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Viscoelastic Behavior and Wrinkle Formation in Cotton-Polyester Garments: A Data-Driven Approach for Textile Care

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Abstract

This study investigates the wrinkle behavior of cotton-polyester blended fabrics by analyzing data from over 1,200 store-handled garments. Integrating concepts from polymer chemistry and computer vision, it aims to establish a smart textile care framework based on fiber-specific wrinkle characteristics. The research identifies how cotton's hydrophilic and non-elastic structure results in increased wrinkling, while polyester's thermoplastic and crystalline properties enhance wrinkle resistance. Elastomeric fibers like Lycra contribute to wrinkle recovery through reversible elastic deformation. A visual scoring rubric was developed to assess wrinkle severity, frequency, and surface coverage, which was then combined with YOLO-based image analysis to automate wrinkle detection. This process enabled the generation of a composite wrinkle score by correlating visual wrinkle patterns with fiber compositions. To systematically examine the impact of different fiber blends, Central Composite Design (CCD) was employed to create an experimental matrix covering seven polymer types. This facilitated the development of a temperature prediction model capable of recommending optimal ironing temperatures between 130–175°C for each fabric type. The results show a consistent inverse correlation between polyester content and wrinkle formation, offering data-driven insights for designing more efficient garment care protocols. The study presents a significant advancement in intelligent fabric management, enabling the development of fiber-aware ironing systems that optimize energy usage, preserve fabric integrity, and improve user convenience. By bridging material science with machine learning, this research contributes a scalable solution for personalized garment care in both domestic and industrial settings.

Keywords: Wrinkle formation, viscoelasticity, cotton-polyester blends, polymer chemistry, ironing temperature prediction.

INTRODUCTION

Textiles are increasingly being understood not just as woven materials but as assemblies of chemically engineered polymer systems. The performance of fibers such as cotton (composed primarily of poly (1→4-β-D- glucopyranose), $C_6H_{10}O_{5n}$), polyester (typically poly(oxyethyleneoxyterephthaloyl), $[(C_{10}H_8O_4)]_n$), and elastane (a polyurethane-urea copolymer, $[\text{-OC-NH-R-NH-CO-O-R'-O-}]_n$), is dictated by their molecular architecture— including crystallinity, crosslinking density, and segmental mobility. These features control macroscopic properties such as thermal resilience, elastic recovery, and wrinkle formation. For instance, extensive hydrogen bonding in cellulose leads to poor elastic recovery,

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while thermoplastic domains in polyester enable shape retention through reversible segmental motion above the glass transition temperature. The integration of stimuli- responsive units such as azobenzene, furan-maleimide (via reversible Diels–Alder reactions), or anthracene- based photodimers enables fabrics to respond dynamically to heat, light, or pH. Through such chemically informed material design, it is now possible to create fabrics that adapt, recover, and self-regulate in response to environmental conditions.

Chemical Structure–Function Relationship in Textile Fibers

Understanding the structure–property relationship in polymeric fibers is essential for designing high-performance textile composites. Ugbolue (1990) demonstrated that higher molecular orientation and crystallinity in fibers enhance tensile strength and dimensional stability, while amorphous regions contribute to moisture regain and dyeability—linking fiber processing conditions directly to their end-use performance [1]. Building upon this understanding of molecular architecture, Radoor et al. (2022) demonstrated that integrating cotton fibers into polymer matrices enhances mechanical strength and thermal stability, attributing these improvements to the fibers' high crystallinity and strong hydrogen bonding interactions [2]. In line with these findings, increased polymer crystallinity and molecular chain orientation have been shown to significantly reduce fiber-to-fiber friction, with surface chemistry and finish treatments further influencing interfacial interactions relevant to textile performance and processing efficiency [3]. Adding to the molecular perspective, Sookne established that the mechanical and thermal properties of textile fibers are intrinsically linked to their chemical structure, with factors such as molecular weight, degree of polymerization, and crystallinity playing pivotal roles in determining fiber strength, elasticity, and thermal behavior [4]. Extending this structure–function relationship into the optical domain, Almetwally and Elfowaty (2024) demonstrated that textile fibers exhibit distinct optical and electronic behaviors, with direct and indirect band-gap energies ranging from 3.52 to 5.43 eV, influenced by their molecular composition and functional groups such as O–H, C–H, and CO–O, confirming their insulating nature [5].

