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# Computer Vision Across the Garment Lifecycle: Applications and Sustainability Implications

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## Abstract

The garment industry faces sustainability challenges involving resource consumption, material waste, product returns, and textile disposal. This structured narrative review examines CV (computer vision) applications across four garment lifecycle stages: design and sample development, manufacturing and quality control, fashion retail and consumption, and post-consumer reuse and recycling. The literature is organized into eight CV task categories and six algorithm families using independent, multi-label coding. Sustainability claims are evaluated by distinguishing empirical lifecycle assessments, factory measurements, consumer behaviour evidence, model-based predictions, and qualitative inference. Comparative studies suggest that digital sampling can reduce environmental burdens, although these outcomes cannot be attributed to CV alone. Manufacturing research reports improved inspection performance and selected operational benefits. In contrast, retail and post-consumer studies predominantly emphasize visual quality, classification accuracy, and processing efficiency, with limited evidence of reduced returns, increased material recovery, or lower emissions. The review identifies a persistent gap between technical performance and verified sustainability outcomes, alongside barriers involving cross-domain robustness, implementation costs, and data interoperability. Future research should integrate CV performance metrics with field measurements and lifecycle assessment to evaluate net environmental impacts.

**Keywords:** sustainable; computer vision; garment; lifecycle

Check for updates

Academic Editor: Bingang Xu

Received: 19 October 2026
Revised: 9 November 2026
Accepted: 11 November 2026
Published: 16 November 2026

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## 1. Introduction

The fashion industry is confronted with escalating environmental challenges stemming from resource-intensive production patterns, continuously growing consumption volumes, and massive textile waste accumulation. Data from the UNEP (United Nations Environment Programme) indicate that the textile sector contributes approximately 2–8% of global anthropogenic greenhouse gas emissions [1]. Currently, global annual textile waste generation reaches around 92 million tonnes, while textile-to-textile recycling supplies less than 1% of the total global fiber market [2]. The above challenges reveal the inherent limitations of the current dominant linear production–consumption paradigm, and emphasize the necessity of improving resource utilization efficiency, prolonging the service life of garments, and constructing circular material flow systems. Existing studies have

confirmed that textile reuse and recycling can effectively reduce the environmental footprint of the fashion industry, though the actual environmental benefits of these approaches are constrained by product substitution ratios and processing parameters [3].

In response to this context, sustainable fashion has progressively become a core priority in both industrial policymaking and circular economy development. The European Commission launched the EU Strategy for Sustainable and Circular Textiles in 2022, which facilitates the development of durable, repairable and recyclable textile products, and defines DPPs (Digital Product Passports) as a key tool to enhance product information transparency and full-lifecycle traceability [4]. However, realizing the sustainability goals throughout the entire garment lifecycle is still confronted with multiple challenges. This is because the information about garment structure, fabric defects, product condition, and fibre composition is often fragmented or incomplete, making efficient assessment difficult. In addition, traditional inspection and classification procedures are heavily dependent on manual operation, which may restrict the consistency, scalability and operational efficiency of relevant processes.

Computer vision (CV) offers a viable pathway to mitigate the aforementioned limitations by converting unstructured visual information into structured data formats, thereby enabling automated visual recognition, quality inspection, and decision-making support systems. Advances in CNNs (convolutional neural networks) and object detection architectures have improved visual feature extraction and object localization [5,6]. ViTs (Vision Transformers) have further augmented the capacity for modeling spatial relational dependencies within image data [7]. More recently, visual foundation models have emerged as an alternative paradigm, leveraging large-scale pretraining strategies and transferable visual representation learning. A representative example is the SAM (Segment Anything Model), which generates segmentation masks from user-defined prompts such as point coordinates and bounding boxes, and demonstrates robust zero-shot transfer performance across diverse image distributions and heterogeneous segmentation tasks [8]. In contrast to conventional task-specific segmentation models, SAM delivers a generalizable framework that may reduce the dependence on extensive task-specific annotated datasets. In garment-related applications, such capabilities may facilitate clothing component segmentation, fabric region extraction, and visual garment condition assessment.

Despite these opportunities, applying foundation models to textile and garment analysis remains challenging. Repetitive patterns, subtle defects, low-contrast boundaries, and fabric deformation may limit the reliability of models pretrained on general-purpose images. Moreover, segmentation and semantic recognition cannot independently determine defect types, fibre composition, garment construction, or physical fit. Domain shifts, limited defect samples, computational costs, and production-line requirements further constrain industrial deployment. Therefore, foundation models should be evaluated against specialized CV methods using textile-specific datasets, with particular attention to cross-domain robustness, defect detection accuracy, annotation requirements, and computational efficiency. Conventional task-specific approaches remain important; for example, a CNN-based system integrated with IoT (Internet of Things) infrastructure has demonstrated automated classification of post-consumer garments into nine categories using camera-acquired images [9]. These considerations highlight the need to evaluate CV technologies beyond their technical performance and to critically examine their actual contributions to garment sustainability.

To address this need, this paper investigates the application of CV technology to advance sustainability in the garment industry, structured around four key stages of the garment lifecycle: design and sample development, manufacturing and quality control, fashion retail and consumption, and post-consumer reuse and recycling. Specifically, Section 2 delineates the literature retrieval procedure, selection criteria and categorical framework.

Section 3 presents a review of CV applications deployed across the four garment lifecycle stages. Section 4 comparatively analyses technical performance and sustainability outcomes, with a supplementary discussion of implementation barriers. Ultimately, Section 5 synthesizes the principal research findings and delineates avenues for future scholarly inquiry.

## 2. Review Scope and Literature Selection

### *2.1. Literature Identification and Selection*

The present study employs a structured narrative review methodology to investigate CV technologies and their associated sustainability implications across the full garment lifecycle. The Web of Science Core Collection was utilized as the primary bibliographic database for literature retrieval. The search scope encompassed publications spanning the period from 2016 to 2026.

The search strategy was structured around three interdependent dimensions: CV technologies, garment-related applications, and lifecycle processes. Representative search terms included "Computer Vision in the Garment Industry", "Computer Vision for Garment Product Development", "Computer Vision in Garment Manufacturing", "Computer Vision for Garment Retail", "Computer Vision for Garment Recycling", and "Computer Vision in Garment Sustainability". These thematic terms served as the initial foundation for retrieving relevant studies across distinct lifecycle stages. Given the variability of terminology across application domains, the subsequent evaluation prioritized the technical functionalities of the included studies rather than relying exclusively on their declared sustainability objectives.

Studies were deemed eligible for inclusion in the core technical review if they met the following criteria: (1) focused on garments or textiles directly linked to garment utilization; (2) investigated a substantive CV task involving visual or spatial data, including but not limited to images, video, point clouds, or spectral imagery; and (3) presented identifiable technical methodologies, experimental results, or application-specific evidence relevant to at least one stage of the garment lifecycle. Studies reporting operational or environmental outcomes received particular emphasis during the assessment of sustainability implications. Studies were excluded from the core CV classification under the following circumstances: when they predominantly addressed unrelated industrial applications, lacked a substantive visual inference task, or provided insufficient information to identify their technical contributions.

To enhance the consistency and reproducibility of the classification procedure, the screened publications were further categorized according to their primary evidential roles. Studies incorporating substantive visual inference, identifiable computational methods, and task-specific evaluation were incorporated into the core CV classification. Benchmark and dataset-related studies were incorporated exclusively under the condition that they implemented and validated relevant CV methods; otherwise, they were retained as methodological references. Geometry reconstruction studies were deemed eligible when garment structures were inferred from images, point clouds, or observed three-dimensional geometry, whereas purely procedural modeling and physical simulation devoid of visual inference were excluded. Studies utilizing hyperspectral imaging were classified as CV applications when spatially resolved image information contributed to the inference pipeline. Research predominantly addressing lifecycle assessment, consumer behavior, or operational sustainability outcomes was retained as supporting evidence but excluded from the algorithmic frequency analysis unless a substantive CV component was independently evaluated. These distinctions were implemented to avert the conflation of technical CV studies with contextual and sustainability-oriented research.

Representative studies were selected for in-depth synthesis on the basis of their methodological contributions, pertinence to garment lifecycle applications, and capacity to elucidate technological advancements, implementation barriers, or sustainability outcomes. Specific emphasis was placed on studies presenting comparable technical performance metrics, industrial observational data, or quantitative environmental and operational outcomes. Accordingly, this review endeavors to deliver a critical synthesis of exemplary research rather than an exhaustive systematic evaluation of all publications within the domain.

### *2.2. Classification and Analytical Framework*

The selected literature was examined using a structured analytical framework including four garment lifecycle stages, eight CV task categories, and six methodological families. The framework was developed to distinguish the functional objectives of CV applications from the computational approaches employed to achieve them. Task categories were defined according to the principal visual inference objectives and evaluated outputs, whereas methodological categories reflected the core computational mechanisms implemented in the corresponding studies.

Lifecycle classification. CV applications were assigned to four lifecycle stages: (1) design and sample development, (2) manufacturing and quality control, (3) fashion retail and consumption, and (4) post-consumer reuse and recycling. The primary lifecycle stage was determined by the intended application of each study. Research addressing multiple stages was examined in relation to the relevant application contexts.

