Evaluating the Accuracy of Fabric Mechanical Digitization Methods

Rosa M. Sánchez-Banderas, Gabriel Cirio, Caitlin Knowles, and Alejandro Rodríguez

***Abstract*—The apparel industry has witnessed a significant shift toward 3D virtual design, driven by advances in simulation and digitization technologies. Central to this transformation are digital twins, which allow designers to test and refine garment designs virtually, reducing reliance on physical prototyping. A critical aspect of this process is accurately capturing the drape behavior of fabrics, as it impacts both the aesthetic and functional properties of garments. Traditional fabric digitization methods involve mechanical testing of fabric samples, but they are labor-intensive, costly, and require specialized equipment. Recently, AI-based digitization techniques have emerged, offering potential advantages in terms of cost and logistics, though their accuracy remains uncertain. This study addresses the gap in knowledge regarding the accuracy of AI-based fabric digitization by utilizing the Cusick drape test—a standardized method for assessing fabric drape behavior. We introduce a reference digitization pipeline based on traditional mechanical testing and perform a comprehensive comparative study of six commercially available digitization methods, including both traditional and AI-based approaches. Using a diverse set of fabrics, we evaluate the accuracy of the digitized fabrics against real-world measurements. Our results demonstrate that AI-based methods can achieve competitive accuracy, while also highlighting areas for further improvement. We present a publicly available dataset containing real fabric properties, their digitized versions, as well as their corresponding real and digital drape metrics, which can serve as a valuable resource for further research and development in fabric digitization.**

***Index Terms*—Digital Fabric, Digitization, Simulation, Computer-Aided Design**

I. Introduction

THe apparel industry has undergone a significant shift towards 3D virtual design in recent years, fueled by breakthroughs in simulation and digitization technologies. At the heart of this transformation are digital twins, which provide designers with a virtual platform to test and refine their designs without the need for physical prototyping.

The way fabric drapes and folds has a profound impact on both the aesthetic and functional aspects of a garment, influencing factors such as fit, comfort, performance, and overall usability. As a result, accurately capturing the drape properties of fabrics is crucial for creating digital twins that faithfully replicate the behavior of their real-world counterparts.

Fabric digitization is typically done by performing mechanical tests on multiple fabric samples with specialized hardware. This approach can yield very accurate results if done carefully, but requires significant effort, skill, as well as physical access to the fabric, making it a complex and expensive process. This has been the *de facto* standard used by the industry and, up until a few years ago, virtually all commercially available digitization services were based on this approach.

In recent years, a new class of methods has emerged that leverages AI to perform this digitization and alleviates the need for skilled operators or access to expensive equipment. Some of these methods only require fabric metadata (typically found in the fabric tag) to perform the digitization, thus avoiding the cost and time investments of fabric sample transport and testing. While their logistical and economic advantages are undeniable, it is unclear how well they perform in terms of accuracy compared to traditional digitization methods. To the best of our knowledge, digitization techniques, be it device-based or AI-based, have not been thoroughly assessed on a large body of fabrics and in a production environment.

Conducting such a large-scale study requires a clear understanding of what *accuracy* means for a digital fabric. We can easily define the accuracy of a digital fabric from a perceptual standpoint: once digitized, a digital fabric is expected to faithfully reproduce the mechanical behavior of its real-life counterpart in a digital setting such as a CAD tool or a Virtual Try-On application. But how can we *measure* how well a digital fabric agrees with its real-life counterpart? More generally, how do we measure the accuracy of a digitization process in a quantitative, repeatable and universal way? How can we compare two digitization processes to know which one is more accurate?

In this work, we aim to address these questions by leveraging the Cusick drape test, a standardized method to evaluate the drape behavior of fabrics. We begin by introducing a fabric mechanical digitization pipeline, building upon state-of-the-art methods using fabric sample testing, to serve as reference. We then review and discuss digital fabric accuracy and propose the systematic use of the Cusick drape test and its digital replica as a tool to assess the accuracy of a digital fabric and, by extension, the accuracy of a mechanical digitization method. Finally, we conduct a comparative study of multiple commercially available digitization methods, with device-based and AI-based approaches. The study is based on a wide and carefully curated range of fabrics with diverse combinations of weight, thickness, weave structure, and composition. Results show the potential of AI-based approaches as an industry-grade digitization tool, and undermines the wide belief that traditional device-based approaches are infallible. The curated dataset is made publicly available to foster further research on the accuracy of fabric digitization.

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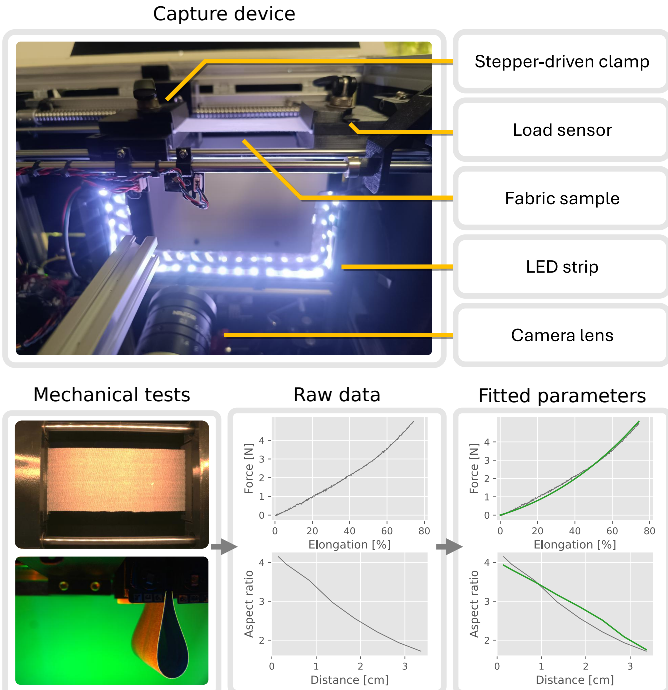

Fig. 1. In our fabric digitization pipeline, fabric samples are tested with a purpose-built device (top). The device consists of a guided stepper-driven clamp that serves two purposes: 1) stretching fabric samples while the load sensor measures the corresponding force response, and 2) bringing the clamped sample ends together to force the fabric sample into a pear-loop shape while the built-in camera takes photographs. The LED strip controls the illumination of the fabric sample to facilitate the segmentation of the photographs. Uniaxial tensile and pear-loop tests gather raw mechanical data (bottom), which is then used to automatically estimate best-fitting digital fabric mechanical parameters.