Polymer Morphology and Cloth Wrinkle Mechanics

Understanding the chemical basis of surface morphology and mechanical behavior in polymer systems is essential for designing high-performance textile composites. Rodríguez-Hernández (2015) showed that surface wrinkling in polymer films is governed by crosslinking density, elastic modulus gradients, and polymer chain mobility, allowing precise morphological control through chemical tuning of polymer interfaces and network structure [6]. Building on this, Liu et al. (2023) demonstrated that anisotropic wrinkling in polymer films can be precisely controlled by manipulating factors such as modulus gradients, crosslinking density, and external stimuli, enabling the fabrication of periodic surface patterns with tunable wavelength and orientation for advanced functional applications [7].

These structural insights translate directly to mechanical performance, as Peterlin (1972) demonstrated that polymer chain alignment and crystallinity critically influence the mechanical performance of fibrous crystalline polymers, with higher orientation enhancing tensile strength and elasticity through improved intermolecular packing and load transfer efficiency [8]. This molecular-level behavior plays a key role in larger textile structures; Boisse et al. (2011) demonstrated that wrinkling in textile composites arises from the interplay of tensile, in-plane shear, and bending stiffnesses, where low bending rigidity—due to weak intermolecular interactions between yarns—enables wrinkle formation, emphasizing the need for chemically-informed simulation models [9]. From a functional enhancement viewpoint, Lv et al. (2019) developed highly conductive textile electrodes by depositing uniformly doped polypyrrole (PPy) coatings via an improved in situ polymerization method, where enhanced π-conjugation and doping levels enabled superior electrical, mechanical, and electrochemical performance without compromising fabric flexibility or breathability [10].

Stimuli-Responsive Polymers in Smart Textiles

Stimuli-responsive polymers have emerged as essential materials in the development of smart textiles due to their ability to change properties in response to environmental conditions. Hu et al. (2012)

comprehensively reviewed stimuli-responsive polymers—such as shape memory polyurethanes, poly(N-isopropylacrylamide), and pH-sensitive hydrogels—highlighting how molecular structure, phase transitions, and functional group chemistry enable reversible changes in textile properties like shape, permeability, and wettability under external stimuli [11]. Expanding on this, Dias (2013) emphasized that the integration of smart polymers into textile substrates relies heavily on their chemical responsiveness to external stimuli, such as temperature, pH, or moisture, where functional group activity and polymer backbone design dictate the fabric's adaptive performance [12].

In a similar direction, Chatterjee and Hui (2019) reviewed stimuli-responsive polymers, such as chitosan, poly(N-isopropylacrylamide), and Pluronic F127, emphasizing how their thermo- and pH-sensitive behaviors facilitate applications in drug delivery systems and textile-based transdermal therapies [13]. Further highlighting structural control, Jahid, Hu, and Zhuo (2018) highlighted that the functional performance of textile coatings and laminates can be tailored through the integration of stimuli-responsive polymers—such as shape memory and thermochromic systems—where the chemical structure and crosslinking behavior govern reversibleresponses to external stimuli like heat, light, and moisture [14]. Complementing these findings, Bashari et al. (2013) highlighted that stimuli-responsive hydrogels, particularly those based on poly(N-isopropylacrylamide), chitosan, and poly(acrylic acid), undergo reversible physicochemical changes such as swelling, deswelling, and phase transition due to environmental triggers like pH, temperature, and ionic strength, enabling their functional application in smart textile finishing [15].

