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ARTIFICIAL INTELLIGENCE FOR CIRCULAR TRANSFORMATION IN FAST FASHION: SYSTEMATIC REVIEW THROUGH THE 12R FRAMEWORK

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Abstract: *The rapid development of artificial intelligence (AI) creates new opportunities for the circular transformation of fast fashion, yet evidence on its contribution to individual circular-economy strategies remains fragmented. This study applies a systematic literature review (SLR) structured around the 12R framework to identify the principal mechanisms of AI application, compare their distribution across circular strategies, and assess whether reported operational improvements are accompanied by demonstrated environmental effects. Publications were identified through Google Scholar and screened using thematic relevance criteria; journal quartile was subsequently applied as an additional source-selection criterion. The analytical stage combined qualitative content analysis, deductive 12R coding, frequency analysis, and comparative synthesis. The results show a strong concentration of research in R1 Rethink and R2 Reduce, particularly in demand forecasting, personalization, inventory optimization, digital design, and quality control. Later-loop strategies are represented much less frequently in the retrieved corpus. However, this imbalance is interpreted cautiously because the search query did not explicitly enumerate all 12R-specific terms. The review also demonstrates that operational efficiency should not automatically be equated with environmental improvement: only evidence based on measurable changes in waste, resource use, or material flows can substantiate such effects. The study contributes a strategy-level mapping of AI applications and identifies directions for more targeted empirical research.*

Keywords: *artificial intelligence; fast fashion; circular economy; 12R framework; textile industry; systematic literature review; sustainability; digital transformation.*

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Introduction

The fast fashion industry has demonstrated sustained growth in the volume of apparel production and consumption over the past decades, accompanied by systemic negative effects: overproduction, the accumulation of textile waste, high resource intensity of production processes, and a considerable carbon footprint. The linear "production–consumption–disposal" model that underlies the business logic of fast fashion contradicts the goals of sustainable development and calls for alternative approaches to organizing industry processes.

One of the most promising directions for transforming the industry is the transition to the principles of the circular economy, which presumes a closed-loop rather than a linear flow of material resources. The conceptual foundation for systematizing the corresponding strategies is the 12R model (Refuse, Rethink, Reduce, Reuse, Repair, Refurbish, Remanufacture, Repurpose, Refabricate, Recycle, Recover, Re-mine), which covers the full spectrum of solutions—from preventing excessive consumption to recovering raw materials at the final stages of a product's life cycle.

In parallel, recent years have seen a rapid expansion in the application of artificial intelligence technologies in the fashion and textile industry: from demand-forecasting systems and generative design to computer vision for sorting and recognizing textile materials. AI is increasingly regarded as a tool capable of supporting the industry's transition toward more sustainable and resource-efficient models, including in the context of marketing—personalizing offers, managing the product life cycle through consumer interaction, and shaping demand consistent with the principles of conscious consumption.

At the same time, the body of research at the intersection of AI and the circular economy in the fashion industry remains fragmented. A significant share of the studies focuses on discrete, predominantly operational applications of the technology—demand forecasting, automated quality control, personalization—whereas deeper strategies for closing the material loop (extending product lifespan, restoration, raw material regeneration) have been studied considerably less. Moreover, the literature insufficiently addresses whether the operational efficiency achieved through AI actually translates into a real reduction in material flows, or whether it may coexist with an increase in consumption intensity driven by the same technologies (in particular, through hyper-personalization and digital marketing).

Thus, despite growing research interest in the application of AI in the fashion industry, the literature lacks a comprehensive, systematized understanding of how specific artificial intelligence technologies relate to the various strategies of the circular economy, and at which stages of the 12R hierarchy their application has been studied most and least extensively. This constitutes a research gap that calls for a systematic analysis of the accumulated scientific literature.

To address this gap, the present study conducts a systematic literature review structured around the following research questions:

RQ1: Which directions and mechanisms of artificial intelligence application in the fast fashion industry are most extensively represented in the scientific literature in relation to the individual strategies of the circular economy (the 12R model)?

RQ2: Which circular economy R-strategies remain the least studied in terms of AI application, and what are the corresponding research gaps?

RQ3: How does the operational efficiency achieved through AI application (demand forecasting, automation, personalization) relate to the actual environmental effect and the prevention of excessive material consumption in the context of the circular transformation of the fashion industry?

