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Article

Digital Twins for a Sustainable Textile Industry: A Critical Analysis of Unexplored Applications and Future Directions

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Abstract

Digital Twin (DT) models are gaining attention as promising tools for improving efficiency, sustainability, and responsiveness in textile manufacturing. This paper provides a critical review of existing DT applications and outlines seven underexplored areas where such systems could offer tangible benefits. By linking DT models with real-time data, textile producers can optimise energy usage, reduce production errors, enhance machine reliability, and accelerate decision-making processes. Moreover, DTs offer long-term opportunities for smarter waste management, personalised production with lower return rates, and better workforce training. The paper concludes with stakeholder-specific recommendations, such as integrating digital product passports for recyclability, and calls for a cross-disciplinary approach to digital transformation in the sector. These findings offer practitioners a roadmap for adopting DT technologies not only as monitoring tools but as strategic enablers for circularity, agility, and competitiveness.

Keywords: Digital Twins; textile industry; predictive maintenance; energy efficiency; defect simulation; personalised production; ergonomics; cybersecurity

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1. Introduction

In the current world, technological advancement and digital transformation are leading factors in the development of industry and society as a whole. This is particularly evident in the textile sector, which has undergone significant changes over the past decade [1]. The innovations that have been created and implemented aim to improve the efficiency, sustainability, and competitiveness of production and textile products [2]. In this dynamic and rapidly changing environment, the concept of Digital Twins (DTs) is emerging as a key tool for achieving high levels of optimisation and sustainable development [3].

DTs represent virtual replicas of real physical systems, processes, or products [4], and are created and maintained with the help of real-time data [5]. They enable in-depth monitoring, analysis, and prediction of the behaviour of real objects without the need to interrupt production or create real, physical prototypes [6]. In other industries, such as aviation [7], automotive [8], and energy [9], DTs have already proven to save resources and time while significantly increasing the reliability and quality of production. In the textile industry, however, despite considerable interest and potential, the application of this concept is still limited [10,11].

It can be said that the application of DTs is focused primarily on standard uses such as clothing design and simulation. Current scientific literature identifies successful examples precisely in this direction: in the fields of design, modelling, and virtual fitting of garments [12–14].

- Reduction in new-model development time

One of the most evident benefits of virtual simulations is the reduction in the time required to develop new models [12]. Traditionally, the process involves multiple stages: design, creation of physical samples, reviews, adjustments, and re-production. This can take weeks, even months. With the implementation of DTs, designers now have the ability to model garments in a digital environment and simulate their behaviour on virtual mannequins [15]. In this way, different materials, colours, cuts, and sizes can be tested in real time. The decision-making cycle is accelerated, and a more dynamic response to fashion trends and market demands is ensured [16]. As a result, new models reach customers significantly faster, without compromising on quality and design [13,17].

- Reduction in the need for physical prototypes

Virtual fitting and digital modelling significantly reduce the need to produce real prototypes [15,17]. In the traditional approach, each design idea often requires at least one, and sometimes several, physical samples, which leads to increased material and energy consumption, production time, and logistics. It should be noted that a substantial portion of these samples ultimately go unused and are discarded. Through DTs, companies can visualise and approve designs based on photorealistic images and simulations [18]. DTs accurately reproduce the texture, movement, and fit of garments [13]. In addition to lowering material and labour costs, they can also reduce carbon footprint [15,17], especially when the transport of physical samples between different production units is involved (for example, between designers and the garment company).

- Optimisation of production processes

The more precise and detailed virtual models created through DTs enable better planning and organisation of the production process [19]. Manufacturers can analyse in advance how a given fabric or seam will behave under real conditions, thus minimising errors in cutting, sewing, and the finishing of the product [13,14]. Visualising the final product through DTs allows designers and production managers to make more informed choices in terms of materials, machines, and technologies [20]. This leads to fewer production defects and higher customer satisfaction, resulting in fewer complaints and returns [17].

- Reduction in waste

Major sources of waste in the apparel industry are inefficiently developed models, frequent corrections, and returned products [21]. Every unsuccessful prototype means expended resources—fabrics, threads, energy, transportation, and human labour—that ultimately go to waste. Digital simulations significantly reduce these losses. Through earlier and more accurate evaluation of design, size conformity, and visual appeal, companies can make better decisions already at the conceptual stage [15,17]. DTs prevent the physical production of defective or unwanted items and reduce the volume of consumer complaints, which are often caused by poor fit or unmet expectations [22].

A more in-depth examination of practices in the textile and apparel manufacturing industry clearly shows that there are many unexplored areas where the potential of DTs has not yet been realised or applied to its full extent.

The present article identifies seven specific niches in which DTs could play a key role. However, their implementation and research are still minimal or absent. These niches include prediction and control of wear in textile machinery, optimisation of textile waste management and recycling, prediction and minimisation of deformations and defects in textile structures, energy efficiency in various production processes, personalised production of textile products, optimisation of the human factor (ergonomics and safety), and ensuring cybersecurity of systems based on DTs.

The significance of these untapped opportunities is immense, both from an economic and an environmental perspective. For example, by using DTs for predictive control of machinery wear [23], textile companies (e.g., spinning or weaving firms) can save substantial resources and prevent unplanned downtime. In the field of recycling and waste management, DTs can enable the creation of entirely new circular economy models [24,25] that optimise material flows and reduce the environmental footprint of the textile industry.

