

Article

Innovation Impact in the Textile Industry: From the Toyota Production System to Artificial Intelligence

Paula Tavares de Carvalho ^{1,2}, José Dias Lopes ³ and Ricardo Jorge Raimundo ^{1,4,*}

¹ ISEC Lisboa—Instituto Superior de Educação e Ciências, 1750-142 Lisbon, Portugal; paula.carvalho@iseclisboa.pt

² BRU—Business Research Unit, ISCTE—Instituto Superior de Ciências do Trabalho e da Empresa, IUL—Instituto Universitário de Lisboa, 1649-026 Lisboa, Portugal

³ ISEG—Instituto Superior de Economia e Gestão, Universidade de Lisboa, 1200-781 Lisbon, Portugal; jose.diaslopes@iseclisboa.pt

⁴ IADE—Faculdade de Design, Tecnologia e Comunicação, Universidade Europeia, 1200-649 Lisbon, Portugal

* Correspondence: ricardo.raimundo@iseclisboa.pt

Abstract: The Toyota Production System (TPS) was a revolutionary approach to automobile production that influenced companies all over the world. The fight against redundancy is at the core of this approach. The textile industry remains one of the most polluting sectors worldwide, which makes environmental sustainability a key concern. In line with national priorities, companies are striving to balance profitability with sustainability, minimizing defects and reducing waste. This study explores the evolution of textile production systems from TPS principles to the integration of Artificial Intelligence (AI) and how they can be used from a sustainability perspective. Smartex, a textile start-up recognized as the winner of the Web Summit 2021 competition, was chosen as the focus of this case study. Employing qualitative research methods, including content analysis of interviews, management reports and website data, the study examines the parallels and distinctions between TPS and Smartex's AI-driven system. The findings highlight how Smartex is revolutionizing the textile industry by leveraging AI to avoid defects and reduce waste, advancing both environmental and commercial objectives. Finally, the implications and limitations of the research are explained.

Keywords: textile industry; toyota production system; artificial intelligence; defects; waste

Academic Editors: Jun (Justin) Li and Francesco Riganti Fulginei

Received: 29 November 2024

Revised: 22 January 2025

Accepted: 30 January 2025

Published: 31 January 2025

Citation: de Carvalho, P.T.; Lopes, J.D.; Raimundo, R.J. Innovation Impact in the Textile: From the Toyota Production System to Artificial Intelligence. *Sustainability* **2025**, *17*, 1170. <https://doi.org/10.3390/su17031170>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Textiles have transitioned from addressing basic human needs to symbolizing fashion, style, and social status. However, this transformation comes with environmental costs. The textile and fashion industries are the second-largest contributors to global pollution after the oil industry. Within the European Union, Portugal ranks as the second-worst country for industrial emissions, largely driven by its textile sector, surpassed only by Latvia. Portugal's emission ratio, measured by fine particle emissions relative to the industry's gross added value, stands at 0.82—substantially higher than Spain's 0.10 and Germany's 0.02 [1].

In response to growing environmental concerns, industries globally are under pressure to integrate sustainability into their production processes. The textile industry in particular has faced scrutiny for its contributions to water pollution, waste generation, and air pollution across the supply chain—from fiber production to fabric finishing [2]. This

study explores how advancements in production methods, particularly through the Toyota Production System (TPS) and Artificial Intelligence (AI), address these challenges by enhancing efficiency, reducing waste, and improving product quality.

The Toyota Production System, as outlined by Womack et al. [3], Ohno [4], Liker [5], and Imai [6], emphasizes lean manufacturing, continuous improvement (kaizen), and the elimination of waste across production processes. By fostering just-in-time production and quality management, TPS principles have significantly influenced the textile industry. These methodologies streamline production workflows, reduce overproduction, and ensure higher consistency in product quality. Furthermore, they promote sustainability by minimizing resource use and waste generation [2].

AI technologies complement the principles of TPS by revolutionizing various facets of textile production. As highlighted by Lee et al. [7], Rai et al. [8], and Choudhury [9], AI enables precision and efficiency in areas such as recipe formulation, color matching, pattern recognition, process optimization, and supply chain management. For example, AI-driven systems can optimize dyeing recipes, leading to reduced chemical usage and lower water consumption [1]. Similarly, AI-powered quality control systems can detect defects early, reducing waste and enhancing overall production efficiency [2]. Sun et al. [10] and Lu and Lu [11] demonstrate how AI enhances decision-making, enabling data-driven strategies that align with the principles of lean manufacturing.

The integration of TPS principles and AI technologies has had measurable impacts on the textile sector, driving increased productivity, higher product quality, and reduced environmental impact [2]. For instance, the application of AI to garment manufacturing has improved process accuracy, shortened production times, and lowered energy consumption [1]. These innovations align with the goals of the Ellen MacArthur Foundation [12] to establish circular economies, further reinforcing the industry's sustainability efforts.

However, achieving the full potential of these advancements requires a robust framework of standards to address automation challenges and ensure quality control throughout the production process [2,13,14]. This study focuses on the transition from traditional TPS methods to Industry 4.0 and Smart Factories. A case study of SMARTEX, a Portuguese company founded in 2018, illustrates this evolution. SMARTEX integrates TPS principles with cutting-edge AI-driven systems to enhance efficiency and sustainability in textile production. By exploring SMARTEX's journey, this research demonstrates how the synergy of lean manufacturing and digital innovation can drive the industry towards a more sustainable future.

SMARTEX has gained recognition for its innovative approach, winning the Web Summit Contest in 2021. The company's solution applies Artificial Intelligence (AI) to detect defects in textile production, thereby minimizing material waste and reducing costs. Its software-as-a-service (SaaS) platform leverages Computer Vision and Machine Learning to automate defect identification, resulting in reduced textile waste, CO₂ emissions, energy consumption, water usage, and capital expenditure.

The study addresses the following research questions and objectives:

- (a) Identify the similarities and differences between TPS applications and contemporary AI-driven technologies in the textile industry.
- (b) Assess the potential of AI in contributing to a less polluting, smarter textile industry.

To achieve these objectives, the study employs a qualitative research approach, which is particularly useful with respect to exploring context-dependent phenomena such as the Artificial Intelligence (AI) in the textile industry, as it allows the ascertaining of a more context-rich data. Moreover, in the context of the textile industry's evolution, qualitative research offers a comprehensive picture on organizational dynamics.

Content analysis is therefore applied to a podcast interview, website materials, and management reports, using NVivo software for data analysis, with manual verification to ensure the accuracy of interpretations. The main categories derived from data analysis were discussed and conclusions were drawn. The article is organized into the following sections: Literature Review, Materials and Methods, Results, and Conclusions.

2. Literature Review

2.1. *Toyota Production System (TPS) and Its Innovation Impact in Reducing Defects and Waste*

Toyota has established itself as a global case study in excellence, being the most valuable company in Japan and, for several years, the leader in the automotive sector worldwide. Beyond its financial achievements, Toyota is a management role model that has inspired countless companies across various industries. The introduction of concepts such as “just-in-time” (efficient stock management with zero inventory costs), “kaizen” (continuous improvement), and “lean” (streamlined production and management) originated with Toyota and are now implemented across industries worldwide. As highlighted by Womack et al. [3] and Liker [5], the principles of TPS—just-in-time (JIT), Jidoka, and kaizen—have been instrumental in establishing new benchmarks for operational excellence and continuous improvement.

