FabAgent: An LLM-based agentic optimization framework for design of sustainable fabrics

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Abstract

The fashion industry emits an estimated four billion tons of CO_2 annually and nearly one-third of this is due to the choice of fibers used in clothing. Despite the critical role of fiber selection, limited research exists on the design of optimal fiber blends because of a lack of available datasets on fiber properties. This paper introduces **FabAgent**, the first large language model (LLM) based agentic optimization framework to discover novel sustainable fabric blends. FabAgent provides a scalable way to extract information from scientific publications and the Internet, compiling a structured data set of **101 fabric materials with 24 attributes each**, making this one of the most comprehensive raw material data sets for sustainable clothing design. Next, FabAgent uses multi-objective evolutionary optimization to explore Pareto optimal solutions over a large design space of possible blends, balancing sustainability, durability, comfort, and cost, while accommodating constraints on allowable yarn compositions. The optimal blend found by FabAgent substantially outperforms many commercially available blends in leading fashion brands such as Banana Republic, Giorgio Armani, GAP, and Nike: **a 30.46–52.71% improvement in environmental sustainability, 15.40–92.21% improvement in cost efficiency, and 68.29-83.49% improvement in comfort**.

1 Introduction

The fashion industry emits around four billion tons of CO_2 annually—6-8% of total global greenhouse gas emissions [1]—making it one of the top 5 polluting sectors, surpassing both aviation and maritime shipping. Besides greenhouse gases, textile production consumes vast amounts of energy, water, and chemicals, while improper waste disposal and microfibre shedding compound environmental damage. On its current trajectory, the fashion industry could occupy over 26% of the global carbon budget under a 2°C warming limit by 2050 [3]. A key driver of emissions is the choice of fabric in textiles, accounting for nearly one-third of the industry's life cycle emissions [4]. For example, producing 1 kg of cotton emits 3.3 kg of CO_2 , whereas 1 kg of polyester (PET) emits 20 kg of CO_2 [4]. Despite the major opportunity to reduce the carbon footprint of the fashion industry, as Muthu et al. [4] [5] note, research in sustainable textiles is hindered by the lack of standard datasets.

This paper introduces **FabAgent**, a generative agent for scalable data discovery and optimal blend design for sustainable fashion. Recently, large language models (LLMs) such as ChatGPT [15-18] have revolutionized data mining, through their ability to analyze vast amounts of textual information to identify and extract key information. FabAgent autonomously extracts information from the Internet and scientific publications, compiling a dataset of 101 fabric materials with 24 attributes each, creating one of the most comprehensive raw material datasets available to date. The FabAgent architecture is designed to prevent model hallucination by enforcing rigorous fact-checking and transparency. Next, using an evolutionary optimization approach, FabAgent explores Pareto optimal blends prioritizing sustainability while balancing durability, comfort, and cost. FabAgent optimization mimics natural selection, enabling robust search through vast design spaces and effectively handles competing constraints such as the number of fibers and minimum or maximum percentage for each fiber. Finally, benchmarking FabAgent-discovered Pareto optimal blends against several popular market options shows FabAgent blend substantially outperforms the commercially available blends. To my knowledge, FabAgent represents the first use of agents to create sustainable and high-performing fabric blends, accelerating research and development in the fashion industry.

2 Previous Work

Muthu et al. [4][5] highlight difficulty of textiles emissions research due to a lack of comprehensive, standardized datasets. Existing datasets such as MADE-BY Benchmark for Fibers [6] which classifies 27 fibers into five categories (Class A– Class E) and The Higg Index, developed by the Sustainable Apparel Coalition (SAC) [7], includes the Materials Sustainability Index (MSI), cover only a limited number of fabrics and attributes, are not easily accessible, requiring expensive licenses.

Several studies use genetic algorithms (GA) and artificial neural networks (ANN) to optimize yarn properties [8–14]. For example, [9] adjusts spinning parameters for 100% cotton to improve tenacity and elongation, while [10] applies multi-criteria optimization model PROMETHEE II/V to optimize Egyptian–Ethiopian cotton blends. A Statistical Design of Experiments approach in [8] tests 60 fiber-blend combinations with fewer experiments, and [11] experimentally examines two-component fiber blends for irregularity, tenacity and unevenness. Response surface methodology (RSM) in [14] is used to optimize properties such as tenacity and elongation but focuses only on flax–cotton blends. In [13], experimental approach is used to show an 80:20 cotton–flax ratio yields the best yarn quality, while [12] shows using experiments that a blend of 40% Tencel, 20% cotton, 20% virgin polyester, and 20% recycled polyester offers superior properties over 60:40 cotton-polyster blend and reduces unsustainable fiber use by 60%.

