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Review on the integrated virtuous cycle system of the AI-applied circular economy-based sustainable textile industry

Abstract

The transition toward a sustainable textile industry requires coordinated changes across raw-material sourcing, manufacturing, product use, resource recovery, and market implementation. This narrative review develops an integrated virtuous-cycle framework connecting four industrial stages—up-stream, middle-stream, down-stream, and commercialization—through circular material flows and artificial intelligence (AI)-enabled decision support. The framework synthesizes strategies for renewable and recycled feedstocks, traceable procurement, low-impact textile processing, design for durability and recyclability, collection and sorting, and circular business models. AI applications are examined as enabling functions for forecasting material demand, optimizing process parameters, detecting defects, supporting automated sorting, and monitoring lifecycle performance. A conceptual feedback architecture is proposed in which operational and post-consumer data inform subsequent design and procurement decisions. The review emphasizes that potential reductions in emissions, water use, and waste depend on technology choice, electricity mix, collection quality, and appropriate lifecycle boundaries; they should not be assumed from circularity or AI adoption alone. Practical implementation requires interoperable data, validated environmental indicators, responsible AI governance, and collaboration across the textile value chain. The proposed system provides a structured basis for evaluating circular textile transitions and identifying priorities for future empirical validation.

Keywords: sustainable textile industry, circular economy, artificial intelligence, textile recycling, lifecycle assessment, resource efficiency, supply-chain traceability, circular business models

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Abbreviations: AI, artificial intelligence; CE, circular economy; ESG, environmental, social and governance; LCA, life cycle assessment; PET, polyethylene terephthalate; RFID, radio-frequency identification; DPP, digital product passport; NIR, near-infrared

Introduction

The textile industry links resource extraction and agriculture to complex manufacturing chains, product use, and end-of-life management. Environmental pressures arise at multiple stages: fiber production requires land or fossil feedstocks; wet processing consumes water, heat, and chemicals; and short product lifetimes increase the throughput of materials. A sustainable transition therefore cannot be achieved by isolated factory improvements. It requires system-level coordination among design, production, consumption, recovery, and market incentives.[1–4]

Circular economy (CE) approaches seek to preserve product and material value through longer use, reuse, repair, remanufacturing, and recycling, while avoiding waste and pollution.[2,5] Yet material recirculation does not automatically deliver lower environmental impacts: transport, reprocessing yields, substitution rates, and energy demand must be assessed across the full lifecycle.[3,6] Artificial intelligence (AI) can help interpret complex data and optimize decisions, but its deployment also introduces costs, infrastructure demands, and governance challenges.

This review develops a four-stage value-chain framework, specifies testable cross-stage information and material feedback mechanisms, and distinguishes documented findings from proposed AI-enabled interventions. The contribution is a conceptual integration rather than a systematic meta-analysis or a report of original experimental results.

Existing circular-textile research has established material-efficiency priorities, the importance of product-life extension, and environmental assessment of reuse and recycling.[1–3,5,6] More recent research examines AI-enabled identification and sorting of textile waste.[7–9] However, a technically successful classifier or a circular product design does not, by itself, establish an operationally viable closed-loop system. The unresolved integration problem concerns how measurements made at sourcing, production, use, recovery, and commercialization are linked to accountable decisions and verified outcomes across organizational boundaries.

The specific contribution of this review is a decision-oriented architecture that couples A physical resource loop, A digital evidence-and-learning loop A commercial incentive loop.

Each stage is assigned inputs, decision rights, quality constraints, measurable outputs, and feedback to earlier stages. The framework is distinguished from a generic circularity diagram by its requirement for functional-unit consistency, cross-stage material-balance reconciliation, uncertainty-aware AI validation, and explicit go/no-go criteria for industrial implementation. These elements are proposed design requirements, not claims that a fully integrated system has already been demonstrated.

Review approach and system boundaries

The review is an interpretive narrative synthesis organized around four interconnected value-chain stages. Its evidence base consists of

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the cited scholarly publications, methodological standards, and policy documents. The conceptual architecture is a proposition for future validation rather than a measured industrial system.

Literature identification, eligibility, and synthesis procedure

The evidence synthesis is narrative and purposive. The initial evidence base comprised fifteen references in the earlier manuscript version, spanning textile environmental impacts, circular-economy theory, recycling, AI-assisted sorting, life-cycle assessment standards, and European policy. For this revision, the relevance of selected source publications and their bibliographic details was checked against accessible publisher or institutional records; no comprehensive database retrieval or quantitative screening exercise was undertaken. Consequently, this manuscript does not report search-result counts, a PRISMA flow diagram, pooled effect sizes, or a claim of systematic completeness.

For transparent interpretation, sources are grouped by evidentiary role:

a. Conceptual or policy frameworks.[2,5,10–12]

b. Environmental assessments and evidence syntheses.[1,3,4,6,13,14]

c. AI or sensor-based textile identification and sorting studies or syntheses.[7–,15]

Evidence is compared using five analytical questions: What process or decision is addressed? What is the empirical or conceptual basis? Which performance measures are reported? What boundary conditions or sources of bias limit transferability? What cross-stage data would be needed to integrate the result into a circular production system?

Eligibility for the interpretive synthesis emphasizes directly relevant peer-reviewed research, authoritative standards, and primary policy documents; sources with unclear provenance or unsupported numerical claims are not used as quantitative evidence. The method does not imply that every relevant study has been located. A future systematic review should prespecify databases, dates, search strings, duplicate handling, eligibility criteria, independent screening, and risk-of-bias assessment before reporting a comprehensive evidence map.

Functional unit and analytical perspective

Comparison among fiber options or recycling routes requires a clearly specified functional unit. A kilogram of textile output may be convenient for factory-level inventories, whereas one year of service or a defined number of wearing and washing cycles better represents the delivered function of apparel. For geosynthetics and technical textiles, the functional unit should additionally capture engineering performance and design service life. A material that requires more energy per kilogram may nevertheless deliver lower impacts per unit of useful service if its lifetime or functionality is substantially improved.[13,14]

Material, information, and value boundaries

Three interconnected boundaries are distinguished. The material boundary tracks virgin and secondary fibers, processing losses, products, and recovered resources. The information boundary encompasses traceability records, sensor data, product specifications, and end-of-life classifications. The economic boundary covers procurement, investment, operating costs, market demand, and the distribution of incentives among actors. Misalignment among these boundaries is a major obstacle to implementing a genuinely closed-loop textile system.

Interpretation of evidence

Statements about possible AI applications in this paper are proposed use cases, not evidence that a particular algorithm has already delivered quantified environmental benefits. Potential gains depend on sensor reliability, training-data representativeness, process integration, and human oversight. Reported environmental outcomes in external studies also depend on geography, electricity mix, displaced production, transport, and allocation conventions. These dependencies should accompany any future numerical comparison.

The framework is organized around four value-chain stages and their feedback links. The synthesis draws on the cited literature and distinguishes published evidence from the proposed architecture. No systematic database search, meta-analysis, or original industrial measurements were performed. The framework is therefore conceptual, and its anticipated benefits require sector-specific empirical testing.

The system boundary covers fiber feedstock acquisition, textile and product manufacture, distribution and use, collection, sorting, recycling, and re-entry into the feedstock system. Cross-cutting digital infrastructure includes material identification, operational monitoring, data exchange, decision models, and lifecycle indicators. Figure 1 summarizes the architecture.

Figure 1 presents the proposed system boundary as a connected sequence of sustainable raw-material sourcing, manufacturing, use, end-of-life recovery, and circular feedback. Its central contribution is to make the return of recovered feedstock to upstream sourcing explicit, rather than treating waste management as an isolated downstream activity. Cross-cutting enablers—data intelligence, traceability, environmental assessment, standards, and collaboration—should be implemented across organizational boundaries. The figure is conceptual and does not imply that all illustrated pathways are currently industrially mature.