The Toyota Production System (TPS), developed under the leadership of Ohno Taiichi, is recognized as the foundation of Lean Manufacturing. TPS introduced the concept of the seven wastes, or “muda” in Japanese, as part of a systematic approach to eliminating inefficiencies. Rooted in its focus on People and Processes, TPS aims to minimize unnecessary losses that negatively affect productivity and profitability.

The system categorizes waste into three main types: i muda: refers to seven types of waste, including transportation, excess inventory, redundant motion, waiting, overproduction, over-processing, and defects; ii mura: denotes unevenness, irregularity, or non-uniformity, which often leads to the creation of muda; and iii muri: represents overburden or unreasonable demands on people or processes, which can arise from mura or overly aggressive efforts to eliminate muda. Ohno [4] and Imai [6] emphasize that TPS is not merely a set of tools but a culture that prioritizes people, processes, and customer satisfaction—an ethos now amplified by AI technologies.

On the one hand, TPS is built on a framework of key principles, such as maximum efficiency, 100% quality, pull system methodologies, respect for people, cellular manufacturing and assembly, and just-in-time delivery [14]. The system emphasizes discretion, pull, and flow, which together enhance quality and systematically eliminate waste [13]. On the other hand, lean manufacturing, central to TPS, focuses on creating value for customers with minimal resource expenditure. It seeks to optimize resource use while reducing or eliminating waste [15,16]. Lean principles have been widely validated across industries, with studies by Manzouri et al. [17], Tripathi et al. [18], and Goktas and Yumusak [19] collectively highlighting the critical role of waste reduction in lean production systems inspired by TPS.

To optimize efficiency and eliminate waste, Jidoka and just-in-time (JIT) are paramount to the TPS developed by Taiichi Ohno and have significantly reshaped manufacturing practices across the globe. JIT is a lean management methodology designed to align production closely with customer demand. Its core principle is delivering the right parts, in the right quantity, at the right time, effectively minimizing waste. By reducing excess inventory, idle time, transportation costs, and overproduction, JIT enhances thus operational efficiency whilst maintaining a customer-first approach [20].

Conversely, the concept of Jidoka, or “autonomous automation”, originated from Sakichi Toyoda’s invention of a loom that would stop automatically when a thread broke. This innovation enabled immediate problem detection, ensuring quality at the source. It

empowers machines with basic decision-making capabilities, allowing them to identify deviations and pause operations whilst awaiting human intervention [21]. Described as “automation with a human touch”, Jidoka reduces dependency on extensive inspections while fostering accountability among operators. This principle encourages a culture of continuous improvement and proactive quality management [16,22,23]. Sakichi Toyoda’s automatic loom, introduced in 1926, illustrated this philosophy by integrating judgment capabilities into machines, eliminating defective products, and reducing wasteful practices. This philosophy of error-proofing and real-time problem resolution has set the foundation for Industry 4.0 practices, where cyber-physical systems, IoT, and AI technologies drive innovation [11].

In this way, the TPS framework is often represented as a house structure, with waste elimination as its ultimate goal: i ceiling: represents the overarching aim of waste elimination; ii pillars: JIT: Ensures the delivery of the right part, in the right amount, at the right time; Jidoka: incorporates automated stops, andon (visual signals), error-proofing mechanisms, in-station quality control, and root-cause analysis (e.g., the “5 Whys” technique); iii core principles: emphasize teamwork, waste reduction, and people-centric innovation; iv foundation: built on leveled production (heijunka), stable and standardized processes, visual management, and the Toyota Way philosophy [24].

TPS is therefore designed to augment human capabilities rather than replace them. Smart machines and well-trained individuals work collaboratively, reflecting Toyota’s commitment to harmony and sustainability as represented in Figure 1.

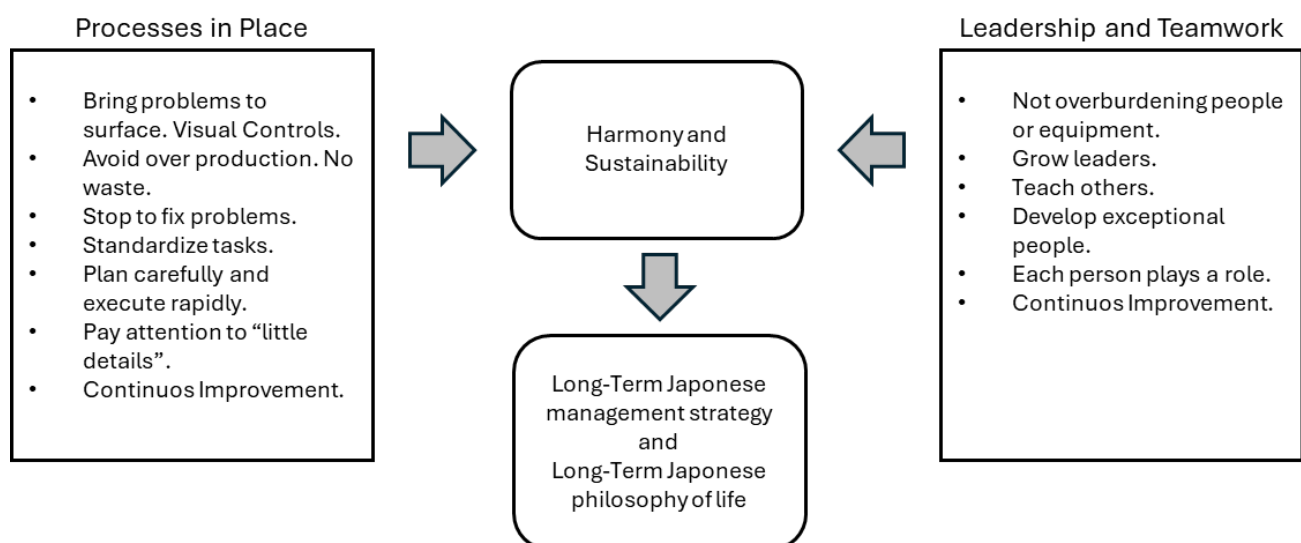


Figure 1. Pillars of Japanese long-term strategy. Source: [14]

This approach aligns with Japanese management principles, emphasizing respect, continuous learning, and intergenerational knowledge transfer. Furthermore, in Toyota factories, problem identification is celebrated as an opportunity for improvement. When an issue arises, the production line halts, and communication tools like sounds, colors, and Kanban boards ensure everyone is informed. This transparency fosters teamwork, allowing operators and suppliers to collaborate toward achieving customer satisfaction.

The TPS come up along an evolution of quality control that spans several industrial revolutions, from preindustrial manual inspection to the current era of Industry 4.0. The main phases are as following: i preindustrial revolution (before 1784): manual processes with minimal focus on quality; ii Industry 2.0: introduction of zero-defect culture, Total Quality Control (TQC), and the Plan-Do-Check-Act (PDCA) cycle; ii Industry 3.0: automation and customer-focused Total Quality Management (TQM), incorporating Six Sigma

and Lean principles; iii Industry 4.0: cyber-physical systems, IoT, and Big Data, emphasizing customer delight and innovative solutions [24].

The textile industry builds upon this cumulative evolution overall and benefits from its innovation impacts overall. Hence, TPS has been adapted within the textile industry to reduce waste, shorten lead times, and improve quality [16]. However, implementing TPS principles in machine-intensive operations presents unique challenges. Manufacturers must tailor TPS methodologies to address specific ergonomic and operational demands rather than adhering rigidly to its original framework [16].