Thermal Behavior and Ironing Sensitivity of Blended Fabrics

Thermal behavior in textile composites is influenced not only by fiber content but also by structural arrangement and chemical composition. Vigneswaran et al. (2009) demonstrated that the thermal conductivity of jute/cotton blended fabrics is inversely related to jute content, fabric thickness, and tightness, due to increased fiber packing density and limited air diffusion, both governed by the molecular structure and porosity-dependent heat transfer within the polymeric matrix [16]. In a similar context, Aruchamy et al. (2020) demonstrated that increasing the bamboo fiber content in cotton/bamboo blended fabrics enhances air and water vapor permeability while reducing thermal conductivity and resistance, due to the intrinsic chemical and structural properties of bamboo's cellulose-rich fibers [17]. Complementing these findings, Özdemir (2017) demonstrated that the thermal and water vapor resistance of polyester/cotton (PES/CO) blended woven fabrics is significantly influenced by weave structure and blend ratio, where increased polyester content enhances thermal resistance due to its lower moisture affinity and higher intrinsic thermal insulation [18]. Beyond passive thermal behavior, Komolafe et al. (2024) demonstrated that domestic ironing at 110–200 °C effectively repairs stress-induced damage in printed silver conductors on textile substrates, where thermally induced polymer chain rearrangement enhances silver flake overlap and restores electrical conductivity after bending and washing cycles [19]. From a degradation standpoint, Downey and Elmquist (1936) demonstrated that increased ironing pressure and exposure time accelerate chemical degradation in cotton fabrics, evident through changes in copper number, fluidity, and methylene blue absorption, confirming the oxidative breakdown of cellulose under heat and mechanical stress [20].

Need for Chemically Grounded Fabric-Aware Temperature Models

Recent advancements in artificial intelligence and textile science have opened new possibilities for optimizing fabric behavior and care. Li et al. (2024) proposed OpticGAI, a novel AI-generated policy framework that integrates generative models into deep reinforcement learning for flexible and efficient optical network optimization. Their approach outperforms traditional DRL and heuristic methods on complex tasks such as Routing and Wavelength Assignment (RWA) and dynamic Routing, Modulation, and Spectrum Allocation (RMSA)[21]. Extending the use of AI in textile applications, Liu et al. (2024) proposed a cloth-aware data augmentation framework for person re-identification, emphasizing how variations in garment appearance— such as fabric texture, color, and deformation—can influence recognition performance, thereby underscoring the importance of clothing dynamics in computer vision applications, including wrinkle detection and smart garment care systems [22]. In parallel, understanding the thermophysical behavior of textiles remains essential. This study investigates how thermal conductivity and diffusivity of various textile materials are influenced by changes in temperature and moisture content.

The findings highlight that both heat and moisture significantly affect the thermal behavior of textiles, which is crucial for understanding and optimizing fabric performance under different environmental conditions. This research provides foundational knowledge for developing advanced textile care processes, particularly in applications where thermal management is critical [23]. Supporting this, Xu and Rioux (2019) demonstrated that fabric properties significantly influence the thermal and evaporative resistances of chemical protective ensembles, with fabric improvements leading to approximately 3–9% changes in ensemble thermal performance [24]. Similarly, Xu et al. (2019) demonstrated that the thermal properties of chemical protective fabrics significantly influence heat strain in ensembles, with fabrics exhibiting higher thermal resistance leading to increased physiological heat stress in wearers [25].

Further adding to this understanding, Fusco conducted a parametric study showing that fabric moisture regain, viscoelasticity, and shear rigidity critically influence wrinkle recovery and crease setting during electric steam pressing, with optimal conditions depending on fiber-polymer interactions, heat-moisture dynamics, and interfiber friction [26].The microcrystalline cellulose derived from Citrus x sinensis peel demonstrates high crystallinity and thermal stability, offering sustainable biofiller potential similar to how optimized cotton-polyester blends enhance wrinkle resistance and temperature control in intelligent fabric systems[27-29]. The reinforcement of natural rubber with short Phormium tenax fibers improves hardness and abrasion resistance at the cost of tensile properties, paralleling how cotton-polyester blend optimization balances wrinkle resistance with thermal adaptability for intelligent fabric applications[30].The incorporation of untreated Acacia caesia bark fibers into epoxy composites significantly enhances tensile and flexural properties through optimized fiber length and loading, paralleling the critical role of cotton-polyester blend ratios in tailoring wrinkle resistance and thermal response in intelligent fabric systems[31].