At the same time, DTs can significantly enhance personalised production, which is becoming increasingly important in the context of changing consumer preferences and sustainability requirements [26]. DTs provide the ability to more quickly and accurately predict defects and deformations in products, leading to improved product quality and durability [17]. Improvements in machine ergonomics and worker safety through virtual simulations and DT-based analyses can also have a significant impact on workers' productivity and health [27,28].

Last but not least, the implementation of DTs also raises serious cybersecurity concerns [29]. As the industry moves toward increasing digitalisation, the risks of cyberattacks and the need for effective protection of digital models are becoming ever more important [30]. This requires targeted solutions and methodologies, which so far have not been sufficiently developed in the context of the textile industry.

The aim of the present paper is to draw the attention of the scientific community and industry practitioners to these untapped opportunities by proposing specific areas for future research and investment. It uses a critical review approach to analyse current DT applications in the textile sector and to identify underexplored opportunities across production and management domains. The findings are based on a cross-analysis of scientific literature, industry reports, and case studies. By examining these niches, the analysis outlines the potential benefits and challenges, setting the framework for future innovative and practically oriented applications of DTs.

The article is structured as follows: Section 2 outlines the general architecture and functionalities of DT systems; Section 3 explores six potential application areas with limited current implementation; Section 4 discusses possible implications for future research and industry practice, which can move the textile industry towards a more sustainable and technologically efficient future.

2. State of Implementation of Digital Twins and Structural Overview

DTs are increasingly being adopted in industrial contexts, but their application in textile manufacturing remains fragmented. So far, the most commonly used applications are observed in the early stages of the product cycle: virtual design [12], garment simulation [14], and partial implementation of sensor systems for machine monitoring [31]. In many cases, there is a lack of full integration between physical production assets and their digital counterparts.

Figure 1 presents a summarised architecture of a DT system in the textile industry. The left side shows the physical production components: textile machines, operators, materials, and the environment. The right side represents the virtual environment, which includes the following:

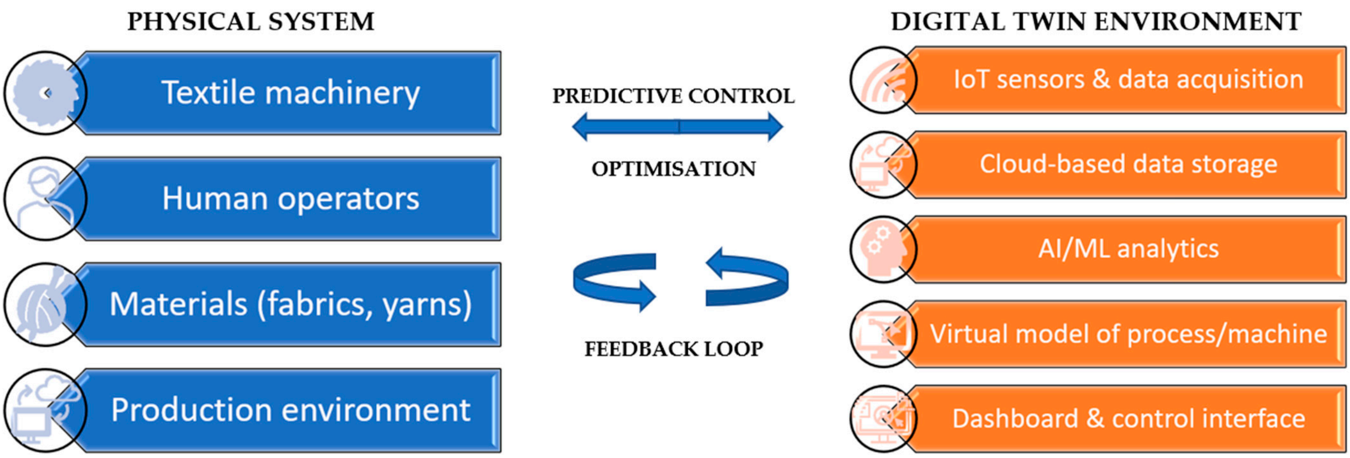

Figure 1. Conceptual architecture of a DT-based system in textile manufacturing.

- Internet of Things (IoT) sensors—collecting real-time data from physical components [32];
- Cloud-based data storage—enabling scalable and secure access to production data [33,34];
- Analytical tools—such as Artificial Intelligence (AI) and Machine Learning (ML), used to process and interpret complex datasets [35,36];
- Simulation models—replicating the behaviour of physical systems under various conditions [32];
- User interface—allowing operators to monitor, manage, and optimise processes [32,37].

The architecture illustrates how data flows from the physical to the digital environment and back again, enabling predictive control and process optimisation.

Three key communication mechanisms exist between the physical and DT environments:

- Predictive control—using forecast data for proactive intervention [38];
- Optimisation—real-time adjustment of parameters to enhance performance [39,40];
- Feedback loop—continuous data flow from the digital copy to the physical system [41].

This architecture highlights that DTs are not passive models but active decision-making platforms [42]. They are essential for the development of intelligent, sustainable, and adaptive textile systems.

To better understand the actual level of DT implementation in the sector, Table 1 provides a comparative overview of current and still-untapped applications. The presented areas cover key production and strategic domains—ranging from design and quality to waste management, staff training, and cybersecurity.

- Design and Prototyping

The comparison and analysis in Table 1 show that the application of DT technologies is mainly limited to the virtual design and prototyping of garments [13,15]. Using software such as CLO 3D [43] or Browzwear [44], designers create garment models that can be visualised on digital avatars. This allows virtual "try-ons" of clothing before any physical samples are made, saving time, materials, and costs. A company like Tommy Hilfiger develops entire collections in 3D first, moving to physical production only after digital approval [45].