The answers to these questions will make it possible not only to systematize existing knowledge on the role of AI in implementing circular economy principles in the fast fashion industry, but also to identify promising directions for further research, including those relevant to marketing practices that shape consumption patterns in the industry.

Methodology

The studies were conducted using methods of sectoral study, descriptive, analytical, and statistical data analysis. As a result, recommendations were presented.

The research was conducted using the systematic literature review (SLR) method. In this design, the structured review, synthesis, coding, and comparison of previous studies constitute the core research method itself; therefore, a separate narrative Literature Review section was not introduced, as it would duplicate the material analyzed within the SLR. PRISMA principles were used to improve the transparency of identification and screening. The scientific methods applied at the analytical stage included qualitative content analysis, deductive categorical coding according to the 12R framework, descriptive frequency analysis, and comparative synthesis. To build the study's information base, a search for scientific publications was conducted in the Google Scholar system. The search strategy was formulated on the basis of the study's main research directions and included a combination of keyword queries: “fast fashion” AND “textile industry” AND “digital technology” AND “AI.” The use of the logical operator AND made it possible to focus the search output on publications simultaneously addressing fast fashion, the textile industry, digital technologies, and artificial intelligence.

The initial search yielded 17,400 results. Given the considerable size of the resulting set, a subsequent thematic screening of the publications was carried out. At this stage, publication titles, keywords, and, where necessary, abstracts and article content were analyzed. From the overall search output, publications corresponding to the study's subject area and revealing the relationship between artificial intelligence and digital technologies on the one hand and the development of fast fashion, the textile industry, sustainable development, resource efficiency, the circular economy, and the digital transformation of the industry on the other were selected. As a result of the thematic selection, a preliminary sample of 186 publications was formed.

The thematic inclusion criteria required a publication to address AI or closely related digital technologies in the fashion/textile context and to contain a substantive link to sustainability, resource efficiency, circular economy, product-life-cycle management, waste prevention, reuse, repair, recovery, recycling, or digital transformation. Records were excluded at this stage when the fashion/textile context was incidental, when AI/digital technology was not part of the research problem, or when no substantive connection with sustainability or circular transformation could be established.

At the next stage, journal-level bibliometric characteristics were considered using the SCImago Journal Rank (SJR) indicator and the corresponding journal quartile. This criterion was used as an additional source-selection restriction and not as a direct measure of the methodological quality of an individual article.

According to the SCImago methodology, journals are distributed into four quartiles: Q1, Q2, Q3, and Q4, where Q1 corresponds to the top quarter of journals by SJR value, and Q4 to the bottom quarter.

As an additional journal-level selection criterion, a Q1–Q2 threshold was established. Publications from Q3 and Q4 journals were not included in the final 12R analytical corpus. Because journal quartile reflects the relative position and impact of a journal rather than the methodological quality of a particular study, the possibility of selection bias introduced by this restriction is acknowledged as a limitation.

The approximately 17,400 Google Scholar results represent the initial search-engine output rather than the number of full texts individually assessed. Sequential screening of titles, keywords, abstracts and, where necessary, article content produced a preliminary thematic set of 186 publications. After application of the Q1–Q2 journal criterion, 146 publications remained; one publication could not be used for full-text 12R coding, resulting in a final analytical corpus of 145 publications. The 12R content analysis reported below refers to this final corpus.

Results

Bibliographic structure of the sample.

For transparency, the descriptive publication-trend figures below refer to the preliminary bibliographic dataset for which year and journal information had been compiled (183 records), whereas the subsequent 12R content analysis uses the final Q1–Q2 full-text analytical corpus of 145 publications. These two stages serve different purposes and should not be interpreted as the same sample. The descriptive set covers 2020–2026: 14 publications in 2020, 24 in 2021, 34 in 2022, 35 in 2023, 39 in 2024, 35 in 2025, and 2 in 2026. The 2026 value reflects only the portion of that year captured by the search and should not be interpreted as a decline in research interest.