JIT and Jidoka have thus revolutionized manufacturing by reducing defects, minimizing waste, and fostering continuous improvement. These principles not only augment operational efficiency but also contribute to sustainable practices, making TPS an enduring model for innovation and excellence. The TPS, known for reducing waste without sacrificing quality, has revolutionized automotive manufacturing and spread to other industries [25]. It emphasizes reducing waste and improving efficiency without compromising quality, which has influenced the textile industry in improving production processes and quality control [26]. It has led to the automation of machinery parts and processes in the textile industry, contributing to the development of intelligent manufacturing systems and the creation of intelligent textile ecology [27,28].

In summary, the Toyota Production System (TPS) has significant impacts, including enhanced operational efficiency, as Lean principles minimize waste and optimize processes, as validated by Tripathi et al. [18] and Sun et al. [10]. It also strengthens quality control through root-cause analysis tools like the “5 Whys” and visual management techniques, ensuring consistent quality. As Choudhury [9] highlights, TPS-inspired practices reduce defect rates and improve customer satisfaction. Additionally, TPS supports sustainability by minimizing resource consumption and waste generation, aligning with the principles of the circular economy, as advocated by the Ellen MacArthur Foundation [12].

2.2. Artificial Intelligence (AI) in Textile Industries

The advent of AI has transformed the implementation of TPS principles, driving a shift from reactive to predictive manufacturing. Advanced analytics, machine learning, and IoT enable manufacturers to anticipate demand fluctuations, optimize resource allocation, and detect anomalies in real time. Lee et al. [7] describe how predictive maintenance, powered by AI, enhances equipment reliability, reducing downtime and associated costs. The integration of Artificial Intelligence (AI) into the textile industry has therefore emerged as a revolutionary solution to address critical challenges, including waste reduction. AI applications cover the entire textile chain, offering innovative approaches to mitigate environmental impact, create sustainable products, and enhance overall efficiency [15].

In terms of waste reduction and sustainability, AI reinforces sustainability in the textile industry by enabling smarter production methods. AI-driven solutions mitigate the industry’s environmental footprint by optimizing processes and resource procedure [15].

Also, the growth of AI has led to the development of intelligent textile tools, automated production lines, and advanced testing systems. These innovations have transformed quality and efficiency standards in the industry. AI applications have become integral to various aspects of the textile industry, including recipe formulation, color calibration, pattern recognition, process optimization, garment manufacturing, quality assurance, and supply chain management. These advancements improve productivity while reducing environmental impact [15].

In the case of textile coloring, AI-driven systems are particularly effective, offering solutions for color formula prediction, flaw detection, and color correspondence. Techniques like Artificial Neural Networks (ANNs) and Adaptive Neuro-Fuzzy Inference

Systems (ANFIS) forecast color strength (K/S) based on process parameters, reducing human intervention and increasing precision [15]. Therefore, rather than replacing human workers, AI enhances their capabilities. Smart machines collaborate with people to improve processes and product quality [29].

As a result, AI addresses challenges related to human precision and quality variation. Techniques such as image processing and neural networks enable 100% error detection accuracy, improving productivity, fiber identification, and workplace safety. AI also assists in demand forecasting and future applications, including virtual yarn modeling and property prediction, which promise to redefine quality and performance standards in textiles [29]. AI facilitates zero-defect manufacturing by predicting textile properties critical for evaluating quality and performance. This holistic approach fosters higher-quality production with reduced waste. However, challenges such as ensuring model transparency, managing complex processes, and building robust AI systems must be addressed to fully realize AI's potential [29].

AI has thus the potential to reshape the textile manufacturing landscape, driving the industry toward a sustainable and efficient future. As AI technologies evolve, they will play an increasingly pivotal role in achieving a balance between productivity, quality, and environmental responsibility.

AI, particularly machine learning (ML), is being applied in the textile industry for various purposes such as color matching, pattern recognition, process optimization, and quality control, leading to enhanced productivity, product quality, and competitiveness [30]. AI technologies, including machine learning and deep learning, are thus transforming conventional textile production, making human workers almost redundant and speeding up the production process [31,32]. These AI-driven techniques are being used to predict fabric properties and hand feel, essential for assessing textile quality and performance, thereby revolutionizing the textile industry [33].

To sum up, within manufacturing ecosystems influenced by the Toyota Production System (TPS), AI applications deliver transformative benefits. AI-powered robotics exemplifies Jidoka principles by autonomously identifying and correcting quality deviations, enhancing efficiency while maintaining precision. Additionally, AI elevates decision-making through Big Data analytics and machine learning, generating actionable insights that drive continuous improvement (kaizen) at unparalleled speeds. In supply chain optimization, AI-driven models aligned with JIT principles synchronize inventory and logistics with real-time demand, minimizing costs and reducing environmental impact [34].

2.3. The Integration Between TPS and AI in Textile Smart Factories

As aforementioned, Artificial Intelligence (AI) forms the backbone of “Smart Factories”. This advanced technology, when flawlessly integrated into production lines, enables organizations to achieve superior outcomes. Smart Factories optimize processes, deliver products to consumers more efficiently, and offer greater customization options [34]. A Smart Factory production system is equipped by definition with diverse resources capable of manufacturing various small-lot products. These systems feature dynamic routing that switches between products automatically and in real time. They also integrate machines, products, information systems, and people via high-speed network infrastructure. Operating in a deeply converged network environment, Smart Factories display self-organization and control functions that distribute operations among multiple entities. Furthermore, they leverage big data—generated in massive quantities—and cloud computing for real-time processing and analysis [35, 36].

Smart Factories are paramount with respect to the mitigation of waste. Literature on production systems, even the most recent, emphasizes the need to combat waste [37]. As noted by Christopher and others [38], the synergy between TPS and AI embodies the

principles of mitigating waste and continuous improvement, driving progress in sectors as diverse as automotive and textiles. This fusion ensures that TPS remains not only a historical milestone but also a dynamic framework for future industrial evolution. Key developments include automation as AI-enabled machines ensure precise operation and defect detection, embodying thus the TPS commitment to quality and waste reduction. Also, it allows predictive maintenance while AI systems monitor equipment performance, preemptively identifying issues to avoid costly breakdowns. And finally, innovations in terms of sustainability, augmenting Lean principles by AI, facilitate as well resource-efficient production and contribute to circular economy goals within a smart system.

However, the role of AI in elevating these systems to unprecedented levels of efficiency and operability remains underexplored. Addressing this gap is a primary focus of this research. This study examines Smartex, a ground-breaking smart textile company that typifies the concept of a Smart Textile Factory assembling both the TPS and AI. Smartex won the prestigious Web Summit award in 2021 and is dedicated to transforming traditional textile factories into “Modern Textile Factories”. Drawing upon Smart Factory principles, Smartex exemplifies the fusion of innovative technologies with advanced production methodologies [39].

By integrating AI and the nine pillars of TPS, Smartex represents a pioneering model for the textile industry. The textile industry is facing hurdles in fully integrating the TPS into textile production, including establishing a comprehensive standards system for intelligent manufacturing and addressing breakpoints in automated production processes [39]. Challenges also include strengthening the quality traceability of the entire textile production process and developing more robust models to ensure the generalization of AI-driven predictions of fabric properties [37].

Artificial intelligence can make the necessary integration between the Toyota system and textile industry, boosting the fight against waste and the move towards sustainability.