However, DTs can be further developed to provide real-time feedback during the creation of the physical prototype. Sensors embedded in the sample garment, for instance, could transmit data on fabric tension in specific areas or the formation of folds [46]. This information, automatically analysed by the DTs, could lead to adjustments in the pattern before the final version is produced.

The integration of DTs throughout the entire design and prototyping process reduces the time-to-market for new models or collections (from months to weeks), decreases the need for physical samples and prototypes, and results in less textile waste [13,47]. It also increases the satisfaction of the teams dealing with the development and marketing of new products.

Table 1. Comparison between current and untapped applications of DTs in the textile industry.

Area	Currently Used	Untapped Potential	Expected Value
Design and Prototyping	3D virtual garments, fitting simulation	Real-time feedback during physical prototyping	Reduced time-to-market, lower material waste
Production Monitoring	IoT-based machine-data tracking	Automated predictive maintenance of specific textile machine parts	Less downtime, cost savings
Quality Control	Manual inspection, some AI-image analysis	Predictive modelling of defects during production	Higher product quality, fewer returns
Supply Chain	Basic logistics visualisation	Real-time supply chain DT simulation	Better forecasting, reduced delays
Sustainability	Lifecycle tracking (partial)	Closed-loop waste management simulations	Increased resource efficiency, reduced emissions
Personalisation	Size-recommendation engines	Fully customised virtual product twins per customer	Better customer satisfaction, fewer returns
Training and HR	e-learning modules	Immersive training via virtual-twin environments	Faster onboarding, fewer human errors
Cybersecurity	Basic firewalls, separate IT/OT systems	Integrated real-time monitoring of DT infrastructure	Reduced cyber risk, increased system resilience

- Production monitoring

Production monitoring is another area of application for DTs. Some textile companies use IoT sensors to monitor key parameters of production machines in real time, such as temperature, vibrations, pressure, or rotational speed [48]. These data are collected and visualised on monitoring platforms, allowing faster detection of deviations and optimisation of current settings. For example, sensors may detect overheating of a machine motor, prompting early intervention and preventing damage [49].

DTs, however, could go beyond simple monitoring by enabling predictive maintenance of specific components rather than the machine as a whole [50]. This means that the system could forecast, based on collected data, the wear of knitting needles in circular knitting machines, chain mechanisms, or pressure rollers in spinning machines, and suggest their replacement before a failure occurs.

In this way, the application of DTs with predictive functionality can significantly reduce unplanned downtime [51] and extend the lifespan of machines and components [52]. Maintenance costs also decrease due to better planning of service activities.

- Quality control

Quality control in the textile industry is still predominantly performed through manual visual inspection by operators [53]. In denim fabrics production, for example, AI-based cameras and software are used to detect visible defects, such as stains, broken yarns, or uneven dyeing through image processing [54]. In automated fabric printing lines, a camera analyses each metre of fabric and signals any deviation in the print position beyond the allowed tolerances [54].

However, the potential for real-time predictive modelling remains largely untapped. With the help of DTs, predictive quality control can be performed even before a defect occurs [55]. The virtual model could use, for instance, data on machine performance, humidity, yarn tension, and material type to predict when and where a defect is likely to appear. During knitting, for instance, the DT could monitor data from sensors that measure yarn tension and temperature data in the working area. In case high yarn tension is combined with low humidity—a high-risk condition—the system would use historical data to send a warning to the operator, recommending a reduction in machine speed to prevent yarn breakage.

The benefits of implementing predictive quality control with DTs include improved consistency and reliability of products, fewer defects and complaints, and a stronger brand reputation in the eyes of customers.

- Supply chain

Some textile companies currently use software tools for visualising and tracking logistics processes, for example, Enterprise Resource Planning (ERP) systems [56] or specialised Supply Chain Management (SCM) solutions [57]. These systems provide traceability of raw materials and finished goods, as well as basic planning of orders and deliveries. They also help optimise inventory levels. For instance, through a tracking system, a yarn manufacturer in Europe can monitor cotton shipments from a supplier in Asia. Periodic data updates allow for the detection of delays or changes in delivery volumes.

An untapped potential lies in the ability to simulate the entire logistic network in real time through a DT of the supply chain [58,59]. This includes transportation, warehousing, intermediate deliveries, and even climate or geopolitical risks. Such a system enables predictive rerouting of shipments, simulation of alternative routes, and impact analysis in case of delays affecting production or customers [60]. For example, if a cargo ship is expected to be delayed due to a severe cyclone in the ocean, the system could simulate alternative logistics scenarios and suggest temporary rerouting of deliveries from a warehouse in another country to avoid production disruption.

By implementing DTs within the supply chain, companies can achieve more accurate forecasting of resource needs and reduce delays and interruptions in logistics. In addition to greater efficiency throughout the entire chain—from raw materials to end customers—it can also ensure better adaptability of the supply network to global events such as pandemics, conflicts, or climate anomalies.

- Sustainability

Sustainability is one of the most significant yet still underdeveloped areas for the application of DTs in the textile industry. At present, some manufacturers use partial solutions to track the lifecycle of their products. These are primarily aimed at labelling material origins [9,61], assessing carbon footprints [62], and evaluating the social responsibility of suppliers [63,64]. Such efforts are often implemented via blockchain [65] or sustainability certification platforms [64] but lack integration with operational production data.