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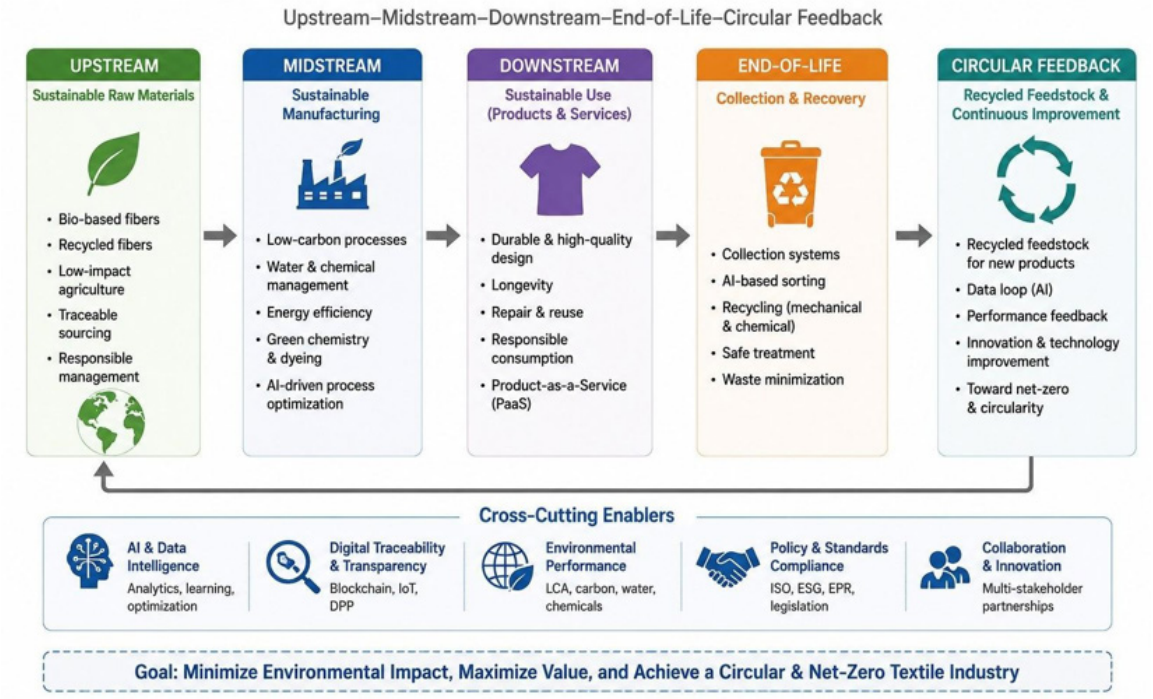


Figure 1 Integrated value chain and material-return pathway for a sustainable textile industry. Conceptual synthesis presented in this review; not measured results.

Scope, evidence selection and synthesis transparency

This is a purposive, narrative, framework-oriented review. The literature was selected for relevance to textile circularity and LCA, material identification and sorting, AI-assisted manufacturing, digital product information, and industrial implementation. The original fifteen-reference corpus was expanded to 31 cited sources for this revision, including recent publications through November 2026. This was not a systematic or exhaustive search; database-specific retrieval dates, screening counts, exclusion logs, and PRISMA flow are not claimed. The synthesis compares process stage, evidence type, potential benefit, operational constraint, and validation status. Published findings are distinguished from conditional extrapolations and the proposed framework.

Contribution relative to existing frameworks

Earlier circular-textile frameworks emphasize material loops and product-life extension,[2,3,5,6] while recent AI reviews organize specific detection and sorting operations.[16] The contribution here is not a new sorting algorithm or an experimentally validated environmental saving. Rather, it is a cross-stage decision architecture coupling material circulation, measured environmental outcomes, product and process information, and commercialization feedback. Its testable feature is a requirement that every proposed AI action be connected to an operational decision, a functional-unit-based baseline, a recovery or quality outcome, and an accountable data owner. Such a coupling remains a research proposition, not a demonstrated sector-wide result.

Up-stream:Transition to sustainable feedstock systems

Material flow accounting and procurement scenarios

For practical deployment, a procurement team could construct a monthly material-flow ledger that records purchased virgin fibers, verified secondary feedstock, incoming contamination, production losses, and the disposition of rejected lots. The ledger would permit comparison of a conventional sourcing scenario with alternatives containing different proportions of recycled or renewable input. Each scenario should be evaluated against required tensile properties, color consistency, supply reliability, and financial risk. Because a high recycled-content percentage may coincide with high processing losses, the assessment should consider the amount of usable fiber ultimately delivered, not merely the mass purchased. Uncertainty intervals can be assigned to supplier-reported environmental data. Where supplier records are unavailable, proxy data should be marked as provisional and prioritized for verification. This approach links upstream sustainability claims to auditable operational decisions and creates a data foundation for later stages of the proposed virtuous cycle.

Renewable and bio-based fibers

The reviewed sustainability literature discusses renewable cellulose resources, bio-based polymers, and emerging microbial or algae-derived materials as promising alternatives to fossil feedstocks. Their sustainability must nevertheless be evaluated across land use, water demand, chemical processing, energy supply, and eventual disposal. Bio-based origin alone does not guarantee biodegradability, recyclability, or low climate impact. A robust sourcing policy should therefore combine material certification with traceable inventory data and lifecycle evaluation rather than rely on feedstock labels.

Recycled feedstock quality and compatibility

Recycled polyester from bottles and textile waste offers a route to reducing virgin polymer demand, but source quality and contamination determine feasible applications. Mechanical recycling may alter polymer molecular characteristics, while chemical recycling

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introduces its own energy and reagent requirements. Cotton-rich waste can be recovered for selected uses, although fiber shortening can restrict direct replacement of virgin spinning-grade material. Blended textiles, coatings, dyes, and accessories complicate sorting and conversion. Consequently, the highest-value recovery route should be selected for each feedstock stream rather than assuming that every waste stream is suitable for equivalent fiber-to-fiber recycling.

Ethical procurement and supply-chain traceability

Environmental performance is inseparable from the social and governance dimensions of procurement. Supplier selection should consider worker safety, labor practices, resource stewardship, and the verifiability of origin claims. Traceability systems can associate material batches with declared composition, supplier identity, certification records, and manufacturing events. Digital ledgers can improve record continuity, but they do not independently guarantee that entered information is true. Auditing, sampling, and clear responsibility for data quality remain essential.

AI-supported material selection

A decision-support model can compare candidate fibers against minimum mechanical properties, process compatibility, cost ceilings, availability, and lifecycle impact indicators. Multi-objective optimization is particularly relevant because the lowest-cost fiber is not necessarily the lowest-impact or longest-lived option. Candidate models should disclose the weight assigned to each objective and include sensitivity analysis. An AI recommendation should be treated as an auditable input to material selection, with final approval retained by qualified engineers and procurement personnel.

Up-stream implementation indicators

Practical indicators include the verified share of recycled input, supplier traceability coverage, rejected incoming material, batch-to-batch property variation, water stress associated with sourcing, and greenhouse-gas emissions under stated boundaries. Indicators should distinguish recycled content from actual recyclability, and renewable content from verified lifecycle performance. A standardized material passport can transmit these attributes to downstream processors and eventually to sorting and recycling facilities.