3. Materials and Methods

This research, due to the specificity of the subject, uses a case study. This methodology was chosen following its advantages. In particular: it allows an in-depth and holistic understanding of complex phenomena as the integration of TPS and AI in the real-life context of textile organization [40–42]. Also, it provides rich and detailed data from multiple sources, inclusive from interviews and podcasts underscoring the depth and transferability of findings [43,44]. It was chosen due to its flexibility, allowing for the use of various data collection and analysis methods, which were tailored to the specific Portuguese textile context [45]. Finally, it allows bridging the gap between theory and practice, which was worthwhile in the unique case of the integration of TPS and AI in the textile industry, which presents sparse and fragmented literature [46,47]. Nonetheless, this methodology presents limitations such as a lack of consensus on its definition and structure, leading to inconsistencies [48], its difficulty in generalizing results as it focuses on specific cases [49,50], and the need to avoid bias, especially when the case selection criteria are not clear [51], which demands careful methodological considerations [52,53]. The study intended to mitigate all those impairments, by being conducted rigorously.

In the vein of the specific case and idiosyncratic textile industry, the focus will be therefore on an analysis of a company that is innovating or contributing for the innovation of the textile industry providing an in-depth understanding of the subject through a content analysis technique to analyze the podcasting content of Textiles Innovation interviews, which are widely accessible online. Interviews made to the top management and experts working in the textile industry all around the world reinforced the analysis.

These contents sources: podcasts, online interviews, and content from corporate websites will be triangulated.

In the era of “big data”, the methodological technique of content analysis can be the most powerful tool in the researcher’s kit. Content analysis is versatile enough to apply to textual, visual, and audio data. Content analysis that is somewhere between a purely empirically derived model and a purely theoretical one is a model known as emergent coding [51]. This approach is derived from the qualitative research concept of grounded theory [52].

The objective of content analysis is to convert recorded “raw” phenomena into data, which are treated in a scientific manner so that a body of knowledge may be built up. In fact, the researcher who wishes to undertake a study using content analysis must deal with four methodological issues: selection of units of analysis, developing categories, sampling appropriate content, and checking reliability of coding [53,54]. Following Yin [55] and Priya [56], our case study will be descriptive as the purpose is to ‘describe’ what is happening concerning innovation in the textile industry in a real-world context.

It is explained ‘why’ and ‘how’ certain sequences of events occur or do not occur, which can be used in subsequent research studies in an extensive way are explored and identified. Following the three basic principles of scientific method, as mentioned in Pra-zad: “1. Objectivity: Which means that the analysis is based on explicit rules, which enable different researchers to obtain the same results from the same documents or messages. 2. Systematic: The inclusion or exclusion of content according to some consistently applied rules whereby the possibility of including only materials, which support the researcher’s ideas—is eliminated. 3. Generalizability: The results obtained by the researcher can be applied to other similar situations” [55].

Recorded interviews are converted into text and coded using the NVivo (qualitative research software) manually to make sure that the meaning fits. Open, Axial and Selective coding will be followed to analyze, categorize, and recognize connections within the data content to be analyzed.

Ideally, the sample represents the whole population on the characteristics of interest [53,54]. Sampling is a major problem for any type of research. We cannot study every case of whatever we are interested in, nor should we want to. Every scientific enterprise tries to find out something that will apply to everything of a certain kind by studying a few examples, the result of the study being, as we say, ‘generalizable’. Concerning sampling, it is not the matter of small or large but the representativeness [54]. The research topic rather than their representativeness which determines the way in which the people to be studied are selected [55–57].

Web summit is a nest of innovating start-up companies. Analyzing the winners of the contest after COVID-19, among more than 70 start-up companies in 2021, SMARTEX, a Portuguese company founded in 2018, was considered the best entrepreneurship and innovative business solution and won the Web Summit’s Contest. The jury of experts recognized the solution that applies artificial intelligence to detect defects in textile production, avoiding material waste, and reducing costs through online software as a service, (SaaS) based on Computer Vision and Machine Learning. This automated identification process reduces textile waste, CO₂ emissions, energy, water, and capital expenditure. For these reasons, SMARTEX is the case study in this research.

Case studies are particularly suitable when questions of the “how” and “why” type are asked and when there is little control over the events under study [55,58]. In addition, the uniqueness of the case study can serve as a guide for identifying good practices, paths to follow or pitfalls to avoid. In this study, as the intention was to show possible ways of combating waste in textiles, the choice was made to study the various innovative applications implemented by Smartex, which is why the case study is suitable for this purpose.

4. Smartex and Smartex Projects

4.1. Introducing the Company

Smartex is dedicated to digitizing the textile industry by providing technical tools, which will allow it to become more efficient, productive, and sustainable. In December 2022, Smartex had almost 200 employees. In one year, they doubled the number of collaborators, most of them engineers. Smartex has the slogan of “We build the tools for a Modern Textile Factory” [39].

The Smartex System is based on three big stones: Core: resource efficiency; Fact: digital management; and Loop: high quality data. The system has high resolution cameras, advanced light analysis, and tailored retrofit so it is possible to install Smartex Core into existing circular knitting machines, automatic roll grading, instant updates, performance insights, fast track quality rolls, indestructible labels, and shareable primary data. The Smartex System reduces waste and defects in the textile industry.

Smartex came out with a new concept of a “Modern Textile Industry” to understand it; it was performed using a content analysis of Smartex “The Modern Textile Factory Report-2023”. In this report, there are twelve articles where textiles partners and experts shared their perspective concerning what kind of approach a Modern Textile Industry should have to be different from the traditional textile approach.

With regard to the content analysis of online interviews and reports, which was carried out between April and July 2024, the following steps were adopted: first, repeated words were collected and classified in the Open Coding Dimension.

Second, the Open Coding with similar characteristics were gathered (Axial Coding) into five dimensions: 1. resources efficient (reduced costs, higher profits, reduced emissions, streamlining work processes to enhance overall efficiency); 2. real time data collection (speed, quality, price, compliance, objective, verifiable, and traceability); 3. data driven decision making (fact-based, revenue generating speed with quality-dependent profits); 4. integrated with its shareholders (vertically integrated facilities, full visibility on the production process to review order progress, identify problem areas, continuously improve); and 5. high quality and safe jobs (safe non-toxic for example, by removing chemicals from the air, innovative places to work, constant training and upskilling, maximize the factory’s investment in technology, deliver products with the right mix of price, speed, quality and compliance).

Third, some connections between these categories that capture the sense of the company were found (Selective Coding) in three categories: Core (resource efficiency), Fact (digital management: real time data collection, data driven decision making, and integrated with shareholders) and Loop (high quality data), in summary representing The Modern Textile Factory.

Gilberto Loureiro, Co-Founder and CEO of Smartex highlight three lessons in “The Modern Textile Factory Report—2023”:

- (1) “Money is ALWAYS king No one will implement systems for “Traceability” or “Sustainability” if those systems don’t save them enough money and resources, while justifying a tangible return on investment”.
- (2) “Money is REALLY ALWAYS king Textile factories risk losing deals over a minute increase in fabric prices, even as low as 1 or 2 cents per kilogram, constituting less than 1% of the fabric’s total cost”.
- (3) “Go local—To effect change in the supply chain, a deep and immersive approach is imperative. It is necessary to engage in on-site activities, provide training, and fly to visit factories in Bangladesh, Turkey, India, and anywhere else necessary. This proactive approach is crucial, especially as these areas may not traditionally attract software start-ups or tech professionals”.

With respect to the interview with Gilberto Loureiro (SMARTEX CEO and co-founder) on the Textiles Innovation Podcast (Spotify open to public in general) by Jessica Owen, deputy digital editor at WTIN., the podcast nº 32 of Textile Innovation—World Textile Information Networking is going to be analyzed. The interview was made in August 2020, and it has a duration of 37 min and 59 s. Now, in this Textiles Innovation, there are 99 Podcast interviews with specialists and top management of textiles companies and research centers all around the world.