II. Related Work

A. Fabric Digitization

Assessing the mechanical properties of fabrics involves two steps: capturing raw data of the fabric's behavior and deriving mechanical parameters from it. While traditional methods use mechanical sample testing devices, recent approaches use fabric metadata and a purposely trained AI model to infer mechanical properties. More exploratory work uses video or photographs instead.

a) Digitization with Testing Devices: The primary method for fabric digitization in the apparel industry is using sample testing devices [1]. Commercial 3D CAD software for apparel often derives mechanical parameters from these devices, which are typically manufactured by the same companies. Popular devices include the CLO Fabric Kit 2.0 [2] and Browzwear's Fabric Analyser (FAB) [3], among others [4], [5], [6], which measure fabric stretch and bending resistance [7]. The raw data (usually force-deformation sequences) is then analyzed to derive mechanical parameters that fit the simulator's needs [8], [9], [10], [11], [12], [13]. Testing devices are considered reliable as they directly test fabric deformation. However, they are complex, slow, expensive, and require skilled operators. Additionally, different devices can yield varying results for the same fabric [14], raising concerns about data accuracy. The lack of standardized models has led to vendor lock-in, where one device is tied to a specific CAD, hindering interoperability. Recent standardization efforts aim to address this by providing vendor-specific documentation [15] and encouraging open raw data formats [16], though adoption has been limited.

b) Digitization from Visual Input: Visual inputs such as photos and videos offer a more flexible approach, removing the need for specialized hardware. While these methods still rely on simulations, the literature divides them into two categories. In the first category, simulations are used to iteratively refine parameters until an objective function is met. Inputs can be single-view images of a garment [17] or video sequences [18], [19]. The optimization loop estimates material parameters by comparing simulations with real data. In the second category, simulation is used as a preprocessing step to build a dataset for learning. In this way, mechanical parameters [20], [21], [22] and friction coefficients [23], [24] can be derived from video or image sequences. Other approaches have used depth images [25], [26]. Data-driven methods [27], [28] use motion descriptors and 3D boundary data to identify similar fabrics. It should be noted that none of these techniques have yet made it outside the lab.

c) Digitization from Metadata: Recent approaches have taken a step further and do not even require a physical sample, relying exclusively on metadata to infer the mechanical properties of the fabric [29], [30]. Machine learning algorithms (or similar methods) are trained on large datasets of fabrics, with inputs such as density, structure, composition and thickness, and mechanical parameters as outputs. Given their simplicity, speed, and cost efficiency, these methods are being steadily adopted by the industry despite being fairly new: SEDDI Textura [31], CLO Fabric Creator [2] and Vizoo physX [32] are not even two years old at the time of writing. One of the objectives of this work is to understand how accurate these methods are compared to traditional testing devices, which have long been considered the gold standard.

B. Digital Drape Accuracy

To measure the accuracy of a digitization method, we first need a way to measure the accuracy of a digital fabric. The literature is scarce when looking at industrial drape evaluation practices. *Validation* is often the term used in the apparel industry to talk about *accuracy* in combination with acceptable error thresholds. The 3D Retail Coalition produced a report listing and categorizing different validation mechanisms employed by a few 3D CAD vendors [33]. To the best of our knowledge, this is the only document focusing on digital fabric validation in the apparel industry.

Vizoo [34] and Browzwear [35] have developed the Drape Validation Workflow [36], where a square fabric sample is draped onto a sphere and the resulting setup is photographed under specific conditions and from different angles. The setup can be easily replicated in a digital environment, allowing for a direct comparison between real and rendered images. Drape accuracy is based on a comparison of the width of the widest points of the digital and real draped fabric. A digital fabric is validated if the digital measurement is within 20% of the real fabric measurement.

CLO [2] follows a slightly different approach. A square fabric sample is draped on a cylindrical support in the real and digital environments. The method then requires calculating the average distance between each fabric corner and the ground, as well as counting the number of flares (i.e. the number of folds of the draped sample as seen from above). A digital fabric is deemed valid if the difference between real and virtual distance measurements is less than 5mm, and if the number of flares matches.

In academia, on the other hand, there seems to be a widespread adoption of the Cusick drape test [37] (or similar ”drapemeter” methods [38]) as a tool to compare digital fabrics to their real counterparts. The Cusick drape test, as defined in the ISO standard 9073-9:2008, allows to quantify fabric drapability by computing the ratio between the circular area of the sample and the area defined by its draped outline (see Section IV-A for more details). Since the setup is easy to replicate inside 3D CAD tools, it has been widely used for digital fabric evaluation [39], [40], [41], [42], [43], [30], for comparing between different digital versions of the same real fabric [29], [30], and as input for mechanical parameter estimation [26], [30].

Another common way of evaluating digital fabrics is by constructing full garments and draping them on mannequins [30], [41], [26], [44], thus allowing to compare fabrics in their most natural setting. While seemingly attractive, this method has the major drawback of being purely qualitative, and therefore requiring an expert eye to validate the drape. In addition, it adds the complexity of accurately digitizing a physical mannequin (or manufacturing one from a digital version) and properly simulating its contact with the fabric. In this paper, we embrace the Cusick drape test for a quantitative evaluation of fabric drape.