CV task classification. Eight task categories were established: (1) recognition and classification, (2) object detection and localization, (3) image and spatial segmentation, (4) defect and anomaly detection, (5) visual retrieval and matching, (6) visual and garment-structure generation, (7) garment geometry and pattern reconstruction, and (8) visual estimation and measurement. These categories were defined according to the types of information inferred from visual observations. Classification referred to the prediction of discrete garment or material attributes, whereas visual estimation and measurement encompassed continuous outputs such as dimensions, spatial positions, and material composition estimates. Detection and localization were distinguished from segmentation according to whether the evaluated outputs involved object locations or spatially resolved regions. Defect and anomaly detection was retained as a separate application-oriented task because identifying deviations from normal textile or garment conditions constitutes a distinct research objective. Garment geometry and pattern reconstruction was restricted to methods inferring structural representations from observed visual or spatial data. Generative approaches producing garment images or structured sewing patterns were classified according to their primary outputs and conditioning objectives. The corresponding task and representative studies are summarized in Table 1.

Methodological classification. Six methodological families were identified: (1) classical image processing and statistical learning, (2) geometric and optimization-based methods, (3) CNNs and other non-Transformer neural networks, (4) Transformer-based methods, (5) GAN-based generative methods, and (6) diffusion-based generative methods. The first four families describe the principal computational approaches used for visual inference and structural estimation, whereas the latter two identify generative modeling paradigms. As these methodological levels may overlap within hybrid systems, algorithm assignments were based on substantive contributions rather than incidental architectural components. The methods and associated studies are presented in Table 2.

**Table 1.** Classification and Distribution of CV Tasks.

| CV Task | Number of Assignments | Corresponding References |
|---|---|---|
| Recognition and Classification | 15 | [9–23] |
| Object Detection and Localization | 8 | [12,22,24–29] |
| Image and Spatial Segmentation | 8 | [12,20,23,25,30–33] |
| Defect and Anomaly Detection | 16 | [18,21,23,24,26,27,29–31,34–40] |
| Visual Retrieval and Matching | 6 | [11,25,41–44] |
| Visual and Garment-Structure Generation | 9 | [45–53] |
| Garment Geometry and Pattern Reconstruction | 5 | [47,54–57] |
| Visual Estimation and Measurement | 7 | [20,25,28,35,58–60] |
| Total | 74 | / |

**Table 2.** Classification and Distribution of Algorithmic Approaches.

| Algorithm Category | Number of Assignments | Corresponding References |
|---|---|---|
| Classical Image Processing and Statistical Learning | 10 | [15,16,23,26,32,33,35–37,60] |
| Geometric and Optimization-Based Methods | 5 | [28,35,57–59] |
| CNNs and Other Non-Transformer Neural Networks | 29 | [9–14,18–22,24–27,29–31,34,36,38–43,55,58,59] |
| Transformer-Based Methods | 10 | [14,16–18,40,44,47,50,54,56] |
| GAN-Based Generative Methods | 3 | [46,48,49] |
| Diffusion-Based Generative Methods | 5 | [45,47,51–53] |
| Total | 62 | / |

CV tasks and methodological approaches were coded independently. Each eligible study was first assigned a primary task category according to its main research objective and principal evaluated output. Additional task labels were assigned only when the study substantively investigated and evaluated multiple visual inference objectives. Similarly, a primary methodological category was identified according to the central computational approach, while secondary methodological labels were recorded when additional techniques made substantial contributions to the proposed framework. Routine preprocessing operations and auxiliary components were not counted as independent methodological contributions. The core CV classification included 52 unique studies. Independent multi-label coding resulted in 74 CV task assignments and 62 algorithm-category assignments. Tables 1 and 2 report the number of assignments and corresponding references for each category, allowing the classification results to be traced to individual studies. Correspondingly, the percentages depicted in Figures 1 and 2 denote the proportions of category assignments.

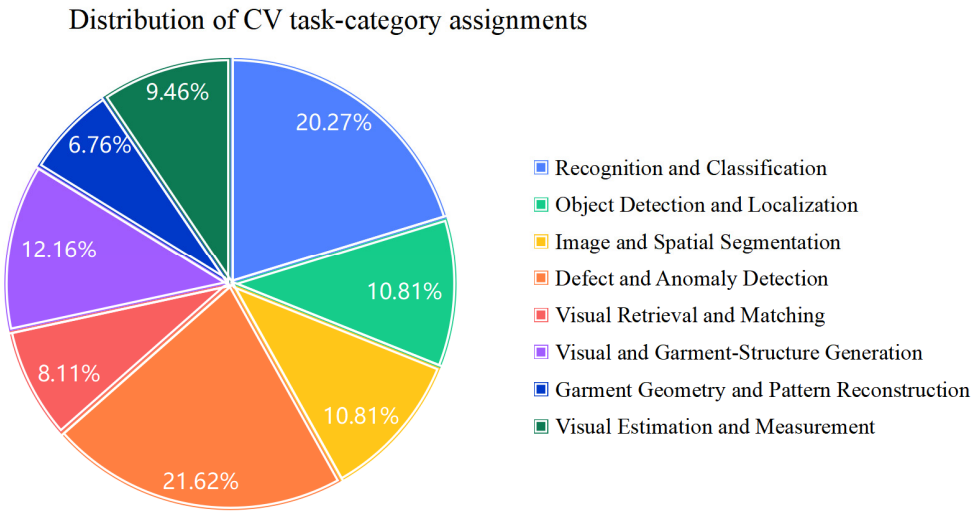



**Figure 1.** Distribution of CV task-category assignments.

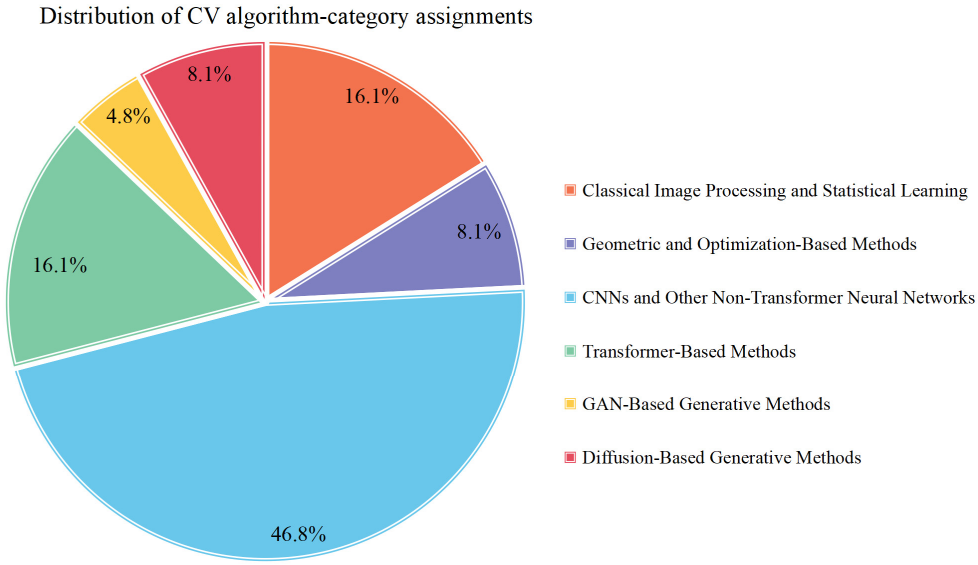



**Figure 2.** Distribution of CV algorithm-category assignments.

## 3. Current Research Status of CV in Various Aspects of Apparel

CV technologies have witnessed growing applications throughout the entire garment lifecycle, creating promising opportunities to enhance resource efficiency and facilitate the development of sustainable fashion. Within the design and product development stage, deep learning-enabled garment structure reconstruction facilitates the development of digital patterns and virtual sampling, which contributes to the reduction in redundant physical sampling processes [54]. During production and manufacturing, CV-based defect detection and quality inspection enable early defect identification and process optimization, which creates opportunities to mitigate material waste and reduce rework [24]. Within the retail and consumption stage, Virtual Try-On technologies optimize garment visualization and can assist consumers in making more informed purchasing decisions [45]. In waste-garment collection and sorting, machine vision realizes automated garment classification and improves the operational efficiency of sorting processes [9]. Furthermore, CV-based condition assessment and sorting frameworks can provide support for reuse and recycling decision-making, which contributes to preserving the value of garments and raw materi-

als [10]. In summary, as illustrated in Figure 3, CV delivers systematic technical support for sustainability throughout the entire garment lifecycle.