The untapped potential lies in creating a DT that covers the entire journey of a textile product: from raw material selection to the recycling stage. Such a model could simulate how different production decisions affect water, energy, and chemical consumption, as well as waste generation. For example, a factory could use a DT to compare two fabric dyeing methods in terms of energy efficiency and residual dye concentration in wastewater. Alternatively, the model could identify which production stages generate the most textile waste and suggest alternative reuse or recycling measures.

The benefits of this approach are substantial: more precise resource management, reduced environmental footprint, compliance with emerging carbon neutrality regulations, and improved transparency for end consumers. In the long term, this would help manufacturers build more sustainable value chains and create a competitive advantage in an increasingly eco-conscious market environment.

- Personalisation

Personalised textile manufacturing is becoming an increasingly important strategic priority, especially in the context of shifting consumer expectations and growing pressure for sustainability. Currently, personalisation is mainly achieved through size-recommendation systems [66]. They use data from previous purchases, body measurements, or simple questionnaires [67]. Such solutions reduce return rates and increase buyer satisfaction, but they remain limited to static models.

There is significant untapped potential in creating a DT not only of the garment but also of the consumer. This would be a dynamic model combining data from 3D body scans, style preferences, movement patterns, and even the climatic conditions in which the garment will be used [68]. The DT could be applied as early as the design stage, automatically adapting the pattern, fabric type, and construction method to the specific customer. In more advanced scenarios, it could simulate the garment's behaviour on a virtual avatar under different conditions (sitting, moving, bending) and predict potential discomfort or deformation.

The expected benefits of implementing DTs are complex. Economically, DTs reduce the need for physical samples and testing, as well as product returns. Socially, the client gains a sense of exclusivity and a deeper connection to the product [69]. From an environmental perspective, on-demand production with digitally validated design minimises excess and waste, aligning with circular economy principles [70]. Through such an approach, DTs can become the foundation of the next generation of "mass personalisation" in the textile industry.

- Training and Human Resources (HR)

Human-factor optimisation in the textile industry is an area where DTs are rarely applied, despite their significant potential to improve productivity, safety, and the overall working environment. In most companies, training is conducted through standard e-learning platforms, video tutorials, or mentoring by experienced colleagues [13]. However, these methods are often non-adaptive and fail to reproduce real scenarios with high accuracy or interactivity. This often results in subjective judgments and inefficient resource allocation.

The untapped potential lies in creating DTs of work processes, operators, and production zones. Virtual models, based on data from movement tracking, biometrics, workload, and task completion times, can simulate how different operations affect fatigue, error risk, or injuries [71]. The system can then suggest reconfiguration of workstations, automation of certain tasks, or staff rotation. Additionally, DTs can be used to simulate training environments [72], allowing new employees to familiarise themselves with procedures and optimal movements in a virtual setting, without real health risks or production defects.

The application of such an approach leads to faster and more effective training, reduced human error, lower physical and mental strain, and enhanced workplace safety. In the long term, it can help reduce staff turnover, increase employee engagement, and improve overall production culture. In this context, DTs serve as strategic tools for managing people, the most valuable resource in any industry.

- Cybersecurity

Cybersecurity of DTs is a critical but often neglected area, especially in the textile industry. The main reason is that digitalisation in textile companies is advancing gradually and unevenly [73]. At present, most production-related systems rely on minimal levels of cybersecurity, where information technology (IT) and operational technology (OT) networks are isolated from each other, and security relies mainly on basic firewalls [74]. This approach is relatively outdated and ineffective in the context of DTs. The requirements for continuous and bidirectional communication between physical and virtual components insist on the highest levels of security to minimise potential vulnerabilities for cyberattacks [75,76].

A DT may process sensitive data related to production, inventory, logistics, and even personnel [77]. An example of such an application would be the implementation of a DT technology that monitors the status of a weaving machine, detecting unusual commands, attempts to access the system from external networks, or modifications in control algorithms.

The benefits of this approach include the prevention of production incidents and the protection of companies' know-how.

The comparative analysis in Table 1 further confirms that there are several areas with high potential for transformation through DT technologies. In this context, the following section of the paper aims to identify and analyse seven specific but underexplored niches where DTs could deliver significant added value—economic, environmental, and social. The investigation is not focused on reaffirming already-known benefits, but rather on uncovering new opportunities. It could serve as a starting point for future development, pilot projects, or interdisciplinary research.

3. Unrealised Potential: Seven Untapped Application Areas for DTs in the Textile Industry

Based on a comparison between existing industrial practices and opportunities outlined in scientific and grey literature, seven underused or entirely untapped niches with potential for the application of DTs in the textile industry have been identified. These are summarised in Figure 2, which charts the framework for the next analysis.

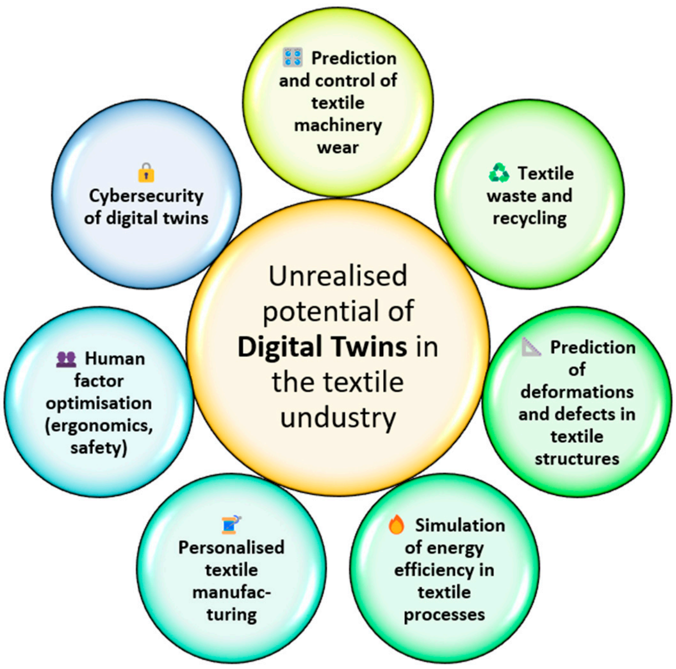

Figure 2. Schematic representation of seven untapped niches with potential applications of DTs in the textile industry.