In contrast, FabAgent's generative AI-based approach is able to automatically collect a much larger dataset and optimizes the blends over a much broader search space than previously reported.

3 Methods

While information about raw materials exists, it is often sparse and scattered across different sources. For example, a journal article may provide details about the water consumption of organic cotton but lack information about its air permeability. FabAgent provides a scalable process that autonomously searches for specific metrics of interest and converts the results into structured data (Appendix Figure 1). The agent gathers information across 24 metrics spanning environmental, durability, comfort, and cost categories (Appendix Table A1) across 101 fiber raw materials (Appendix Table A2).

3.1 Agent Design

The **FabAgent** system is designed using **LangChain** [23], a framework that enables the development of applications powered by LLMs. LangChain facilitates the integration of LLMs into complex workflows by offering modular tools for querying, data processing, and decision-making. FabAgent leverages these tools to create an intelligent, adaptive pipeline for collecting and organizing sustainability-related data on fabric materials. Importantly, **FabAgent** is designed to search, observe, and reason using real-world data while staying grounded in facts by requiring direct quotes and source references for each metric. This approach ensures a highly reliable dataset and avoids model hallucination. The architecture can be broken into the following steps:

A. Action-Oriented Query Generation: FabAgent is designed to systematically collect data for each metric of every material. For each material-metric pair, the agent generates an action to retrieve the specific property of interest (Appendix Figure 2). For instance, when tasked with finding water_consumption [L/kg fiber] for Organic Cotton, the agent generates a *Thought:Action:*

```
{
  "action": "Search",
  "action_input": "organic cotton water consumption liters per kg fiber"
}
```

The query is then executed using **SerpAPI** [24], returning relevant search results.

B. Observation and Reasoning: Based on search results, the agent records an observation, such as:

```
"Observation: Today water consumption for Organic Cotton..."
```

From the observation, the agent will generate a thought. Sometimes the agent will determine it needs more information, so it will do a follow-up search based on the observations it received

```
Thought:I need to refine my search to find a specific and
 ↪  credible source for the organic cotton water consumption
```

and then it generates a more refined Search based on this thought.

C. Grounding in Facts to Avoid Model Hallucination: Once the agent determines it is done, it will generate the final output as JSON containing two keys: the exact value and source_explanation with the quote where it got the value (Appendix Figure 3). FabAgent then runs a follow-up search on that quote and stores the top link as a source reference. If the agent could not find specific information about the material-metric pair, it is explicitly asked to record “N/A”. The final JSON for the given material and metric pair has the following fields: **Value**: The extracted metric; **Source Explanation**: A direct quote providing context; and **Link**: A URL for verification (see example in Figure 3). If information is unavailable, the agent explicitly records “N/A.” The collected data, including values, source explanations, and references, is compiled into a single JSON file for all materials and metrics.

3.2 Optimization Framework

FabAgent uses a multi-objective optimization framework to discover the best blends of materials under four competing objectives: minimizing environmental impact and cost, while maximizing durability and comfort. FabAgent implements the evolutionary optimization algorithm called Non-Dominated Sorting Genetic Algorithm II (NGSA-II) [19] for finding the optimal blend. NGSA-II is a good choice due to its ability to find a well-distributed set of optimal solutions (Pareto front) for problems with multiple conflicting objectives, while also being computationally efficient. FabAgent uses NSGA-II in Pymoo for implementation [20].

A. Scoring Function: Environment and cost objectives were minimized, while durability and comfort objectives were maximized by taking the negative of the averaged scores. The “environmental” score for a blend was the mean of its water consumption, greenhouse gas emissions, land use, pesticide usage, bio-degradation time, and energy consumption attributes. The “cost” score was the mean of its raw material cost, processing cost, dyeing cost, waste percentage, and energy attributes. The “durability” score was the mean of the tensile strength, elongation at break, Young’s modulus, abrasion cycles, burst strength, and UV resistance attributes. The “comfort” score was the mean of the moisture regain, air permeability, thermal conductivity, wicking rate, static resistance, and UV protection attributes.

