggregation of architectures that already exist in adjacent sectors.

5.7 Sustainability and Economic Viability

Sustainability features prominently, but primarily through an economic lens. Participants highlight applications where AI could make sustainability measures viable at scale, including [52]:

- automated sorting and classification of post-consumer textiles,
- material identification and labelling,
- data-driven ESG analysis and resource planning.

The underlying assumption is pragmatic: sustainability gains will materialise where AI reduces cost, complexity, or waste sufficiently to align environmental goals with economic incentives.

Summary

The World Café 2025 reveals how AI is **experienced, interpreted, and questioned** across a broader cross-section of the industry, complementing the expert-driven webinar evidence. AI has already begun to shape daily work — particularly in data-intensive and administrative tasks — but adoption remains uneven and strongly dependent on organisational context, data maturity, and skills. Trust emerges as the decisive currency: participants articulate clear red lines around data access, cybersecurity, and accountability, and look toward 2030 with a focus on collective capability-building rather than rapid technological advancement.

Key takeaway: The World Café shows that the textile industry sees AI not as a fully autonomous force, but as a useful tool whose value depends on trust, data quality, and human oversight. Making AI truly relevant by 2030 will require collective action: not just individual pilots, but shared learning, clear guardrails, and stronger industry-wide capabilities.

6 – Recommendations

This chapter offers orientations for action, not definitive answers. AI adoption unfolds in diverse organisational contexts, under evolving regulatory conditions, and with an uncertain long-term division of responsibilities between humans and machines. The recommendations are therefore intentionally facilitative — designed to help organisations manage the transition while capabilities, roles, and expectations continue to evolve. Figure 9 summarises the key dimensions addressed in the following recommendations.

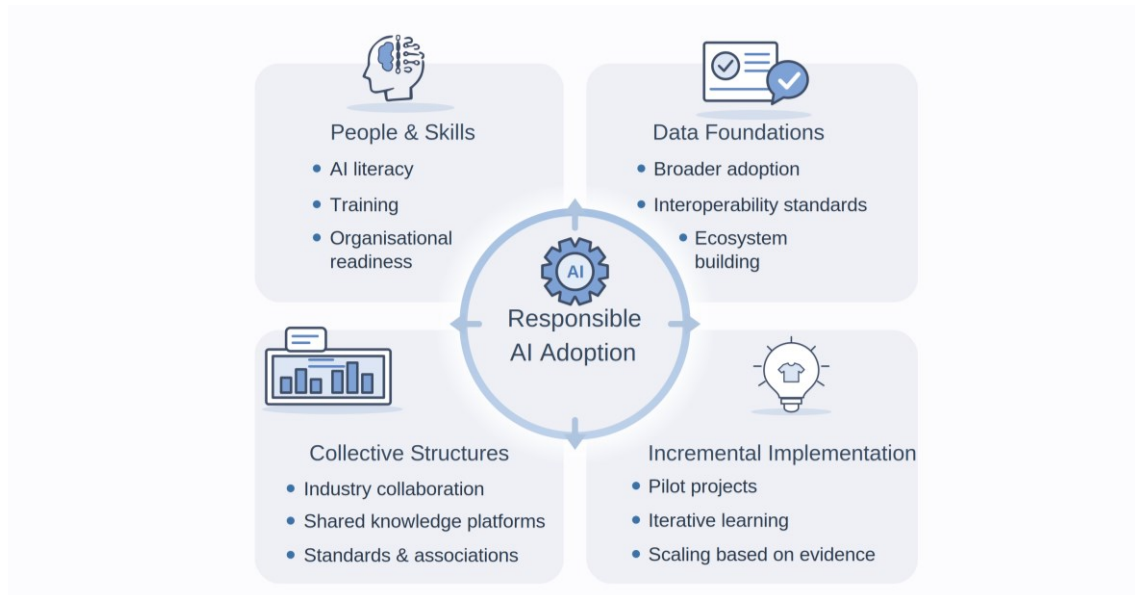


Figure 9: Key dimensions for responsible and sustainable AI adoption in the textile industry

6.1 Invest in People Before Scaling Technology

Skills and organisational readiness are the most critical success factors for AI adoption. A consistent recommendation is to:

- prioritise AI literacy across roles, not only among specialists,
- equip managers to understand AI outputs well enough to ask the right questions,
- support operators and staff in using AI as a tool.