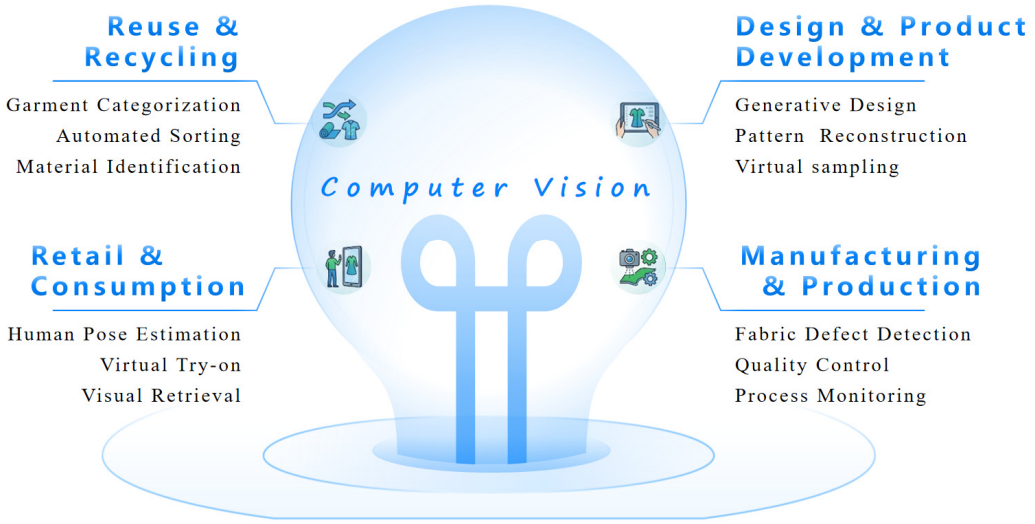



**Figure 3.** Computer vision applications across the garment lifecycle.

### *3.1. Computer Vision-Driven Garment Design and Sample Development*

Garment design and sample development cover four core processes: style visualization, pattern construction, virtual fitting, and physical sampling. Traditional development workflows often involve repeated pattern adjustments and physical sample production, which can increase material consumption and development costs. Driven by the continuous technological progress of CV and deep learning, digital garment development has gradually expanded its scope from basic visual feature recognition to multiple advanced directions including generative design, three-dimensional modeling, sewing pattern reconstruction, and virtual sampling.

Early studies focused on extracting garment features and generating design representations. The DeepFashion2 dataset has constructed a standardized benchmark for clothing detection, landmark estimation, segmentation and retrieval tasks, which can provide critical fundamental visual information for garment analysis [25]. Subsequently, conditional GANs (generative adversarial networks) have facilitated the generation of garment images based on fashion sketches and fabric textures, providing effective support for rapid iterative exploration of design schemes [46]. With the continuous advancement of CLOTH3D and TailorNet research, learning-based methods have been further introduced into three-dimensional garment modeling and deformation prediction tasks under varying body shapes and poses [61,62].

Recent studies have paid increasing attention to transforming visual garment information into structured sewing patterns. NeuralTailor adopts a point-level attention mechanism to reconstruct two-dimensional sewing patterns from three-dimensional garment point clouds [55], while Sewformer applies a two-level Transformer to predict sewing patterns from a single image [56]. Parametric pattern modeling and large-scale datasets, including GarmentCode and GarmentCodeData, have further provided support for editable garment structures and automated pattern generation [63,64]. Subsequent research, differentiable simulation and body-aware garment modeling have improved the physical consistency and adaptability of digital garments [57,65,66]. In more recent studies, multimodal diffusion Transformers have achieved structured sewing pattern generation from text, images and incomplete patterns, which extends the scope of generative design beyond visual appearance [47].

The aforementioned technologies can reduce repeated physical sampling by enabling earlier design evaluation and digital modification. Existing research has further examined the sustainability benefits of virtual garment sampling via empirical studies and LCA (lifecycle assessment). Based on factory data collected from four garment models, a comparative LCA verified that, under the tested evaluation conditions, substituting traditional physical sampling with virtual sampling can reduce global warming potential and primary energy demand by approximately 85–90%, cut water consumption by 86–91%, and shorten sample preparation time by up to 73% [67], as illustrated in Figure 4. Similarly, a comparative investigation on conventional, hybrid, and fully digital sampling workflows for T-shirt development reveals that the fully digital sampling scenario achieves an approximately 95% reduction in aggregate environmental burden, which demonstrates the great potential of virtual sampling in cutting down material consumption and mitigating environmental impacts [68]. Recent literature reviews have also explored the role of virtual sampling and digital fashion technologies in facilitating the construction of more resource-efficient design and production systems [69]. These findings indicate that virtual sampling can reduce environmental burdens under the evaluated scenarios, although the benefits arise from integrated digital workflows and cannot be attributed exclusively to CV algorithms.

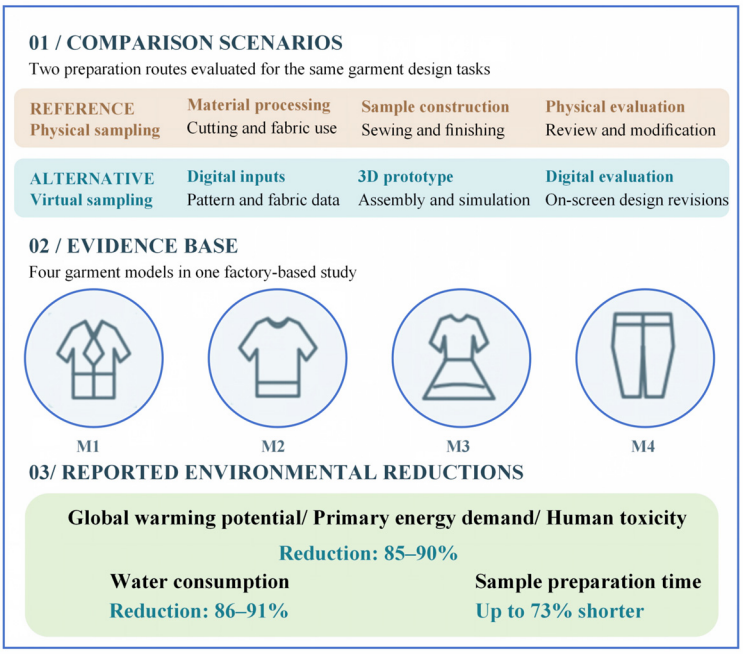



**Figure 4.** Environmental benefits of virtual garment sampling. Data from Ref. [67].

From the standpoint of lifecycle information management, CV-based garment analysis may further facilitate the establishment of structured product records. Recognized garment components, reconstructed pattern features, and visually derived design attributes can potentially furnish supplementary data for future DPP-compatible systems. Nevertheless, such outputs necessitate standardized descriptions and traceable links to identifiable products. Inferred garment geometry and simulated fabric properties must additionally be differentiated from independently verified material specifications. These distinctions are imperative to ensure that digital design information remains interpretable and reliable across subsequent lifecycle stages.

### *3.2. Computer Vision-Driven Garment Manufacturing Optimization and Quality Control*

Garment manufacturing encompasses a series of interconnected processing procedures, including fabric inspection, spreading, cutting, sewing, and final quality control. Product

defects and processing deviations will propagate along the subsequent production stages, ultimately leading to increased material consumption, higher rework requirements, and elevated overall production costs. CV can realize automated surface inspection, defect localization, fabric positioning, dimensional measurement, and sewing process monitoring, thereby providing reliable technical support for enhancing manufacturing quality and improving resource utilization efficiency.

Fabric inspection illustrates how changes in CV methods have been driven by the limitations of textile production. Early-stage methodologies employed statistical texture descriptors, Gabor filters, and wavelet transforms to differentiate defects from regular fabric patterns [70]. While these hand-crafted approaches exhibit computational efficiency, they are contingent upon assumptions regarding texture regularity and feature selection, thereby limiting their generalizability across complex fabric types. Learning-based approaches facilitate the extraction of more adaptable feature representations, albeit their performance is contingent upon the availability and diversity of training image datasets.

One primary challenge in supervised defect detection arises from the severe class imbalance inherent to industrial datasets, which typically comprise abundant normal samples alongside an extremely limited number of rare defect instances. To address this constraint, Mei et al. proposed a multi-scale convolutional denoising autoencoder trained exclusively on defect-free fabric images, leveraging reconstruction discrepancies to localize anomalous regions, as demonstrated in Figure 5 [30]. Alternatively, within the supervised paradigm, Mobile-Unet integrated lightweight convolutional architectures with class-balanced learning strategies, enhancing defect segmentation performance while concurrently constraining computational overhead [31]. Furthermore, motif-based unsupervised convolutional learning was explored to facilitate anomaly recognition without necessitating extensive manual annotations of defective regions [34].

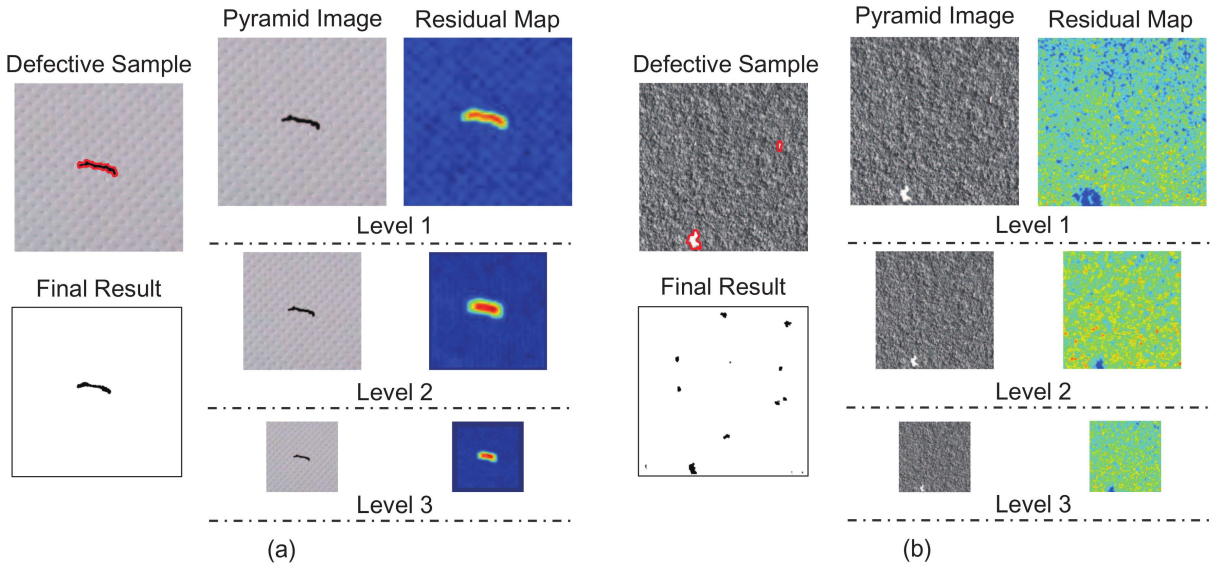



**Figure 5.** Multi-scale fabric defect detection results obtained using the MSCDAE model: (**a**) cotton fabric and (**b**) canvas fabric. The figure presents the defective samples, intermediate pyramid images and residual maps at three resolution levels, and the final detection results. Reproduced from Mei et al. [30], © 2018 by the authors, under the CC BY 4.0 license (https://creativecommons.org/licenses/by/4.0/).