B. Imputation and Log-Scaling Data: To handle missing data in the dataset, FabAgent applies a k-nearest neighbors (KNN) [21] imputation method. Each missing metric value is estimated as the mean metric value from the three most similar materials in terms of their known attributes, weighted by similarity. In the corresponding source explanation of the metric we added the source of the data (e.g., ”Imputed from nearest neighbors: Material A, Material B, Material C”) for transparency. FabAgent then applies a logarithmic transformation [22] to normalize metric values and reduce skewness before optimization.

C. Repair operator: To capture real-world manufacturing constraints, FabAgent allows the user to input a custom parameter K which sets the maximum number of raw materials in the final blend. The algorithm introduces a ”repair” operator that keeps only the top K fraction values in each solution, setting all others to zero, and then normalizes the remaining fractions to sum to 1. Using this optimization framework, FabAgent evolves a population of candidate blends, each restricted to K materials, and generates a Pareto front of non-dominated solutions balancing the objectives.

4 Results

To compare to a real-world baseline, I benchmarked the performance of the blends discovered by FabAgent against commonly used blends from top fashion brands such as Banana Republic, Giorgio Armani, and GAP. In particular, I calculated the environment, cost, durability, and comfort scores of each fabric blend using the scoring metric defined in the previous section and then compared it to the scores achieved by FabAgent’s blends. Tables 1 and 2 reports results from a particular fabric blend that achieved high scores on all categories. Tables 3-6 show a comparison to some common fabric blends used in top fashion brands.

Table 1 shows the optimal blend discovered by the model. Here since K=5, the final blend was a composition of 5 raw materials. **Table 2** summarizes the environmental, durability, cost, and comfort scores of this blend. Note that lower environmental and cost scores are better since those are being minimized, while higher durability and comfort are better since those are being maximized.

Table 1: Model Optimal Blend (K=5)

Material	**Proportion (%)**
Coir (Coconut Fiber)	28.46%
Abaca (Manila Hemp)	7.47%
Recycled Polyester (rPET)	54.85%
Lyocell (Tencel)	1.45%
Glass Fiber	7.77%

Table 2: Scores for the Model Optimal Blend

Metric	**Score**	**Optimal Direction**
Environment	0.895	Lower is better
Cost	0.262	Lower is better
Durability	2.163	Higher is better
Comfort	3.027	Higher is better

Table 3 compares the performance of the model discovered blend to several commercial blends. We compare fabrics used in four mainstream clothing brands: GAP Cargo Pants, Giorgio Armani Suit, Nike Shorts and Banana Republic Sweater. The blends selected are also commonly used in other clothing items from these brands.

Table 3: FabAgent Blend versus Commercial Fabric Blends (Scores)

Metric	**FabAgent**	**GAP Pants**	**GA Suit**	**Nike Shorts**	**BR Sweater**
Environment (Lower better)	**0.895**	1.287	1.893	1.465	1.316
Cost (Lower better)	**0.262**	0.310	3.363	0.433	0.328
Durability (Higher better)	**2.163**	2.140	2.193	1.964	2.115
Comfort (Higher better)	**3.027**	1.650	1.771	1.799	1.678

Against GAP Cargo Pants (100% Organic Cotton), the FabAgent blend has **30.46**% sustainability score improvement, **15.40**% cost score improvement, **1.09**% durability score improvement, and **89.49**% comfort score improvement. Against Giorgio Armani Suit (100% Cashmere), the FabAgent improves sustainability by **52.71**%, cost by **92.21**%, and comfort by **70.89**%, with a **-1.36**% drop in durability. Compared to a mixed blend of two materials: 96% Nylon and 4% Spandex, commonly used in Nike shorts and other apparel, the FabAgent blend improves sustainability by **38.93**% , cost by **39.47**%, durability by **10.15**% durability, and comfort by **68.29**%. Finally against a mixed blend of three materials: 85% Organic Cotton, 14% Nylon and 1% Elastane, commonly used in Banana Republic apparel, FabAgent blend improves sustainability by **32.01**%, cost by **20.07**%, durability by **2.31**%, and comfort by **80.45**%.

These results suggest that the model blend is not only outperforming one kind of blend, but a variety of blends consistently, and by a quite substantial margin in sustainability, cost, and comfort, with sometimes just a marginal reduction in durability.

5 Conclusion and Future Work

This paper introduces **FabAgent**, an agentic optimization framework for discovering novel sustainable fabric blends. A key contribution of this work is the automated and scalable methodology used to compile a dataset of 101 fibers with 24 attributes each, making it one of the most comprehensive datasets for sustainable fashion research. FabAgent then iterates over a large combinatorial search space to find blends that compare favorably against many commercially available blends.