Up-stream transformation begins with the selection of raw materials. Renewable cellulosic feedstocks, responsibly managed natural fibers, recycled polymers, and emerging bio-based materials can diversify supply, but their sustainability depends on land use, process chemistry, energy sources, and verified sourcing. A recycled feedstock should be evaluated for contamination, quality, and displacement of virgin material rather than classified as environmentally preferable by label alone.[1,3]

Recycled PET from bottles and textile waste is commercially relevant, while textile-to-textile recycling faces additional challenges from blended fibers, dyes, finishes, and variable feedstock quality. Design specifications and procurement contracts should therefore communicate fiber composition and anticipated recovery routes. Supply-chain traceability, potentially supported by digital product records and physical markers, can connect upstream choices to later collection and recycling.[12]

AI can assist feedstock forecasting, supplier risk screening, image-based identification, and composition classification when sufficiently representative training data are available. Its outputs require human verification and explicit quality thresholds, especially where incorrectly identified blends would compromise recycling. Environmental and labor-related claims should be assessed independently through recognized auditing and LCA procedures.

Figure 2 distinguishes three interdependent loops: a physical material circulation pathway, an energy and carbon performance pathway, and a digital feedback pathway. Material recycling alone cannot demonstrate a net environmental benefit; the energy intensity and yield of collection, sorting, and reprocessing must also be assessed. The data loop provides a proposed means to reconcile operational measurements with environmental inventories and to revise process decisions. These flows should be evaluated with consistent system boundaries and an explicit functional unit.

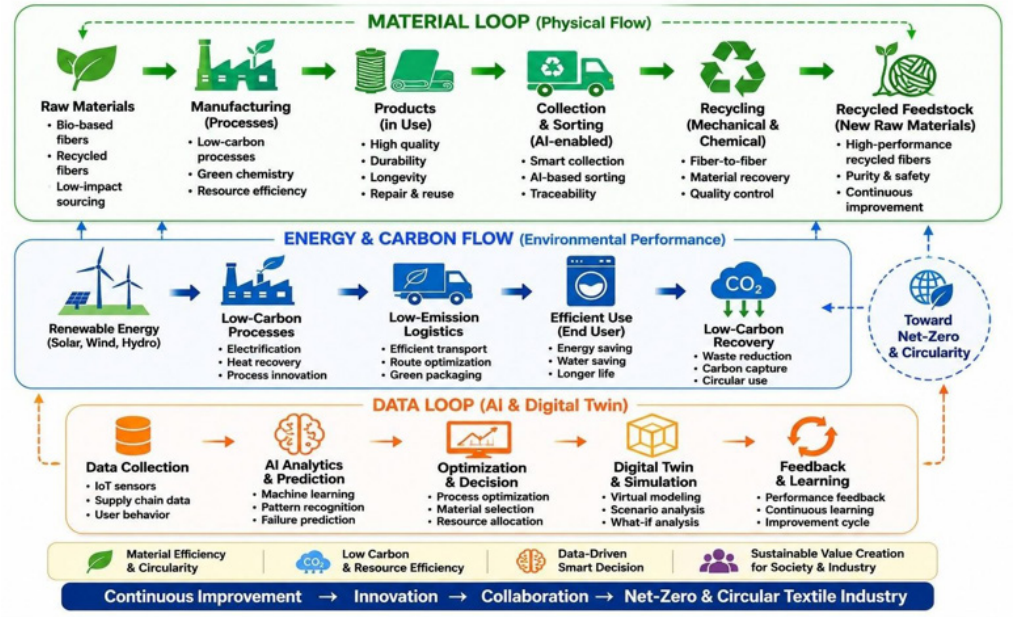


Figure 2 Three complementary loops: physical materials, energy/carbon accounting, and AI-enabled data feedback. Conceptual synthesis presented in this review.

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Middle-stream: Sustainable design and low-impact manufacturing

Process-level evaluation protocol

A process-level evaluation should specify the product grade, machine configuration, operating schedule, and quality acceptance criteria before environmental indicators are compared. In spinning, waste per unit of accepted yarn and electrical demand per unit of output can be monitored together. In dyeing, the relevant indicators may include water intake, effluent loading, thermal energy, color difference, and the proportion of lots requiring correction. For finishing, chemical dosage, product durability, and worker exposure may be critical.

Measurements should cover normal variability rather than a single demonstration run. If an AI control system is introduced, its performance should be compared with a well-defined baseline over equivalent product mixes and operating conditions. An improvement in process efficiency is meaningful only if acceptable quality is maintained. Documentation of data gaps and unplanned downtime is also necessary to avoid overstating the benefits of a pilot project.

Design for durability and circularity

Product design establishes the constraints under which circularity will later be attempted. Material combinations, coatings, fasteners, seam construction, and colorants can improve immediate performance while making disassembly or recycling more difficult. A design-for-circularity protocol should document fiber composition, expected durability, repairability, and the anticipated end-of-life route. Mono-material structures can simplify some recovery pathways, but they should not be imposed where they would compromise safety or essential technical performance.

Spinning, fabric formation, and finishing

Spinning and fabric formation generate both energy demand and recoverable losses. Process monitoring can track yarn irregularity, breakage, loom efficiency, and fabric defects so that corrective action occurs before substantial scrap accumulates. In dyeing and finishing, low-liquor-ratio systems, water reuse, process heat recovery, and careful chemical substitution may reduce resource intensity. However, a claimed reduction in water consumption should be accompanied by wastewater-quality data and the electricity or thermal energy required by the alternative process.

Closed-loop process water and chemicals

Industrial water recirculation should be designed around contaminant accumulation, salt balance, membrane fouling, and discharge requirements. Chemical management similarly requires inventories of substances, exposure controls, and appropriate handling of concentrated residuals. Closed-loop terminology should not imply zero releases unless mass balances and monitoring substantiate that outcome. For each process, a baseline and an operational monitoring plan are necessary to evaluate whether circular interventions shift impacts from one category to another.

Digital process control and predictive maintenance

AI-enabled manufacturing can combine temperature, flow, vibration, power, and quality measurements to predict off-specification output or equipment degradation. A practical deployment sequence begins with calibrated sensors, stable data acquisition, process engineers' validation of labels, and comparison against simpler statistical control methods. Models should be assessed on out-of-sample production batches and under changing operating conditions. The primary sustainability pathway is the avoidance of rework, downtime, and rejected products, not the mere installation of an algorithm.

Energy and carbon management

Factory-level carbon management requires an inventory that separates purchased electricity, on-site fuels, and upstream material emissions. Temporal variation in the electricity supply can change the impact of electrically driven thermal processes. Energy optimization should therefore account for throughput, product quality, scheduling constraints, and emissions factors rather than minimize electricity use in isolation. A plant-level dashboard can make these trade-offs visible, provided the data are quality controlled and the reporting boundary is consistently maintained.

Quality assurance and worker-centered transition

Automation should strengthen, not bypass, quality assurance. Engineers need interpretable defect categories, thresholds for manual review, and procedures for model drift or sensor failure. Workers also require training in data interpretation and safe intervention. These organizational requirements are especially important for small and medium-sized textile enterprises, where investment constraints and fragmented information systems can prevent the adoption of sophisticated platforms despite their theoretical advantages.

The middle-stream includes spinning, weaving or knitting, dyeing, finishing, and assembly. Sustainable design should begin with intended service life and end-of-life pathways. Durability, reparability, fiber compatibility, and separable components can reduce replacement and improve recovery, although single-material design may conflict with performance requirements in protective and technical textiles.

Manufacturing priorities include efficient motors and thermal systems, reduced-liquor-ratio dyeing, chemical substitution, wastewater treatment and reuse, material yield improvement, and renewable energy where feasible. Process savings are site- and technology-specific; percentage reduction claims require measured baselines, functional equivalence, and stated system boundaries.[1,3]

AI-supported manufacturing may use sensor streams to forecast defects, adjust dyeing conditions, schedule maintenance, reduce off-specification output, and balance water or energy demand. A practical architecture connects process sensors to validated predictive models, operator decision interfaces, and auditable records. Model drift, data gaps, and cybersecurity risks should be managed throughout deployment.

