ADVANCING THE RECYCLING OF TEXTILES VIA MIXED FIBER CLASSIFICATION AND SEPARATION

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Abstract
Global fiber production reached an all-time high of 132 million tonnes in 2024. Waste management of textiles has been rather ineffective. 75% of materials used in clothing are landfilled or incinerated, and 23% of discarded clothes are collected for recycling, however, less than 1% of the recovered fibers are used to produce new fabric. Spurred by the urgency of reducing the environmental footprint of textiles and recovering value from used textiles, this paper highlights challenges and recent advances to (i) classify textiles at the macroscopic level (i.e., garment), and (ii) separate blended textiles at the molecular scale (i.e., cotton and polyester fibers). The former is a key component of mechanical recycling, while the latter falls under chemical or molecular recycling. The recycling of textiles is impeded largely by a lack of actionable information about the content of the fabric, in turn, caused by insufficient capabilities of current spectroscopic identification techniques. High-throughput, automated sorting is developed through the utilization of visible and infrared spectroscopy, including hyperspectral methods, combined with machine learning (ML) for rapid identification of textile composition. This will enable the subsequent separation of higher and lower value textile grades, and identify "disruptors" for fiber-to-fiber textile recycling, such as flame retardants and water repellent finishes, that are typically difficult to detect. Blended or mixed textiles pose challenges for mechanical recycling which cannot separate fibers from the blend. However, separation of fiber blends can be achieved by selectively dissolving or depolymerizing specific types of fibers in the blend. The separation of cotton and polyester through dissolution or hydrolysis is discussed. The developments presented here can promote sustainable practices in the textile and waste management sectors, hence facilitating the shift towards a circular economy.

Keywords: mechanical recycling, sortation, chemical recycling, advanced recycling, upcycling, circular economy

1. Introduction and Motivation
Nearly 14% of global plastics waste is generated by the textile and clothing industry which reached a record high of 132 million tonnes produced in 2024, up from 125 million tonnes in 2023.[1,2] 63% of textile fibers are made up of petroleum derived polymers such as polyester, polypropylene, nylon, and acrylic whose manufacture and disposal lead to significant carbon dioxide (CO_2) emissions. Naturally derived fibers such as cotton, the material from which 26% of clothing is made, also carry a significant environmental impact in the form of water depletion and pollution from pesticide and fertilizer use during its cultivation. [3] Recycled textiles comprise a scant 7.6% of the global textiles market and 6.9% of that same market is carried by polyester fibers made from recycled plastic bottles. This means that less than 1% of the global fiber market is comprised of textiles produced from recycled textile fibers. [1,4] A 2015 study revealed that the textile industry was responsible for contributing 1.2 billion tons of CO_2 to global emissions. This number is expected to increase as much as 26% by 2050. [2,3]

In the United States, only 15% of textiles are recycled or donated. The remaining 85% end up in landfills.[5] Most of these fibers will remain there for millennia and will do little else but contribute to pollution and slowly leach pollutants and microplastics into the environment. [6-9] While initiatives for the recycling and upcycling of textiles are helping to provide incentive for moving toward sustainability and a circular economy, the recycling of textiles is largely impeded by difficulties in obtaining useful information regarding the textile composition.[10] Globally, regulation and legislation have yet to catch up with the necessities of the recycling industry. Additives, treatments, and low weight % inclusions (<5%) can go unreported on care labels [11] and, even if the necessary regulations were put into place today, the millions of tons of textile waste we have already in circulation would still need to be dealt with. In particular, blended or mixed textiles present several challenges for mechanical recycling which cannot separate fibers of different types from their blend.[4,12] Additionally, current spectroscopic techniques have not yet risen to meet the challenge of accurately determining the compositions of these materials. [10] In response, there has been a steadily growing effort in both industry and academia to find ways to overcome these hurdles. (iide infra, Review of Related Work)

Motivated by the necessity to reduce the environmental footprint of textiles and to valorize used or discarded textiles, our research aims to advance (i) the identification of textiles at the macroscopic level (i.e., clothing items), and (ii) the separation of blended textiles at the molecular scale (i.e., cotton and polyester fibers). The former is a key component of mechanical recycling, while the latter falls under chemical or molecular recycling. These developments will help facilitate the shift toward a circular economy which, in turn, should incentivize sustainable practices in the textile and waste management sectors.