III. Mechanical Characterization from Physical Samples

Traditional digitization methods, as previously discussed, follow a two step approach for mechanical fabric digitization: raw data capture through physical sample testing, followed by mechanical parameter derivation from the raw data. In this section, we discuss some of the most common industrial practices for both steps of the digitization process. In this light, we describe our own device-based digitization pipeline, illustrated in Figure 1, which tries to address some of the shortcomings of existing methods, notably by including simulation in the parameter derivation step. We will call it the *Reference* method in the remainder of this paper, since it will serve as a reference for our comparison of digitization methods in Section V.

A. Raw Data Capture from Sample Testing

We focus on the two primary deformation modes relevant to digital garment simulation: in-plane (stretch) and out-of-plane (bending) elasticity. These are not the only mechanical properties that affect drape: friction [45], [24] and hysteresis [46], for example, can be modeled and fitted as well. However, these are less explored, and there are no systematic solutions

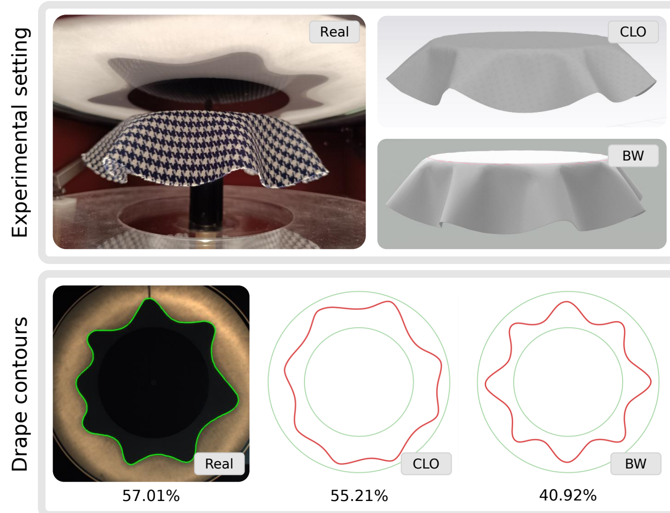

Fig. 2. The Cusick drape test (top left) evaluates the drape of a circular fabric sample under its own weight by quantifying its contour (bottom left). We replicate the test in CLO and Browzwear CAD tools by using fixed nodes during simulation (top right) and automatically processing the projected geometry contour (bottom center and right).

in CAD applications for the apparel industry, which typically resort to predefined, fixed values.

Fabrics exhibit non-linear and anisotropic stretch behavior. Several experimental settings have been proposed in the literature to capture these properties, typically variations of multi-axial [12], [11] or uni-axial [4], [13] tensile testing setups, the latter being the most widely adopted method by industry professionals. This test applies controlled strain to fabric samples, recording force-elongation curves that reveal the non-linear stress-strain relationships. The capture of fabric bending properties lacks the same consensus regarding the apparatus and is addressed differently across various pipelines, both in academia [11], [47], [48] and in industry [1]. For instance, the CLO Fabric Kit [2] uses the cantilever test (a modified version of the ASTM D1388 standard [49]), measuring the deflection profile of a horizontally clamped fabric strip, while the Browzwear FAB [3] unaxially compresses a short fabric sample to induce buckling and records the resulting force measurements [1]. Both tests are applied to rectangular fabric samples cut in three directions (warp, weft and bias) to account for anisotropy. We refer the reader to Section 2 of the Supplementary Document for details on sample preparation and testing.

In our *Reference* method, we rely on a purpose-built capture device (Figure 1, top) supporting two types of physical experiments: uniaxial tensile testing and hanging pear-loop testing [48]. The pear-loop test evaluates the natural curvature of the fabric under its own weight. By controlling the motion of parallel clamps holding a suspended fabric strip, the test induces distinctive pear-shaped loops. The bending properties of the fabric can be obtained from the geometric profiles of the loops. We resorted to using pear-loop testing rather than cantilever due to the superior robustness of the pear-loop test when dealing with curling fabrics [49], while showing similar sensitivity to the cantilever test. To simplify the analysis, a loop height-to-width ratio is computed, producing a simplified yet informative metric for characterizing the fabric's bending properties. This geometric approach was preferred to using force sensors, given the very small bending forces at play. The Browzwear FAB, for instance, needs to resort to a fallback test (a clamped fold test) when the force-based method is not enough.

B. Mechanical Parameter Estimation

To the best of our knowledge, industrial digitization methods such as the CLO Fabric Kit and the Browzwear FAB derive mechanical parameters by fitting the *equations* of the analytical constitutive model of the digital fabric to the raw data [15]. This method requires very little computation, is almost instantaneous, and makes sense from a theoretical point of view. In practice, however, constitutive models are only one piece of the puzzle when it comes to simulating a digital fabric. Other factors, such as the mesh discretization type, mesh resolution, locking effects, and convergence thresholds significantly influence the resulting mechanical behavior [50], [26]. Using analytical equations does not take them into account.

In the *Reference* method we formulate parameter estimation as an optimization problem: we search for the mechanical parameters that best match experimental data. To achieve this, we employ a simulation-in-the-loop optimization strategy. For each data point, we impose the measured displacement at the contours of the digital fabric sample, simulate the sample to equilibrium, and evaluate the simulation output against the real forces for tensile tests, and height-to-width ratios for pear-loop tests. This process is more costly than simply fitting the analytical model equations, but it is simulator-specific, and can therefore counter, to some extent, the possible biases introduced by the simulator-specific factors mentioned above. Consequently, the simulator used for the optimization step must be the same simulator used for draping once the fabric has been digitized.

We use the cloth simulation engine proposed in [50], requiring the estimation of three stretch parameters and three bending parameters. Many real fabrics exhibit Poisson effect, but the Poisson ratio is not estimated by the digitization methods we study in this work, so we refrain from fitting it as well, resorting to a predefined value of zero for all fabrics.