Hybrid approaches show that handcrafted features continue to complement deep learning rather than being uniformly replaced. Gabor features incorporated with Faster R-CNN yielded enhanced detection performance under the specified experimental conditions [26],

whereas FA-YOLO explicitly targeted the optimization of the trade-off between detection accuracy and computational efficiency [27]. Significant deployment-related challenges persist. Micro-defects necessitate fine spatial resolution, yet higher-resolution inspection inherently increases inference latency and restricts production-line throughput. Concurrently, normal texture variations, fabric deformation, and illumination fluctuations can induce false alarms or degrade performance on unseen fabric samples. While unsupervised learning mitigates the scarcity of defect annotations, it does not independently resolve the cross-fabric domain adaptation problem. Consequently, future comparative evaluations should encompass unseen-fabric testing, detection sensitivity stratified by defect size, processing throughput, and false-stop rates, rather than regarding benchmark accuracy as a sufficient indicator of industrial applicability.

In the procedures of fabric handling and cutting, computer vision technology enables the implementation of fabric boundary extraction, component localization, robotic grasping and dimensional inspection. A vision-guided robotic system integrated real-time image recognition, CAD information and learning-based grasping optimization to automate the fabric transfer process between cutting and sewing operations [28]. Additionally, image alignment, homography transformation and edge detection have been adopted to identify contour deviations of cut textile components [35]. The aforementioned methods can provide effective information for positioning and quality verification, but marker planning and cutting optimization are still independent computational tasks that require further integration with existing manufacturing systems.

During sewing, CV applications have expanded from detecting stitch abnormalities to supporting automated fabric manipulation and process control. CNN feature maps extracted from pretrained VGG-16 networks have been used for broken-stitch detection, achieving 92.3% accuracy under the reported experimental conditions [36]. Image-processing approaches combining HSV colour-space analysis and edge detection have also been integrated into industrial sewing-machine inspection systems [37]. More recently, robotic sewing frameworks have incorporated visual contour recognition, learning-based grasping, seam tracking, and force control to improve flexible fabric manipulation [58]. Related research has further investigated multimodal perception and human–robot skill transfer for robotic collaborative sewing [59]. These developments suggest increasing integration between visual perception and manufacturing execution.

Overall, CV applications in garment manufacturing have progressed from fabric-level defect inspection toward integrated fabric handling, cutting-quality assessment, and sewing-process monitoring. Their potential sustainability contributions include earlier defect identification, reduced rework, and improved material utilization.

A factory-based investigation of deep learning-assisted visual inspection used Markov chain modeling to estimate reductions of 92–98% in defective material waste and approximately 1.3% in operating costs under the evaluated weaving conditions [38]. In garment manufacturing, a production improvement framework integrating machine vision-based error prevention with standardized work reported a reduction in sewing rework rates from 28.43% to 8.94%, together with a decrease in garment production cycle time from 23.74 to 16.54 min in its evaluated scenarios [29]. Furthermore, the VISCAR framework combined multi-scale visual defect detection, edge computing, and closed-loop information management to support resource-efficient quality inspection in yarn production [39]. An integrated CNN-based, Transformer-based, and IoT-based inspection approach also reported improvements in manufacturing efficiency and material waste reduction [40]. These studies suggest that CV may contribute to sustainable manufacturing by detecting defects earlier, limiting defective material propagation, and reducing unnecessary processing.

Beyond the scope of immediate quality control, CV-derived inspection outputs can further facilitate the traceability of garment manufacturing processes. Defect categories, detected locations, inspection timestamps, and associated production batch identifiers may be converted into structured quality records. When integrated with product information systems, such records can enhance manufacturing traceability and provide supplementary inputs for DPP-oriented information management. Nevertheless, robust data integration necessitates standardized defect definitions, calibrated inspection systems, and mechanisms to associate inspection outputs with identifiable products or batches. The incorporation of such information into future DPP implementations will further hinge on product-specific requirements and applicable data-sharing protocols.

### *3.3. Computer Vision-Based Fashion Product Retrieval and Sustainable Retail*

Fashion e-commerce retail plays an important role in sustainable apparel consumption, particularly in relation to informed purchasing decisions, product returns, and resource utilization. However, the reliance on digital images and product descriptions often limits consumers' ability to accurately assess garment appearance, fit, and material characteristics, potentially leading to unsuitable purchases, returns, and additional transportation and packaging requirements. CV offers opportunities to address these challenges through garment attribute recognition, visual product retrieval, multimodal search, and Virtual Try-On. By improving product information accuracy and supporting more informed purchasing decisions, these technologies may help reduce avoidable returns and associated resource consumption. Nevertheless, their actual sustainability benefits depend on measurable changes in consumer behavior, product returns, and overall environmental impacts.

Early research focused on extracting visual attributes and establishing searchable garment representations. The DeepFashion dataset introduced more than 800,000 fashion images with clothing attributes and landmarks, supporting garment recognition and cross-domain retrieval [11]. Subsequently, Fashionpedia combined instance segmentation with fine-grained attribute localization, enabling more detailed identification of garment categories, components, and design features [12]. Visual retrieval then developed from image similarity matching toward interactive attribute manipulation. Memory-augmented attribute networks allowed users to modify garment characteristics, such as colour, during image-based search [41]. Multimodal retrieval methods further integrated image and textual queries into shared semantic representations [42], while CNN-RNN architectures combined garment visual features with structured search conditions [43]. The Fashion IQ benchmark subsequently introduced natural-language feedback and Transformer-based interactive retrieval, extending visual search toward more flexible consumer-product interaction [44].

Recent research has also examined the practical consumer experience of fashion visual search. Experimental evidence indicates that the variety of retrieved products influences shopping satisfaction through search costs and experiential benefits [71]. These findings suggest that CV-based retrieval can improve product information access and matching efficiency. However, better retrieval performance or consumer satisfaction does not necessarily lead to fewer purchases, lower return rates, or reduced environmental impacts.

The developmental trajectory of image-based Virtual Try-On technology is governed by three interrelated objectives: enhancing garment-body alignment fidelity, preserving intrinsic garment details, and minimizing computational overhead. Early-stage methodologies integrated garment segmentation, spatial alignment, and generative synthesis into a unified pipeline. VITON-HD mitigated alignment artifacts while enabling the generation of high-resolution try-on outputs [48]. Subsequently, the Dress Code dataset expanded the taxonomy of garment categories incorporated into model development and evaluation

workflows [49], while ST-VTON pioneered self-supervised Vision Transformer learning for image-based garment transfer tasks [50]. These advancements redirected scholarly focus from standalone garment warping paradigms toward correspondence learning across more heterogeneous image datasets and clothing categories.

Diffusion-based approaches have further enhanced the synthesis of visually plausible garment appearances. TryOnDiffusion integrates deformation and image generation within a unified architecture [51], while StableVITON models semantic correspondence between clothing and the target body in latent space [52]. CatVTON subsequently mitigates preprocessing and computational overhead [53]. However, visual fidelity and physical fidelity constitute distinct evaluation objectives. A generated silhouette or wrinkle pattern may exhibit realistic appearance without being derived from the actual dimensions of the sewing pattern, fabric stiffness, stretch properties, or body-garment contact mechanics. In contrast, inverse garment simulation explicitly optimizes pattern geometry and material parameters to reproduce draped garment shapes [57], while physically based refitting employs simulation constraints when adapting garment patterns to different body morphologies [66].

Such differentiation carries significant implications for sustainability assertions. Image-based VTON systems may facilitate visual product communication, yet a photorealistic output alone is insufficient to substantiate dimensional fit, pattern feasibility, or wearing comfort.

Empirical research has examined whether digital fitting technologies can influence purchasing behaviour and product returns. Randomized field experiments in online retail demonstrated that providing virtual fit information reduced fulfilment costs associated with returns and customers ordering multiple sizes for home try-on, while also increasing conversion rates and order value [72]. An experimental evaluation of a virtual dressing room further found significant improvements in the communication of garment shape and fit compared with conventional online shopping interfaces [73]. These findings support the potential of digital fitting technologies to reduce purchase-related uncertainty, although they do not establish the environmental performance of specific computer vision algorithms.