2. Review of Related Work

2.1. Identification of Textile Type in Textile Recycling

Currently available commercial solutions to these problems include the FiberSort program in the Netherlands [13] and the SipTex program in Sweden [14]. They are both near-infrared (NIR) spectroscopic-based sorting solutions for textiles, which rely on NIR technology to identify fiber composition, and pneumatic air steams to push textiles off a conveyor into the appropriate bin. The FiberSort process reports a sorting rate of 1 piece/item per second, which is comparatively slow with other methods reporting speeds of up to 100 items/second. The installation of the entire system also represents a higher capital expenditure which, in turn, results in an increased price per sorted ton. ANDRITZ Laroche SAS [15] and Valvan [16] are other major players in automated textile waste sorting systems. Refiberd [17] commercialized a technology that combines a hyperspectral imaging system with artificial intelligence to detect fiber composition and contaminant presence in textile waste.

The Sortile [18] and Matoha [19] technologies focus on low-cost systems that are based on point-scanning of textiles with NIR. These systems are easy to use and can be sold to individual sorter facilities (such as Goodwill). These systems do not apply to autonomous sorting and, further, require multiple scans of multiple inner/outer layers in order to properly identify textiles comprising multiple fabric types (e.g., jackets with outer layers that might be disruptive to recycling).

TrinaMix [20] has developed handheld and mobile phone compatible NIR spectrometers for bioimaging and materials identification. Among the proposed use cases for these devices is the identification of textiles for recycling. These systems do not have autonomous sorting but can cover the 1000-3000 nm spectral range and are compatible with a smartphone, making them highly portable and versatile.

Outside of industry, NIR/SWIR/MIR (SWIR: short-wave Infrared, MIR: mid-infrared) spectroscopy is being coupled with ML models to address a wide range of problems in the textiles industry. Huang et al. [21] in 2022 demonstrated that the combination of hyperspectral imaging (HIS) and convoluted neural networks (CNNs) is capable of high accuracy sorting and classification of textile materials. In September 2025, Kampik et al. [22] reported on their success in utilizing SWIR HSI to identify hazardous industrial contaminants (acrylonitrile and triethylene glycol) on textiles. In January 2026, Gorla et al. addressed problems with the identification and sorting of low percentage elastane blends using NIR HSI. [23]

2.2. Molecular Recycling of Textiles

Mechanical recycling of textiles works best with mono-material fabrics of cotton, linen, wool, and acrylics. However, most textile fabrics are made from blended natural and synthetic fibers. For example, blends of cotton and polyester offer comfort and durability, while elastane or spandex confers stretch to textiles. The complex intermixing of cotton and polyester, and the rubbery behavior of elastane make their separation by current mechanical recycling methods infeasible. To overcome this roadblock, the separation of fiber blends can be accomplished by selective dissolution of or depolymerization of specific polymers. These processes fall under chemical or molecular recycling. [12]

Cotton and polyester can be separated from blends through their selective dissolution in solvents, hydrolysis, hydrothermal treatment, and enzymatic hydrolysis. For example, a deep eutectic solvent selective for cellulose can leave polyester fibers intact, while 5–15 wt% NaOH in water at temperatures between 70 and 90 °C can hydrolyze polyethylene terephthalate (PET) into its monomers terephthalic acid (TPA) and ethylene glycol (EG) while preserving the cotton fibers. Elastane can be selectively removed from textile blends through dissolution (e.g., using a 70:30 vol% THF:DMSO (tetrahydrofuran: dimethyl sulfoxide) solvent mixture), aminolysis, or solvolysis, while preserving the integrity of the other fibers in the blend.