Several methods have been proposed in the literature to solve simulation-in-the-loop optimization problems. Recent approaches leverage differentiable simulation to enable gradient-based optimization, including cloth parameterization [51], [52], [53], [54], but these frameworks introduce practical challenges due to the increased complexity of the simulator implementation. Given the relatively low dimensionality of our parameter space, we opt for the COBYLA algorithm [55], a derivative-free optimization method well suited for problems with a small number of parameters. This approach provides an efficient and effective means of parameter estimation without the need for complex derivative computations.

We adopt a cyclic coordinate descent scheme [56] for our fitting pipeline to decompose the optimization process into a series of simpler univariate problems. This approach can require, in general, many cycles to converge, but for our case it is justified by two key observations. First, due to our assumption of a zero Poisson ratio, the stretch parameters for weft and warp can be fitted independently, leaving shear (bias) as the only coupled stretch parameter. Second, we assume that the fabric sample behaves in a near-inextensible regime when folded under its own weight, which leads to a decoupling of the in-plane and out-of-plane modes. Based on these assumptions, we structure our fitting pipeline by cycling over the six parameters in order, starting with stretch weft, warp and bias, followed by bending weft, warp and bias. Two cycles are typically sufficient to converge.

IV. Evaluating Digital Fabrics

In order to evaluate the mechanical accuracy of a digital fabric, we first need to identify and understand *what* is going to be evaluated, and what is the corresponding *ground truth* (i.e. what are we going to evaluate against). The mechanical behavior of a digital fabric can be *observed* or *measured* in many different ways: as a set of mechanical parameters (e.g. stretch and bending stiffness in different directions), as draped geometry (e.g. vertices and faces after simulating a piece of fabric in a specific setup), as experimental testing data (e.g. force/elongation plots from a digital test), etc. All are valid representations, ranging from purely quantitative (stiffness numbers) to purely qualitative (draping shape). However, not all representations are useful for evaluation purposes.

Let us consider mechanical parameters. While they help quantify a physical phenomenon (the mechanical behavior of the fabric), they are more related to the internals of the simulator rather than the perceived fabric behavior. In particular, they are tied to the specific constitutive models used by the underlying mechanical simulator. Consequently, they do not have a corresponding *ground truth* in the real world unambiguously characterizing the real fabric. Even comparing between sets of mechanical parameters is problematic. Different sets of parameters can result in very similar drapes [29], and the mechanical parameter space is not necessarily perceptually meaningful: bending parameters, for example, are much more sensitive to changes in the lower end than in the higher end.

Experimental testing data, on the other hand, does have a corresponding *ground truth* in the real world. A stretch test can be run on the real fabric, and a digital replica of the test can be run on the digital fabric. The outputs, i.e. the two sets of experimental data, can be compared. While this approach is interesting, it has its own limitations. Sophisticated precision equipment, as well as qualified operators, are required in order to run real-world tests, making it expensive and error-prone. In addition, mechanical parameters are usually derived from these tests in the first place as seen in Section III: using the same tests, or even similar ones, for evaluating the digitization accuracy introduces a strong bias in the process. Moreover, these tests typically evaluate isolated behaviors (e.g., the response of a small fabric piece to uniaxial stretch in a single direction), and are therefore incapable of reflecting interactions between different deformation modes.

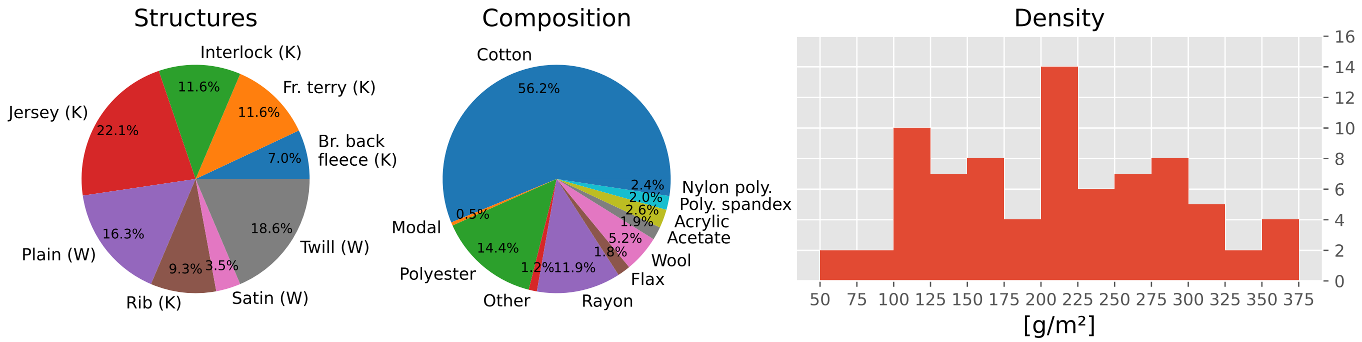

Fig. 3. Distribution of our dataset (86 fabrics, 61.6% knits, 38.4% wovens). From left to right: knit (K) and woven (W) structures, composition (accumulated percentage), density histogram.

Somewhat similar to experimental testing data, draped geometry also represents the mechanical behavior of the fabric after running the fabric through a test. The main difference lies in the nature of the output: in the case of draped geometry, the output is qualitative (the shape of the draped fabric), while in the case of experimental testing data the output is quantitative (usually force-elongation samples). Draped geometry has a corresponding *ground truth* in the real world, the draped fabric. Compared to experimental testing, the draping test itself can be much simpler, free of expensive sensors, actuators and skilled operators. Since the output is qualitative, the difficulty lies in converting the draped fabric (being real or digital) into a usable, meaningful and objective quantity, independent of the subjective assessment of a textile expert. To this end, and as described in Section II, the industry has developed several ways to quantify drape, among which there is the Cusick drape test.