The sustainability relevance of these technologies is further supported by studies examining apparel returns and reverse logistics. Research based on actual fashion e-commerce transactions identified product-specific return patterns and the operational challenges associated with purchasing multiple sizes [74]. A carbon footprint assessment of online and offline apparel sales also highlighted the importance of incorporating return logistics into environmental comparisons between retail channels [75], as shown in Figure 6. However, improved digital shopping experiences may simultaneously increase purchasing activity, potentially offsetting some benefits of reduced returns. Consequently, the sustainability effects of CV-based retail technologies should be evaluated using actual return rates, purchasing volumes, reverse logistics activities, and lifecycle environmental impacts rather than visual quality or consumer satisfaction alone.

From a sustainability perspective, CV-based retrieval and Virtual Try-On may improve product information accessibility and support more informed purchasing decisions, potentially reducing certain mismatched purchases and returns. Visual recognition may also facilitate product attribute management and the redistribution of existing inventory. However, these applications have primarily been evaluated through retrieval accuracy, image quality, computational performance, and consumer experience. Their environmental benefits remain insufficiently established because improved shopping convenience may also encourage additional consumption. Future research should therefore integrate CV evaluation with actual return records, purchasing behaviour, inventory utilization, and

lifecycle environmental assessment to determine whether these technologies contribute to measurable improvements in apparel retail sustainability.

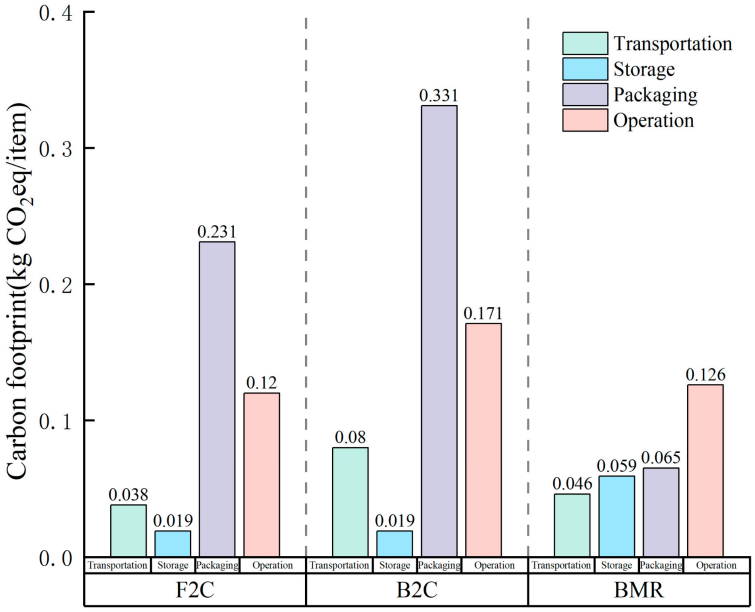



**Figure 6.** Stage-level carbon footprints of three apparel sales models: factory-to-consumer (F2C), business-to-consumer (B2C), and brick-and-mortar retail (BMR), including transportation, storage, packaging, and operations. Reproduced from Tang et al. [75], © 2026 by the authors, under the Creative Commons Attribution 4.0 International License (CC BY 4.0; https://creativecommons.org/licenses/by/4.0/).

CV-based attribute recognition and multimodal retrieval can further enhance the consistency of product information across heterogeneous retail platforms. Structured depictions of garment categories, observable design characteristics, and product attributes are capable of being correlated with existing product records, thereby potentially underpinning DPP-compatible information services. Nonetheless, product-level visual attributes must be rigorously differentiated from personal data acquired via consumer-oriented applications. Images and body-related data collected for virtual try-on should not be automatically incorporated into persistent product records. Consequently, privacy protection protocols, data minimization strategies, and appropriate access control mechanisms are indispensable when contemplating the integration of retail CV systems with broader lifecycle information infrastructures.

### *3.4. Computer Vision-Driven Decision Support for Garment Reuse and Recycling*

Waste-garment classification and automated sorting are essential for improving textile collection efficiency and directing post-consumer garments toward appropriate reuse and recycling pathways. Conventional manual sorting is labor-intensive and subject to variations in garment condition, deformation, colour, and material composition. CV has therefore been applied to garment-category recognition, colour classification, condition assessment, and automated sorting decisions, with recent developments extending from conventional image processing to deep learning and multimodal perception.

The field of post-consumer garment sorting has evolved from the identification of visible garment attributes to the determination of whether an item should be channeled into reuse or material recycling pathways. Early machine vision systems primarily focused on garment category and color classification. Tian et al. developed an attention-enhanced model trained on a dataset of approximately 27,000 discarded garments, and evaluated

its operational stability during a short-term industrial deployment [13]. However, the visual characteristics of sorting-line images rarely align with those of clean product photographs. The TexSortML benchmark demonstrated that variations in garment presentation, including rotation and crumpling, can significantly degrade classification performance [14]. Consequently, color sorting systems have also addressed imaging and calibration requirements under recycling-factory environmental conditions [15]. These studies indicate that dataset representativeness and presentation variability remain central determinants of deployment reliability.

Accordingly, subsequent studies integrated visible garment condition and reuse suitability into classification datasets [16], followed by the deployment of Vision Transformer methodologies for reusability assessment [17]. Gomes et al. advanced this research direction by integrating clothing classification, vision-language assessment, material-family cues, and explicit routing rules [18], as shown in Figure 7. While this framework progresses toward operational decision support, its controlled end-to-end pilot implementation achieved correct final routing outcomes in 66.7% of cases. This outcome highlights a critical distinction: precise recognition of individual visual attributes does not ensure an appropriate reuse or recycling decision, particularly in scenarios where material composition cannot be verified via RGB imaging.

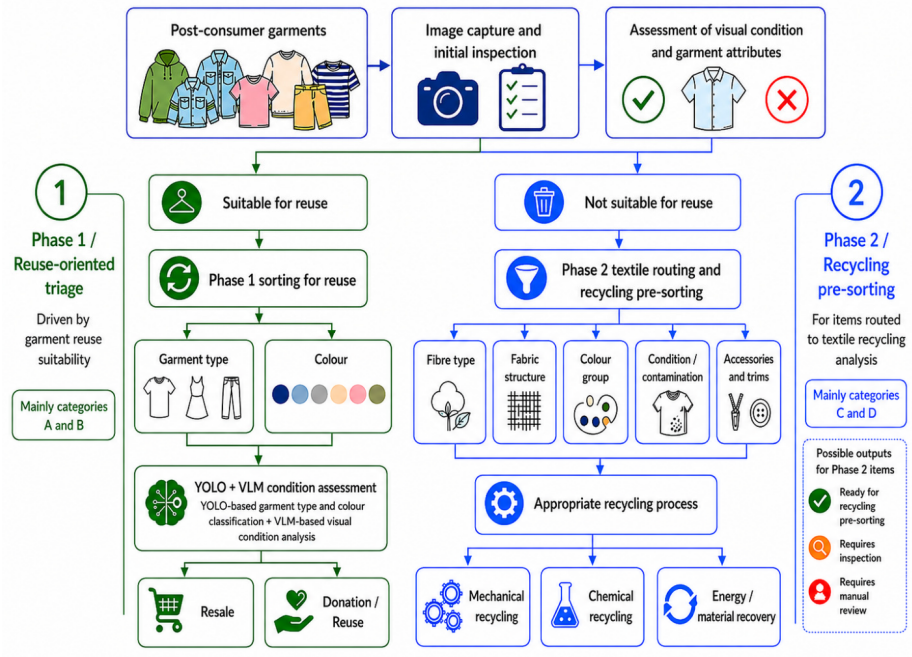



**Figure 7.** Process for separating post-consumer garments into reuse and recycling pathways. Reproduced from Gomes et al. [18], © 2026 by the authors, under the Creative Commons Attribution 4.0 International License (CC BY 4.0; https://creativecommons.org/licenses/by/4.0/).

Near-infrared hyperspectral imaging was implemented to estimate polyester content in recyclable textiles [60], while spectral data coupled with convolutional networks enabled fibre classification [19]. Investigations into blended textiles and elastane underscored the difficulty of distinguishing minor components and overlapping spectral signatures [32]. Emerging learning-based hyperspectral approaches have developed material-classification models [20], while spatial mapping identified localized recycling disruptors [33], and analyses of contaminated textiles assessed interference from surface stains [21]. Hyperspectral sensing therefore provides information unavailable from conventional colour images, yet mixed fibres, chemical treatments, and contamination persist as confounding factors for interpretability.

These advances indicate the necessity of integrating visual condition evaluation with material identification and formalized downstream routing criteria. Such integrated frameworks warrant validation under industrial sorting environments and in alignment with material-specific recycling specifications. Critically, classification accuracy and correct route allocation constitute intermediate technical metrics. Their environmental implications remain ambiguous until empirical studies quantify actual reuse rates, recovered fibre yields, material purity, processing losses, and corresponding lifecycle impacts.

At the post-consumer stage, CV-derived information may constitute supplementary inputs to garment condition documentation and reuse and recycling decision-making pipelines. Observable manifestations of wear, staining, damage, and garment category classification may be systematically captured via visual inspection, while hyperspectral imaging can yield complementary data to support material identification tasks. In scenarios where reliable product identifiers are accessible, the aforementioned observational data may be correlated with existing product records to facilitate downstream decision processes. Nevertheless, automated condition assessment performance remains susceptible to interference from garment deformation, surface contamination, and variability in image acquisition conditions. Furthermore, visually inferred attributes and spectral estimation outputs must be rigorously distinguished from formally verified fibre composition data. The absence of standardized product identifiers, heterogeneous grading criteria, and predictive uncertainty thus represent critical barriers to DPP-enabled textile sorting and recovery operations.