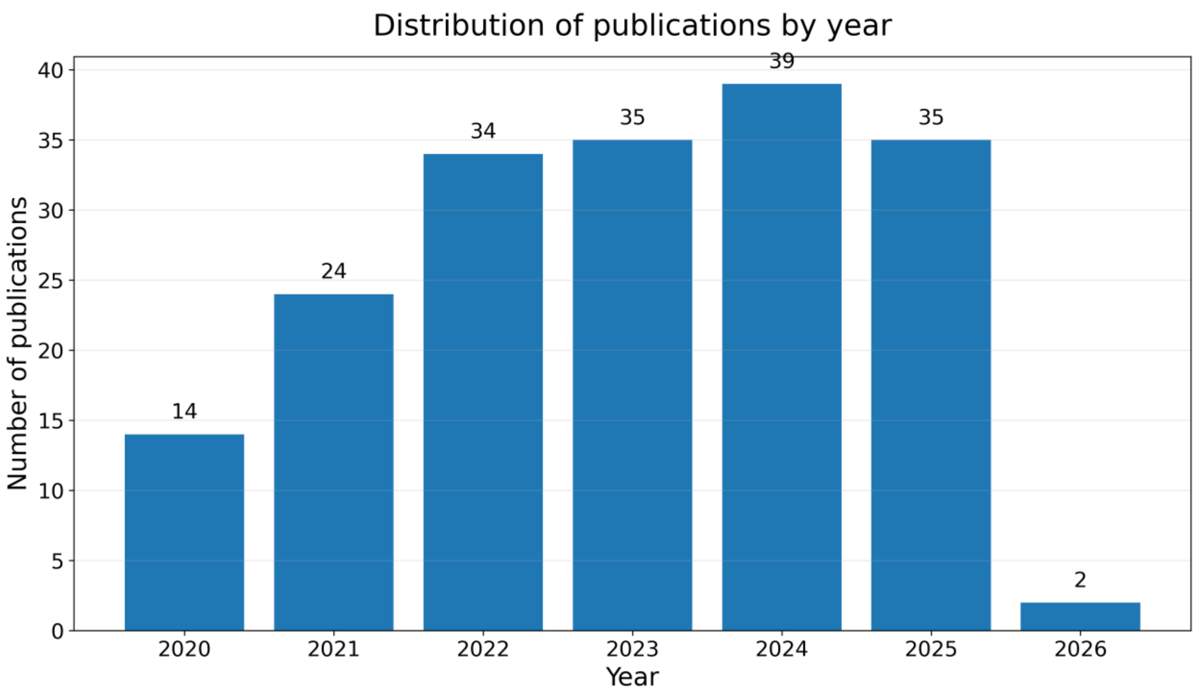

Figure 1. Distribution of publications by year

The observed dynamics indicate the formation of a stable research trend. The most intensive growth is observed in the first half of the 2020s, which coincides with the rapid diffusion of generative AI, computer vision, digital twins, demand-forecasting systems, and intelligent sorting technologies. Recent reviews also record the expansion of AI applications from production forecasting and optimization to garment condition assessment, textile sorting, and support for reuse and recycling.

The distribution of publications by journal is more fragmented (Figure 2). The largest number of papers in the formed sample was published in Sustainability—17. This is followed by the International Journal of Fashion Design, Technology and Education with 5 publications; Fashion and Textiles, the Research Journal of Textile and Apparel, The Journal of The Textile Institute, and Business Strategy and the Environment with 4 publications each. Three papers each are found in Technological Forecasting and Social Change, Textile Research Journal, Current Opinion in Green and Sustainable Chemistry, IEEE Transactions on Engineering Management, and Annals of Operations Research. The remaining leading journals are represented by two publications each.

