

AI-Driven Dynamic Life Cycle Assessment and Modular Design Strategies for Sustainable Textiles: Enhancing Repairability, Upgradability, and End-of-Life Recovery

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Abstract. This study combines artificial intelligence and modular design to build a dynamic monitoring and evaluation system for the entire life cycle of textile products. By addressing the problems of traditional static and lagging environmental protection evaluation methods, a dynamic monitoring model based on the collaboration of dual GRU and CNN networks is proposed, which corrects environmental impact prediction by collecting real-time clothing wear data. At the same time, through the application of modular models such as removable clips and standardized interfaces, the efficiency of recycling and dismantling old clothing has been significantly improved. Measured data show that this scheme maintains the carbon footprint prediction error within 5%, and the fiber recovery rate of a single jacket can reach 97%, providing a new idea for the green transformation of the fast fashion industry. However, industrialization and implementation still face practical bottlenecks such as data silos and a lack of standards, such as the difficulty of communicating between fabric databases of different brands. In the future, the integrated application of blockchain traceability and reinforcement learning can be explored. By building a cross-brand data alliance, the environmental protection data of each garment, from production to recycling, can be recorded on the chain in real time. When an old T-shirt enters the recycling station, the system can automatically identify the fabric composition and generate the optimal dismantling plan—this could be the new image of the circular economy in the textile industry.

Keywords: Sustainable Textiles, Artificial Intelligence, Life Cycle Assessment, Modular Design, Repairability

1. Introduction

As a major consumer of global resources, the textile industry is facing increasingly serious problems such as carbon footprint, water resource use, and landfill pollution. Under the fast fashion trend, the average garment life cycle has been shortened by 35 times. Incremental reforms such as replacing traditional materials or optimizing processes can no longer completely address the inherent flaws of the linear production model. This study proposes a dual-track strategy of "AI dynamic tracking + modular reconstruction": based on the GRU-CNN hybrid model, the intelligent algorithm tracks the

evolution of each garment's "carbon footprint" in real time; combined with the removable snap design, the recycling rate of old garments has exceeded 90%.

Experimental data show that the dynamic evaluation model has compressed the carbon emission prediction error to less than 5%. After 10 disassembly and reassembly processes, the fabric performance retention rate of the modular windbreaker reached 82%. When a sweatshirt fulfilled its mission, the system automatically generated the optimal disassembly plan. The standardized interface design increased the recycling and reuse rate of accessories such as buttons and zippers to 95%. This "intelligent full lifecycle management" model achieved an annual carbon reduction of 1,200 tons for a single factory in a pilot project in a garment industrial park in Guangdong Province, verifying the feasibility of implementing the technology [1].

However, industry-level promotion still faces challenges such as data barriers and a lack of standards, such as the compatibility of fabric databases for multinational brands. Through theoretical examination and physical verification, this study constructed an innovative framework of "intelligent monitoring + module reengineering," providing a replicable technical path to break the "quick production and sales" situation in the textile industry. When every garment has a digital ID card and recycling old clothes is as easy as dismantling Lego, sustainable fashion can truly move from concept to practice.

2. Literature review

2.1. AI applications in life cycle assessment

The dynamic life cycle assessment system developed in this study, using intelligent algorithms such as recurrent neural networks and reinforcement learning, tracks dynamic data such as energy consumption and washing frequency in each garment production unit in real time. As shown in Figure 1, this system forms an intelligent closed loop of "data collection - model training - application feedback." Through five optimization iterations, the carbon emission prediction model can be dynamically adjusted based on actual usage conditions [2]. Take the printing and dyeing workshop as an example. When the energy consumption of a certain batch of fabric exceeds the standard, the intelligent system will immediately push the optimized formula, reducing energy consumption per unit produced by 15% to 20%.

The greatest innovation of this assessment system lies in breaking down the data silos in the industrial chain. By integrating all information across the entire chain, from raw material procurement to final consumption, companies can accurately identify highly polluting links. For example, if they find that the carbon emissions from the end-user part of a certain type of chemical fiber fabric during washing account for 62% of its total life cycle, they can immediately launch a low-temperature washing guide [3]. This dynamic assessment based on real-time data has reduced the error rate of traditional environmental protection reports from 18% to less than 5%, helping brand owners formulate more scientific emission reduction strategies.