Training should focus on understanding AI capabilities and limits, interpreting outputs and uncertainty, and maintaining responsibility and judgement. Without this foundation, technical investment risks remaining underutilised.

A related concern is the preservation of critical thinking. During the transition toward greater AI use, the risk is not only that systems make more decisions, but that human judgement may gradually atrophy if AI outputs are routinely accepted without challenge [9], [10]. Maintaining critical thinking is therefore not a soft cultural objective but an operational requirement: human oversight is meaningful only when people retain sufficient expertise, confidence, information, time, and

authority to question or override the system. Training and team design should be evaluated on this basis as well as on technical proficiency.

6.2 Treat Data as Shared Infrastructure, Not Exhaust

AI performance and trust depend fundamentally on data quality, structure, and governance. A key step forward is to:

- treat data as strategic infrastructure,
- invest in interoperability and standardisation,
- clarify data ownership, access rights, and responsibilities.

At the industry level, this implies supporting pragmatic standards rather than rigid specifications, enabling data-sharing arrangements where incentives and sovereignty are aligned, and avoiding fragmentation through isolated, incompatible solutions.

The most concrete instantiation of this principle is the **data-space model** (see Section 2.6), in which participants exchange data directly under shared governance rather than through a central platform owner. For an industry shaped by many SMEs and significant data-sensitivity concerns, this model offers a credible path to interoperability without forcing companies to surrender control of their own information. Associations and pre-competitive consortia have a particular role to play here, both as neutral conveners and as operators of the lightweight shared services (identity, security, data-model standards) that data spaces require.

6.3 Design AI for Effective Human Involvement and Governance

Successful AI applications should not be designed around a fixed assumption that either human decision-making or maximum automation is always preferable. Instead, organisations should determine case by case how the different components of decision-making — objective-setting, analysis, recommendation, selection, execution, monitoring, and accountability — should be distributed between people and AI systems. The appropriate arrangement depends on the task, its risk profile, the reversibility of errors, the maturity of the technology, and the organisational context. A practical recommendation is to:

- design AI systems around clearly defined human roles, escalation paths, and intervention points,
- provide functional transparency regarding system capabilities, limitations, and expected failure modes,
- embed mechanisms for monitoring, human oversight, and — where necessary — override or interruption.

This includes defining which decisions may be supported, delegated, or automated; documenting system scope, assumptions, and limitations; and assigning responsibility, review procedures, and escalation rules in a clear and

operational way. The point is not that human involvement is always the preferred end state, but that trust, accountability, and regulatory compliance depend on autonomy, oversight, and responsibility being matched appropriately to each use case.

6.4 Proceed Incrementally and Learn Systematically

The sources consistently caution against large, high-risk AI bets. Instead, a phased approach is recommended:

- start with bounded use cases where value and risk are well understood,
- evaluate impact and organisational fit,
- scale selectively based on evidence and learning.

This approach reduces risk, builds internal capability, and allows governance structures to mature alongside technical deployment.

6.5 Use Collective Structures to Reduce Individual Burden

Many challenges associated with AI adoption — skills development, regulatory interpretation, standardisation — cannot be addressed effectively by individual companies, especially SMEs. A key step forward is to:

- leverage industry associations as neutral conveners,
- engage in pre-competitive collaboration,
- share experiences, best practices, and learning artefacts.

Examples include joint pilot projects, shared training initiatives, and sector-specific knowledge platforms (e.g. controlled “Textile GPT” concepts).