## 4. Analysis of the Contributions of Computer Vision to Sustainability Throughout the Garment Lifecycle

### *4.1. Cross-Lifecycle Implications for Sustainable Garment Engineering*

During design and sample development, CV primarily supports digital garment representation and pattern reconstruction, with sustainability benefits associated with substituting physical samples through virtual development workflows. Manufacturing applications emphasize defect detection and process control, where CNN-based detection and segmentation methods are widely investigated to improve inspection accuracy and prevent defective materials from progressing through production. In fashion retail, multimodal retrieval and generative Virtual Try-On aim to improve product information and purchasing decisions, whereas post-consumer applications focus on garment classification, sorting decisions, and material identification to support reuse and recycling. These differences indicate that the sustainability contribution of CV is highly dependent on its specific operational function rather than the adoption of a particular algorithm. To provide a comparative assessment of CV applications across the garment lifecycle, Table 3 summarizes representative studies in terms of application scenarios, CV tasks, algorithms, evaluation datasets, technical performance, reported sustainability outcomes, and study limitations.

Table 3 reveals a persistent gap between technical performance and verified sustainability outcomes across garment lifecycle applications. Existing studies predominantly evaluate CV systems using task-specific metrics, such as detection accuracy, mean average precision, F1 score, and processing time. Although these metrics demonstrate advances in visual recognition and computational efficiency, they do not directly establish reductions in material consumption or environmental impacts. For example, improved defect detection accuracy and sewing inspection performance have been demonstrated experimentally, but their effects on actual fabric waste remain insufficiently quantified [26,36].

**Table 3.** Cross-Lifecycle Comparison of Computer Vision Applications and Their Sustainability Contributions.

| Application Scenario | Reference | Core CV Task | Dominant Algorithms | Test Datasets/Scenarios | Key Performance Metrics | Reported Sustainability Outcomes | Study Limitations |
|---|---|---|---|---|---|---|---|
| Sewing-pattern reconstruction | Liu et al. [56] | Pattern reconstruction | Two-level Transformer (SewFormer) | SewFactory; approximately 1 million synthetic images | Stitch F1: 95.7%; panel-count accuracy: 88.7% | Potential sampling reduction; not quantified | Limited handling of unusual stitching and accessories |
| Fabric defect detection | Chen et al. [26] | Defect detection and localization | Gabor-enhanced Faster R-CNN | Fabric defect image experiments | mAP: 94.57%; baseline: 78.98% | Waste reduction not quantified | Limited real-time and cross-fabric validation |
| Defect detection impact modelling | Carvalho et al. [38] | Automated defect detection | Deep learning; Markov-chain modelling | Factory-calibrated weaving simulation | No paired field validation of detection accuracy and waste savings | Modelled >90% waste reduction; 1.3% cost savings | Factory-specific modelling assumptions |
| Sewing defect inspection | Kim et al. [36] | Stitch defect detection | VGG-16 feature maps; image processing | Normal, defective and rotated sewing images | Accuracy: 92.3%; processing time: 0.22 s | Rework reduction not quantified | Reliance on synthetic defect samples |
| Vision-assisted sewing quality control | Vergara et al. [29] | Visual error prevention | Machine vision; Poka Yoke | Garment factory intervention | Sewing rework: 28.43% → 8.94%; cycle time: 23.74 → 16.54 min | Rework reduced from 28.43% to 8.94% | Single-factory, simulation-based validation |
| Virtual Try-On | Chong et al. [53] | Image generation and Virtual Try-On | Diffusion model (CatVTON) | Public Virtual Try-On datasets | Memory use reduced by over 49% versus diffusion-based baselines | Environmental benefits not quantified | Mask sensitivity and image distortion |
| Used-garment classification | Tian et al. [13] | Garment classification | CNN; attention mechanisms | Approximately 27,000 garments; industrial evaluation | Classification accuracy improved from 68.28% to over 90% | Sorting-related benefits not quantified | Residual sensitivity to visual variations |
| Used-garment reusability assessment | Okumura et al. [17] | Reusability classification | Vision Transformer | Used-clothing images; five-fold cross-validation | F1 score: 0.98 | Reuse benefits not quantified | Limited real-world sorting validation |
| Reuse and recycling routing | Gomes et al. [18] | Classification and routing | YOLO; ConvNeXt; VLM | Controlled synthetic-image pilot | Stage 1 accuracy: 80.0%; Stage 2 routing accuracy: 66.7% | Recycling benefits not quantified | Small synthetic dataset; no field validation |
| Textile material identification | Mäkelä et al. [60] | Material composition estimation | NIR (Near-Infrared) hyperspectral imaging; regression | Polyester-containing waste textiles | Polyester-content prediction error: 2.2–4.5 percentage points | Recycling benefits not quantified | Errors with layered and glossy textiles |

A limited number of studies have examined the operational consequences of CV-enabled interventions. Carvalho et al. [38] estimated reductions in defective-material waste through operational modelling, whereas Vergara et al. [29] reported improvements in production rework rates and cycle time. However, the former relies on model assumptions, while the latter evaluates an integrated intervention whose benefits cannot be attributed exclusively to CV. Similarly, advances in Virtual Try-On and post-consumer garment classification have primarily been assessed through image quality, computational efficiency, and classification performance, rather than measured changes in purchasing behaviour, material recovery, or lifecycle emissions.

To further assess the reliability of reported sustainability benefits, this review distinguishes five evidence categories: empirical lifecycle assessments (E1), factory-level measurements (E2), consumer behavioural and transactional evidence (E3), model-based predictions (E4), and qualitative reasoning (E5). Table 4 summarizes representative studies reporting quantitative environmental or operational outcomes, together with their evidence levels and limitations.

As summarized in Table 4, the primary-inventory LCA by Erdem et al. [67] (E1) provides quantified environmental comparisons for virtual sampling, while Baek and Kim [68] (E4) report a scenario-dependent aggregate environmental score rather than a measured reduction attributable to CV. In manufacturing, the Markov-chain estimates reported by Carvalho et al. [38] (E4) should not be equated with factory-measured waste savings; Vergara et al. [29] reported improvements in rework rates and production cycle time through factory-informed operational modelling. However, the simulated outcomes should not be treated as independently verified field measurements, and the corresponding environmental benefits remain unquantified. Observed retail returns (E3) similarly cannot establish net reductions in shipping emissions or rule out increased consumption. In post-consumer sorting, reported routing accuracy and sorting-action success support technical feasibility but leave environmental benefits at E5: neither study quantified recovered-fibre yields or system-level electricity requirements.

Consequently, the lower environmental burdens from digital sampling must be assessed against computing and hardware impacts, Virtual Try-On should be evaluated for rebound effects, and automated sorting requires an energy-and-material-balance comparison before net environmental claims can be made.

### *4.2. Technical and Organizational Barriers to Implementation*

Despite recent advancements in CV, its industrial deployment remains impeded by technical reliability, implementation expenses, and data interoperability issues. High performance demonstrated on experimental datasets does not inevitably equate to stable operational performance under real-world production conditions. Furthermore, the practical utility of CV is contingent upon its integration with pre-existing equipment, personnel, and decision-making workflows.

#### 4.2.1. Technical Robustness and Industrial Integration

A key challenge lies in sustaining robust CV performance amid variable industrial conditions. For fabric inspection, disparities in texture, color, and defect morphology exacerbate recognition complexity [70]. The scarcity of rare defects and class imbalance in training datasets further impair model generalization capabilities [31]. In real-world production settings, non-uniform illumination, fabric displacement, deformation, and vibration introduce additional sources of systematic error. Furthermore, the TexSortML benchmark underscores the criticality of evaluating garment recognition performance under realistic deformation conditions [14].

**Table 4.** Reported Quantitative Outcomes and Sustainability Evidence Gaps in Representative Garment Studies.

| Lifecycle Stage | Reference | Intervention/Comparison | Quantitative Outcomes | Evidence Type and Level | Task | Key Limitations |
|---|---|---|---|---|---|---|
| Design and sample development | Erdem et al. [67] | Virtual vs. physical sampling; four garment models. | GWP, toxicity, energy: ↓ 85–90%; water: ↓ 86–91%; preparation time: ↓ up to 73%. | E1: Factory-informed LCA | Digital sampling | Workflow-level estimates; CV effect not isolated. |
| Design and sample development | Baek and Kim [68] | Physical, hybrid vs. digital T-shirt sampling. | Weighted impact score: 1.00 → 0.05 (↓ 95%, digital scenario). | E4: Scenario-based LCA | 3D simulation | Composite score depends on scenario assumptions. |
| Manufacturing and quality control | Carvalho et al. [38] | Deep-learning defect detection; simulated loom operation. | Predicted defect waste: ↓ 92–98%; operating costs: ↓ 1.3%; output: ↑ 1.3%. | E4: Markov-chain model | CV defect detection. | Waste savings projected, not field-measured. |
| Manufacturing and quality control | Vergara et al. [29] | Standardized work + vision-assisted Poka Yoke. | Sewing rework: 28.43% → 8.94%; labelling: 18.02% → 3.88%; cycle: 23.74 → 16.54 min. | E4: Factory-informed simulation and operational modelling; E5: Environmental inference | Vision-assisted error prevention. | CV effect not isolated; waste and $CO_2$ unmeasured. |
| Retail and consumption | Hwangbo et al. [76] | 3D Virtual Try-On; 11,029 transactions. | Product return rate: ↓ 27%. | E3: Consumer behavioural evidence; E5: Environmental inference | 3D visual fitting. | Single-retailer study; carbon and rebound unmeasured. |
| Post-consumer reuse and recycling | Gomes et al. [18] | Image-only reuse/recycling routing. | Routing accuracy: Stage 1, 80.0%; Stage 2, 66.7%. | E5: Environmental inference | CV-based routing. | Synthetic-image pilot; recovery and $CO_2$ unmeasured. |
| Post-consumer reuse and recycling | Ru et al. [22] | Hyperspectral + RGB sorting at 1.0 m/s. | Sorting success: cotton 95.0%; polyester 97.5%; blends 85.0%. | E5: Environmental inference | Spectral–RGB CV. | Fibre recovery, electricity use and net LCA unmeasured. |

Note: ↑ and ↓ indicate increases and decreases, respectively; → indicates a change from the initial value to the final value.