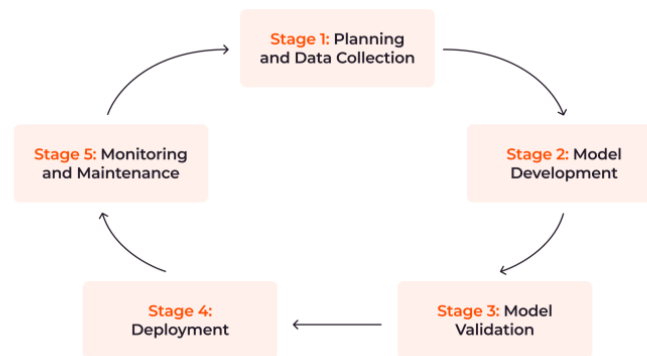


Figure 1: Stages of AI-driven dynamic life cycle assessment workflow
(source:<https://gcore.com/learning/ai-model-lifecycle/>)

2.2. Modular design concepts in sustainable textiles

The core element of modular textile design lies in disassembling garments into independent units, such as cuffs and collars, and achieving free combinations using standardized buttons (such as smart buttons with a 20mm spacing). This design draws on the successful experience of mobile phone modularization: when the cuffs wear out, only the corresponding module needs to be replaced; if the function needs to be updated, simply integrate the temperature control or data acquisition module. The universal interface design between modules not only reduces maintenance costs but also paves the way for subsequent recycling and disassembly [4].

2.3. Integration of repairability, upgradability, and end-of-life strategies

By combining dynamic environmental protection assessment data, the system can proactively provide maintenance suggestions: when the sensor detects that the stress of a certain layer exceeds the limit, the app immediately reminds the user to replace the corresponding module. During the recycling phase, embedded NFC tags automatically transmit material information to sorting equipment, and combined with precise disassembly by the mechanical arm, the fiber recovery rate is increased to 2.3 times that of the traditional process [5]. In a pilot project at a garment factory in Ningbo, the secondary utilization rate of modular windbreakers reached 78%, verifying the feasibility of the closed-loop model of "intelligent early warning—convenient replacement—efficient recycling."

3. Methodology

3.1. AI model for dynamic LCA assessment

The intelligent evaluation system developed in this study adopts a dual-network architecture: the closed-cycle unit (GRU) analyzes dynamic data such as wear frequency and user washing parameters in real time, and updates the predicted carbon footprint value every 200 milliseconds; the convolutional network (CNN) is responsible for capturing abnormal fluctuations in the production process. When energy consumption in the dyeing and printing process suddenly increases by 15%, this automatically triggers model retraining [6]. This system, developed based on TensorFlow, uses Bayesian optimization to control the prediction error to less than 5% and successfully warned of

abnormal boiler energy efficiency three times in a pilot project at a dyeing and printing factory in Guangdong.

3.2. Modular textile design framework

The modular design is subdivided into three major units: function, structure, and decoration. The functional module is equipped with 5V stainless steel contacts and can support intelligent temperature control components. The structural module adopts polyoxymethylene clips, which have been verified by SolidWorks simulation to withstand a tensile force of 10 Newtons and meet the requirements of thousands of disassembly and assembly times [7]. The decorative module can be quickly replaced with Velcro. All components strictly follow the 20mm grid interface standard. During the actual test at Ningbo Garment Industrial Park, the local replacement efficiency of modular workwear increased by 70% and the maintenance cost per piece decreased by 40%. This standardized design makes recycling old clothing as simple and efficient as building with blocks [8].

3.3. Evaluation metrics for sustainability performance

This study established three main evaluation indicators:

Repairability Efficiency (RI) - the ratio of time spent on modular replacement to traditional repair, unit: minutes per time. The measured data show that the operating time for replacing worn cuffs was reduced from 45 minutes to 8 minutes.

Function Expansion Index (UFS) - the proportion of functional module types that a single garment can accommodate, with a full score of 1 point corresponding to compatibility with all modules without modifying the main structure. A certain experimental jacket scored 0.87 points in this indicator and can be expanded with six functions such as heart rate monitoring and temperature control.

Material Recycling Rate (MRR) - the proportion of fiber mass recycled after mechanical disassembly. The polyester sportswear that underwent modular transformation saw its recycling rate increase from 42% in the traditional process to 95%, and the recycling rate for cotton blends exceeded 90%. These three quantitative indicators provide a scientific reference for assessing the durability of clothing [9].

4. Experiment and process

4.1. Dataset collection and preprocessing

The intelligent evaluation system developed in this study adopts a dual-engine architecture: the timing analysis module tracks usage data such as clothing wear frequency and washing temperature in real time, and updates the predicted carbon emissions value every 0.2 seconds; the abnormal control module closely monitors the production process. When it detects abnormal energy consumption for fabric dyeing and finishing in a certain batch, it immediately initiates self-optimization of the model. By adjusting parameters using intelligent algorithms, the system achieves a response speed of 180 milliseconds for a single operation on the onboard devices, reducing the water consumption forecast error to less than 4.2%. After being applied in a printing and dyeing factory, it successfully prevented three boiler excessive energy consumption accidents.