Critical comparison of AI-enabled manufacturing options

AI-based defect recognition and predictive control may reduce avoidable waste, but performance depends on the distribution of product types, lighting, sensors, machine condition, and label quality. High accuracy on curated training images is not equivalent to reduced industrial scrap. Appropriate comparisons should report defect-level precision and recall, false-rejection cost, production throughput, rework avoided, and performance after a production-line or product-style change. A simpler statistical-process-control baseline should be included to identify the incremental value of machine learning.

Predictive maintenance similarly requires a counterfactual: unplanned downtime and replacement parts under the existing maintenance policy versus the proposed model. Digital twins should

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be treated as calibrated, purpose-limited simulation and decision systems rather than exact live replicas of a factory. Their useful validation metrics include forecast error, time synchronization, intervention latency, and stability under sensor failure.

Computational energy, hardware replacement, cybersecurity, and workforce training are costs that must be included in any net sustainability claim.

Critical evidence on manufacturing AI

Industrial inspection research compares supervised and unsupervised defect-detection approaches and explicitly discusses training-label availability and implementation costs.[17] Recent reviews of zero-defect manufacturing and fabric inspection document progress in detection, prediction and prevention, while noting the need for representative datasets and robust production integration.[18,19] A weaving-manufacturing case study further evaluates operational effects of deep-learning-based defect detection.[20] These sources support the feasibility of targeted inspection use cases, but do not establish that a factory-wide AI platform necessarily reduces lifecycle impacts. The appropriate counterfactual is conventional inspection or statistical process control under matched product mix and operating hours; model energy, false alarms, operator workload and rejected-material mass should be measured together.

Down-stream: Durability, recovery, and circular value

Recovery-pathway decision matrix

A recovery decision matrix can separate products by condition, composition, contamination, and feasible end markets. Items suitable for direct reuse should be assessed for functional integrity and realistic demand.

Repairable products require estimates of labor, parts, and additional service life. Materials suitable for recycling require evidence of technical compatibility with the intended recovery process and a market for the resulting output. Heavily contaminated or structurally unsuitable items need an appropriate residual management route. The decision matrix should avoid assuming that the pathway with the highest nominal recycling rate necessarily has the lowest environmental burden. Transportation, washing, sorting losses, and displaced virgin production all influence the outcome. AI may assist classification and routing, but uncertain cases should be reviewed manually. This arrangement makes recovery outcomes traceable and generates valuable evidence for the next cycle of material and product design.

Extending useful service life

Durability links manufacturing decisions with the environmental impacts of use. Garments may be discarded for reasons unrelated to mechanical failure, including fashion preferences and changes in fit, whereas technical textiles may be retired after a specified exposure or performance threshold. Service-life extension strategies must therefore be tailored to the product category. Repair, maintenance, modular replacement, and reliable performance information can delay replacement, but the actual environmental benefit depends on whether a new purchase is displaced.

Collection and reverse logistics

Recovery begins with accessible collection, clear ownership of used products, and economical reverse logistics. Collection programs should distinguish reusable items from recyclable materials and nonrecoverable residues. Transportation and storage requirements may be substantial for low-density textile waste, and poorly designed incentives can encourage collection without meaningful reuse or recycling. Tracking collection yield, contamination, and final destinations is necessary to distinguish circular outcomes from simple diversion claims.

Sorting and fiber identification

Automated sorting can combine imaging, near-infrared measurements, product labels, and manual inspection to classify composition and condition. Yet blended fibers, dark dyes, finishes, and multilayer structures may lower classification confidence. Facilities should record uncertainty and direct ambiguous items to further testing rather than force an incorrect category. A representative validation dataset must include realistic contamination and material diversity, not only laboratory-clean samples.[7–9]

Reuse, remanufacture, and recycling hierarchy

Direct reuse often preserves more embedded product value than conversion back to raw material, but hygiene, condition, safety, and market demand determine feasibility. Remanufacture and redesign can preserve selected components, while mechanical and chemical recycling may recover fibers or molecular feedstocks. The appropriate sequence should be established using product-specific environmental and economic evidence. Disposal remains necessary for certain hazardous or heavily contaminated materials; a credible circular system must document these residual streams.

Technical textiles and geosynthetics

Industrial textile applications illustrate the importance of function-based assessment. Geotextiles, filters, protective fabrics, and reinforcement materials are frequently specified for demanding environmental conditions and long service lives. The ability to recover an installed material may be limited by contamination, embeddedness, or safety constraints. In these cases, improved durability, lower-impact installation, and reduced maintenance may provide more realistic sustainability benefits than an assumed closed material loop. Any comparison must preserve engineering performance and safety requirements.

The down-stream encompasses distribution, product use, repair, reuse, collection, sorting, and disposal. Extending useful life can reduce production demand if longer service displaces new purchases; the magnitude of benefit depends on actual user behavior and substitution.[3,6] Industrial textiles such as geosynthetics, filtration media, and protective fabrics also require durability and safety evaluations specific to their use conditions.

Effective circularity requires collection infrastructure, material identification, and sorting systems that deliver recycling-compatible fractions. Design for disassembly, identifiable material content, and the avoidance of problematic blends can improve the feasibility of recovery. Mechanical and chemical recycling should be compared using yield, recovered quality, energy demand, emissions, and handling of residues rather than a single recycling-rate metric.[7,9,15]

AI-based visual sorting, spectroscopy-assisted classification, logistics forecasting, and product-condition assessment may improve operational decisions. Nevertheless, these functions should be benchmarked against conventional alternatives and evaluated for classification errors, cost, worker impacts, and energy use.

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Evidence-based assessment of sorting and recycling routes

Faghih, Saki, and Moore[7] systematically examined AI-enabled textile sorting and identified the persistent difficulties of blended fibers, heterogeneous datasets, and industrial scalability. These findings support the feasibility of computer-assisted identification as a research direction, but they do not establish universally transferable sorting accuracy. Near-infrared and image-based methods have complementary information content: optical images can describe visible appearance, whereas spectral measurements may provide stronger clues about chemical composition.[7,9] Coatings, dark colorants, moisture, aging, and multilayer structures can still compromise identification. Ambiguous fractions therefore require a reject or manual-verification pathway.

The environmental preference among reuse, mechanical recycling, and chemical recycling is context-dependent. Sandin and Peters[3] found that avoided production and replacement assumptions strongly influence the environmental value of reuse and recycling. Mechanical recycling may have comparatively modest chemical demand but can shorten fibers or reduce polymer quality; chemical routes may recover molecular feedstocks while imposing additional heat, solvent, purification, and residual-management burdens. The correct comparison is not a nominal recycling percentage but useful recovered output per functional unit, including sorting yield, processing losses, displaced virgin production, energy mix, and end-market quality.

A practical recovery decision should therefore use a transparent routing hierarchy: first verify safe reuse or repair; then assess fiber-to-fiber recycling feasibility and required purity; finally assess alternative recovery or compliant residual treatment. For each option, disclose uncertainty in recovery yield, displacement ratio, and logistics. This decision hierarchy is a proposed implementation tool, not a universal ranking applicable to every textile category.

Evidence-based comparison of recovery technologies

A consequential LCA of European textile-to-textile recycling scenarios identifies assumptions about displaced production and future recovery pathways as important determinants of net impacts.[21] Comparative assessment of industrial recycling alternatives likewise requires explicit allocation and processing assumptions.[22] A multi-criteria comparison of nine waste-textile recovery technologies illustrates that energy demand, technical maturity and economics may favor different routes.[23] A denim-to-fabric recycling case provides a product-specific example of quality and environmental evaluation rather than a universal recycled-content target.[24] Hence sorting purity, recovery yield, downstream yarn quality, electricity mix and real market substitution should be recorded before a closed-loop pathway is described as preferable.