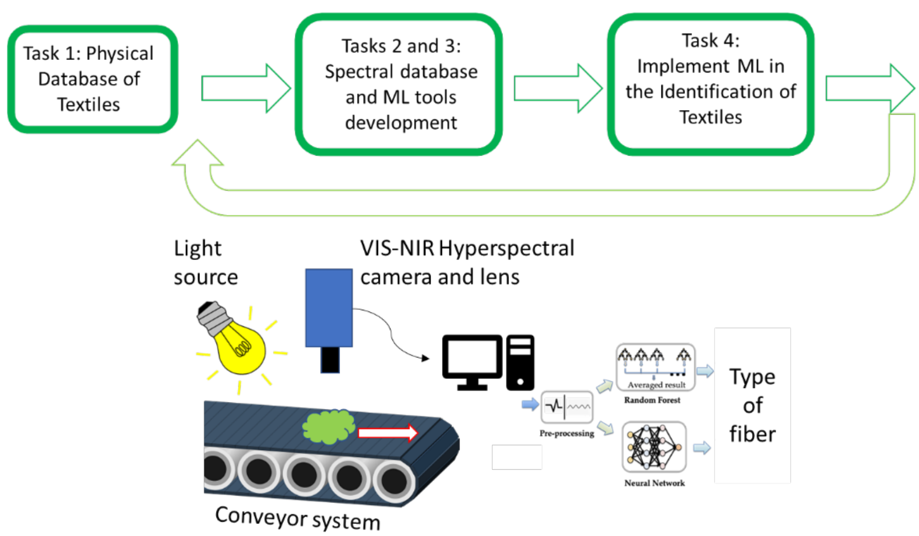
A recent review article from our team [12] introduces the concepts of mechanical, chemical, and biological recycling of textiles, and focuses on the molecular recycling process that are explored for the separation of fiber blends such as polycotton (cotton and polyester) and elastane-containing blends.

3. Technology Approach

3.1. Overview

Our research utilizes near-, short-wave, and mid-infrared (NIR, SWIR, and MIR) spectroscopy combined with machine learning (ML) for rapid identification of textile composition. This enables the subsequent separation of higher and lower-value textile grades (resale, rag, fiber reclaim, and chemical recovery), and also identifies "disruptors" for fiber-to-fiber textile recycling such as elastane and carbon-black ink that are typically difficult to detect using existing spectroscopic techniques. The project deliverables are a comprehensive spectral database for different types and composition textile materials and its implementation in a testbed for IR spectroscopy and imaging characterization.

The project comprises four tasks. Task 1 encompasses the sourcing and organization of a comprehensive set of textile samples, and the characterization of their chemical composition and structure/features. Task 2 achieves non-invasive identification of textile fibers using reflectance spectroscopy in the near and mid infrared regions, and develops a comprehensive database of infrared spectra for many types of textiles. Task 3 develops novel data science and informatics techniques for textile spectra analysis, and the identification of the composition of "unknown" textile samples. Task 4 validates the ability of our ML methodology to determine the fiber composition in unknown textiles using infrared sensors and hyperspectral imaging in a conveyor belt that simulates a recycling facility environment.



3.2. Spectral Database of Textiles

We are currently employing NIR/SWIR/MIR reflection spectroscopy to classify and sort post-industrial and post-consumer textile fibers consisting of natural, synthetic and blended materials. Through the combination of reflection Fourier transform infrared (FTIR) spectroscopy in the 600 – 8000 cm^{-1} region (1.25 to 16.7 microns) and NIR spectroscopy in the 900 nm – 1700 nm region, we are in the process of building a comprehensive spectral database of textile fibers. Our quickly growing dataset consists of optical images, FTIR spectra and NIR hyperspectral images of approximately 450 samples extracted from 127 unique garments (as of January 2026) covering a range of materials including cotton, polyester, poly/cotton blends, acrylic, nylon, viscose, rayon, elastane, bamboo, leather, polyamide, modal, silk, wool, lycra, and cashmere. To our knowledge this is the first database to combine optical images, FTIR spectra, and NIR hyperspectra. In addition to our own data, we have also obtained permissions from other organizations such as NIST to incorporate the data they have obtained in the same space into our database.

Hyperspectral imaging (HSI) in the NIR/SWIR region using a line-scan sensor positioned above a conveyor system is currently being assessed for textile fiber sorting in a recycling process based on ML-enabled recognition. As the textile sample passes through the scan region, a single row of pixels, each capable of obtaining fully resolved spectral data in the NIR region, generates a hyperspectral data cube containing complete X, Y, and wavelength data that is then analyzed and processed by ML equipped software allowing for spatially resolved textile classification. This allows for the simultaneous identification of not only the bulk textile but also any disrupters (printed images, zippers, contaminants, etc.).