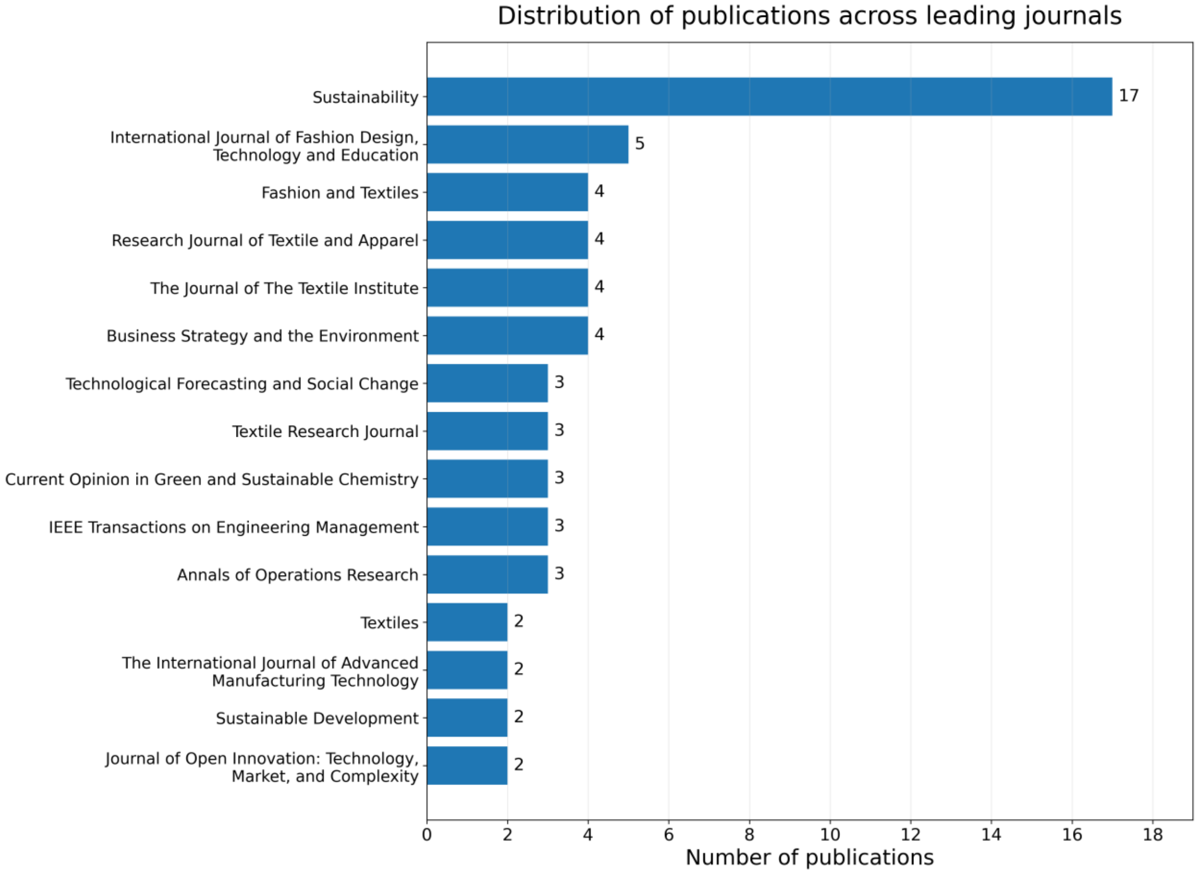

Figure 2. Distribution of publications by leading journals

This structure demonstrates the interdisciplinary nature of the research field. Studies are published simultaneously in journals covering sustainable development, textile technologies, production management, innovation, operations, and digital transformation. This confirms that the application of AI in the circular fashion industry lies at the intersection of engineering-technological and managerial approaches. At the same time, the concentration of publications in Sustainability is notable but not absolute: most of the research is distributed among specialized industry-specific and interdisciplinary journals.

Content analysis results: analysis of the 12R strategies

The systematization of the final analytical corpus in the 12R matrix reveals a pronounced imbalance in representation. R1 Rethink (71 coded publications) and R2 Reduce (64) are the most extensively represented. These are followed by R0 Refuse (18), R3 Reuse (17), R7 Repurpose and R9 Recycle (13 each), R4 Repair (8), R5 Refurbish, R6 Remanufacture, and R11 Re-mine (4 each), and R10 Recover (2). No direct confirmed example was coded for R8 Refabricate. Because one publication may contribute to more than one R-strategy, these frequencies are coding counts and are not expected to sum to the number of publications. The imbalance indicates concentration within the retrieved corpus, but it should not be treated as definitive evidence that research on the less represented strategies is absent.

An important limitation is that the original search query was formulated around fast fashion, textile industry, digital technology, and AI and did not explicitly enumerate every 12R-specific term. Consequently, studies framed primarily through terms such as repair, refurbish, remanufacture, refabricate, recover, or re-mine may have been under-retrieved. The low frequencies of several R-strategies therefore may reflect both the current orientation of AI research and the boundaries of the search strategy.