The processing speed of production lines constitutes another pivotal constraint. Industrial inspection systems are required to complete image processing within the limited production cycle, while minimizing the occurrence of missed defects and false alarms. In robotic fabric handling and sewing operations, visual perception must additionally be coordinated with grasping, positioning, and motion control to adapt to the characteristics of deformable materials [28,58]. Accordingly, deployment feasibility relies on the overall system responsiveness, rather than recognition accuracy alone.

An industrial case study was presented by Kuo et al. [23], who designed and implemented an automated inspection system for real-world woven fabric production lines. The system was equipped with an industrial CMOS (Complementary Metal-Oxide-Semiconductor) camera to perform defect inspection on fabrics conveyed at a speed of 20 m/min, attaining an overall defect recognition rate of 96.60%. The implementation integrated illumination correction, image processing, and defect classification modules. This case illustrates the criticality of synchronizing image acquisition, illumination configuration, and processing speed under operational production conditions.

Comparable challenges are encountered in post-consumer textile sorting applications. Tian et al. [13] reported classification accuracy exceeding 90%, compared with a 68.28% benchmark from earlier research, and further evaluated system stability during a two-week industrial deployment. Nevertheless, garment deformation, occlusion, and inter-class color similarity remained persistent factors degrading recognition performance. Additionally, the relatively limited evaluation duration constrains the generalization of conclusions regarding long-term robustness across multiple production facilities.

Distinct technical constraints are encountered across other lifecycle-stage applications. Virtual Try-On systems are capable of generating visually convincing garment images, yet such output does not equate to reliable physical fitting accuracy; for instance, the CatVTON model remains susceptible to mask errors and image reconstruction artifacts [53]. In the textile recycling sector, hyperspectral material identification performance is compromised by fabric structural characteristics and intrinsic optical properties [60]. These limitations demonstrate that technical validation protocols must be tailored to the specific requirements of individual applications, rather than relying solely on image-level accuracy metrics.

#### 4.2.2. Economic and Organizational Barriers

Implementation costs constitute a formidable barrier, particularly for SMEs (small and medium-sized enterprises). Industrial CV systems typically entail capital outlays for high-resolution imaging sensors, controlled illumination infrastructure, computational hardware, and equipment integration, alongside recurring expenses associated with routine maintenance. Further costs accrue from image annotation, periodic model retraining, and system adaptation to evolving product specifications or dynamic production environments. These recurring financial obligations warrant comprehensive consideration in conjunction with upfront capital investment.

Organizational readiness represents an equally critical determinant of successful implementation. Majumdar et al. [77] identified critical barriers to Industry 4.0 adoption within the textile and apparel sector, encompassing shortages of skilled personnel, inadequate managerial commitment, and prohibitive implementation costs. These findings indicate that the deployment of CV systems extends beyond mere technical installation. Routine system operation necessitates structured staff training, sustained managerial support, and clearly delineated role responsibilities.

A further critical challenge lies in the seamless integration of CV systems with pre-existing industrial workflows. Defect detection systems are required to establish bidirectional communication pipelines to transmit inspection outcomes to frontline operators

or supervisory process control equipment. Analogously, automated textile sorting necessitates tight synchronization between visual classification modules, robotic material handling subsystems, and downstream recycling decision-making frameworks. For SMEs with constrained technical and capital resources, phased deployment strategies and human-in-the-loop inspection paradigms may represent more economically viable implementation pathways relative to immediate, fully automated system adoption.

Accordingly, the economic viability of CV systems necessitates evaluation through a comprehensive framework encompassing both implementation expenditures and ongoing operating costs. Relevant evaluation indicators encompass equipment capital investment, image annotation workload, maintenance requirements, false-stop induced production losses, labor demand, and production throughput. Such systematic assessments are indispensable for determining whether technical enhancements deliver commensurate operational value within specific industrial operating contexts.

#### 4.2.3. Standardization, Data Interoperability, and Digital Product Passports

Standardization constitutes another barrier to industrial adoption, particularly within the textile recycling sector. Existing regulatory classification systems and CV-based taxonomic categories serve distinct functional purposes. The European List of Waste differentiates discarded clothing and textile waste via separate waste codes [78]. Regulation (EU) No 1007/2011 governs textile fibre nomenclature and fibre composition labelling requirements [79]. In contrast, a large proportion of CV systems classify garments based on visual attributes, garment type, color, or observable condition. Such classification outputs do not necessarily provide the material composition information required to inform recycling decision-making processes.

This inconsistency is especially pronounced in blended textile systems. RGB-based classification methodologies cannot reliably ascertain precise fibre composition, while spectral measurement techniques may also be perturbed by multilayered or glossy fabric structures [60]. Accordingly, visual inference outputs must not be regarded as experimentally validated material measurements. Industrial sorting systems would gain substantial benefit from harmonized classification lexicons, standardized evaluation protocols, and explicit delineations between predicted attributes and experimentally verified attributes.

The Ecodesign for Sustainable Products Regulation (EU) 2024/1781 enacted by the European Union establishes the normative framework for DPPs, which underscores the standardization, machine readability, and interoperability of product information [80]. Apparel products are designated as one of the priority product categories within this regulatory framework, whereas the specific DPP compliance obligations and phased implementation schedules remain contingent upon subsequent product-specific regulatory provisions.

CV technology can provide infrastructural support for the DPP framework by producing structured records documenting observable garment characteristics. The potential data fields encompass product identifiers, garment category classifications, detected defects, condition evaluations, measurement methodologies, prediction confidence levels, and verification statuses. The linkage of these records with product-level information systems would enhance their applicability across manufacturing, reuse, and recycling operations. Nevertheless, model-generated predictions must maintain clear distinction from experimentally verified fibre-composition datasets.

The necessity of robust data traceability is substantiated by Dzidzienyo et al. [81], who systematically analyzed primary data elements across diverse stages of the textile supply chain and identified pronounced heterogeneity in their traceability capabilities. Their empirical findings further validate the imperative for standardized data management protocols and verification procedures. Accordingly, subsequent research on CV applications should

focus on elucidating the mechanisms by which visual observations can be transformed into interoperable, traceable, and decision-supportive product records.

As illustrated in Figure 8, industrial deployment should be evaluated in terms of both operational performance and measurable sustainability outcomes. Carvalho et al. [38] estimated potential waste reduction and cost savings using a factory-specific Markov model. Vergara et al. [29] documented performance improvements derived from an integrated framework encompassing standardized work protocols and vision-assisted inspection. The aforementioned findings furnish empirically valuable operational evidence, yet fail to substantiate commensurate environmental benefits that can be exclusively attributed to CV technology.

Subsequent empirical field investigations should consequently evaluate detection reliability, processing throughput, implementation expenditures, and actual alterations in material waste generation or resource recovery efficiency. In contexts where environmental benefits are asserted, the supplementary energy consumption and material demands associated with cameras, computing infrastructure, and automated equipment must also be taken into consideration. The integration of technical performance assessment, organizational feasibility analysis, and lifecycle-based environmental impact evaluation is imperative for ascertaining the tangible sustainability contribution of CV technology across the garment industry.