3.3. Machine Learning Tools to Identify Textile Type

Our work leverages the rise of AI, ML, informatics, and other data science techniques to improve the analysis of convoluted spectra from complex textile samples, thus helping us to identify their types and compositions. Our efforts include methodological AI/ML advancements in the context of textile IR spectra; building and optimizing both classification and composition analysis (regression) models for different contexts (i.e., sorting objectives, constraints); testing and benchmarking various available techniques; identification of characteristic and robust spectral features for selective frequency sampling (i.e., potential identification via few individual frequencies rather than full spectra); developing best-practice guidelines for AI/ML workflows; and implementing corresponding end-to-end software solutions. We also explore the utility of AI/ML for decision-making in the sorting process, e.g., via uncertainty quantification to determine (and act on) the confidence in every individual prediction.

The foundation for this work is our textile IR spectral database, which includes data compiled from literature and open data collections (i.e., over 200 textile and 1100 auxiliary polymer IR spectra, as of November 2025), as well as the data generated as part of this project. It provides ground truth data for the training, validation, and testing of our AI/ML models. Our database software infrastructure stages, cleans, validates, and ingests data from the different sources (either individually or in bulk). It also allows for quick and flexible updates of our relational database schema (e.g., changes in data or meta-data entries stored, ontology used, or table structure) to adjust for changing research demands. Both the schema and the database itself are dynamically extensible. As the database increases in size, our software infrastructure allows for on-the-fly retraining of the AI/ML models derived from it.

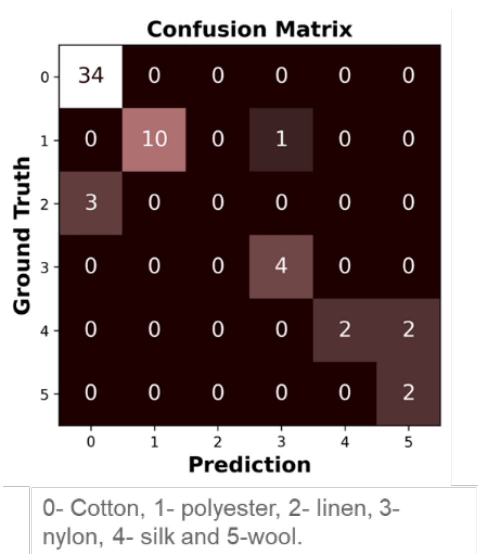


Figure 1: Confusion matrix of a local discriminant analysis classifier for six common pure fiber types, showing the predictive performance for the test set.

Our AI/ML modeling pipeline includes data pre-processing steps to standardize (e.g., with respect to frequency range and resolution), scale, and normalize the available spectra, and truncate spectral regions at the edges of the detection limit with poor signal-to-noise ratios. Hyperspectral images are pre-processed to distinguish between sample and background pixels, average spectra are computed over all sample pixels, and a variance analysis is conducted to identify frequency-dependent signal-to-noise patterns. Both the full hyperspectra as well as the averaged spectra derived from them are stored in the database and used for different models.

The next step in the modeling pipeline concerns feature transformation and dimensional reduction approaches for a more compact, information-dense representation of the spectral data. We are exploring and comparing the utility of both the original spectral representation and those resulting from, e.g., principal component analysis (PCA), singular value decomposition (SVD), and t-distributed stochastic neighbor embedding (t-SNE).

We then implemented and tested a number of standard classifier approaches. Even relatively simple techniques such as linear discriminant analysis (LDA) showed reasonably good performance in identifying different pure fibers (90% accuracy; see Figure 1). A comprehensive benchmarking study to compare the performance of standard classifiers (e.g., k-nearest neighbor (kNN), linear discriminant analysis partial least square (LDA-PS), support vector machines (SVMs), decision trees, and random forest classifiers) is ongoing. A key challenge that emerged concerns limited and imbalanced training data availability, resulting in classes with only few samples in train-, validation-, and/or test-sets and thus poor recognition. We are addressing this issue by employing tailored sampling and training strategies. We also explored the utility of augmenting the spectral data with synthetic spectra generated by mixing or adding Gaussian distributed random noise of different magnitude to the former (see figure on the right). However, the results were not very promising. Overall, misclassifications typically occurred for chemically similar or related fiber types or for rare fiber classes that are undertrained.