R0 Refuse is among the highest-priority circular economy strategies, as it involves preventing the emergence of the need for a material product or for individual resource-intensive operations. In the fashion industry, this logic manifests through digital fashion, virtual design, digital prototypes, and the transfer of part of the interaction with clothing to a virtual environment [1, 2, 3].

Studies on AI-based fashion design demonstrate the possibility of creating and evaluating design options before manufacturing physical samples [4, 5]. Virtual try-on, personalized recommendations, and AI-driven design also reduce the need for certain physical operations at the product selection and development stage [6]. The contribution of AI to Refuse therefore lies primarily in replacing individual material prototypes with digital ones and in preventing unnecessary operations.

However, digitalization alone does not guarantee an absolute environmental effect. Faster development and lower costs of creating new designs can simultaneously increase the number of models and the intensity of consumption. Therefore, the relationship between AI and R0 should be assessed through the actual prevention of material flows rather than merely through the fact of applying a digital technology [7, 8].

R1 Rethink is the most extensively represented strategy in the studied sample. Its specificity lies in changing not a single operation but the very logic of value creation and delivery. Studies of digital transformation show that AI, big data, and digital platforms make it possible to restructure design, forecasting, customer interaction, and supply chain management processes [7, 9, 10, 11].

On-demand production occupies a special place here. Analysis of consumer behavior data and AI-driven forecasting make it possible to bring production volumes closer to actual market demand. This creates an alternative to the traditional “make-to-stock” mass-production model and links Rethink to the subsequent Reduce strategy [7, 8, 14].

AI also supports the transition to service- and platform-based business models. Digital technologies can enable personalization, rental, resale, and the assessment of product condition and residual value—that is, they can change the way consumers obtain value without necessarily increasing primary production [10, 24, 23]. Rethink therefore performs a system-forming function and links digitalization to several subsequent R-strategies.

R2 Reduce ranks second in terms of representation in the sample and is characterized by the most evident causal link between AI and resource efficiency. One of the central mechanisms is demand forecasting. In the study by Dos Santos et al., a Digital Twin combines discrete-event simulation with an artificial intelligence model to support operational planning within a company [13]. Other studies consider AI forecasting as a means of inventory management, increasing production flexibility, and reducing overproduction [8, 14, 10].

The second mechanism is intelligent quality control. Machine and deep learning are applied to image processing and defect detection, making it possible to identify deviations earlier and reduce the volume of defective output and rework [15].

The third mechanism relates to virtual try-on and size recommendations. A more precise match between a product and the buyer's parameters and preferences reduces the uncertainty of online purchasing and potentially decreases returns [10]. Together, these mechanisms form a sequence: data → forecasting/recognition → a more accurate decision → a reduction in unnecessary output, material losses, returns, and logistics operations. R2 is therefore one of the most technologically mature areas of AI application in the context of the circular fashion industry.

Within R3 Reuse, AI primarily reduces the informational and transactional barriers to reuse. Digital rental platforms, the sharing economy, and resale enable the actual period of a product's use to be extended by connecting an already existing product with a new user [10, 17, 16].

Recommendation, visual search, and personalization algorithms can facilitate the selection of items on the secondary market, while condition- and residual-value-assessment models can support decisions on reselling, renting, or returning a product to circulation [11, 24]. The main contribution of AI to Reuse therefore lies not in the physical transformation of the product but in increasing the likelihood of its next use cycle.

R4 Repair and R5 Refurbish are represented considerably less than Rethink and Reduce, although from the standpoint of the circularity hierarchy, extending product lifespan preserves a substantial share of the materials and energy already invested. For Repair, a promising direction is the application of machine learning in product design for repairability, condition diagnostics, and the selection of a restoration method [19, 21, 22].

Refurbish involves a more comprehensive renewal of the product. In this area, AI can be used to assess condition, residual value, and the economic feasibility of restoration. Studies on circular business models emphasize the importance of digital analytics and AI-based residual value assessment for financing and scaling reuse and restoration models [24, 23, 16].