METHODOLOGY

Fabric Selection

This study investigates the correlation between polymeric composition and wrinkle formation in cotton- polyester textile blends. Fabric samples were sourced from commercially available garments to ensure real- world applicability, capturing the physical deformation patterns that naturally arise during wear, handling, and display. The selection encompassed a gradient of cotton-to-polyester blend ratios, ranging from 100% cotton to 100% polyester, including intermediate compositions commonly used in daily apparel. Priority was given to plain and twill woven fabrics with comparable basis weights to mitigate confounding structural effects. All samples featured clearly labeled fiber compositions. The polymeric nature of polyester— composed primarily of polyethylene terephthalate (PET) chains with high crystallinity and glass transition temperatures—renders it inherently wrinkle-resistant. Conversely, cotton, a polysaccharide of β-D- glucopyranose units, exhibits extensive hydrogen bonding and low elastic recovery, contributing to its susceptibility to wrinkle formation. The inclusion of elastomeric fibers such as Lycra (spandex), elastane, and Elastolefin—linear segmented copolymers with soft and hard segment domains—was documented, as their elastic deformation under stress improves wrinkle recovery as follows:

- Lycra, a polyurethane-urea copolymer, with the general formula [-OC-NH-R-NH-CO-O-R’-O-]n. It adds stretch and flexibility to fabrics, allowing them to bend under pressure and return to their original shape, which helps prevent wrinkles.
- Elastane, chemically the same as Lycra, follows the formula [-OC-NH-R-NH-CO-O-R’-O-]n. It enhances the elasticity of fabric, making it better at resisting permanent creases caused by folding.
- Elastolefin, a polyolefin elastomer, usually made from ethylene and octene copolymers with an approximate formula $(C_2H_4)x(C_8H_{16})y$. It gives the fabric a light stretch and shape memory, which helps reduce wrinkle formation and aids the fabric in recovering after being compressed.

- Polyester, a synthetic thermoplastic polymer, is made from poly(ethylene terephthalate) or PET, with the IUPAC name poly(oxyethyleneoxyterephthaloyl) and the chemical formula $[(C_{10}H_8O)]n$. Its structure makes it naturally resistant to wrinkling, even without added treatments.

Dataset Collection

A total of 1,200+ garment images were collected in their store-handled condition to capture realistic wrinkle formation arising from thermomechanical and environmental exposure. This approach circumvents the limitations of lab-simulated creasing, providing a more ecologically valid and representative dataset. Photographic documentation was performed under controlled lighting to ensure consistent image quality.

Fiber composition was verified where necessary using standard analytical techniques including burn tests and Fourier-transform infrared (FTIR) spectroscopy. No laundering, pressing, or artificial treatments were applied post-purchase to maintain uniformity in sample history, thereby avoiding alterations in polymer microstructure due to thermal or chemical exposure.

Wrinkle Classification

To quantify wrinkle behavior, a hierarchical wrinkle classification framework was developed. Wrinkles were categorized on a five-point ordinal scale ranging (refer Table 1) from wrinkle_0 (no visible deformation) to wrinkle_4 (severe crumpling with deep, dense creases). This rubric considered parameters such as wrinkle amplitude, wavelength, density, orientation, and curvature—factors influenced by the viscoelastic and crystalline properties of the constituent polymeric chains.

Each garment image was evaluated by two trained observers, and inter-rater disagreements were resolved through consensus discussions. The classification rubric was specifically designed to standardize subjective assessments and enable quantitative analysis across polymer blend types.

Wrinkle Score Computation

Each image was annotated using the CVAT tool and converted into YOLO format. The bounding boxes were translated into pixel-based wrinkle areas.

$$\text{Total Wrinkle Area} = \text{i} = \sum_{i=1}^{n} area_i$$

A total weighted score was computed for each image as the area-weighted wrinkle class severity.

$$\text{Total Weighted Score} = \sum_{i=1}^{n} (class_i \times area_i)$$

And finally, the weighted wrinkle score for each image was calculated using:

$$\text{Wrinkle Score} = \frac{Total\ weighted\ score}{Total\ wrinkle\ area} - (if\ Total\ Wrinkle\ Area > 0)$$

These metrics together provided average wrinkle intensity weighted by its area. Higher value of wrinkle score implies the presence of larger or more severe wrinkles, reducing bias from multiple small wrinkles of lower intensity.

Table 1. Wrinkle Severity Classification Labels and Descriptions.