Limits of AI-enabled sorting

NIR-based textile identification studies demonstrate the potential of machine-learning classifiers, including benchmark comparisons of convolutional and hybrid architectures.[8,25,26] However, hyperspectral research identifies challenges from blends, localized contaminants and minor constituents.[27,28] A 2026 systematic review of 173 primary studies reports uneven technology readiness across operational stages, especially post-consumer condition assessment and attachment removal.[16] Image-only garment routing can support reuse triage,[15] but image appearance cannot by itself reliably establish polymer composition. Industrial implementation therefore requires uncertain-item rejection, ground-truth sampling, calibration drift checks and cost-per-tonne monitoring.

Commercialization: Converting sustainability into market value

Market acceptance and procurement specifications

Market adoption depends on whether circular products satisfy customer expectations for price, performance, appearance, and reliability. Procurement specifications can support demand for recovered fibers by defining measurable quality requirements and appropriate verification procedures. Long-term supply agreements may help recyclers invest in sorting and processing equipment, but contracts should allow for realistic variation in waste-stream composition. Buyers should distinguish minimum recycled-content requirements from wider lifecycle performance criteria. A product can satisfy the former while performing poorly under the latter.

Commercial performance indicators might include repeat purchase rates, repair uptake, return rates, verified product lifetime, and net revenues after collection and processing costs. Tracking these variables alongside environmental metrics makes it possible to assess whether the circular business model can sustain itself without concealing trade-offs or relying exclusively on promotional claims.

Circular business-model design

Commercialization closes the economic feedback loop by turning sustainability improvements into procurement preferences, service offerings, and reinvestment capacity. Potential models include repair services, resale, product leasing, take-back programs, and recycled-content supply agreements. Each model needs a transparent assessment of operating costs, return rates, product losses, and actual substitution of new production. Circular revenue does not by itself establish an environmental gain.

Evidence-based environmental communication

Environmental labels and sustainability reports should distinguish verified measurements from projected improvements. Product claims are most credible when they specify system boundaries, functional units, data sources, and independent assurance where appropriate. Labels and certification schemes address different attributes and should not be treated as interchangeable proof of overall sustainability. Marketing language must also avoid presenting a product as environmentally benign solely because it contains a recycled or bio-based component.[10,11]

Economic feasibility and equitable participation

Business viability depends on stable feedstock supply, product quality, infrastructure utilization, and demand for secondary materials. Contractual arrangements can distribute costs and incentives across collectors, recyclers, manufacturers, and retailers. Small suppliers may face disproportionate compliance costs, making shared digital infrastructure and harmonized data requirements useful. Evaluation should include employment conditions, affordability, and access to circular services alongside profitability.

Digital product information and market feedback

A digital product record can connect upstream composition and manufacturing history to maintenance instructions, verified claims, and recovery guidance. Aggregated sales and returns data can reveal which products have longer service lives or higher recovery yields. Such feedback can influence subsequent product design and sourcing decisions. Privacy, commercial confidentiality, interoperability, and responsibility for correcting records must be addressed before information sharing becomes dependable.[10,11]

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Commercialization translates technical improvements into products, procurement decisions, and viable services. Circular business models include repair services, resale, take-back programs, leasing where appropriate, and manufacturer-supported material recovery. Their success depends on consumer acceptance, logistics, product design, regulatory conditions, and the economics of recovered materials.[2,5]

Environmental claims should be specific, verifiable, and proportionate to supporting evidence. Lifecycle disclosures, material-content certification, and transparent reporting can help purchasers compare alternatives; however, certifications differ in scope and do not universally establish overall product sustainability. AI-enabled demand prediction and inventory optimization may reduce unsold goods, provided that efficiency gains do not encourage greater aggregate consumption.

Figure 3 illustrates a common AI sustainability intelligence layer operating across upstream, midstream, downstream, end-of-life, circular feedback, and impact assessment. A shared architecture can link forecasting, quality prediction, sorting, process optimization, and environmental reporting, while preserving stage-specific constraints. Multi-objective optimization should not assume that lower cost, lower emissions, greater durability, and improved circularity are always aligned; the resulting trade-offs require transparent reporting and human review.

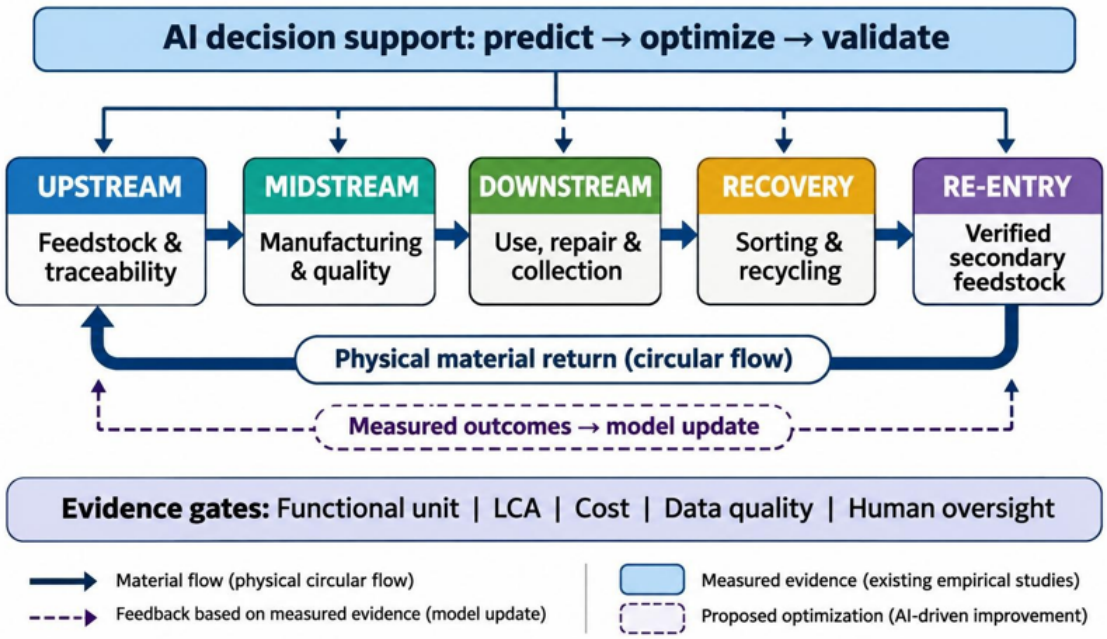


Figure 3 Simplified AI-enabled circular textile architecture. Solid arrows show proposed material flows; dashed arrows show proposed data feedback. Conceptual schematic, not a demonstrated closed-loop installation.

Techno-economic assessment and SME implementation barriers

Financial feasibility should be assessed over the equipment lifetime rather than inferred from improved sorting or manufacturing accuracy. A minimum business case includes capital expenditure for sensors, conveyors, data infrastructure and integration; recurring expenditure for maintenance, software, calibration, cloud or local computation, and skilled labor; and revenue or savings from reduced defects, recovered material, lower utilities, and improved product value. Net present value and payback period should be stress-tested against throughput, recovered-fiber prices, electricity tariffs, and collection contamination.

Small and medium-sized textile enterprises may lack the data volume, dedicated IT personnel, and investment capacity required for enterprise-scale digital twins. A proportionate pathway begins with material ledgers and low-cost metering, advances to one validated use case (such as defect detection or energy monitoring), and only later connects suppliers and recyclers through interoperable identifiers. Shared testing facilities, sectoral data standards, and human-in-the-loop review can reduce deployment risk. These are implementation recommendations requiring prospective economic validation, not evidence of already achieved returns.