6.6 Align AI Adoption with Economic and Sustainability Goals

Sustainability-oriented AI applications gain traction where they also improve economic performance. A pragmatic recommendation is to:

- focus on use cases where AI reduces waste, cost, or complexity,
- evaluate sustainability impact alongside operational metrics,
- avoid separating environmental goals from business realities.

This alignment increases the likelihood that sustainability-related AI initiatives can scale and endure.

6.7 Follow a Staged Maturity Pathway

The recommendations above should be understood as a sequenced pathway rather than a checklist. Following the logic of the Industry 4.0 Maturity Index [53, pp. 17–21], AI adoption becomes more robust when companies first establish reliable digital foundations, connect systems and data flows, and create visibility into operations before moving toward predictive and adaptive capabilities. This staged approach is particularly relevant in the textile industry, where digital

maturity remains uneven across firms and value-chain segments. A textile-specific operational counterpart to this generic maturity ladder — *digital blind* → *digital see* → *digital act* → *digital decide* → *digital control* — has been articulated in a recent practitioner contribution (see Section 4.3) [43] and provides a useful diagnostic at the line or process level alongside the company-level Industry 4.0 Maturity Index (Figure 10).

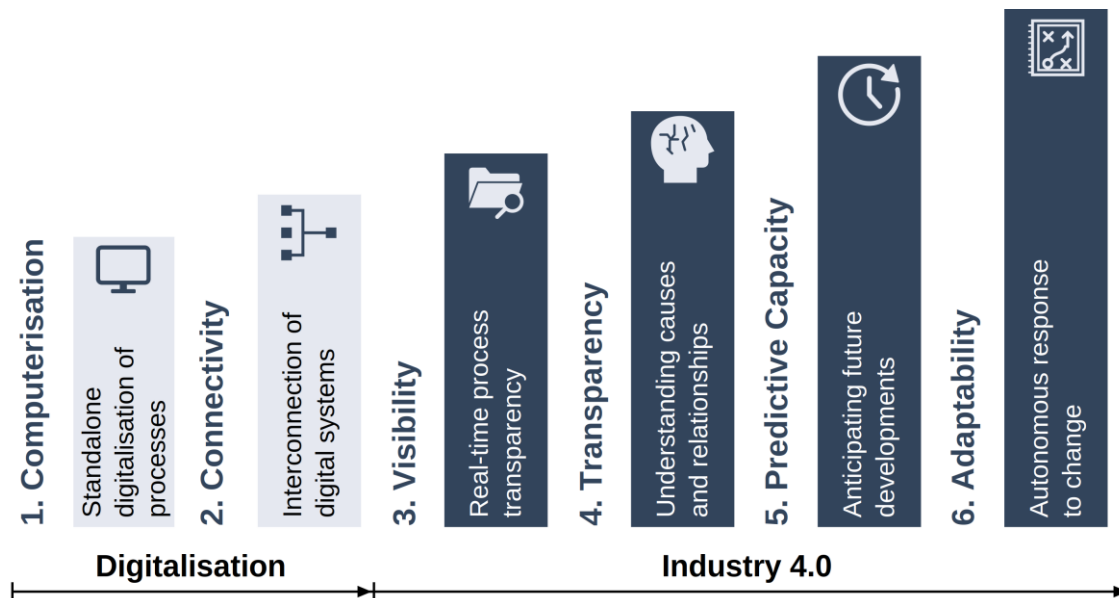


Figure 10: Staged pathway of digital and AI-related maturity, adapted from the Industry 4.0 Maturity Index [53]: from computerisation and connectivity to visibility, transparency, predictive capacity, and adaptability

Summary

These recommendations are deliberately **enabling rather than prescriptive**: the textile industry does not face a single starting point, and companies differ widely in digital maturity, resource base, regulatory exposure, and strategic priorities. What follows from the preceding analysis is a practical principle — successful AI adoption is not primarily a matter of technological ambition, but of organisational discipline. Firms need to strengthen the conditions under which AI can create value (skills, data quality, governance, cross-functional coordination) before expecting scalable results. Many of the required enablers extend beyond the individual firm, making cooperation across companies, associations, and research institutions a strategic necessity — especially in a fragmented industry shaped by many SMEs.