Each niche, from machine maintenance and energy efficiency to personalisation, waste management, and cybersecurity, is examined individually. The focus is placed on the description and relevance of the niche, the role of DTs in the respective area, possible barriers and limitations to implementation, as well as potential applications, including hypothetical examples.

3.1. Prediction and Control of Wear in Textile Machinery

The wear of key components in textile machines, such as needles, cylinders, combs, rollers, and others, is a common issue that directly impacts production efficiency and the quality of the final product. Technical failures related to worn parts lead to unwanted interruptions, increased defect rates, and, as a consequence, order delays. In most textile companies today, wear control is performed through periodic inspections and manual diagnostics, which often detect the problem only after actual damage has occurred [78].

The introduction of a DT in this area offers the potential for early diagnostics and predictive maintenance. The virtual model of the production machine, either a rotor spinning machine, circular knitting machine, or a dyeing unit, will collect and analyse real-time data from sensors monitoring parameters like vibration, temperature, pressure, operating speed, and load. Based on this data, the DT will perform simulations and calculate the likelihood of mechanical failure, and, if necessary, propose specific interventions, e.g., replacement of a worn part, out-of-routine lubrication, or temporary load reduction.

The economic benefits of such a prognostic system include reduced losses due to breakdowns and production downtime. The environmental benefits involve fewer defective products and more efficient use of resources. From a social perspective, greater process predictability facilitates operators' work and improves labour organisation.

Nevertheless, there are certain barriers. From a technological perspective, not all machines, especially older ones, are designed for easy integration of IoT sensors [49]. Financially, the investments in the required hardware and software, as well as staff training, can be considerable. The human factor should not be underestimated either, as employees must be trained to work with the system, rely on its analyses, and act proactively.

Possible applications and examples (hypothetical scenarios) of DT application involve:

- High-speed knitting production

In a company with circular knitting machines, a DT monitors production parameters like vibrations and needle-bed temperature. The model detects accelerated wear when a specific type of thread (e.g., synthetic polyfilaments) is used and predicts a risk of needle breakage within the next 36 h. The system automatically recommends reducing machine speed and sends a notification to maintenance for preventive replacement during off-hours, thus avoiding unplanned downtime.

- High-temperature textile dyeing

In a dyeing installation that processes large fabric batches, the DT monitors pressure and temperature in the circulation system (which includes a pump, heat exchanger, piping, valves, and a dyeing vessel). When deviations from standard values are detected, the simulation model forecasts a failure of the pump seals after 50 cycles. The system recommends replacing them as part of routine maintenance, preventing costly shutdowns and contamination of the product.

- Centralised machine control

In a large wool-weaving factory with various machine types, from worsted carding machines to weaving looms—a centralised DT platform analyses data from the entire line. Based on machine load and historical wear patterns, the system generates a dynamic maintenance schedule that prioritises the highest-risk machines. Thus, the DT optimises the workload of the service team.

3.2. Textile Waste and Recycling

The production of textiles generates a significant amount of waste at almost every stage of the chain [79]: from spinning to fabric manufacturing, finishing processes, and garment cutting. Although some larger enterprises apply basic practices for separation or reuse of the waste, systematic and digitally managed tracking of the waste is still rare [80]. This leads to low efficiency and limited possibilities for sustainable resource management.

The implementation of DT technology in this field would allow for real-time tracking, modelling, and optimisation of textile waste flows. By collecting data on generated leftovers, machine parameters, types of fibres, yarns, fabrics (woven, knitted, non-woven), and specific production batches, the DT can recognise recurring patterns. This makes it possible to predict when and where surpluses are likely to occur. In addition, through simulations of alternative scenarios, the DT can propose changes and optimisations in production to reduce the waste.

One of the most significant barriers to effective recycling in the textile industry remains the sorting of textile waste. Despite progress in the development of insulation panels made from recycled materials [81], for example, identifying the physical and thermal properties of textile waste still requires specialised testing and remains a challenge. In this context, DTs can play a key role by enabling the creation of so-called "digital passports": metadata embedded in each garment (e.g., information about fibres, dyes, origin, and recyclability) [82]. This would facilitate both automated sorting and future processing of textile products. Integrating such an approach into waste management platforms could accelerate the transition to a circular economy by making material composition and lifecycle data traceable and standardised.

Among the main benefits are economic gains from reducing material losses (fibres, yarns, fabrics) and production costs. The environmental effect of DT implementation would be a reduction in pollution through improved sorting and recycling. From a social perspective, such a system would contribute to compliance with environmental regulations and the development of a better public image of the textile brand.