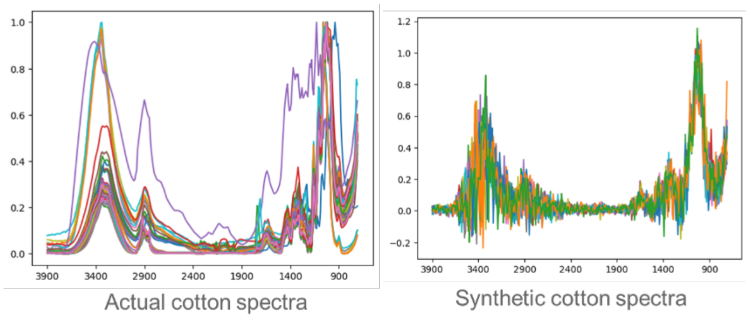


Figure 2: Comparison of physical cotton IR spectra (left) and synthetically generated spectra (right).

As classifiers are essentially limited to identifying pure fibers or select standard blends, we have also been pursuing regression algorithms to predict the continuous composition of textiles with respect to their constituent fibers. Our initial focus has been on fully connected deep neural network (DNN) models, which exhibit both promise as well as unexpected challenges due to their flexibility and data needs. As the best AI/ML model framework is not known a priori, we perform systematic model and hyper-parameter optimization within our in-house genetic algorithm auto-ML approach that has been shown to significantly outperform the commonly employed tree-structured parzen estimator. The AI/ML model creation follows usual best practices, e.g., data volume requirements; separate train-, validation-, and testset error analysis and comparison; optimized regularization to avoid overfitting; cross-validation to avoid training bias. We also evaluate the impact of these practices in the specific context of IR spectra analysis and develop corresponding insights and guidelines (e.g., with respect to training set design).

Our work also seeks to augment the classifier and regressor results with uncertainty quantification techniques to assess the trustworthiness of each individual prediction. Only high-confidence predictions will be acted upon in the sorting, while low-confidence predictions may be discarded or funneled into secondary reevaluation, based on the tolerance of a given sorting objective.

The software infrastructure implemented in this work is written in Python and utilizes AI/ML-domain libraries (e.g., Pandas, scikit-learn, PyTorch, TensorFlow). The database code utilizes a structured query language (SQL) based relational database management system in conjunction with a Django web framework. This work also leverages our in-house *ChemEco* software ecosystem, specifically its *ChemBDDB* and *ChemML* suites.

4. Discussion

4.1. Perspective on Identification of Textile Type

The wide variety of chemical and structural composition found in textile fibers combined with intricate chromatic and textural properties make them complex materials to recycle. In addition, the diversity of fibers and their blends, dyes, additives, and contaminants, in addition to chemical treatments used in textiles, renders their analysis and identification challenging. Optical microscopy and machine vision, while extremely useful, are limited to visual characteristics and cannot determine a fiber's chemical composition without complementary technologies. For instance, different vibrational spectroscopy approaches, such as NIR, MIR, and Raman rely in the molecular spectral signatures of the chemical functional groups found in the fibers for classification. While this offers significant advantages, they may still encounter serious limitations and obstacles, such as the presence of textile dyes and other contaminants, ageing, and blended compositions that significantly hinder the identification of textile fibers. ML, computer vision, and HSI have emerged as potential solutions for complex classification problems due to their scalability, accuracy, and capability to be integrated with sensors. For these efforts, NIR and MIR techniques are advantageous over visible (VIS) light spectroscopy methods since the impact of color tint is low, and the chemical information is richer. Between the two, NIR offers more available and cost-effective sensors, but MIR is attractive due to the freedom from convoluted vibrational overtone bands that totally complicate NIR spectra. Furthermore, the reflected intensity in the MIR region is generally higher and more spectrally resolved compared to NIR, and it is more suitable to black and dark tinted fibers. We have recently demonstrated the value of MIR spectra in the identification of plastics type. MIR information is not publicly available for textiles. [24] Our efforts in this project build a comprehensive and complementary MIR and NIR database of textiles combined with HSI images and microscopic optical images.

The HSI system which we utilize in this project can be applied to virtually all fiber material classes including viscose, nylon, acrylic, and wool/silk and deep-learning and regression methods can identify blend composition more precisely than what is included in manufacturer tags. This is of importance to economics, as wool/silk items, while typically being a low percentage of overall feedstocks, have a significantly higher fiber value but are only recycled at 7% of the overall wool production [1]. Hence, the identification of wool/silk can increase revenue. Our HSI can identify layering and inclusion of elastane in parts of the garments, such as cufflinks and collars.