Digital product passports: implementation and economic evidence

Recent textile-specific DPP reviews identify interoperability, data ownership, and lifecycle-data completeness as adoption barriers.[29] An empirical study involving 105 manufacturers in three textile-exporting countries reports uneven readiness for digital traceability.[30] Consumer and producer evidence also suggests that traceability information may affect willingness to pay, although this does not demonstrate a net environmental benefit.[31] Consequently, DPP implementation should begin with verified fiber composition, batch identifiers and repair/recovery instructions before expanding to high-cost product-level environmental claims.

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Integrated AI-enabled virtuous-cycle framework

Illustrative end-to-end implementation scenario

Consider a hypothetical textile producer that records feedstock composition, spinning losses, dyeing resource use, and product specifications in a shared information system. A distributor subsequently records product returns, while a recovery partner reports sorting categories and the quality of reclaimed materials. The producer can use these observations to identify designs that are difficult to recover or material blends associated with excessive manufacturing waste. A forecasting model may estimate the availability of recycled feedstock, and an optimization model may propose alternative product recipes subject to strength, color, cost, and emission constraints. Proposed changes would be tested in limited production batches and evaluated using the same functional unit as the baseline. If the changes meet quality requirements and improve verified environmental outcomes, the producer can scale them and update its purchasing agreements. This is an illustrative scenario, not a documented industrial case study. Its purpose is to demonstrate the specific information exchanges required for a measurable virtuous cycle.

Figure 4 expands the end-of-life subsystem from collection through AI-assisted identification, recycling-route selection, quality prediction, recovered feedstock, and renewed manufacturing. The proposed intelligence hub is intended to combine material composition, contamination, sorting confidence, process conditions, and product-quality feedback. In practice, mechanical, chemical, and emerging bio-based recycling routes must be compared on recovery yield, residual quality, occupational safety, energy demand, and environmental burden; none should be presumed universally preferable.[7–9,12,15]

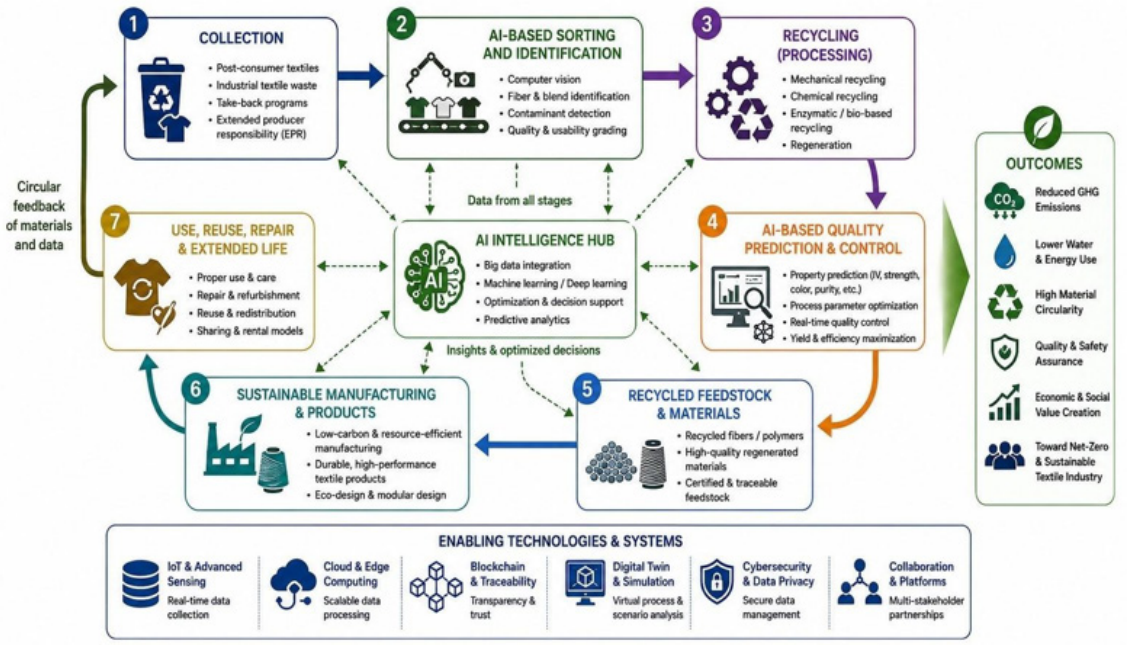


Figure 4 Proposed end-of-life pathway from collection and identification to recycling-route selection, quality control, and recovered feedstock. Conceptual synthesis presented in this review.

Distinct analytical roles of Figures 1–6

Figure 1 defines the value-chain boundary and material return path; Figure 2 separates physical material circulation from energy/carbon accounting and digital feedback; Figure 3 assigns AI decision functions to individual value-chain stages; Figure 4 details operational recovery decisions and quality gates; Figure 5 distinguishes the functions of LCA, digital product information, and ESG governance; and Figure 6 presents a proposed scenario-testing digital twin. Their purpose is complementary rather than six alternative representations of the same architecture. In a production layout, repeated labels and decorative subelements should be reduced, and each caption should retain the unique analytical question stated here.

Architecture of the coupled feedback loops

The proposed architecture contains a physical resource loop and a digital learning loop. The physical loop moves recoverable products and material streams toward reuse, remanufacture, and feedstock recovery. The digital loop moves measured information in the reverse direction: field performance, returns, sorting outcomes, and recycling quality inform sourcing and design. Commercialization supplies the economic incentives and investment needed to maintain both loops. A failure in any stage can interrupt the system even when the remaining stages are individually optimized.

Figure 5 places life cycle assessment (LCA), digital product passports (DPP), and environmental, social and governance (ESG) reporting in a shared information architecture. LCA quantifies environmental impacts under specified assumptions; a DPP organizes traceable product-level information; ESG broadens the evaluation to governance and social outcomes. AI can support data validation, hotspot identification, scenario analysis, and decision prioritization, but cannot substitute for independently verified inventory data or responsible disclosure. Data access, confidentiality, provenance, and version control are essential for trustworthy use.[10,11,14]

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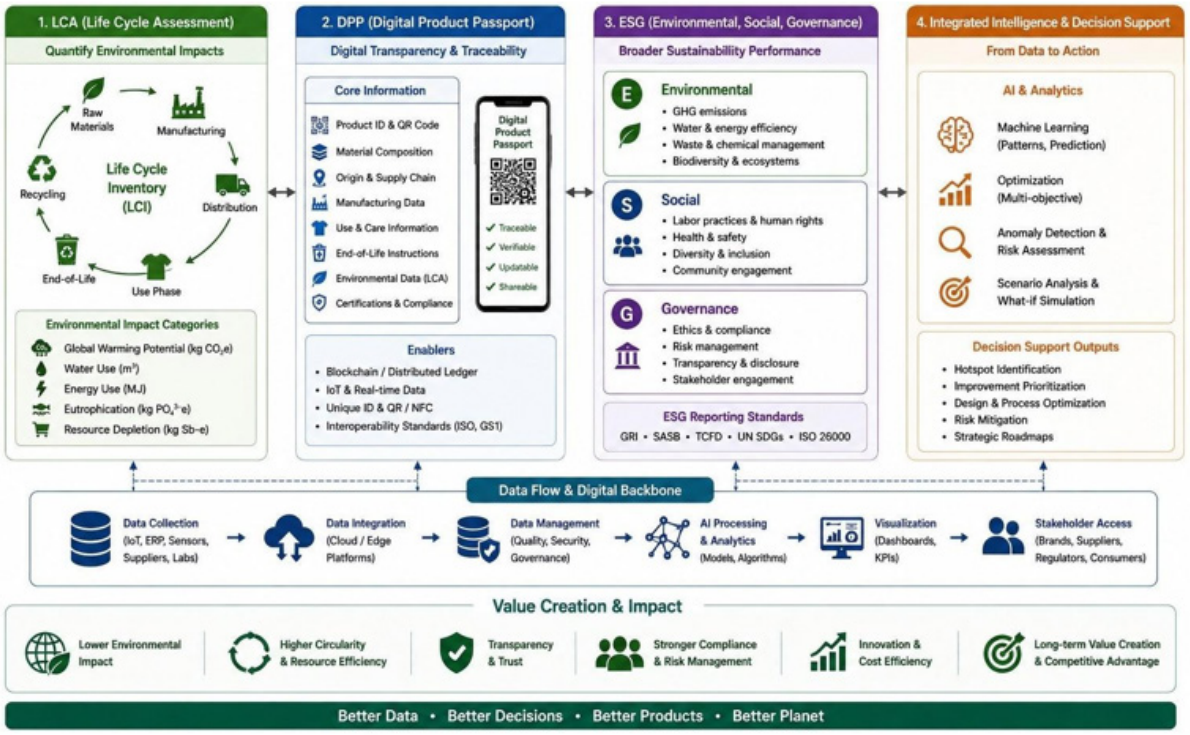