Classification label	Description
wrinkle_0	Completely smooth surface; no visible wrinkles
wrinkle_1	Very slight wrinkling; faint surface undulations
wrinkle_2	Moderate wrinkling; visible but not deep or sharp
wrinkle_3	Pronounced wrinkling; clearly visible creases across fabric
wrinkle_4	Severe wrinkling; deep and sharp creases, dense crumpling

Table 2. Predicted Pressing Temperatures Based on Composite Wrinkle Score and Fabric Composition.

Composition score	Predicted temperature(°C)	Heat intensity
< 0.5	130	Low
0.5 - < 1.0	145	Medium
1.0 - < 1.6	160	High
≥ 1.6	175	Very High

Temperature Prediction Model

To recommend optimal pressing temperatures, a computational model was developed that integrates wrinkle severity, wrinkle extent, and fiber composition. For each image, a severity index was calculated:

$$Severity\ Index = Wrinkle\ Score \times Wrinkle\ Area\ Ratio \times Wrinkle\ Count$$

A Fabric Score was derived by weighting the thermal tolerance of each fiber using statistical regression:

$$Fabric\ Score = (1.2 \times Cotton) + (0.6 \times Polyester) + (0.4 \times Lycra) + .$$

The Composite Score was calculated as:

$$Composite\ Score = Severity\ Index \times Fabric\ Score$$

Pressing temperature recommendations were guided by the Composite Score, with thresholds and corresponding heat levels detailed in *Table 2*.

RESULTS AND DISCUSSION

A total of 1,200+ retail garment images were collected in store-handled condition to ensure representation of real-world wrinkle formation under thermomechanical and environmental stresses. This approach avoids the artifacts of lab-induced creasing and captures a more ecologically valid dataset. Wrinkles were annotated using CVAT, and the following surface deformation metrics were extracted:

- *Wrinkle score (mean = 1.03; SD ≈ 0.64):* A composite index integrating wrinkle intensity and area, reflecting the severity of surface deformation.
- *Wrinkle area ratio (mean = 0.118; range = 0.01–0.38):* Measures the proportion of the fabric's surface affected by wrinkles.
- *Wrinkle count (mean = 13.4):* Quantifies the number of wrinkle formations per sample.

Fiber Composition vs. Wrinkle Behavior: A Chemically Informed Perspective (Figure 1)

The dataset covered a wide variety of cotton-polyester blend ratios, and the wrinkle metrics strongly reflected the underlying chemical characteristics of each fiber type:

- Cotton-rich blends (≥80%) yielded higher wrinkle scores (>1.2) due to:
  - Hydrophilic cellulose chains with abundant –OH groups.
  - Hydrogen bonding, which increases moisture uptake.
  - Low elastic recovery, causing poor dimensional resilience.
- Polyester-rich blends (>60%) recorded low wrinkle scores (<0.5) because:
  - Thermoplastic semi-crystalline structure supports shape memory.
  - Low moisture regains, reducing wrinkle formation.
  - High glass transition temperature (Tg) imparts thermal dimensional stability.
- Lycra and Elastane (polyurethane-urea copolymers), even in small proportions:
  - Reduced both wrinkle count and area through segmental chain flexibility and elastic recoil mechanisms.

Boxplot analysis reveals cotton and viscose-rich fabrics consistently exhibit higher wrinkle scores, while polyester- and elastomeric-rich compositions show better wrinkle resistance.