Examples of how DTs might be applied include the following hypothetical cases:

- Minimising waste in a spinning mill

In a spinning enterprise, a DT monitors in real time the drafting systems of both roving and ring-spinning machines. The model collects data from sensors located in the drafting systems (e.g., on the pressure rollers), which record parameters such as pressure, drafting speed, sliver density, and fibre moisture content. The analysis of the collected data reveals that at certain levels of pressure and speed, increased waste is generated, most often as residue around the drafting or pressure rollers. The DT simulates alternative settings and recommends a fine adjustment of the pressure. Additionally, the system could classify the collected waste by its quality and propose possibilities for reuse in other products, such as yarns with higher linear density or non-woven webs.

- Garment cutting with minimal waste

In a garment factory, a DT of the cutting process monitors in real time the layout of the pattern pieces on the fabric spread. The model analyses the leftover pieces (external and internal waste) and suggests an optimised arrangement for the next order with the aim of reducing fabric loss. For orders with similar geometry, the system could recommend batch processing in order to utilise even the smallest offcuts.

- Waste management within a circular factory

In a circular factory with a rotor spinning unit that uses both virgin and recycled fibres, a DT monitors the incoming and outgoing flows of fibres and yarns. When an increased defect rate is detected in connection with a specific raw material, the system identifies a potential issue related to the supplied material, such as a deviation from specifications or incompatibility with the machine settings. The analysis is based on indicators such as the frequency of yarn breakages during spinning, sliver irregularity, and elevated short-fibre content. The DT simulates alternative processing scenarios and suggests corrective actions:

for example, reducing the proportion of recycled fibres, adjusting room humidity, or changing the rotor machine speed. This enables timely adaptation and improves recycling efficiency without compromising the quality of the final product.

3.3. Prediction of Deformations and Defects in Textile Structures

Defects in textile macrostructures—woven or knitted—are one of the main causes of production losses. They result from various factors, such as residual tension in the threads, dropped stitches, broken warp threads, or deviations during dyeing or printing [83]. Most of these issues are detected too late, after the fabric or the product made from it has already been produced, and sometimes only during customer inspection. Standard quality control relies primarily on visual checks at the entry/exit points of the company [84], as well as on automated imaging systems, which are still limited in their application [85]. However, neither visual nor automatic inspections provide the ability for defect prediction and early response.

A DT applied in this area can combine real-time sensor data (e.g., thread tension, temperature, humidity, production speed) with predefined control models to predict the occurrence of defects. This virtual model simulates how specific production conditions, such as environmental changes, component wear, or the use of threads with reduced strength, would affect the textile macrostructure. When risk thresholds are reached, the system can suggest timely adjustments: reducing weaving speed, replacing the yarn guide, changing humidity, or lowering the tension.

The expected benefits are significant. From an economic perspective, early problem prediction leads to less waste, higher fabric quality, and lower costs for returns and complaints. Environmentally, the need for re-production and related resource consumption is reduced. Socially, customer trust is improved, and the transparency of the production process is increased.

The challenges of DT implementation include the need for high-quality input data and the development of accurate models representing the behaviour of materials and machines. The system must also be adapted to different types of input textile raw materials and variations in the production line. In addition, not all factories have the necessary infrastructure for integrating sensors and maintaining analytical platforms.

Below are some possible scenarios where DT could be used:

- Sportswear manufacturing

A high-tech sportswear company implements a DT that simulates how different knitted macrostructures respond to repetitive physical movements (e.g., running or cycling). The model tracks fabric tension along its length and zones of increased friction. It also analyses the risk of deformations in areas such as knees, elbows, and shoulders. Based on these simulations, designers adjust the pattern and select more durable fibres/yarns for the sensitive zones.

- Automotive textiles

A manufacturer of automotive upholstery uses a DT that simulates long-term seat loading under various temperatures and humidity conditions. The model predicts how the textile structure will be worn or fade after two years of use. Based on this, engineers replace the original fabric with a more durable alternative, reducing the need for warranty replacements.

- Medical textiles

A medical textile factory creates a virtual model of surgical garments subjected to sterilisation (high temperature, steam, chemical agents) and subsequent use in an operating-room environment. The DT reveals that after the third sterilisation, the fabric in certain areas loses elasticity. This leads to the replacement of specific yarns in the fabric macrostructure or reinforcement of vulnerable zones, thus increasing safety and comfort for medical staff while reducing the cost of frequent garment replacement.

3.4. Simulation of Energy Efficiency in Textile Processes

Energy consumption in the textile industry is high, particularly during thermal processes such as wool washing, lustering, sizing, dyeing, heat setting, and others. However, accurate data on actual energy use at each stage of the production line is often lacking [86]. As a result, the ability to forecast peak loads and energy losses is limited. In most cases, optimisation relies on general energy reports, which do not support dynamic energy management [87].

A DT applied in the context of energy simulation can model in real time how a specific production process consumes energy, depending on the material, machine configuration, and environmental factors such as ambient temperature or humidity. Based on sensor data and production schedules, the system simulates energy flows and identifies where losses accumulate. This enables the implementation of corrective actions: changing the processing sequence or adjusting parameters. The DT can suggest shifting operations to time slots with lower consumption and lower energy costs.

The benefits of such a model are related to the direct reduction in energy costs and the achievement of targeted environmental indicators. In addition, the use of simulation scenarios through a DT allows manufacturers to test energy efficiency during the implementation of new products or technologies already at the planning stage.

The main challenges include the need for reliable and calibrated sensors, as well as the adaptation of the virtual model to different types of machines and textile technologies. Collaboration between energy managers, technologists, and IT specialists is also essential for successful integration.