Some similarities between the Toyota Production System (TPS) and the Smartex Production System could be found as summarized at Figure 2.

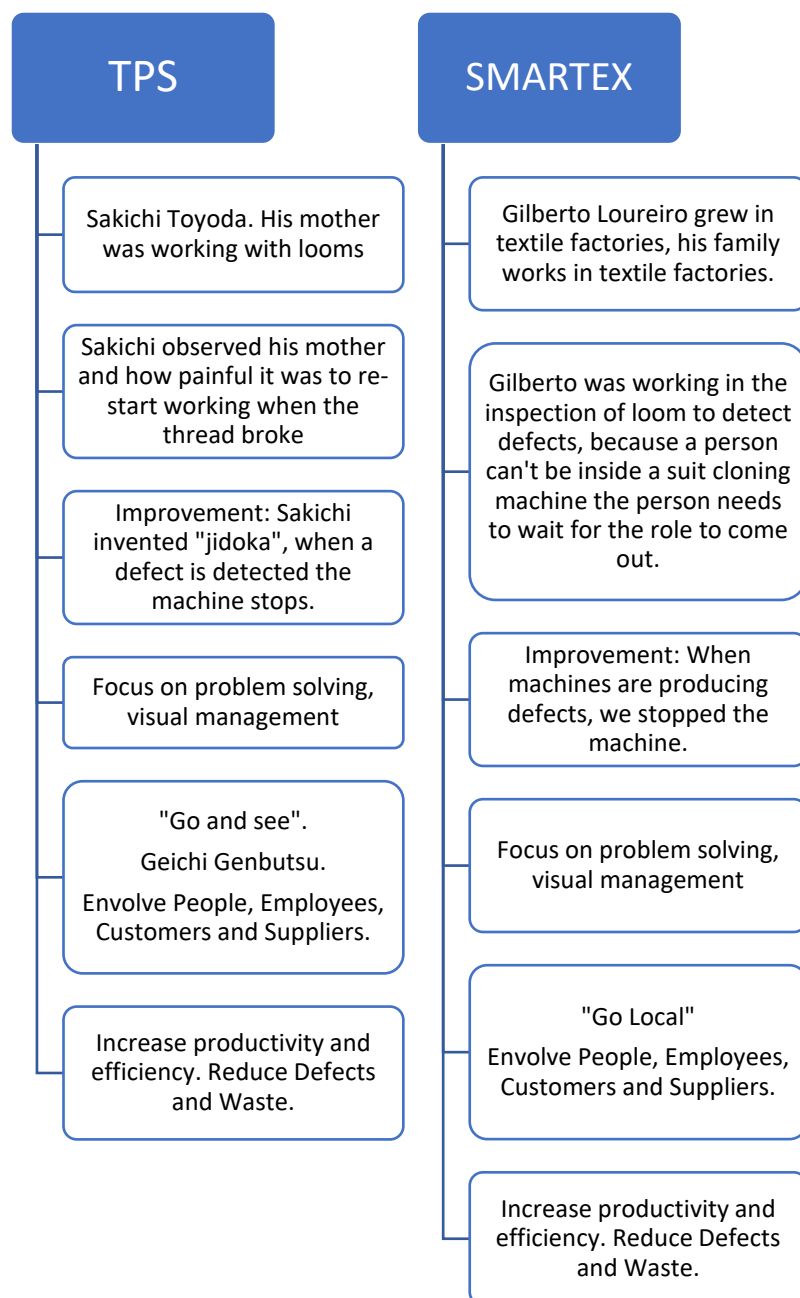


Figure 2. Similarities between Toyota and Smartex Production System. Source: Based on literature review and content analysis of podcast interview [58–60] (Textiles Innovation at Spotify) with Smartex CEO: Gilberto Loureiro in August 2020. (Interview with free access to public in general at Spotify- Textile Innovation).

At Smartex the circle knitting machines have cameras that are monitoring and giving information. These cameras are scanning all the time for abnormalities and then either they act as a warning system, or stop the machine. Further the company can go and fix it, while working out what was going wrong. Partnership is very important to Smartex, as for instance facilities at Hong Kong tested Smartex devices in terms of circular knitting machines. Investors such as fashion for goods are also key partners.

“In Europe, we have already clans using the full device companies like tint tech, textiles or polo PK, and one of the largest manufacturers in Europe is. Also is starting to use our devices. We have interest from many companies in Turkey, Brazil, India”. (Gilberto Loureiro, Smartex CEO, 2020).

To the three Smartex stones (Core, Fact, and Loop), the author adds the importance of people and partnership, and the philosophy of “Go Local” is pointed out by Gilberto Loureiro (Smartex-CEO) in the company report “The Modern Textile Factory Report—2023.

4.2. The Smartex Projects

Yin [55] argues that, in case study research, the issue is not to generalize over some broader population, as the case study is not based on a sample. Reliability refers to the consistency and repeatability of producing a case study’s findings [55,56]. In the light of the presented concepts of AI and TPS [4,8] widely discussed above, it is now carried out a presentation of Smartex key case studies.

Smartex cases studies are presented openly on their website (<https://www.smartex.ai/case-studies>, accessed in 30 December 2023). These case studies have been applied to textile companies using the following Smartex textile solutions.

4.2.1. Impetus

In 1973, IMPETUS Group started as a small textile enterprise and grew into a global leader in the industry. With a vertically integrated structure, it has a team of 860 persons (693 in Portugal) and crafts 4.65 million articles annually. Specializing in seamless and Cut and Sew underwear, IMPETUS has their own fashion brand and innovates through research and development, boasting Europe’s top-notch facilities and sustainable practices. Smartex conducted a four-week pilot study at Impetus. The goals of this project included reducing the quantity of rolls with the need for inspection, as well as decreasing fabric waste while improving quality and traceability. In the case study, Impetus was using 12 Smartex machines; it had a four-week duration, a 24 Payback Period in months and a 1.5 ROI of contract period.

“Through seamless integration of Smartex LOOP & FACT, we precisely target and address problem areas, leading to an impressive 50% reduction in inspected rolls”.—Joana Cunha, Quality Director. (<https://www.smartex.ai/impetus>, accessed in December 2023).

4.2.2. Ekoten

Ekoten Tekstil is a prestigious knit fabric producer in Europe and one of the major textile exporters of Türkiye.

Top global brands trust Ekoten as an industry-leading solution partner to supply sustainable, fashionable, and functional fabrics. They currently have 120 circular knitting machines. When the case study was made, Ekoten had 17 Smartex machines, the case study had 13 months of duration, concluding a 9 Payback Period in months and 3× ROI of contract period. The defects detected were oil/hole: 5%, elastane/yarn: 60%, and needle/sinker: 35%.

“Smartex reduces our defective production rate while providing a transparent & 100% automatically controlled environment with a sustainable & innovative approach”.—Serdin Çelik, Manufacturing Execution System Manager. (Based in the information available online at <https://www.smartex.ai/ekoten>, accessed in December 2023).

4.2.3. Tintex

Tintex Textiles was founded in 1998. It is a Portuguese company which crafts smart jersey knit fabrics and develops sustainable strategies along with the whole production process. When the case study was made, Tintex had 21 Smartex machines, the case study had 70 days of duration, concluding an 11 Payback Period in months and 3× ROI of contract period. The defects detected were oil/hole: 8%, elastane/yarn: 51%, and needle/sinker: 41%.