It is worth noting that the types/compositions of garments available in the second-hand market tend to vary with the time of the year and the geographic location (e.g., in the Northeast there are more wool products going to secondhand than, for example, in much warmer climates). The ageing of these garments could also be impacted by geographical environmental factors.

4.2. Perspective on Machine Learning Tools to Identify Textile Type

Textile samples represent complicated mixtures of fibers/materials, morphologies, dyes, additives, and contaminants, and each of these will contribute to the spectral signature of a given sample. Rather than just being additive, certain signals may mask or boost other signals, potentially in a non-linear fashion. Overall, these spectra tend to be highly complex and convoluted, and they may exhibit challenging signal-to-noise ratios. The combinatorial space is practically infinite, and a naïve comparison with limited reference data can easily fail to correctly identify a given sample. However, modern data science (including AI and ML) is ideally suited to tackle such a complicated data analysis problem, as it is capable of exposing subtle, often hidden patterns and correlations. That being said, a particular challenge in many domains including textile identification is the relative sparseness and uncertain quality of the available training data needed to create robust AI/ML models. Another practical consideration is the tradeoff between accuracy and speed of these AI/ML models. A one-size-fits-all approach is bound to fail. We thus aim to deliver bespoke AI/ML models optimized for different sorting objectives and requirements that may be encountered in actual textile sorting settings.

4.3. Perspective on Molecular Recycling of Textiles

Several companies are developing and scaling molecular recycling technologies for the processing of blended textiles, The table below (adapted from [2]) summarizes the recycling process used, its output, and the scale for companies active in the molecular recycling of textiles.

#	Company	Founded	Location	Process	Output	Scale
1	Ambercycle	2015	Los Angeles, USA	Biological recycling process	PET pellets and fiber	Pilot plant
2	BlockTexx	2018	Loganholme, Australia	Chemical Process	PET and Cellulose	Commercial scale plant
3	Circ	2011	Danville, Virginia	Hydrothermal process	Cellulose, terephthalic acid TPA, and ethylene glycol EG.	Commercial scale plant
4	Worn Again Technologies	2005	Nottingham, England	Solvent-based dissolution	PET and Cellulose	Pilot plant
5	Purfi	2018	Waregem, Belgium	D'Elastane™ technology	PET fiber	Not mentioned
6	Textile Change	2019	Vejle, Denmark	Chemical Process	PET and Cellulose	Pilot plant
7	Sodra (OnceMore®)	2022	Växjö, Sweden	Chemical Process	Cotton fiber	Commercial scale plant
8	Phoenxt	2018	Germany	Solvent-based process	PET, Cellulose	Not mentioned
9	Eeden	2022	Münster, Germany	Chemical Process	Cotton fiber, TPA, EG	Not mentioned
10	Zhejiang Jiaren	2012	Zhejiang, China	Chemical Process	DMT	Commercial scale plant

Several of the companies highlighted above are relatively new and relatively small (start-ups). Recent successes include Ambercycle signing multiple off-take agreements including one over $70M euros with Inditex, Syre [25] building a $100M facility in NC, and Reju [26] announcing on January 20, 2026 plans to establish a $390 million textile regeneration hub in Rochester NY. This activity points towards financial feasibility (or at least the potential) for molecular recycling of textiles and, with the EU and several states in the US having introduced Extended Producer Responsibility (EPR) legislation in the last year [27-30], it would appear that we are reaching a turning point.

It is not publicly known what activities the above companies have regarding automated sorting systems, but there are connections between sortation and processing. The spectroscopic and ML output obtained in the context of textile identification can be further utilized for refining processing conditions in the subsequent molecular recycling of textiles. For example, if a known UV stabilizer is detected in PET textiles at high concentration, and it is known that this requires a longer processing time/higher temperature for solvolysis, then the process parameters can be adjusted accordingly.

5. Conclusions and Recommendations

The textile sector is under pressure because of its high energy and water consumption, environmental pollution, and the emission of greenhouse gases. Textile reuse and recycling can be a sustainable solution for the reduction of textile waste, the reduction of virgin materials required for textile production, and the corresponding reduction of environmental impact.