A. *The Cusick Drape Test*

The Cusick drape test [37], [57] is an industry standard method for measuring the drape of a fabric (ISO 9073-9:2008). It provides a high-level quantitative measure of a fabric's drape, known as the drape coefficient (DC) or drape ratio.

During the test, a circular fabric sample of 30 cm in diameter drapes over a support disk of 18 cm in diameter solely under its own weight (Figure 2, top left). The sample is held, or ”sandwiched”, between the support disk and a top-applied disk. The drape coefficient is then calculated as the ratio between the area of the draped outline and the area of the original circular fabric sample (Figure 2 bottom left), expressed as a percentage. Several factors influence a fabric's drape coefficient: stiffness, density, thickness, structure, composition, etc. In general, fabrics with greater flexibility and lighter weight typically exhibit lower DC values, indicating more drapability. In contrast, thicker, denser, and stiffer fabrics tend to have higher drape coefficients and are therefore perceived as less drapable.

In addition to the DC, several other metrics can be derived from the Cusick drape test for a more nuanced characterization of the fabric [57], [58], [59], [60], [61]. Carrera-Gallissà and collaborators [62] analysed these metrics and found that the fold number (FN), the fold height (FH) and the drape unevenness (DU) can be used as *secondary* metrics to complement the DC in accurately characterizing the fabric drape shape and its symmetry. We focus on these four metrics in this work.

The ISO standard precisely defines how to obtain the area of the draped outline: thanks to a carefully positioned light source and a parabolic mirror, the shadow of the draped outline is projected onto a paper sheet, which is then used to compute the area. More recent approaches [63], [30] label themselves as Cusick drape test or drape testing, but differ from the ISO Standard in the use of a photograph of the fabric taken from above rather than its projected shadow, with the advantage of greatly simplifying the testing device. Since lenses are not orthographic, these methods introduce some perspective considerations, but they are still valid as long as different approaches are not mixed together.

The Cusick drape test is not without limitations. First and foremost, it is more sensitive to bending properties than stretch properties. In addition, and like any testing method, it has a margin of error, mainly due to human manipulation and nondeterministic fabric behavior. We have found that the mean repeatability DC error is around 1% (in line with what is reported in commercial documentation [63]), and the front/back error (i.e. by not distinguishing between front and back faces of the same fabric) is around 4%. We refer the reader to Section 4 of the Supplementary Document for more details.

The simplicity and effectiveness of the Cusick drape test in quickly assessing fabric behavior have made it a very practical tool. There are off-the-shelf devices, and custom ones can be easily built with minimal equipment. In addition, the Cusick drape test is extremely easy to replicate in a virtual environment.

B. *The* Digital *Cusick Drape Test*

We replicate the Cusick drape test inside the different CAD tools by first creating a 30 cm diameter circular fabric piece. Then, instead of introducing additional geometry for the two circular disks, we mimic the ”sandwiching” of the fabric by fixing (freezing) the nodes inside the central 18 cm diameter circular region. This approach is much simpler than explicitly modeling and positioning the disks, and has the crucial advantage of avoiding collision dynamics altogether. Collisions often suffer from inexact behaviors and will inevitably introduce some bias, especially at sharp edges. Figure 2 shows the digital Cusick drape test inside CLO's and Browzwear CAD tools. We refer the reader to Section 5 of the Supplementary Document for the specific setup within each software.

After setting the digital fabric parameters, we run a drape simulation and export the resulting fabric geometry. From this data we calculate the drape coefficient by orthographically projecting the contour of the geometry onto the plane parallel to the vertical axis (e.g. the XZ plane if gravity acts along the Y axis). This resulting 2D outline is equivalent to the shadow projected on the paper sheet in the real-world Cusick drape test. From here, we simply calculate the area of the shape and compute the ratio as described in Section IV-A to obtain the DC. We follow a similar procedure to derive the additional metrics (FN, FH, DU) from the drape outline, which we describe in Section 3 of the Supplementary Document.

Using the Cusick drape test, we can therefore evaluate the accuracy of a digital fabric by comparing between real-world and digital metrics. Since we rely on drape rather than physical data, we can evaluate fabrics regardless of the underlying simulation model. This is particularly interesting for the many cases where force data is hard or even impossible to obtain: CAD for apparel [35], [2], Position-Based dynamics [64], and non-physically-based simulators. In addition, the test is easy to implement in both real and digital environments. This makes it a powerful evaluation tool for digital fabrics and, by extension, for digitization methods.

V. Comparative Study

Using the Cusick drape test as an evaluation tool for digital fabrics, we are now able to assess the accuracy of different digitization methods. In particular, we focus on industry-grade digitization methods, which we divide in 2 categories:

- three methods based on traditional fabric sample testing using capture devices. The first method is the reference method (REF), described in Section III, with simulation-in-the-loop parameter estimation. The other two are well established methods from the apparel industry, catering to two different vendors of CAD for apparel: the CLO Fabric Kit [2] for CLO (KIT-CLO), and the Browzwear FAB [3] for Browzwear (FAB-BW). There are several other vendors, such as Optitex [6], Lectra [65], and Style3D [66], with device-based digitization for their own CADs. However, we limited ourselves to the (arguably) most popular methods in the 3D design space to keep the work tractable.
- four methods based on machine learning, requiring only fabric metadata: SEDDI Textura [31] for CLO (TEX-CLO), SEDDI Textura for Browzwear (TEX-BW), CLO Fabric Creator [2] for CLO (FC-CLO), and Vizoo physX [32] for Browzwear (PHX-BW). Other machine learning methods include, as of today, Frontier.cool [67] and Bandicoot Imaging [68].