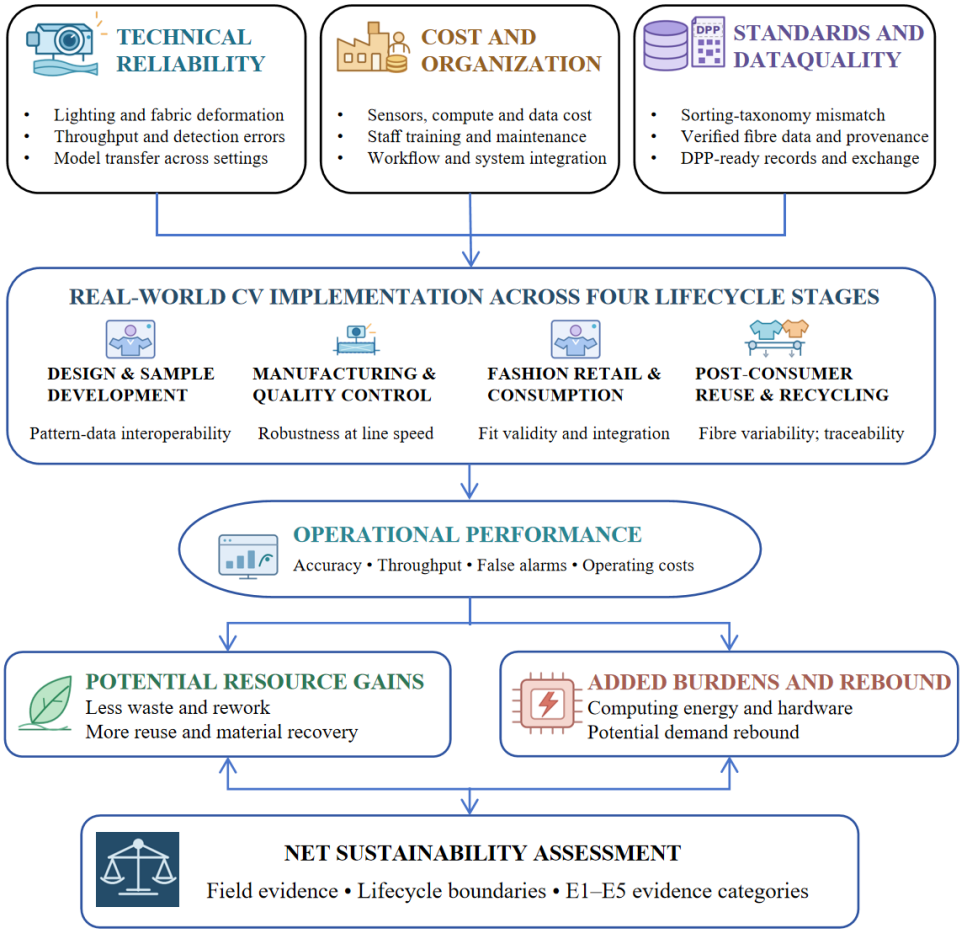



**Figure 8.** Conceptual framework of barriers to real-world computer vision implementation and sustainability assessment across four garment lifecycle stages.

## 5. Conclusions

### *5.1. Summary*

The present structured narrative review investigates CV applications across the four phases of the garment lifecycle: design and sample development, manufacturing and quality control, fashion retail and consumption, and post-consumer reuse and recycling. Through the analysis of CV application tasks, algorithmic paradigms, technical performance metrics, and reported sustainability outcomes, this review identifies both the opportunities and limitations associated with CV-enabled sustainability interventions.

The reviewed literature indicates a shift from conventional visual recognition methods toward deep learning, multimodal analysis, and generative frameworks. Nevertheless, such technological advancement has not been paralleled by commensurately rigorous environmental validation. In the phase of design and sample development, comparative lifecycle assessments have documented potential environmental benefits derived from digital sampling; however, these outcomes cannot be solely attributed to CV algorithms. Manufacturing-related studies offer empirical evidence of enhanced inspection performance and, in specific cases, reductions in rework volumes or operational expenditures. Conversely, research concerning Virtual Try-On and post-consumer textile sorting remains predominantly centered on visual quality, classification accuracy, and algorithmic efficiency, with limited direct quantification of alterations in return rates, material recovery efficiency, or environmental impacts.

Analyses presented in Tables 3 and 4 identify a persistent discrepancy between technical performance and empirically demonstrated sustainability outcomes. Furthermore, the differentiation among empirical lifecycle assessments, factory-level measurements, consumer studies, model-based forecasts, and qualitative reasoning underscores the heterogeneous robustness of the existing evidence base. These results imply that the sustainability contribution of CV should be evaluated via quantifiable operational and environmental outcomes, rather than being extrapolated solely from enhancements in algorithmic performance.

### *5.2. Future Research Directions*

(1) Methodological direction: Correlating CV performance with quantifiable environmental outcomes. Existing studies routinely report improvements in detection accuracy, classification efficacy, or processing velocity without establishing their associated environmental implications. Future research should establish coupled evaluation frameworks that integrate CV performance metrics with operational measurements and LCA. For instance, industrial investigations could compare material losses, inspection errors, and energy consumption prior to and following CV deployment under standardized production conditions. Evaluation boundaries should encompass sensor operation, computational energy demands, equipment-related impacts, and potential rebound effects. A prominent methodological challenge involves disentangling the contribution of CV from that of concomitant process optimization. Accordingly, controlled field experiments and transparent baseline comparisons would yield more robust evidence regarding the net environmental effects attributable to CV.

(2) Technical direction: Advancing data-efficient and cross-domain generalizable CV models. The heterogeneity of textile materials and operational environments constitutes substantial impediments to reliable industrial deployment. Alterations in fabric texture, color, deformation, illumination, and defect characteristics may degrade model performance, while the scarcity of annotated samples elevates training and maintenance expenditures. A critical research inquiry pertains to whether CV models can sustain dependable performance on previously unobserved textile categories and production environments under limited labeled data conditions. Future investigations ought to examine few-shot learning,

self-supervised representation learning, domain adaptation, and domain generalization paradigms tailored to textile-specific applications. Evaluation frameworks should extend beyond conventional random dataset partitions to incorporate cross-fabric, cross-factory, and cross-condition testing protocols. Furthermore, model robustness should be assessed in conjunction with inference speed, annotation requirements, and computational overhead. The residual challenge lies in attaining transferable performance without compromising the operational reliability and throughput mandated for industrial implementation. The adaptation of visual foundation models to textile-specific tasks also warrants further investigation, particularly to determine whether transferable representations can reduce annotation requirements and improve cross-domain generalization without compromising industrial reliability or computational efficiency.

(3) System-level direction: Establishing interoperable CV data pipelines across the garment lifecycle. Although CV technologies have been examined at discrete lifecycle stages, information generated across design, production, consumption, and recycling phases is rarely integrated within a unified framework. This fragmentation constrains the traceability of garment attributes, production defects, material composition, and end-of-life decisions. Future research should investigate how CV-derived information can be converted into interoperable records that facilitate information exchange across lifecycle stages. Potential approaches include linking visual garment attributes, digital pattern data, manufacturing inspection records, and material identification outcomes via standardized identifiers and data structures. Compatibility with evolving DPP requirements also merits investigation. Nonetheless, inconsistencies in classification systems, incomplete records, proprietary data formats, and organizational data-sharing constraints remain substantial barriers. Pilot studies involving manufacturers, retailers, and recycling operators are required to evaluate the feasibility, accuracy, and resource demands of such integrated systems.

(4) Ethical Direction: Evaluating classification bias and its implications for textile recycling. Models trained on constrained or imbalanced datasets may exhibit divergent performance on fibre blends, dark-hued textiles, heavily worn garments, or material classes underrepresented within the training corpus. Such performance disparities may compromise reuse and recycling decision-making, and potentially channel recoverable materials toward low-value processing or disposal pathways. Future investigations should assess class-specific error rates, uncertainty estimates, and downstream sorting decisions across variable fibre compositions and wear conditions. Representative datasets, independently authenticated material labels, and human-in-the-loop validation frameworks may facilitate the identification and mitigation of such risks. Critically, fairness evaluation should transcend classification accuracy metrics to encompass the implications of sorting decisions for material recovery and circular resource utilization.

Collectively, future scholarly inquiry ought to transition from validating the technical feasibility of computer vision applications to quantifying their environmental performance under authentic operational contexts. Advancements in integrated environmental assessment, data-efficient model development, lifecycle data interoperability, and ethically aligned automated decision-making represent core prerequisites for ascertaining whether computer vision can yield empirically substantiated, scalable sustainability dividends across the entire garment lifecycle.

**Author Contributions:** Conceptualization, writing—original draft preparation, writing—review and editing X.S.; writing—review and editing, supervision, methodology, R.C. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by the Science and Technology Department of Zhejiang Province, China, under the 2024 Key Research and Development Program ("JianbingLingyan+X" Initiative), Project Title: Art and Virtual Technology Integrated Design: Techniques and Applications under

the Background of Digital Intelligence, Grant No. 2024C01210; the General Research Project of Zhejiang Provincial Department of Education, Grant No. 2026105005-F; the Regular Research Project of Hangzhou Philosophy and Social Science Planning. Grant No. Z24YD063; the Project from Keyi College of Zhejiang Sci-Tech University, Grant No. KY2024031 and the Project from Keyi College of Zhejiang Sci-Tech University, Grant No. KY2026003.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** No new data were created or analyzed in this study. Data sharing is not applicable to this article.

**Conflicts of Interest:** The authors declare no conflicts of interest.

## Abbreviations

| | |
|---|---|
| 3D | Three-Dimensional |
| CAD | Computer-Aided Design |
| CMOS | Complementary Metal-Oxide-Semiconductor |
| CNN | Convolutional Neural Network |
| CV | Computer Vision |
| DPP | Digital Product Passport |
| EU | European Union |
| F1 | F1 Score |
| GAN | Generative Adversarial Network |
| GWP | Global Warming Potential |
| HSV | Hue, Saturation, Value |
| IoT | Internet of Things |
| LCA | Lifecycle Assessment |
| mAP | Mean Average Precision |
| NIR | Near-Infrared |
| R-CNN | Region-Based Convolutional Neural Network |
| RGB | Red, Green, Blue |
| RNN | Recurrent Neural Network |
| SAM | Segment Anything Model |
| SMEs | Small and Medium-Sized Enterprises |
| UNEP | United Nations Environment Programme |
| ViT | Vision Transformer |
| VLM | Vision-Language Model |
| VTON | Virtual Try-On |
| YOLO | You Only Look Once |

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