DT implementation may take the form of various energy applications, such as these hypothetical examples:

- Optimisation of drying in a dyeing unit

In a dyeing facility, a DT simulates the drying process under various settings of temperature, air flow, and fabric type. The model determines that at a lower temperature, compensated by longer drying time, the same fabric quality is achieved with 18% less energy consumption. The system automatically recommends a new settings profile.

- Peak-hour energy-load management

In a large weaving mill, the DT forecasts the energy consumption of all active production lines for the next 6 h. Based on the simulations, the system suggests shifting part of the processes to off-peak hours in order to avoid exceeding the contracted capacity and incurring additional charges from the energy provider.

- Comparison between conventional and energy-efficient technologies

A factory is planning to replace its old heat-setting line with a new model. Before purchasing, a DT is created to simulate the production process with both types of equipment under identical parameters. The simulation shows that the new technology will reduce energy consumption by 22% while maintaining the same capacity, thus justifying the investment.

3.5. Personalised Textile Production

The growing demand for individualised products is driving a shift in the textile manufacturing model: from mass production to on-demand production. Currently, personalisation is mainly achieved through standard garment configurations, size and colour selection, and sometimes the use of 3D visualisations [88]. However, the link between the specific customer and the actual production process remains limited and poorly automated [89]. DTs can play a key role in creating a fully adaptive and individualised production system with high capacity. The so-called "customer twin" would include information about body shape (e.g., from 3D scanning), style preferences, usage conditions (profession, climate), and even feedback from previous purchases. This model can be used to automatically generate personalised products and wearing simulations. At the same time, it could calculate the required materials and suggest machine settings.

The benefits include a significant reduction in product returns and higher customer satisfaction. At the same time, waste is reduced, and the flexibility of the production process is increased. Personalised production driven by a DT can be fully automated and optimised in terms of logistics, resources, and delivery time.

The challenges of implementing DTs include the need to integrate customer data while ensuring confidentiality and security. Additionally, it requires adaptation of manufacturing equipment to accommodate small production series and the ability to implement rapid changes in both design and logistics.

One often-overlooked consequence of personalisation is the increased risk of textile waste, especially when customised garments are returned by dissatisfied customers [90]. Due to their unique features, these items may be difficult to resell or recycle. DT technologies can address this issue by offering pre-purchase virtual simulations of the product: customers may visualise fit, movement, and styling before placing an order. This could reduce the likelihood of returns and help minimise waste associated with personalised fashion.

Possible applications and hypothetical scenarios for the application of DTs in personalised textiles may include the following:

- Online clothing order with a virtual customer

A customer orders a sports T-shirt through an online platform. After 3D scanning and selecting a preferred model, the DT simulates how the T-shirt fits during different movements. The system automatically adjusts the length, width, and reinforcement zones. Production begins without the need for fitting or samples, and delivery is completed within 48 h.

- Personalised work uniform

A workwear factory uses DTs of the client's employees, including data on body shape, type of work performed, and climatic conditions of the workplace. The system creates individualised uniforms with different zones for protection, breathability, and ergonomics. This improves comfort, including thermophysiological comfort, thus increasing the safety levels. At the same time, the application of DTs reduces costs related to replacing uncomfortable garments or periodic uniform renewal.

- Personalised underwear with anatomical modelling

A luxury underwear brand implements a DT of the customer, which uses anatomical data and preferences from previous orders. The system simulates the behaviour of the item during various positions and movements. This enables the creation of a precisely fitting product with enhanced comfort without the need for fittings or physical visits.

3.6. Optimisation of the Human Factor (Ergonomics, Safety)

In the textile industry, the human factor remains a key component, especially in operations requiring manual actions, such as sorting, quality control, cutting, and sewing [91]. Very often, working conditions, workload, and the ergonomic design of workstations are based on standard assumptions [92], without accounting for individual differences between operators or the dynamic conditions of production [93].

A DT in this area can model not only the machines and production environment but also human interaction with them. By using data from sensors, motion-capture systems [94], biometric devices [95], or wearable technologies [96], a virtual human model is created. It can collect data on movement, posture, workload, and even physiological indicators (such as heart rate or temperature). This allows for the simulation of work situations and the identification of high-strain operations or potential accident risks. In this way, the working environment can be adapted to employees without compromising the quality and productivity.

The benefits of implementing DT technology in this area include, from the workers' perspectives, increased safety, reduced physical fatigue, and fewer injuries. From the company's perspective, it improves shift planning and enables faster training. In the long term, productivity is enhanced, and employee turnover is reduced due to higher job satisfaction.

The main obstacles to DT implementation are related to the initial investment in equipment and the need to adapt production design to personalised ergonomics. At the same time, additional work should be performed to ensure the confidentiality of personal data. Staff training is also required, along with a commitment to follow the recommendations of the DT system.

The hypothetical scenarios for the application of DTs for ergonomics and safety of the human factor may include the following:

- Simulating working posture in a sewing department

In a garment factory, a DT of a dressmaker is used to simulate her working posture at different machine heights and material positions. The model identifies that the current configuration causes strain on the back and shoulders after four hours of work. After adjustments are made, complaints decrease, and absenteeism is reduced.

- Virtual training of new employees

Through simulations in a digital environment, new operators go through the basic actions and common errors on a real production line for men's clothing, without the risk of accidents. The system tracks how long it takes to master movements and provides personalised instructions to improve performance.