A. Fabric Dataset

We have collected a dataset of 86 real fabrics with a wide range of mechanical behaviors. Our fabric dataset was curated by experienced textile engineers to roughly represent the typical fabric distribution found in the apparel industry [69]. Figure 3 shows the distribution of fabric properties, such as density, structure and composition.

We have then performed the Cusick drape test on the entire set of fabrics to obtain DC, FN, FH and DU metrics. To minimize the repeatability error of the test, we have done several repetitions for each fabric and use the average as ground truth for our comparisons. In addition, our tests were done on both the front and the back side of each fabric, and we have purposely averaged the metrics without making a per-side distinction. This is to take into account the lack of such distinction in the digital fabric model of CAD simulators, where the bending stiffness is treated as symmetric in both out-of-plane directions. We have also automated the metric calculation process by using a carefully calibrated camera to take photographs of the projected shadow rather than manually drawing and cutting the outline, and used a computer vision algorithm to extract the shadow area from the photographs. For more details, we refer the reader to Section 3 of the Supplementary Document.

To have a reference range for the different digitization methods, we included the method from Section III in the study. Since this method is on par with state of the art fabric digitization techniques, its accuracy error will serve as a lower bound to compare against. Similarly, we also evaluate a naive baseline estimator that always produces the average metrics of the entire dataset. The accuracy error of this baseline model serves as upper bound and any digitization approach should be expected to perform better.

We then digitized the real fabrics from the dataset using the 7 digitization methods (REF, KIT-CLO, FAB-BW, TEX-CLO, TEX-BW, FC-CLO and PHX-BW), and then ran digital Cusick drape tests on all of the digital fabrics. For KIT-CLO, TEX-CLO and FC-CLO we used CLO's CAD software, while for FAB-BW, TEX-BW and PHX-BW we used Browzwear's CAD software (VStitcher). For REF, we used SEDDI's CAD software (Author). The KIT-CLO and FAB-BW digitizations were contracted to several independent third party vendors, while the rest were done by the authors using either capture devices (REF) or commercial software packages (TEX-CLO, TEX-BW, FC-CLO, PHX-BW). We had to make minor metadata adjustments for a few fabrics when using metadata-based digitization methods: we refer the reader to Section 6 of the Supplementary Document for more details.

B. Results and Analysis

The main results are summarized in Figure 4, which compares the DC values of all 7 digitization methods with the ground truth for all fabrics in the dataset. Table I summarizes the absolute error metrics on the drape coefficient and the Pearson correlation coefficient r of all digitizations with the ground truth.

The best performing method, as expected, is REF, with a mean absolute error of 7.4. The next best performing method is KIT-CLO, increasing the error to 10.9. It should be noted that these two methods, while device-based, show

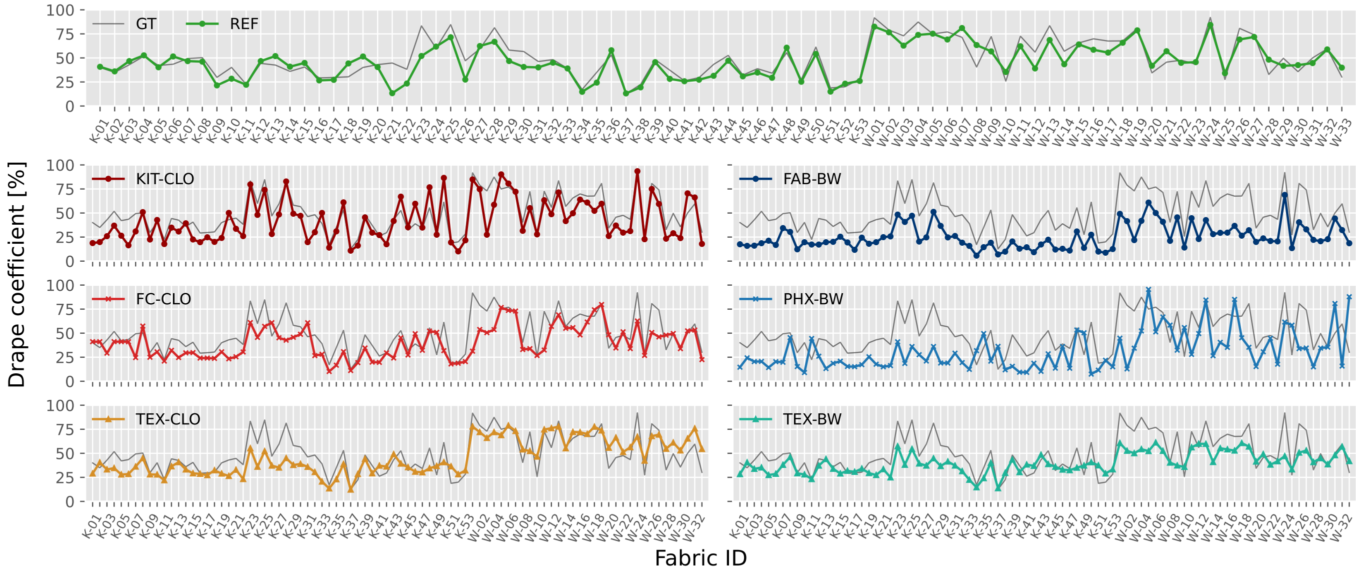

Fig. 4. Comparison of the DC values from all 7 digitization methods with the ground truth (GT) for all fabrics in the dataset. The x axis is the fabric ID (K for knits, W for wovens), and the y axis is the Drape Coefficient. The real (thin, in grey) and its corresponding digital (thick, in color) drape coefficients are plotted for each fabric.

TABLE I

MAIN STATISTICAL RESULTS FOR THE DRAPE COEFFICIENT METRIC: MEAN ABSOLUTE ERROR (MAE) FOR EACH DIGITIZATION METHOD, MINIMUM (MIN) AND MAXIMUM (MAX) ERRORS, VARIANCE, AND PEARSON CORRELATION COEFFICIENT r.