The low representation of these strategies in the retrieved corpus suggests that AI is discussed much more often in connection with sales, forecasting, and production efficiency than with systematic extension of the lifespan of already manufactured clothing. Given the search-strategy limitation noted above, this pattern should be interpreted as an area requiring targeted future investigation rather than as proof of an absolute research gap.

R6 Remanufacture is represented by a limited number of studies. The potential of digital technologies here relates to component identification, suitability assessment, and support for closed-loop supply chains. Studies of circular supply chains show that digital technologies and AI can improve traceability, the coordination of reverse flows, and decision-making regarding the return of resources to production [26, 22, 25].

The evidence base for R7 Repurpose is broader. AI can classify textile waste by composition and properties, thereby helping to select a new use for the material. Spectroscopy technologies combined with machine learning and deep learning, which enable the automatic recognition of textile materials, are particularly important here [27, 8]. In this case, AI converts a heterogeneous waste stream into an informationally described secondary resource, for which a more suitable route—reuse, upcycling, or recycling—can be determined.

For R8 Refabricate, no direct confirmed examples were identified within the retrieved and coded corpus. This finding should be interpreted as non-identification under the present search strategy rather than as evidence that such applications do not exist. Technological preconditions are nevertheless visible: AI-enabled identification and sorting can generate more homogeneous secondary raw-material streams [27, 8], while digital technologies can support closed production loops [4, 25].

Within the reviewed corpus, most studies do not trace the subsequent stage—the direct use of these methods in manufacturing new yarn or fabric from recovered raw materials. Targeted searches using refabrication-specific terminology are therefore required before a definitive research gap can be claimed.

In R9 Recycle, the most concrete role of AI relates to composition recognition and automated sorting. Tsai and Yuan demonstrate the combination of infrared Raman spectroscopy with machine learning and deep learning for the automatic sorting of textile waste [27]. The significance of this approach is determined by the fact that recycling quality depends on the purity and homogeneity of the input stream.

Other studies also link digital technologies to the modernization of recycling systems, reverse logistics, and more precise management of waste flows [8, 11, 29, 25]. Thus, the technological chain can be represented as "sensor-based composition determination → AI classification → sorting → formation of a homogeneous stream → recycling." Unlike many conceptual applications of AI, a sufficiently concrete technological architecture is already emerging for R9.

R10 Recover is represented by only two publications. Digital technologies can support life cycle assessment and process parameter optimization, including scenarios for handling residual streams and energy recovery [30, 31]. However, direct applied research on AI-controlled energy recovery specifically for textile waste remains insufficient.

R11 Re-mine also remains underdeveloped. The potential relevance of this strategy is increasing with the development of smart textiles and e-textiles containing sensors, conductive elements, and other components that may require selective extraction [33, 34, 32]. In such a system, AI can be used to recognize complex compositions and support component routing; however, the existing literature still predominantly describes technological preconditions rather than mature industrial solutions.

Conclusion

The systematic 12R coding shows that AI research in the retrieved fast-fashion and textile corpus is concentrated primarily in R1 Rethink and R2 Reduce. The most frequently identified mechanisms concern demand forecasting, personalization, inventory and production optimization, digital design, and automated quality control. By contrast, several strategies associated with product-life extension and later material loops are represented by substantially fewer coded publications. Because the search query did not explicitly include every 12R-specific term, these low frequencies are interpreted as limited representation in the present corpus rather than definitive evidence of absent research.

The analysis further indicates that operational efficiency and circularity are not equivalent. AI-supported improvements can reduce specific inefficiencies, but an environmental benefit should be claimed only where measurable reductions in waste, resource use, emissions, returns, or material flows are demonstrated. This distinction is central to the answer to RQ3 and prevents technological efficiency from being treated automatically as environmental performance.

Future research should therefore combine broader strategy-specific search strings with empirical assessment of material and environmental outcomes. Particular attention should be paid to repair, refurbishment, remanufacturing, refabrication, recovery, and re-mining, as well as to industrial case studies that quantify the effect of AI on physical resource flows. A further priority is the development of an integrated model linking AI technologies, stages of the textile product life cycle, and the 12R hierarchy so that digitalization of a linear fast-fashion system can be distinguished from digitalization that contributes to measurable circular transformation.

Conflict of Interest
The authors declare no conflicts of interest.
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