Figure 5 Distinct functions of LCA, digital product passports (DPP), ESG reporting, and AI decision support. Conceptual synthesis presented in this review.

Data layers and interoperability

A minimum data architecture comprises material identity, production history, product performance, use-phase events, recovery classification, and environmental inventory records. Each dataset should have a defined owner, timestamp, unit, quality flag, and access policy. Consistent identifiers are needed to associate batches and products across organizational boundaries. Without such foundations, even advanced machine-learning systems can produce misleading recommendations because the underlying data are incomplete or incompatible.

Decision-support and optimization workflow

The proposed workflow begins with measurement and validation, proceeds through prediction of quality, resource demand, or recovery yield, and ends with constrained multi-objective optimization. Suggested actions should be screened for safety, regulatory compliance, cost, and environmental performance before implementation. After deployment, measured outcomes are compared with predictions and used to recalibrate the model. This closed-loop learning process provides a more defensible definition of AI integration than a collection of unrelated digital tools.

Figure 6 proposes a digital twin that integrates material, process, product, supply-chain, recycling, and sustainability models with real-world measurements. A practical implementation should begin with narrowly scoped, validated models and a clear synchronization schedule, rather than assuming comprehensive real-time visibility from the outset. The twin can test hypothetical changes in material sourcing, production settings, product life, collection logistics, and recycling routes; measured outcomes should subsequently be fed back to update both models and operating decisions.[14]

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Figure 6 Proposed digital-twin architecture linking textile material, process, product, and recovery data. Conceptual schematic, not a verified real-time industrial deployment.

Digital twin and scenario analysis

A digital twin can represent selected material flows, production assets, or reverse-logistics networks using periodically updated measurements. Scenario analysis may explore changes in recycled feedstock availability, collection efficiency, energy prices, or product lifetime. Results remain conditional on model structure and input assumptions. Digital twins should therefore communicate uncertainty and should not be described as exact replicas of real-world sustainability performance.

Governance and cybersecurity

Cross-company information exchange introduces governance risks, including inaccurate sustainability claims, unauthorized disclosure of supplier data, and cyber threats to production systems. A practical governance model should define data permissions, validation responsibilities, human approval points, and procedures for correcting model errors. Independent verification of key environmental indicators can help distinguish measurable improvements from optimistic forecasts.

The proposed system operates through two coupled loops. The physical loop returns collected materials from down-stream operations to upstream feedstock preparation. The information loop sends use-phase, recovery, and environmental-performance data back to designers, suppliers, and manufacturers. Commercialization provides the economic incentives needed to sustain these loops. AI acts as a decision-support layer rather than as an independent guarantee of sustainability (Table 1).

Table 1 Proposed stage-specific AI functions and indicators. Indicators are illustrative and are not empirical results

Stage	AI-enabled function	Illustrative performance indicators
Up-stream	Feedstock prediction and composition identification	Virgin-material displacement; traceable input share
Middle-stream	Process control and predictive maintenance	Energy/water per functional unit; defect rate

Implementation should begin with interoperable material and process data, transparent allocation rules, defined functional units, and baseline measurements. Pilot projects can compare AI-assisted and conventional operations under equivalent conditions. Environmental evaluation should address direct resource savings as well as the computational and hardware footprint of digital infrastructure.

Pilot implementation and falsifiable evaluation design

A feasible pilot can be organized around a manufacturer, a brand or distributor, and a recovery operator handling a defined product family. Phase 1 records at least one baseline production and recovery period, with batch-level mass balance, electricity, thermal energy, water, accepted quality, product service assumptions, and collection

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outcomes. Phase 2 introduces traceable product or batch identifiers and records sorting confidence and recovered material specifications. Phase 3 tests a narrowly defined AI decision—such as feedstock blending, defect rejection, or recovery-route selection—against the existing operating rule on comparable production lots. Phase 4 evaluates whether improvements persist over time and under changing material composition.

Predefined acceptance criteria should include non-inferior mechanical or functional quality, measurable change in accepted output and recovery yield, model performance on held-out and time-separated samples, and net lifecycle impacts per stated functional unit. The evaluation must include sensor and computing electricity, transport, rejected fractions, and avoided production assumptions. Economic evaluation should report capital and recurring costs and a sensitivity analysis; worker training, privacy, and safety should be audited independently. If environmental or economic criteria are not met, the proposed intervention should not be characterized as a successful circularity improvement.

Economic feasibility and scale-up decision gates

A practical pilot could involve one spinning/weaving or dyeing facility, one product distributor and one sorting/recycling partner. Phase A establishes twelve months of baseline records where available (or clearly labels a shorter baseline), a functional unit, accepted-product quality thresholds and data-access agreements. Phase B introduces a narrowly scoped intervention, such as defect prediction or NIR-assisted sorting, with matched conventional operation as a comparator. Phase C audits the mass balance, recovery yield, electricity and heat, rejected goods, labor hours, model inference energy and uncertainty. Phase D applies a go/no-go gate: only interventions meeting safety, quality, cost and verified environmental criteria proceed to scale-up. These phases are a proposed protocol, not a completed industrial trial.

For economic appraisal, total annualized cost should include sensors and computing hardware, installation, software, model maintenance, cybersecurity, workforce training, data exchange, sorting rejects, and downtime. Benefits should be reported as avoided scrap, reduced rework, verified resource savings, improved recovery value and actual sales, without double counting. Net present value and payback can be explored across optimistic, central and adverse scenarios; no numerical return is claimed without plant-specific cost data. For SMEs, shared services and low-complexity baseline controls should be evaluated before a full digital-twin deployment.

Figure interpretation and limitations

Figures 1–6 are complementary conceptual schematics. Figure 1 defines the value-chain boundary; Figure 2 distinguishes material, energy/carbon and data loops; Figure 3 summarizes stage-specific AI decisions; Figure 4 details end-of-life recovery; Figure 5 distinguishes LCA, DPP and ESG information functions; and Figure 6 outlines a prospective digital-twin architecture. They do not depict measured industrial outcomes. The figures should be viewed at full page width for legibility; the captions identify their distinct analytical roles.