	MAE	Min	Max	Variance	r
REF	7.37	0.00	31.38	40.75	0.88
Baseline	15.95	0.04	42.76	121.69	-
KIT-CLO	10.91	0.22	45.56	62.56	0.85
FC-CLO	12.31	0.03	60.47	127.13	0.72
TEX-CLO	11.58	0.33	36.34	61.77	0.74
FAB-BW	24.05	5.33	51.15	107.47	0.87
PHX-BW	25.09	0.30	66.14	190.29	0.36
TEX-BW	12.65	0.26	45.03	90.92	0.78

TABLE II

STATISTICAL RESULTS FOR THE SECONDARY METRICS: MEAN ABSOLUTE ERROR (MAE) AND PEARSON CORRELATION COEFFICIENT r OF THE RESPECTIVE METRIC FOR EACH DIGITIZATION METHOD.

	FN		FH		DU	
	MAE	r	MAE	r	MAE	r
REF	1.69	0.59	3.62	0.64	10.54	0.19
Baseline	1.81	-	4.94	-	9.67	-
KIT-CLO	1.31	0.64	4.49	0.65	8.62	0.28
FC-CLO	1.42	0.48	5.23	0.48	10.21	0.18
TEX-CLO	1.47	0.33	5.11	0.54	11.71	0.13
FAB-BW	2.99	0.45	5.93	0.15	10.07	0.05
PHX-BW	2.67	0.25	6.25	0.11	11.69	-0.12
TEX-BW	1.99	0.21	4.76	0.32	12.18	0.12

an error that is far from insignificant, proving that device-based digitizations have their own limitations in terms of accuracy. Closely following come TEX-CLO and FC-CLO, which slightly increase the error to 11.6 and 12.3 respectively. This is remarkable, since they are very close to the results of KIT-CLO by only using fabric metadata and without ever needing physical access to the real fabric. Also similar in performance is TEX-BW, with an error of 12.6.

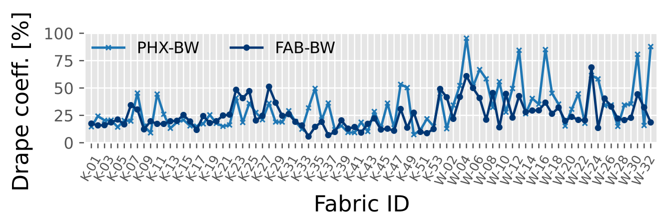

Fig. 5. Comparison of PHX-BW (cross, light blue) with FAB-BW (dot, dark blue) digitization methods. The x axis is the fabric ID (K for knits, W for wovens), and the y axis is the drape coefficient.

Surprisingly, next in line we find the baseline model with an error of 15.9, followed by far by FAB-BW and PHX-BW, with respective errors of 24 and 25.1. The plots in Figure 4 show that the source of these large errors is a strong bias in both cases, leading to lower drape coefficients, suggesting an underestimation of fabric rigidity. This is also supported by the fact that the correlation coefficient of FAB-BW is very similar to the other two device-based methods (REF, KIT-CLO) despite the higher MAE. The fact that TEX-BW does not show this same bias suggests that the issue is not with the digital test. This leads us to speculate that the problem lies in the Browzwear FAB digitization method having a consistent estimation bias. Since the Vizoo physX model was likely trained to match the outputs of the Browzwear FAB, it inherited the same bias. Figure 5 indeed shows a better agreement between the two digitizations, and the Pearson correlation coefficient of PHX-BW with respect to FAB-BW ($r = 0.46$) is larger than that of PHX-BW with respect to ground truth ($r = 0.36$), although it arguably remains weak. This analysis is speculative, and the lack of source code access to Browzwear's simulation software prevents us from investigating any further.

1) Secondary metrics: Table II summarizes the results for the secondary metrics FN, FH and DU. Additional plots can be found in the Supplementary Document. Some trends observed for the DC emerge here as well. In particular, FH shows exactly the same trend for all the digitizations. FN yields similar results, but in this case favoring the CLO-based digitizations, even over REF.

A clear difference, however, is found on the metrics' correlation to their real fabric counterparts, which are very degraded with respect to the DC results. This is even more evident for DU, where very low and even negative correlations are found. To rule out a possible limitation of the Cusick test itself, we assess the reliability of the metrics obtained from the real fabrics by computing the Intraclass Correlation Coefficient (we report ICC(2,1) values [70], but all ICC variants yield almost identical results). For reference, the DC measurements show an ICC value of 0.99, hinting at an excellent reliability. We see a drop for FN and FH with ICC values of 0.86 and 0.85 respectively, although still suggesting a good reliability [71]. A notable drop is found for the DU metric with an ICC value of 0.56, pointing at a moderate reliability [71], which can partially explain the poor observed performance. Further examination of the results shows that the mean DU value for real fabrics is 24.81, while the mean DU values for all digitized fabrics fall in the range [13.64 – 19.46] for all digitization methods. This reveals an interesting phenomenon: digital fabrics tend to produce more isotropic drapes than real fabrics, regardless of the digitization approach and the simulation engine used. Although surprising at first, this result is, in fact, reasonable: real fabrics exhibit slightly spatially varying mechanical properties, gained both during construction [72] (uneven yarns and manufacturing imperfections), and during usage (elastoplastic behavior from folding, washing and manipulation due to internal friction [46]). Commercial fabric simulators, on the other hand, apply spatially homogeneous mechanical properties to fabric pieces and ignore internal fabric friction, leading to a more even behavior. In addition, commercial simulators tend to rely on triangle-based discretizations, which are known to suffer from some degree of locking that can result in artificially decreased anisotropic behavior [73].

2) Analysis by fabric property: We have also analyzed the DC of all digitization methods by grouping fabrics in different clusters, in an attempt to identify the influence of specific fabric properties on digitization accuracy.