Major apparel brands in the United States have made significant commitments to utilizing a certain percentage of recycled content in their items within the next decade. The main route by which most brands currently meet recycled content in polyester, the most common textile fiber, is via bottles that have been turned into fiber. Bottling companies, such as Coca-Cola have also made commitments to using at least 50% recycled material in packaging by 2030. However, there are not enough bottles for both textile/apparel manufacturers and bottling/packaging manufacturers to meet their commitments, Hence, there is significant demand in the apparel industry to find economical means to recover polyester from post-industrial and post-consumer textiles.

In addition to the market pull, there is a policy push. The European Union (EU) Strategy for Sustainable and Circular Textiles [31] includes mandatory Extended Producer Responsibility (EPR) for textiles with eco-modulation of fees. California's SB-707 Responsible Textile Recovery Act of 2024 [29], as well as recent legislation in other states [27-27], are also requiring EPR for textiles. The Producer Responsibility Organization (PRO) will likely be heavily involved in technology decisions that will be used at sorting facilities.

Our research aims to develop adaptive sorting technologies that incorporate ML advances to sort post-industrial and post-consumer textiles into various market grades on the basis of the textile composition and contaminants present. Key value propositions are the use of hyperspectral information in automated systems, and the focus on areas (wavelengths) of the spectrum not currently utilized. This is expected to significantly improve the current textile sorting in the United States which is done primarily by manual systems (i.e., require a person to place the fabric in front of a scanner).

Textile sorting will result in a sizeable stream comprising blended textiles. Value from such blended textiles can be extracted through chemical or molecular recycling processes that recover single types of fibers or their monomers. Single-type fibers can be spun into new fibers, while monomers can be polymerized into virgin fiber feedstock. The effectiveness, scalability, and environmental impact of molecular recycling techniques for textiles merit further research. Well-defined feedstock benefits process efficiency and economics. Sorting technology is key to this end.

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About the Authors

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Prof. Alexandridis' research utilizes molecular interactions and supramolecular assemblies to develop processes that are environment friendly and energy efficient, and products with desired properties and function. Alexandridis is leading projects on chemical recycling, recycling of multilayer films, and recycling of textiles. He has authored over 200 articles and 6 US patents (Google Scholar h-index 86 and 27,500 citations). [www.cbe.buffalo.edu/alexandridis]

Charutha Dassanayake

Charutha received his bachelor's degree in Chemistry from the University of Peradeniya, Sri Lanka. He is currently a 3rd-year PhD student working under Prof. Velarde using vibrational spectroscopy to study various environmental pollutants and probe molecular surfaces.

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Prof. Hachmann is the Director of the Engineering Science in Data Science graduate program and a Leadership Member of the Institute for Artificial Intelligence & Data Science (IAD) at the State University of New York (SUNY) at Buffalo. His research fuses molecular modeling with virtual high-throughput screening and modern data science to advance a data-driven discovery and rational/inverse design paradigm in the chemical and materials disciplines.

Brian Iezzi

Dr. Iezzi is an active researcher and inventor in the textile industry, and has demonstrated sustainability leadership as a clean technology startup founder, chairing a sustainability fund granting board, and through international life cycle assessment projects. He holds degrees in Textile Engineering and Materials Science & Engineering from North Carolina State University and the University of Michigan, respectively.

Shea Myers

Dr. Myers was awarded his PhD in Chemistry from SUNY-Buffalo in the Summer of 2025 specializing in X-ray crystallography and photodynamic materials. He has since begun a postdoctoral position working on this project on advancing sorting and classification technologies utilizing mid-IR hyperspectral imaging and FTIR.

Shwetabh Tripathi

Shwetabh received his undergraduate degree from the Indian Institute of Technology (IIT) Kanpur. He is currently a 3rd-year PhD student working under Prof. Hachmann on creating a spectral database of textiles and developing machine learning models for the identification and determination of textile fiber composition.

Marina Tsianou

Prof. Tsianou leads research that involves the design, development, and characterization of molecularly-engineered materials with desirable functionalities. She contributes to textile recycling with expertise in nanostructured polymers in films and on surfaces, surface modification, solvent-treatment of cellulose fibers, and dyes and pigments.

Luis Velarde

Prof. Velarde's research utilizes visible to mid-IR lasers and state-of-the-art spectroscopy to characterize molecular structure and dynamics at interfaces in photovoltaics, plasmonics, nanoelectronics, and materials of environmental impact. In the field of plastics recycling, Velarde leads projects on advanced sorting using mid-IR sensors and machine learning.