While these results are promising and demonstrate the potential of using agents in sustainable fashion design, there are several directions for future work. I am continuing to extend the database to include more fibers and benchmark against more commercial blends. FabAgent's scoring currently may not account for some real-world manufacturing constraints, such as which fibers may not mix together well. These can be incorporated as constraints to the optimizer. I am also exploring partnerships to manufacture promising blends in yarn form to experimentally validate these findings. Additionally, this study focuses on cradle-to-gate impacts, which represent about one-third of total emissions. Future work will examine downstream processes, including transportation, consumer use, and end-of-use recycling, to refine the comparative advantages of specific fibers.

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A Appendix

Figure 1: FabAgent Data Collection Architecture

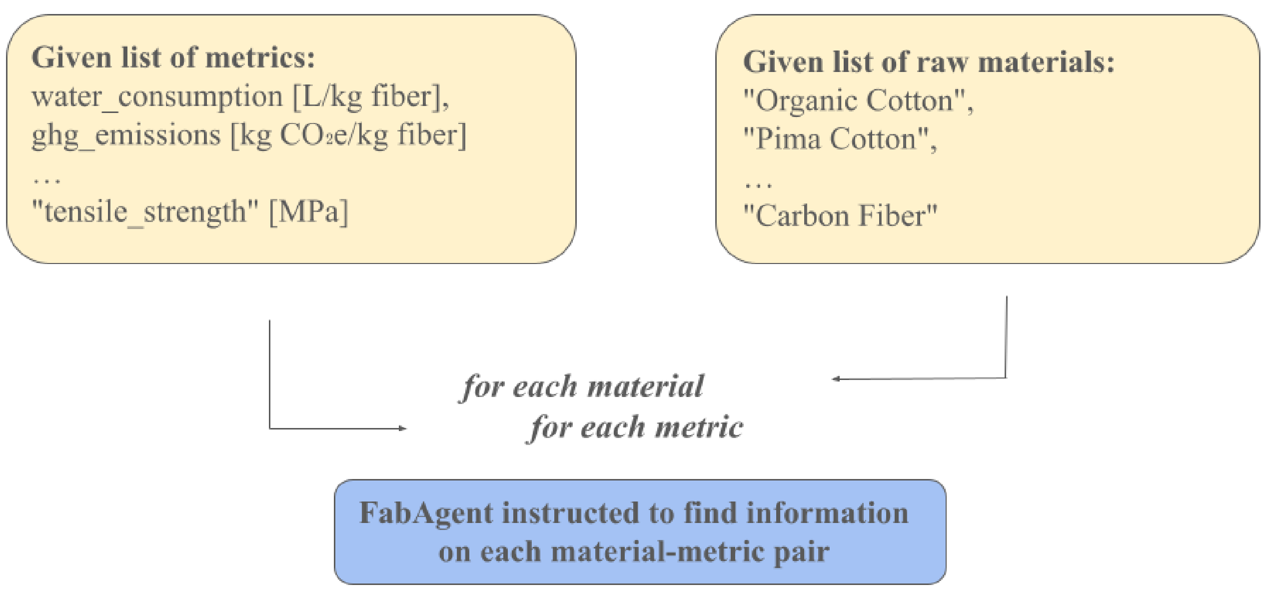

Figure 2: FabAgent Search Function