“Smartex systems improved our efficiency & our defective rate. As a vertical company we highly value the traceability tools & waste prevention of this unique technology.”—Ricardo Silva, CEO. (Based on the information available online at <https://www.smartex.ai/tintex>, accessed in December 2023).

4.2.4. Clothius

The name “Clothius” comes from the Greek “clotho” meaning “to spin”. Clotho was believed to weave the thread of life. It is currently equipped with 20 circular looms and 22 circular looms specialized for tubular and 3D meshes.

By reducing their defect rate, Clothius has improved fabric quality and strengthened customer satisfaction. When the case study was made, Clothius had five Smartex machines, the case study had 9 months of duration, concluding a 6.5 Payback Period in months and 6× ROI of contract period. The defects detected were oil/hole: 1%, elastane/yarn: 12%, and needle/sinker: 87%.

“No longer needing to manually inspect our rolls saves us valuable time & resources while helping optimize our production to be cleaner & 100% automatically inspected with Smartex”.—Vitor Barroso, Knitting Manager. (Based on the information available online at <https://www.smartex.ai/clothius>, accessed in December 2023).

4.2.5. Merboy Tekstil

Merboy Tekstil was founded in 1970 and currently produces 50 thousand meters of fancy and printed fabrics per day. They export over 50% of their production. By reducing their defect rate, Merboy Tekstil has improved fabric quality and strengthened customer satisfaction. It is one of the leading knitted fabric manufacturers in its sector. The organization has an innovative vision and produces at a competitive level both domestically and internationally. When the case study was made, Merboy had 15 Smartex machines, the case study had 7 months of duration, concluding a 5 Payback Period in months and 7× ROI of contract period. The defects detected were oil/hole: 10%, elastane/yarn: 30%, and needle/sinker: 60%.

“With Smartex I am more comfortable & confident in our production knowing we are not producing defects”.—Merve Erden, Machine Operator. (Based on the information available online at <https://www.smartex.ai/merboy>, accessed in December 2023).

4.2.6. Brito Knitting

It was founded in 1996. By reducing their defect rate, Brito Knitting has improved fabric quality and strengthened customer satisfaction. When the case study was made, Brito Knitting had five Smartex machines, the case study had 9 months of duration, concluding a 16 Payback Period in months and 2.5 × ROI of contract period. The defects detected were oil/hole: 6%, elastane/yarn: 47%, and needle/sinker: 47%.

“With the arrival of Smartex, our company managed to decrease the quantity of defects & increase production due to the newfound freedom that the system gives our workers.”—Vitor Barroso, Knitting Manager. (Based on the information available online at <https://www.smartex.ai/brito-knitting>, accessed in 30 December 2023).

4.2.7. Familitex

Familitex was founded in 1999. Familitex is one of the main Portuguese companies in the sector, with a great production capacity of circular knitted fabrics for clothing. Currently, they have 88 circular knitting machines and produce about 22,000 kg of fabrics per day. When the case study was made, Familitex had 28 Smartex machines, the case study had 6 months of duration, concluding a 14 Payback Period in months and 2× ROI of contract period. The defects detected were oil/hole: 8%, elastane/yarn: 51%, and needle/sinker: 41%.

“By reducing their defect rate, Familitex has improved fabric quality and strengthened customer satisfaction. “Smartex acts as my defect defence lawyer, arming us with crucial information on any issues that may occur along the supply chain”.—Ruben Matos, Planning Manager. (Based on the information available online at <https://www.smartex.ai/familitex>, accessed in 30 December 2023).

In summary, SMARTEX presented on their website their case studies of textile companies using their solutions, and the following waste prevention results, as Table 1.

Table 1. Waste prevention in textile factories using Smartex textile solutions.

Textile Factories	Fabric Saved (Kg)	Water Saved (Litres)	Energy Saved (Kwh)	CO ₂ Saved (Kg)
Ekoten	10.400	1.164.800	93.600	23.300
Tintex	3.220	360.640	28.980	7.216
Clothius	16.626	1.862.112	149.634	37.258
Merboy	32.384	3.627.008	291.456	72.572

Source: Based in the information available at <https://www.smartex.ai/case-studies> accessed in 30 December 2023).

As displayed, the results are consistent, showing savings in fabric, water, energy, and CO₂. The logic behind the Toyota system [61] is viable, even in sectors as different from the original automotive sector as textiles.

The Smartex solution integrates AI related technologies and the pillars of TPS, and it does so using a real-time control system.

Artificial intelligence, on top of smart factories solutions, can boost the fight against waste. This case study thus provides valuable information on how modern textile factories can achieve greater efficiency, sustainability, and adaptability in today’s competitive landscape.

5. Conclusions

The sustained success of Toyota as one of the most valuable motor companies globally is no coincidence. From its inception, Toyota embraced smart management approaches. Rather than replacing human workers, Toyota’s technological innovations have augmented their capabilities, emphasizing the collaboration between smart machines and skilled individuals. A cornerstone of Toyota’s philosophy is training employees to work intelligently and efficiently, guided by the principles of The Toyota Way, which centers on respect for others and continuous improvement. This ethos is encapsulated in the concept of “Toyota Value is looking ahead”, a philosophy that evolves over time and remains timeless in its relevance.

The Toyota Production System (TPS) has a distinctive approach to waste management, which remains a focal point even as production systems have evolved into smart factories. What becomes evident from examining this evolution is that the foundational principles of TPS—particularly its focus on waste reduction and efficiency—are not only preserved but advanced in modern systems.

Smartex integrates TPS principles with Artificial Intelligence (AI) to create “Modern Textile Factories”. Similar to Sakichi Toyoda, who revolutionized textiles by addressing inefficiency, Smartex founder Gilberto Loureiro, also from a textile family, identified problems in textile production and devised innovative solutions to reduce defects and waste. Smartex is making notable contributions to textile factory efficiency, fostering sustainability and reducing environmental impacts by saving resources such as fabric, water, energy, and CO₂ emissions. Through case studies, Smartex’s technologies have demonstrated measurable improvements in these areas, proving the efficacy of AI in addressing the textile industry’s challenges.

While focusing upon the similarities and differences between TPS and AI-based technologies in the textile industry, this study highlights the parallels between Toyota’s traditional waste-reduction strategies and the advanced capabilities offered by AI technologies in textile production. Both rely on data-driven insights to improve operational efficiency and quality. However, AI introduces a paradigm shift: while lean systems traditionally respond to issues after they occur, AI enables immediate action based on real-time data, minimizing waste to unprecedented levels.

With respect to the potential of AI in creating smarter and more sustainable textile factories, the potential of AI in the textile industry is evident through significant benefits, including enhanced efficiency (e.g., Impetus, Tintex), defect reduction (e.g., Ekoten, Tintex, Merkboy Tekstil, Familitex), and improved sustainability (e.g., Ekoten, Clothios). AI transforms traditional production systems into more advanced models capable of immediate, data-driven interventions, ushering in a future of near-zero waste production. These innovations are pivotal for achieving industrial circularity and addressing global sustainability challenges.

Textiles is an area where reducing waste and aligning with sustainable practices are fundamental. Combining the TPS philosophy with the potential of Artificial Intelligence makes it possible, as illustrated in the SMARTEX case, to develop new tools to implement reduction and alignment.

5.1. Practical Implications

This study identifies several practical implications for the textile industry. In particular: smart technologies help reduce waste, aligning with sustainability goals; it enhances workflow management as automation improves efficiency and reduces manual interventions, ensuring both product quality of customized products. It ends up reducing costs, as it lowers operational costs. Finally, it contributes to global sustainability as AI and smart production systems reduce the environmental footprint of textile manufacturing while redefining the global textile economy.