- Monitoring fatigue and preventing accidents

Workers in a finishing unit wear devices that transmit data on heart rate and skin temperature. When accumulating fatigue or critical rises in physiological indicators are detected, the DT alerts the supervisor about the need for a break or staff rotation. This prevents errors and improves the health and wellbeing of the team.

3.7. Cybersecurity of DTs

As digitalisation in the textile industry expands, data and system security become critically important [73]. DTs, by their nature, create a constant link between physical and virtual realities [97]. This makes them vulnerable to cyber threats, including sabotage, unauthorised access, data manipulation, or attacks that could lead to production shutdowns or the loss of sensitive information [29]. The DT of a sewing machine or weaving loom, an intelligent cutting line, or even a logistics process can be maliciously exploited if not properly secured, especially in fashion textiles, where speed and intellectual property are critical [98].

Implementing a DT with built-in cybersecurity requires the development of a secure infrastructure that includes data encryption [99], access authentication [100], real-time activity logging and monitoring [101], as well as automatic anomaly detection [102]. In addition to technological measures, organisational policies are also necessary to regulate who has access to critical systems, when, and how [103].

The benefits of implementing secure DTs include the protection of the company's intellectual property and the continuity of production processes. At the same time, it builds greater trust among partners and clients and ensures compliance with European and international data protection regulations.

The main challenges lie in the lack of cybersecurity expertise within textile companies. The complexity of integration with existing systems or the need to build an entirely new cybersecurity infrastructure often lead some organisations to hesitate to invest in this invisible yet vital protection. For small companies, maintaining cybersecurity adds an additional cost on top of the already significant expense of building a DT system.

The possible applications of DTs with cybersecurity systems include the following hypothetical examples:

- Protection against unauthorised access in a dyeing facility

The DT of an automated dyeing line detects an attempt to remotely send a command to alter the concentration of a chemical in the bath. The system blocks the action and triggers a notification to the administrator, preventing a potentially serious incident.

- Anomalies in IoT-sensor data

Within a weaving factory, the DT registers a discrepancy between the actual vibrations of a weaving machine and the data reported by the sensor. The system suspects that the sensor has been compromised or replaced and temporarily excludes its input from decision-making processes until an on-site technical inspection is conducted.

- Protection of a cloud-based simulation platform

A fashion company uses cloud infrastructure for DT simulations related to new products. The system applies two-factor authentication, geographic access restrictions, and encryption for every modification to the virtual model. This ensures that data on materials, patterns, and innovations remain protected from industrial espionage.

4. Discussion

The analysis of the seven unrealised niches for the application of DTs in the textile industry reveals a wide range of opportunities, varying in both technological complexity and potential added value. Although all the areas discussed are significant, their short-term applicability is not equal.

The most realistic niches for near-term implementation appear to be those where high levels of automation and IoT integration already exist. These include the use of DTs for predicting machine wear, detecting defects in textile structures, and simulating energy consumption. DT systems can rely on already existing sensor networks. Moreover, the three niches are directly linked to cost reduction and improved production efficiency; factors that make it easier to convince management to invest. Additionally, these applications often require only limited adaptation of the production process, which makes them technically feasible even in more conservative environments.

On the other hand, niches such as personalised production and human-factor optimisation require not only technological innovations but also a fundamental transformation in work organisation and logistics, as well as customer relations. Although their potentials are significant in the context of long-term sustainability and personalised value, their implementation would require substantial structural changes and interdisciplinary efforts.

The most recent area—cybersecurity of DTs—holds strategic importance, particularly in light of the increasing digital connectivity of textile companies. It is especially critical given the rising demands for data protection and the prevention of production incidents, yet it often remains overlooked due to its "invisible" value. This is precisely why it must be integrated from the very beginning of any digitalisation-related project.

It is also important to note that the seven niches should not be viewed in isolation; they have natural interconnections. The improved prediction of machine failures via DTs can lead, for example, to reduced defects and waste. The enhanced energy efficiency can contribute not only to sustainability but also to the optimisation of operator workload. These connections between the different niches make the DT concept especially suitable for taking a more integrated and sustainable approach to developing the textile and apparel industry.

5. Conclusions

The present study has shown that the potential of DTs in the textile industry goes beyond their current applications. A systematic analysis of seven key but underdeveloped niches—from predictive maintenance and energy simulation to personalisation and cybersecurity—reveals new opportunities to move the sector towards more efficient, flexible, and sustainable production.

Particularly promising are those areas where DTs can rely on existing infrastructure, such as sensors, IoT networks, or production databases and generate measurable value in the short term. Predictive machine diagnostics, defect simulations, and energy flow modelling are good examples. Other more complex applications, such as personalised production and digital modelling of human participation, require longer-term strategies but can offer a significant competitive advantage for innovative manufacturers.

The recommendations that can be formulated based on the analysis of DT applications in textiles are summarised according to stakeholders as follows:

- For researchers: To develop interdisciplinary models that combine engineering simulation, behavioural data, and economic analyses within DTs.
- For the industry: To start with pilot projects in niches with the lowest barriers to implementation, testing and validating the added value of the DT technology on a small scale.
- For software and platform developers: To focus on modular and adaptable solutions that can be integrated with different types of machines and production systems.
- For policymakers and institutions: To encourage investments and standards related to the digitalisation of production, with an emphasis on cybersecurity, energy efficiency, and sustainable resource management.

In conclusion, DTs have the potential to improve existing processes in the textile industry and to lay the foundation for a new production paradigm—one that is more precise, adaptive, and sustainable. However, realising this potential requires targeted actions, interdisciplinary collaboration, and a long-term vision.

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