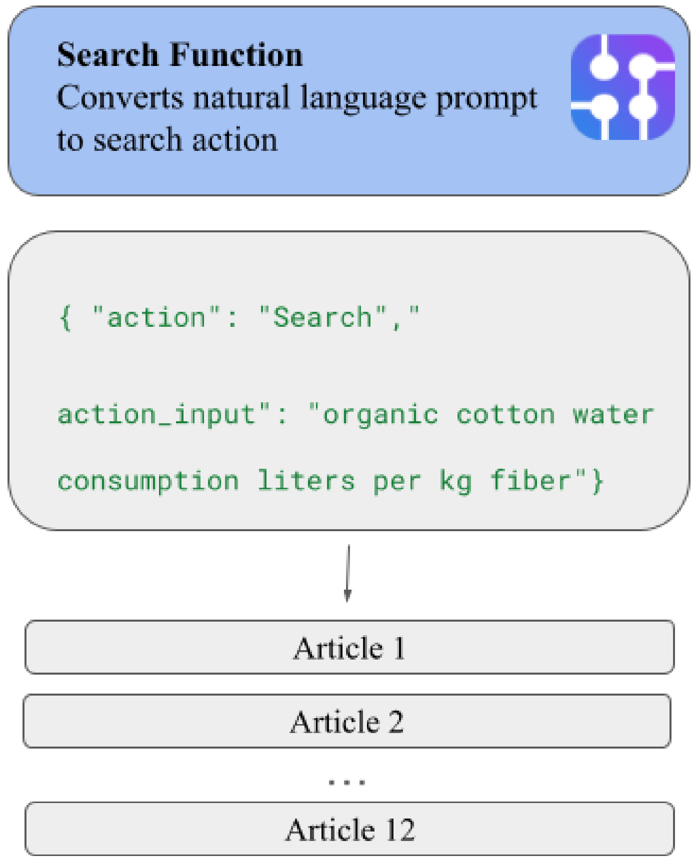

Figure 3: FabAgent Observation and Thought Function

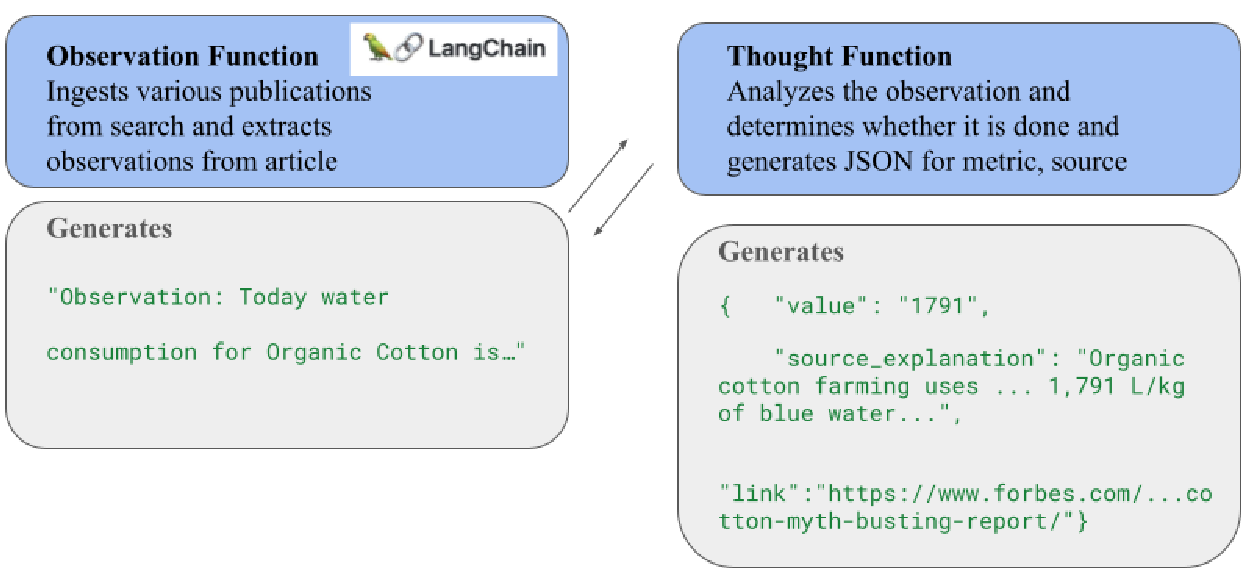

TABLE A1: METRIC CATEGORIES FOR EACH RAW MATERIAL

Name [UNIT]	**Type**
water_consumption [L/kg fiber]	Environmental
ghg_emissions [kg COe/kg fiber]	Environmental
land_use [m^2/kg fiber]	Environmental
pesticide_usage [kg/hectare]	Environmental
biodegradation_time [months]	Environmental
energy_consumption [kWh/kg]	Environmental
tensile_strength [MPa]	Durability
elongation_at_break [%]	Durability
Young's_modulus [GPa]	Durability
abrasion_cycles_to_failure [cycles]	Durability
burst_strength [kPa]	Durability
UV_resistance [% strength retained after 100h]	Durability
moisture_regain [%]	Comfort
air_permeability [L/s/m^2]	Comfort
thermal_conductivity [W/(m·K)]	Comfort
wicking_rate [mm/second]	Comfort
static_resistance [ohms]	Comfort
UV_protection_factor [UPF]	Comfort
raw_material_cost [$/kg]	Cost
processing_cost [$/kg]	Cost
dyeing_cost [$/kg]	Cost
waste_percentage [%]	Cost
energy_cost [$/kg]	Cost
total_manufacturing_cost [$/kg]	Cost