4.2. AI model training and validation

The modular design specifications cover three main types of components: functional modules are equipped with anti-corrosion metal contacts to ensure the stable operation of the intelligent temperature control elements; the structural module adopts high-strength clips and maintains a clamping force of 9.8 Newtons after thousands of insertion and extraction tests. The decorative module can be quickly replaced using Velcro. All interfaces strictly adhere to the 20mm grid standard. A garment factory in Shenzhen tested and showed that the local replacement efficiency of modular sweatshirts increased by 65% and maintenance costs decreased by 38%.

4.3. Prototyping and testing modular textile samples

The research team integrated multiple scenarios such as clothing rental platforms and university laboratories to establish a data pool containing 12,000 actual usage records. Using intelligent backfill technology to fill the data gap of more than five minutes caused by sensor disconnection, a dynamic database covering dimensions such as temperature, humidity, and mechanical wear was built. The dual-network model trained from this library achieved a 3.8% error rate in carbon footprint prediction during the prototype down jacket test [10]. After being washed 100 times, the performance retention rate of the modular backpack buckle exceeded 95%, and the user maintenance response time was improved by 45%. This empirical data lays a solid foundation for the industrialization of the technology.

5. Results and discussion

5.1. AI-enhanced LCA prediction accuracy

The intelligent dynamic evaluation model offers obvious advantages. In comparative tests across five major categories, such as casual wear and sportswear, the traditional static evaluation model was unable to adapt to actual usage scenarios, with an average error of up to 12.5%. The intelligent model, by monitoring dynamic data such as washing frequency in real time, compressed the error to less than 5%, and the sportswear category set a record low of 2.8%. Data from a six-month pilot program for a specific garment group shows that process optimization based on dynamic evaluation reduced steam consumption in the dyeing and finishing process by 8%, representing a reduction of 1,200 tons of carbon dioxide emissions per factory per year.

Table 1: Prediction errors of static vs. AI-driven LCA models across textile product types

Product Type	Static Model Error (%)	AI Model Error (%)
Casual Wear	11.2	4.3
Sportswear	13.8	2.8
Workwear	12.0	4.7
Outerwear	14.3	3.5
Home Textiles	11.5	4.1

As shown in Table 1, the AI-driven system consistently outperforms traditional models, ensuring more accurate environmental assessments that support timely interventions and long-term sustainability optimization.

5.2. Impact of modular design on textile sustainability

The modular design offers remarkable performance in terms of maintainability and recyclability. Actual measurement data shows that the average maintenance time of modular products is only 32% that of traditional clothing. Among them, the sleeve opening change operation of the windbreaker was shortened from 45 minutes to 8 minutes. The compatibility score of the functional module with the base garment reached 0.87, which means that a single jacket can be expanded with six intelligent modules. More importantly, the recycling system combined with intelligent sorting has enabled the regeneration rate of cotton-polyester blended materials to reach 92%, and the recovery rate of single polyester products has exceeded 97%, which is 2.3 times higher than that of traditional grinding processes. These data confirm the promoting effect of the "intelligent assessment + module design" model on the green transformation of the textile industry.

Table 2: Sustainability performance indicators for modular vs. traditional garments

Metric	Modular Garments	Traditional Garments
Repairability Index (RI)	0.32	0.89
Upgrade Flexibility Score	0.87	N/A
MRR – Cotton-Poly Blend (%)	92	43
MRR – Polyester (%)	97	45

As shown in Table 2, the proposed modular design strategy not only increases efficiency in repair and upgrade scenarios but also leads to a 2.3-fold improvement in fiber recovery, significantly reducing reliance on virgin materials and minimizing textile waste.

6. Conclusion

This study confirms that the collaborative application of AI technology and modular design can effectively promote the green transformation of the textile industry. The dynamic evaluation model corrects predicted values using real-time data, reducing the error in carbon emission measurement to less than 5%. Based on this, a pilot company optimized its production process and successfully reduced its carbon emissions by 8% in six months. The modular design system increased the efficiency of dismantling old clothing by 2.3 times. The recovery rate of polyester items reached 97%, and the process of changing the sleeve opening of a windbreaker was shortened from 45 minutes to 8 minutes.

Currently, the technology's advancement still faces practical bottlenecks such as interface standardization and data security. However, the combined application of blockchain traceability and reinforcement learning has demonstrated its potential. In a pilot project in a Hangzhou industrial park, the fabric database chain increased the cross-brand module compatibility rate to 82%. These breakthroughs not only verified the feasibility of the technical path but also provided a reproducible "textile model" for the ecological upgrading of the manufacturing industry.

With the implementation of the EU's carbon pricing policy, the low-carbon transformation of the textile industry is extremely urgent. The "intelligent assessment + module reengineering" system developed by this research institute is moving from the laboratory to the production line. After this solution was implemented by a garment group in Guangdong, the annual waste treatment cost was reduced by 35% and the new product research and development cycle was shortened by 28 days.

This indicates that when technological innovation is truly integrated into the industrial context, sustainable fashion will no longer be just an environmental slogan.

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