Key takeaway: AI adoption in the textile industry will not succeed through technology alone, but through a realistic transition strategy that aligns systems, people, and organisational structures. The decisive factor is not whether AI is available, but whether companies can build the capabilities and conditions to use it responsibly and at scale.

Conclusion

This white paper has examined Artificial Intelligence in the textile value chain as a response to accumulated structural pressures, not a technological novelty. Demographic change, skills shortages, market volatility, and rising requirements for quality, transparency, and sustainability form the backdrop against which AI has gained relevance — pressures that are neither temporary nor isolated but shape the operating conditions of the industry as a whole.

The analysis shows that the textile industry is not starting from zero. Decades of digitalisation have produced significant automation, data generation, and process optimisation. Yet the digital landscape remains fragmented: data exists but is often poorly integrated, decision-making relies heavily on human expertise that is becoming scarcer, and earlier waves of digitalisation have not resolved coordination complexity across functions and value-chain stages.

AI enters this context not as a capability with one fixed role, but as a flexible technological option whose function may range from decision support to partial delegation and, in some cases, substitution of specific cognitive tasks.

Its defining feature is the ability to operate under variability, uncertainty, and incomplete information — recognising patterns, structuring data, generating predictions, recommending interventions, and increasingly executing bounded workflows or process adjustments. Its value emerges where complexity exceeds the capabilities of rule-based systems, where human attention has become a limiting factor, and where organisations seek to extend, redistribute, or reconfigure cognitive work.

Evidence from the webinar series demonstrates that AI is already delivering value in specific, well-defined applications — quality inspection on the shop floor, decision support beyond it, and generative tools for knowledge-intensive work — without removing human responsibility. The World Café 2025 adds an essential collective perspective: AI is experienced across the industry as an incremental change rather than a disruptive break, with tangible benefits in daily work tempered by clear red lines around data control, cybersecurity, and accountability. Looking toward 2030, the emphasis shifts from individual experimentation to **collective capability-building**: skills development, shared standards, and collaborative learning are identified as prerequisites for making AI a useful and trusted technology at scale.

Taken together, these findings point to a central conclusion: the impact of AI on the textile industry will depend less on technological breakthroughs than on coherence — between digital foundations and AI applications, between human capabilities and machine autonomy, and between organisational practices, regulatory frameworks, and collective action.

In the current transition phase, human expertise remains important for defining objectives, interpreting context, handling exceptions, supervising system boundaries, and accepting accountability. This should not, however, be understood as proof that every decision or operational workflow will remain substantively human-led in the long term.

The long-term allocation of decision-making between humans and AI remains uncertain. One possible development is that routine analytical, coordination, and operational tasks are increasingly performed by AI agents, while human roles shift toward orchestration, governance, exception handling, and strategic direction. Decision rights may also become more concentrated at higher organisational levels. However, it remains open whether substantive human judgement will continue to be necessary for strategy and whether human orchestration will remain necessary in operations as systems become more capable.

The outcome will not be determined by technical efficiency alone. Trust, acceptance, regulation, accountability, resilience, and the value placed on human agency will influence how much autonomy organisations and societies permit. In some contexts, retaining meaningful human participation may be preferred even where it reduces apparent efficiency. The challenge is therefore not simply to preserve human control or maximise automation, but to determine where human involvement remains substantively valuable and where greater machine autonomy is responsible and advantageous.

AI does not offer a shortcut around the structural challenges facing the industry. It does, however, provide capabilities that can help manage complexity, preserve or redistribute scarce expertise, and support resilience when embedded thoughtfully. The strategic task ahead is to manage the transition deliberately — aligning AI capabilities, human roles, decision rights, governance, and organisational values with the industry's economic and societal realities.

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