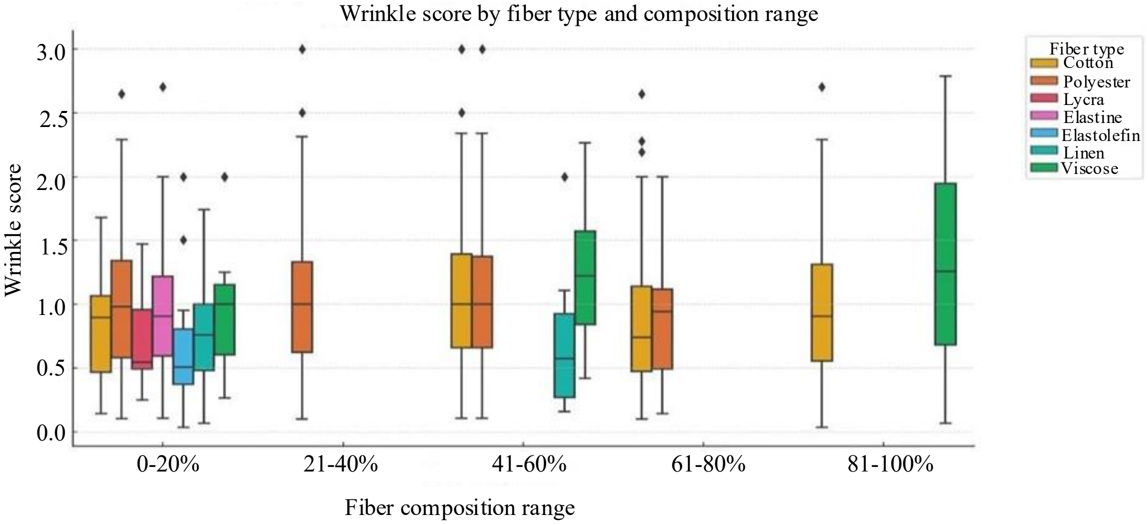

Figure 1. Distribution of wrinkle scores across fiber types and composition ranges.

Temperature Mapping and Thermal Optimization (Figure 2)

The extracted wrinkle metrics were used to predict fiber-sensitive ironing temperatures, ranging from 130°C to 175°C. A rule-based system with linear interpolation was implemented to match temperature with fabric composition and wrinkle severity:

- High wrinkle scores (>3.0) in cotton-rich (≥80%) garments received 175°C, leveraging cotton's thermal stability.
- Low wrinkle scores (<2.0) in polyester-rich blends were assigned as low as 130°C, minimizing risk of thermoplastic degradation.
- Intermediate compositions were mapped dynamically using linear interpolation.