5.2. Research Limitations

This research is limited in terms of the generalizability of its findings, as it focuses on a single case study. The results may not fully represent the broader textile industry due to variations in resources, market conditions, and organizational dynamics. Additionally, the adoption and outcomes of TPS and AI vary significantly across regions and sectors, influenced by factors such as resource availability and readiness for smart factory systems. Future research should comprehend comparative studies across diverse textile subsectors (e.g., fashion); longitudinal research in investigating the long-term impacts of AI and

smart systems on operational efficiency, sustainability, and waste reduction; and finally, to focus on AI-based development of sustainable, durable, and innovative textile materials to address environmental concerns and market demands.

Author Contributions: Conceptualization, P.T.d.C. methodology, P.T.d.C.; software, P.T.d.C.; validation, J.D.L., formal analysis, P.T.d.C.; investigation, P.T.d.C.; resources, P.T.d.C. and R.J.R.; data curation, P.T.d.C.; writing—original draft preparation, P.T.d.C.; writing—review and editing, R.J.R.; visualization, J.D.L.; supervision, J.D.L.; project administration, R.J.R.; funding acquisition, J.D.L. All authors have read and agreed to the published version of the manuscript.

Funding: One of the authors would like to thank FCT, I.P., the Portuguese national funding agency for science, research and technology, under the Project UIDB/04521/2020

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable

Data Availability Statement: No new data were created

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Pordata. Viewed in December 2023. Available online: <https://www.pordata.pt> (accessed on December, 2023).
2. Desore, A.; Narula, S.A. An overview on corporate response towards sustainability issues in textile industry. *Environ. Dev. Sustain.* **2018**, *20*, 1439–1459. <https://doi.org/10.1007/s10668-017-9949-1>.
3. Womack, J.P.; Jones, D.T.; Roos, D. *The Machine That Changed the World: The Story of Lean Production*. Harper Perennial: New York, NY, USA, 1990.
4. Ohno, T. *Toyota Production System: Beyond Large-Scale Production*; Productivity Press: New York, NY, USA, 1988.
5. Liker, J.K. *The Toyota Way: 14 Management Principles from the World's Greatest Manufacturer*; McGraw-Hill: New York, NY, USA, 2004.
6. Imai, M. *Gemba Kaizen: A Commonsense, Low-Cost Approach to Management*; McGraw-Hill: New York, NY, USA, 1997.
7. Lee, J.; Bagheri, B.; Kao, H.-A. A Cyber-Physical Systems Architecture for Industry 4.0-Based Manufacturing Systems. *Manuf. Lett.* **2015**, *3*, 18–23.
8. Rai, H.; Gupta, R.; Kumar, S. AI and IoT in Manufacturing: The Next Frontier. In *Advances in Manufacturing*; Stefanini Group: Southfield, MI, USA, 2021.
9. Choudhury, A.K.R. *Sustainability in the Textile Industry: Production Processes and Environmental Impact*; Springer: Berlin/Heidelberg, Germany, 2021.
10. Sharma, S.S., Vivek, V. and Malviya, A. AI-Enhanced Predictive Maintenance in Intelligent Systems for Industries. In Proceedings of the 2024 International Conference on Advances in Computing Research on Science Engineering and Technology (ACRO-SET), Indore, India, 27–28 September 2024; IEEE: Piscataway, NJ, USA, 2024.
11. Mohiuddin Babu, M.; Akter, S.; Rahman, M.; Billah, M.M.; Hack-Polay, D. The role of artificial intelligence in shaping the future of Agile fashion industry. *Prod. Plan. Control.* **2024**, *35*, 2084–2098.
12. Ellen MacArthur Foundation. *A New Textiles Economy: Redesigning Fashion's Future*; Ellen MacArthur Foundation: Isle of Wight, UK, 2017.
13. Antosz, K.; Pasko, L.; Gola, A. The Use of Artificial Intelligence Methods to Assess the Effectiveness of Lean Maintenance Concept Implementation in Manufacturing Enterprises. *Appl. Sci.* **2020**, *10*, 7922. <https://doi.org/10.3390/app10217922>.
14. Carvalho, P.M.O.T.d. *Japanese Income Tourism: An Exploratory Study of Portuguese Luxury Hotel Management Strategy (Before and After COVID-19)* [Tese de Doutoramento, Iscte—Instituto Universitário de Lisboa]. Repositório Iscte. 2021. Available online: <http://hdl.handle.net/10071/26200> (accessed on 30 December 2023).
15. Sharma, A.K.; Pinca-Bretotean, C.; Sharma, S. Artificial intelligence in lean manufacturing paradigm: A review. *E3S Web Conf.* **2023**, *391*, 01163. <https://doi.org/10.1051/e3sconf/202339101163>.
16. Sahu, B.; Manoria, A.; Tripathy, S. Application of Lean Tools in different Industries: A review. *Turk. J. Comput. Math. Educ.* **2021**, *12*, 2428–2435.