TABLE A2: RAW MATERIALS (BROKEN DOWN BY FIBER CATEGORY)

Category	**Material**
Plant-Based Fibers	Organic Cotton
	Pima Cotton
	Egyptian Cotton
	Recycled Cotton
	Hemp
	Flax (Linen)
	Jute
	Ramie
	Sisal
	Bamboo (Unspecified)
	Mechanically Processed Bamboo
	Chemically Processed Bamboo
	Kapok Fiber
	Coir (Coconut Fiber)
	Abaca (Manila Hemp)
	Piña (Pineapple Leaf Fiber)
	Banana Fiber
	Nettle Fiber
	Lotus Fiber
	Soybean Fiber
Animal-Based Fibers	Wool (Generic)
	Merino Wool
	Shetland Wool

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Category	**Material**
	Lambswool
	Cashmere (Goat Hair)
	Mohair (Angora Goat)
	Angora (Rabbit Hair)
	Alpaca Wool
	Vicuna Wool
	Camel Hair
	Yak Wool
	Qiviut (Muskox Wool)
	Llama Fiber
	Down Feathers
	Mulberry Silk
	Tussar Silk
	Eri Silk
	Muga Silk
	Spider Silk (Natural)
	Peace Silk (Ahimsa Silk)
Synthetic Fibers (Petroleum-Based)	Polyester
	Recycled Polyester (rPET)
	Coolmax (Moisture-Wicking Polyester)
	Nylon (Generic)
	Nylon 6
	Nylon 66
	Recycled Nylon
	Acrylic
	Spandex (Lycra)
	Elastane
	Modacrylic
	Olefin (Polyolefin)
	Vinyon
	Polypropylene
	Cordura (Durable Nylon)
	Dyneema (Ultra-High Molecular Weight Polyethylene)
Semi-Synthetic Fibers	Viscose (Rayon)
	High-Wet-Modulus Rayon
	Modal (Beech Tree-Derived)
	Micromodal
	Lyocell (Tencel)
	Bamboo Rayon (Viscose from Bamboo)
	ECOVERO™
	Cupro
	Acetate
	Triacetate
	SeaCell (Algae-Based Fiber)
Other Bio-Based & Innovative Fibers	Soy Silk (Soy Protein Fiber)
	Milk Fiber (Casein-Derived)
	Corn Fiber (Ingeo)
	Corn-Based PLA Fibers
	Orange Fiber (Citrus Byproduct)
Leathers & Alternatives	Leather (Traditional)
	Vegan Leather (Generic)
	Recycled Leather
	Suede
	Piñatex (Pineapple Leather)

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Category	Material
	Mycelium Leather (Mushroom-Based) Apple Leather Grape Leather Cactus Leather Desserto (Cactus-Based Leather) Woocoa (Coconut & Hemp-Based) Vegea (Wine Byproduct) Zoa (Lab-Grown Collagen) Cork Fabric Bananatex (Banana Fiber-Based) SCOBY Leather (Kombucha-Based)
Regenerated Nylon & Similar	ECONYL (Regenerated Nylon)
Blended Fibers	Poly-Cotton Blend Cotton-Polyester Blend Wool-Nylon Blend Wool-Silk Blend Silk-Linen Blend Cotton-Spandex Blend Elastane-Cotton Blend Elastane-Polyester Blend Lyocell-Wool Blend Bamboo-Cotton Blend
Specialty Fibers	Carbon Fiber Glass Fiber Metallic Fibers (Silver, Gold, Stainless Steel) Ceramic Fibers Aramid Fiber (Kevlar) Aramid Fiber (Nomex)
Recycled & Upcycled Materials	Recycled Denim Recycled Wool Deadstock Fabrics Ocean Plastic Fabrics
Coated & Treated Fabrics	Waxed Cotton Gore-Tex (Waterproof, Breathable Membrane) Waterproof Breathable Membranes UV-Resistant Fabrics Antimicrobial Treated Fabrics
Natural Dyes & Finishes	Indigo Madder Root Cochineal Logwood Osage Orange
Miscellaneous	Fur (Ethically Sourced or Faux) Velvet Lace Spider Silk (Synthetic)