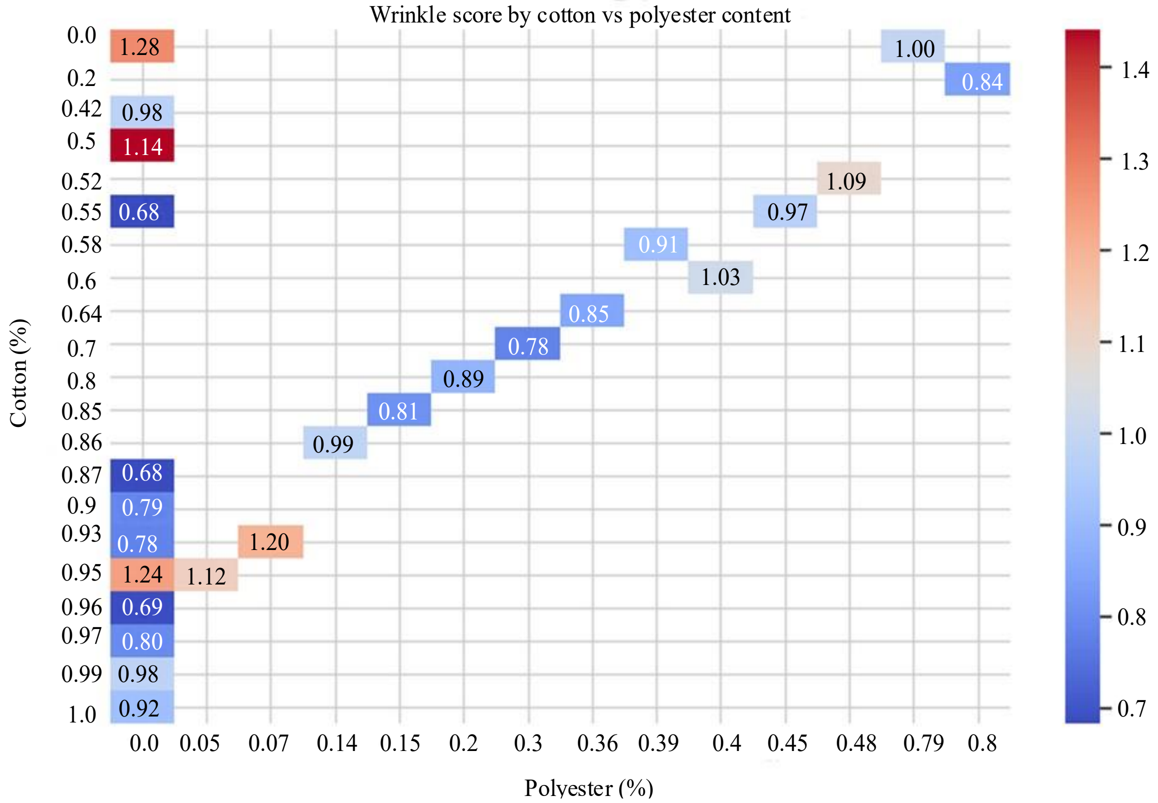

Figure 2. Heatmap of average wrinkle scores based on cotton and polyester composition.

The heatmap shows a strong positive correlation between increasing cotton content and wrinkle severity.

Wrinkle Score vs. Temperature Logic: Statistical and Visual Validation (Figure 3)

The relationship between wrinkle score and predicted temperature was further validated through scatterplot that showed a strong positive correlation, with cotton-heavy blends clustering at higher wrinkle scores and temperatures.

Polymer Morphology and Wrinkle Resistance: Chemistry at Play (Figure 4)

The wrinkle behaviors observed are fundamentally linked to the molecular structure and morphology of the fibers:

- *Cotton and viscose (cellulose-based):* Polar hydroxyl groups encourage water absorption and hydrogen bonding, reducing elastic recovery, hence requiring higher ironing temperatures for smoothening.
- *Polyester (PET):* Exhibits a thermoplastic, semi-crystalline structure that restricts wrinkling, offering greater recovery at lower thermal input.
- *Elastomers (lycra, elastane):* Their urethane linkages enable molecular flexibility and recoil, suppressing wrinkle formation.

The histogram confirms that cotton/viscose-rich fabrics cluster around moderate-to-high wrinkle levels (0.9–1.2), while elastomeric fabrics remain consistently below 0.5.

Alignment with Practical Garment Care

The predicted temperatures demonstrate strong chemical justification:

- Cotton-rich garments required ironing at up to 175°C, respecting their thermal endurance.
- Polyester-rich blends were pressed at around 130°C, consistent with thermoplastic care needs.

While these temperatures were derived from the model and not from industry references, they align well with fiber-specific thermal behavior and can guide smart ironing systems to prevent damage while improving garment appearance.