Evidence-to-decision synthesis: verified studies versus proposed architecture

The published defect-detection review by Ozek et al.[19] summarizes computer-vision and machine-learning approaches, but its surveyed accuracy figures should not be interpreted as verified energy or carbon savings in a specific factory. Similarly, the empirical producer–consumer study by Becchi et al.[31] reports a consumer survey (n = 415) and expert-based prioritization of digital product passport information; these results support interest in traceability, not a demonstrated reduction in textile lifecycle impacts. A multi-criteria assessment of nine textile recovery technologies[23] highlights the need to consider environmental impacts, costs and technological maturity simultaneously. The distinctive contribution of the present article is therefore a proposed linkage among stage-specific operational decisions, traceable feedback, and explicit validation gates; it is not a claim that this entire architecture has already been implemented (Table 2).

Table 2 Evidence-to-decision matrix. Published findings are distinguished from prospective validation requirements

Evidence domain	What the cited literature supports	What a textile-industry pilot must still verify
Fabric defect detection[19]	Published review of AI and conventional inspection methods	Held-out precision/recall, rejected output, rework, electricity and total cost versus a conventional baseline
Recycling route selection[23]	Multi-criteria environmental, economic and technological trade-offs across nine recovery routes	Local feedstock yields, contamination, electricity mix, allocation rules and saleable output
Digital product passports[31]	Producer priorities and consumer perceptions (survey n=415)	Actual record accuracy, return and reuse behavior, interoperability and implementation cost

Discussion: Opportunities, trade-offs, and research needs

Measurement, reporting, and verification considerations

A credible assessment of the integrated system requires a measurement plan that distinguishes inputs, intermediate flows, outputs, and avoided burdens. For each manufacturing facility, the plan should identify meters and records used for electricity, thermal energy, water, chemicals, raw materials, and waste. For products, it should document composition, expected service life, functional performance, and end-of-life outcomes. For recovery partners, it should record received mass, rejected mass, sorted fractions, recovered output, and destinations. Consistent time periods and units are necessary to prevent double counting when information passes between organizations. The data should be reconciled through periodic material balances and spot checks. Environmental comparisons should disclose the selected allocation approach for recycling and the assumptions about displaced virgin production. Sensitivity tests should cover uncertainty in collection rates, recovery yields, energy supply, and product lifetime. When model predictions guide decisions, reports should also disclose validation samples, prediction errors, and changes in performance after deployment. Independent verification of selected indicators can strengthen confidence, but verification scope and limitations must be clearly described.

These practices provide a practical basis for testing whether a claimed virtuous cycle produces measurable environmental improvements rather than simply moving burdens across stages.

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Finally, transparent reporting of unsuccessful trials is valuable: it helps distinguish technologies that are operationally robust from approaches that perform well only under narrow experimental conditions.

Policy, standards, and cross-sector coordination

The effectiveness of a circular textile transition also depends on the wider institutional setting. Consistent terminology for recycled content, recoverability, and lifecycle emissions helps prevent incompatible claims across suppliers and markets. Standardized reporting fields can lower the transaction cost of sharing material information, while independent verification can increase trust. Collection systems and recycling infrastructure require coordination among municipalities, brands, waste managers, and manufacturing firms. Technical textiles may require separate pathways because their service conditions, contamination profiles, and safety obligations differ from those of apparel. Public procurement and sector-specific performance standards can create demand for durable and verifiably lower-impact products, but they should not inadvertently exclude smaller suppliers unable to afford complex reporting systems. Policy evaluation should therefore consider both environmental effectiveness and implementation equity.[10,11]

Avoiding burden shifting and rebound effects

An intervention can lower one impact while increasing another. Water-saving dyeing may require additional energy; chemical recycling may reduce waste while increasing solvent or heat demand; and easier access to low-cost products may increase total consumption. These effects require lifecycle assessment and careful comparison against plausible counterfactuals. The integrated framework is useful precisely because it makes interstage trade-offs visible rather than optimizing a single facility or indicator.

Proposed validation design

Future work could test the framework through longitudinal case studies involving a textile manufacturer, a product distributor, and a recovery partner. Baseline and post-intervention material balances would document virgin input, product output, waste, recovery yield, and energy use. AI predictions would be evaluated against held-out observations, while environmental impacts would be calculated under consistent functional units and boundaries. Economic outcomes and social safeguards should be reported alongside resource indicators.

Research priorities for reliable AI

Key research needs include composition identification for blended textiles, robust prediction under changing feedstocks, transfer learning between facilities, and uncertainty-aware optimization. Public benchmark datasets and transparent reporting of model errors would improve comparability. Researchers should also investigate whether simple process control methods achieve similar benefits at lower cost, particularly in small enterprises. Model sophistication is not an end in itself.

Limits of the proposed review

framework synthesizes the cited literature and represents a conceptual proposal. It does not constitute a systematic search with a reproducible database protocol, nor does it present original field measurements. Illustrative environmental claims cannot be generalized without specified technologies and system boundaries; therefore, they have not been presented as universal quantitative conclusions. Future publication-grade assessment would benefit from a documented literature search and expanded, independently verified references.

The main contribution of the framework is its integration of sourcing, manufacturing, use, recovery, and commercialization into a single feedback architecture. It highlights the limitations of fragmented optimization: improvements in a dyeing process, for example, may be offset by low product utilization or poor recycling outcomes. Likewise, high collection rates are not equivalent to high-quality material recovery.

Several trade-offs require explicit analysis. Recycling can involve polymer degradation, solvent management, and substantial energy use. Durable multi-material textiles can be difficult to separate. Traceability systems can be costly for smaller suppliers, and AI models trained on narrow datasets may perform poorly on unfamiliar materials. Rebound effects and uncertain displacement rates further complicate environmental claims.[3,5,6]

Future studies should quantify stage-to-stage material flows, validate sorting accuracy across representative fiber blends, compare circular scenarios through consequential or attributional LCA as appropriate, and report economic feasibility alongside environmental outcomes. Robust studies should publish data provenance, model uncertainty, functional units, and sensitivity analyses. Governance should address data ownership, worker participation, privacy, and independent verification of sustainability claims.

Synthesis of evidence, proposals, and unresolved uncertainties

Established evidence supports the need to assess textile reuse and recycling with realistic substitution assumptions[3] and shows that AI-assisted textile identification is a promising but still constrained technical field, especially for blended and contaminated textiles.[7,9] The literature does not establish that integrating these tools automatically reduces whole-system emissions or makes textile-to-textile recycling commercially viable.

The contribution advanced here is the proposed coupling of material flows, digital evidence, and commercial incentives with auditable stage gates. Its distinctiveness lies in identifying what must be measured and compared before a circular-AI intervention can be judged successful. The principal unresolved questions concern cross-firm interoperability, data ownership, industrial model drift, recovery quality, allocation choices in LCA, and affordable deployment for smaller firms. These are priorities for field validation rather than conclusions supported by new experiments.

Conclusion

A phased implementation roadmap is recommended. The initial phase establishes material inventories, basic process measurements, and a shared vocabulary for product composition and environmental indicators. The second phase connects manufacturing data to downstream product and recovery records. The third phase introduces targeted prediction and optimization where baseline data demonstrate a meaningful decision problem. The fourth phase evaluates system-level results using transparent lifecycle boundaries, verified material balances, and economic performance indicators. Progression between phases should depend on measured readiness rather than on a predetermined technology schedule. In this way, the proposed integrated system can serve as a structured research and management agenda for sustainable textiles while remaining open to empirical revision.

A sustainable textile industry requires more than the adoption of recycled feedstocks or individual low-impact processes. This review proposes an integrated virtuous-cycle system linking up-

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stream materials, middle-stream production, down-stream durability and recovery, and commercialization through physical circular flows and data feedback. AI can support forecasting, process optimization, sorting, and monitoring, but its contribution must be validated against measurable environmental and operational indicators. The framework offers a practical conceptual structure for cross-stage collaboration and a research agenda for testing whether integrated circular systems deliver durable reductions in resource consumption, waste, and emissions.

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Conflicts of interest

The authors declare that they have no conflicts of interest.

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