17. Manzouri, M.; Ab-Rahman, M.N.; Che Mohd Zain, C.R.; Jamsari, E.A. Increasing production and eliminating waste through lean tools and techniques for halal food companies. *Sustainability* **2014**, *6*, 9179–9204.
18. Tripathi, V.; Chattopadhyaya, S.; Bhadauria, A.; Sharma, S.; Li, C.; Pimenov, D.Y.; Giasin, K.; Singh, S.; Gautam, G.D. An Agile System to Enhance Productivity through a Modified Value Stream Mapping Approach in Industry 4.0: A Novel Approach. *Sustainability* **2021**, *13*, 11997.
19. Goktas, H.O.; Yumusak, N. Applying the Delphi Method to Assess Critical Success Factors of Digitalization While Sustaining Lean at a Lean Automaker. *Sustainability* **2024**, *16*, 8424.
20. Duraković, B.; Halilovic, M. Industry 4.0: The New Quality Management Paradigm in Era of the Industrial Internet of Things. *Int. J. Inform. Vis.* **2023**, *7*, 580–587.
21. Liker, J.K. The Toyota Way in Services: The Case of Lean Product Development. *Academy of Management Perspectives*. 2006. Available online: <https://www.researchgate.net/publication/200552295> (accessed on 30 December, 2023).
22. Villalba-Diez, J.; Gutierrez, M.; Losada, J.C.; Martín, M.G.; Sterkenburgh, T.; Losada, J.C.; Benito, R.M. Quantum JIDOKA.Integration of Quantum Simulation on a CNC Machine for In-Process Control Visualization. *Sensors* **2021**, *21*, 5031. <https://doi.org/10.3390/s21155031>.
23. Shabur, M. A. A comprehensive review on the impact of Industry 4.0 on the development of a sustainable environment. *Discover Sustainability*, **2024**, *5*, 97.
24. Ryalat, M.; Franco, E.; Elmoaqet, H.; Almtireen, N., & Al-Refai, G. The integration of advanced mechatronic systems into industry 4.0 for smart manufacturing. *Sustainability*, **2024**, *16*, 8504.
25. Harolds, J.A. Quality and safety in healthcare, part LXXXVIII: Introduction to the Toyota production system. *Clin. Nucl. Med.* **2023**, *48*, e278–e280.
26. Larue, O. *The Toyota Economic System: How Leaders Create True Prosperity Through Financial Congruency, Dignity of Work, and Environmental Stewardship*; Productivity Press: New York, NY, USA, 2023.
27. Tian, G.; Shi, Y.; Deng, J.; Yu, W.; Yang, L.; Lu, Y.; Zhao, Y.; Jin, X.; Ke, Q.; Huang, C. Low-Cost, Scalable Fabrication of All-Fabric Piezoresistive Sensors via Binder-Free, In-Situ Welding of Carbon Nanotubes on Bicomponent Nonwovens. *Adv. Fiber Mater.* **2023**, *6*, 120–132.
28. Gupta, S.; Chandna, P. A case study concerning the 5S lean technique in a scientific equipment manufacturing company. *Grey Syst. Theory Appl.* **2020**, *10*, 339–357.
29. Vermeulen, A.; Pretorius, J.H.C.; Viljoen, A.J. Industry 4.0—Artificial Intelligence (AI) contribution to capability maturity. In *ASEM 42nd International Annual Conference Proceedings*; American Society for Engineering Management: Huntsville, AL, USA, 2021; ISBN: 979-8-9853334-0-4.
30. Kistamah, N. The Applications of Artificial Intelligence in the Textile Industry. In *Artificial Intelligence, Engineering Systems and Sustainable Development: Driving the UN SDGs*; Emerald Publishing Limited: Leeds, UK, 2024; pp. 257–269.
31. Akhtar, W.H.; Watanabe, C.; Tou, Y.; Neittaanmäki, P. A new perspective on the textile and apparel industry in the digital transformation era. *Textiles* **2022**, *2*, 633–656.
32. Sikka, M.P.; Sarkar, A.; Garg, S. Artificial intelligence (AI) in textile industry operational modernization. *Res. J. Text. Appar.* **2024**, *28*, 67–83.
33. Tu, Y.F.; Kwan, M.Y.; Yick, K.L. A Systematic Review of AI-Driven Prediction of Fabric Properties and Handfeel. *Materials* **2024**, *17*, 5009.
34. Davenport, T.H. *The AI Advantage: How to Put the Artificial Intelligence Revolution to Work*; MIT Press: Cambridge, MA, USA, 2018.
35. Cleary, F.; Srisa-An, W.; Henshall, D.C.; Balasubramaniam, S. Emerging AI Technologies Inspiring the Next Generation of E-Textiles. *IEEE Access* **2023**, *11*, 56494–56508.
36. Rodrigues, D.; Pereira, R. How Can Artificial Intelligence Help Improve Fashion Sustainability? In *Digital Technologies and Transformation in Business, Industry and Organizations: Volume 2*; Springer Nature: Cham, Switzerland, 2023; pp. 43–61.
37. Eglash, R.; Robert, L.; Bennett, A.; Robinson, K.P.; Lachney, M.; Babbitt, W. Automation for the artisanal economy: Enhancing the economic and environmental sustainability of crafting professions with human–machine collaboration. *Ai Soc.* **2020**, *35*, 595–609.
38. Christopher, M. *Logistics and Supply Chain Management*; Pearson Education: London, UK, 2016.
39. Smartex. *The Modern Textile Factory Report—2023*; Smartex: Boston, MA, USA, 2023.
40. Glette, M.K.; Wiig, S. The headaches of case study research: A discussion of emerging challenges and possible ways out of the pain. *Qual. Rep.* **2022**, *27*, 1377–1392.

41. Avery, A.; Cresswell, K.; Crowe, S.; Huby, G.; Robertson, A.; Sheikh, A. The case study approach. *BMC Med. Res. Methodol.* **2011**, *11*, 100.
42. Tomaszewski, L.E.; Zarestky, J.; Gonzalez, E. Planning qualitative research: Design and decision making for new researchers. *Int. J. Qual. Methods* **2020**, *19*, 1609406920967174.
43. Ngulube, B. The Contribution of Case Study Research in Information Science. In *Handbook of Research on Connecting Research Methods for Information Science Research*; IGI Global Scientific Publishing: Hershey, PA, USA, 2020; pp. 95–113.
44. Davis, C.; Wilcock, E. Case studies in engineering. In *Effective Learning and Teaching in Engineering*; RoutledgeFalmer: New York, NY, USA, 2004; pp. 51–71.
45. Armstrong, R. The use of clinical case studies to develop clinical reasoning in sports therapy students: The students' perspective. *Int. J. Ther. Rehabil.* **2016**, *23*, 230–241.
46. Maggetti, M. Mixed-methods designs. In *Handbuch Methoden der Politikwissenschaft*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 193–210.
47. Sabono, F.; Widiastuti, I.; Sudradjat, I. Potential Advantages and Disadvantages of Case Study as Methodological Approach in Streetscape Research. *Nakhara J. Environ. Des. Plan.* **2024**, *23*, 411–411.
48. Álvarez, C.Á.; San Fabian Maroto, J.L. The selection of case studies in education research = La elección del estudio de caso en investigación educativa. *Gaz. Antropol.* **2012**, *28*, 14.
49. Unluer, S. Being an insider researcher while conducting case study research. *Qual. Rep.* **2012**, *17*, 58.
50. Steiner, A. Case studies in research on environmental policies: Advantages and limitations. *Rev. Sociol. Política* **2011**, *19*, 141–158.
51. Nivelio, J.J.O.; Coello, J.A.C.; Pereira, G.G.C.; Passos, F.O.; Guerrero, C.A.V.; Silveira, P.M.; Silva, V.Z. Evaluating voltage drop snapshot and time motor starting study methodologies—An offshore platform case study. *Electr. Power Syst. Res.* **2021**, *196*, 107187.
52. Glaser, B.; Strauss, A. *The Discovery of Grounded Theory: Strategies for Qualitative Research*; Sociology Press: Mill Valley, CA, USA, 1967.
53. Khan, S. Qualitative Research Method: Grounded Theory. *Int. J. Bus. Manag.* **2014**, *9*, p224. <https://doi.org/10.5539/ijbm.v9n11p224>.
54. Prasad, B.D. Content Analysis A method in Social Science Research. In *Research Methods for Social Work*; Rawat: New Delhi, India, 2008; pp. 173–193.
55. Yin, R. *Case Study Research and Applications: Design and Methods*, 6th ed.; SAGE Publications: New York, NY, USA, 2014.
56. Priya, A. Case Study Methodology of Qualitative Research: Key Attributes and Navigating the Conundrums in Its Application. *Sociol. Bull.* **2021**, *70* 94–110. <https://doi.org/10.1177/0038022920970318>.
57. Neuendorf, K.A. *The Content Analysis Guidebook*, 2nd ed.; Cleveland State University; SAGE Publications; Asia-Pacific Pte. Ltd.: Singapore, 2017; ISBN 9781412979474.
58. Samuel-Azran, T.; Laor, T.; Tal, D. Who listens to podcasts, and why? The Israeli case. *Online Inf. Rev.* **2019**, *43*, 482–495. <https://doi.org/10.1108/OIR-04-2017-0119>.
59. Perks, L.G.; Turner, J.S. Podcasts and productivity: A qualitative uses and gratifications study. *Mass Commun. Soc.* **2019**, *22*, 116–196. <https://doi.org/10.1080/15205436.2018.1490434>.
60. Stemler, S.E. *Emerging Trends in the Social and Behavioral Sciences*; Scott, R., Kosslyn, S., Eds.; John Wiley & Sons, Inc.: Hoboken, NJ, USA, 2015; ISBN 978-1-118-90077-2.
61. Toyota Motor Company. *Toyota Value*; Toyota Motor Corporation: Toyota City, Japan, 2024.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.