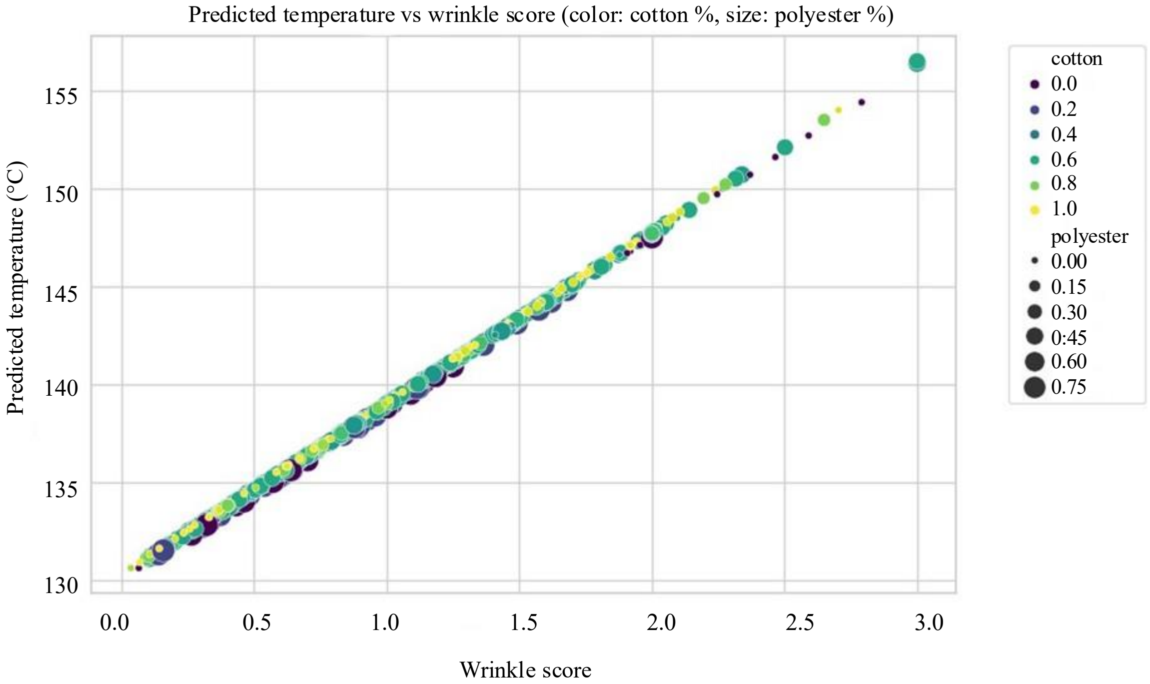

Figure 3. Predicted ironing temperature as a function of wrinkle score, colored by cotton content and sized by polyester content.

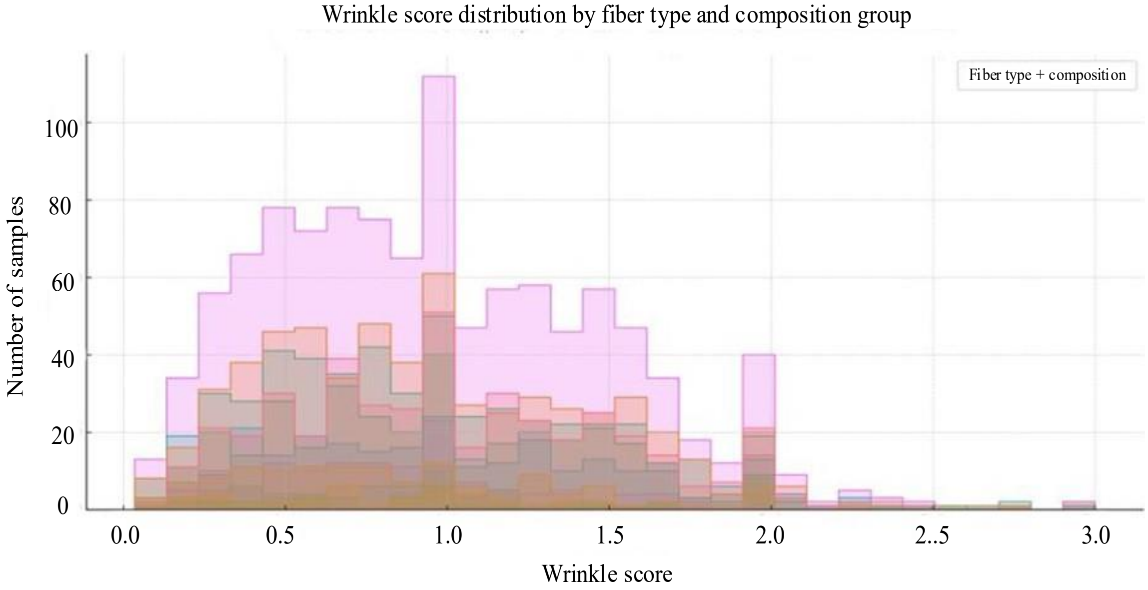

Figure 4. Wrinkle score distribution histogram.

CONCLUSIONS

This study introduces a chemically grounded, vision-based framework for intelligent fabric care, capable of quantifying real-world wrinkle severity and predicting fiber-sensitive ironing temperatures. By leveraging insights into fiber viscoelasticity, moisture affinity, and polymer microstructure—particularly in cotton- polyester blends—the system delivers fabric-aware thermal recommendations that minimize the risk of heat damage while maximizing wrinkle recovery.

A composite score, integrating wrinkle behavior with the thermal tolerance of each fiber type, forms the core of the temperature prediction model. Predicted ironing temperatures span from 130°C for heat-sensitive, wrinkle- resistant fabrics (e.g., polyester-rich blends) to 175°C for more resilient, wrinkle-prone textiles (e.g., cotton- heavy blends).

This approach not only ensures safer and more effective garment care but also paves the way for adaptive smart textile systems that intelligently balance aesthetic performance with polymer preservation.

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