To study *fabric density*, we have split the fabrics into 4 buckets of equal range and computed the per-cluster DC MAE, which is shown in Figure 6. We see that device-based methods tend to perform similarly in all density ranges, particularly for REF and CLO-KIT. Metadata-based methods, on the other hand, seem to consistently perform best for lower density fabrics, even outperforming device-based methods, but show decreasing performance as density increases. This analysis reveals a useful insight for practitioners: metadata-based digitization methods are already comparable with device-based methods for low-density fabrics.

Unfortunately, doing a similar analysis based on *fabric structure* (as shown in Figure 6) or based on *fabric composition* doesn't reveal any relevant trends, probably due the small number of samples in each cluster. We leave this fine-grained analysis for future work, as it requires a significantly larger dataset.

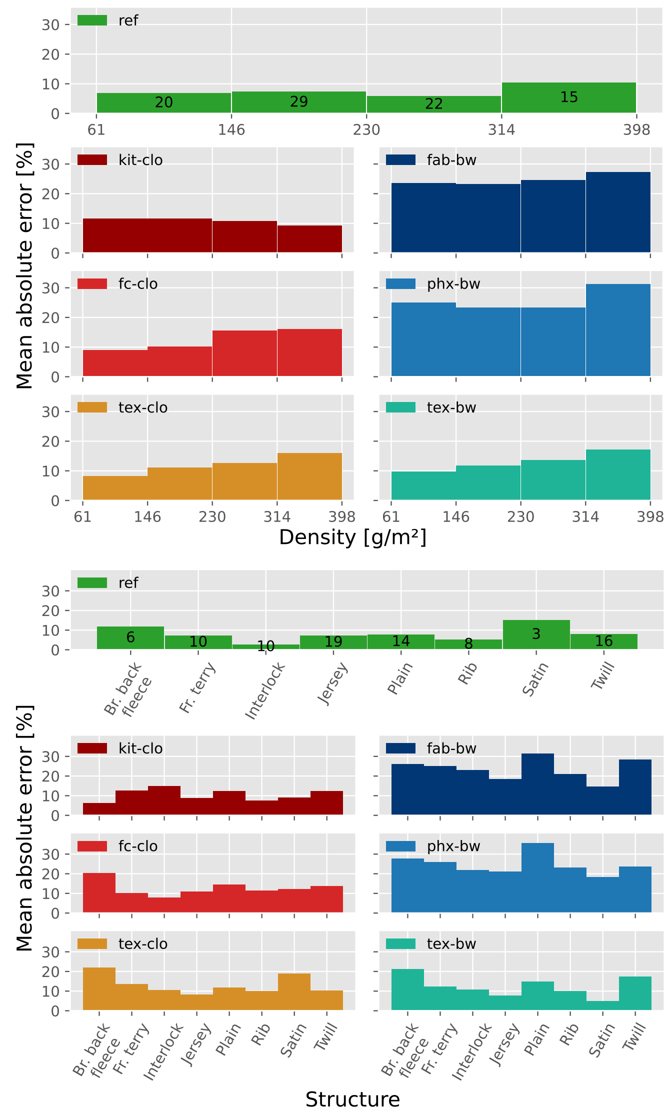

Fig. 6. Mean absolute error of the drape coefficient for all digitization methods, grouped by different fabric properties. Top plots group fabrics in four buckets based on density. Bottom plots group them by structure.

3) Device vs Metadata Digitization: We now compare device-based and metadata-based digitization methods. Figure 7 shows actual versus predicted plots for the drape coefficients, including the perfect fit line and the regression line, while Figure 8 shows the corresponding residual plots to provide further insight into their behaviors.

The residual plots of the three device-based approaches show relatively constant variance throughout the domain, that is, homoscedasticity. A slight increase in variance is observed in the central part of their residual plots but, in our context, this is expected given the increased sensitivity of the Cusick drape test in that middle range. The REF method shows no bias, which, together with the homoscedasticity property, suggests good estimation capabilities and reliability across the range of fabrics. The KIT-CLO method shows a slight underestimation bias in the low rigidity range but maintains good overall accuracy, reflected in its corresponding regression line. The FAB-BW method, on the other hand, exhibits the clear underestimation bias previously discussed, becoming less accurate and reliable as fabric rigidity increases.

The residual plots (Figure 8) of all metadata-based digitization methods (TEX-CLO, TEX-BW, FC-CLO, PHX-BW) show similar homoscedasticity properties as well, which suggests that their underlying models are able to capture most of the non-linear relationships present in the data. Interestingly, their Actual vs. Predicted plots (Figure 7) reveal some degree of underestimation bias for fabrics in the high rigidity regime. This effect is less evident in the case of TEX-CLO, but becomes significant in TEX-BW, FC-CLO and PHX-BW, and may explain the slightly lower correlation coefficient of these digitization methods compared to the device-based methods (with the exception of PHX-BW, which has a significantly lower correlation, as previously discussed). We speculate that this may be a consequence of the fact that the apparel industry tends to favor low to mid rigidity fabrics [74], [58]. Figure 9 shows the histogram of the real drape coefficients for all fabrics in our dataset, indeed showing a skew towards lower values. Fabric density and rigidity are slightly correlated ($r = 0.26$ between fabric density and DC for our dataset), so this could also explain, at least in part, the results of our density-wise analysis. Estimation models trained on datasets reflecting this uneven distribution can naturally lean towards more prevalent characteristics, leading to the bias observed in our study. Augmenting the training dataset with underrepresented fabrics in the mid to high rigidity range should naturally improve the performance of metadata-based digitization tools, and is therefore a promising avenue for future work.

VI. Conclusion

For digital garments to become pervasive in the apparel industry, practitioners must be able to trust the behavior of these digital twins. With this goal in mind, digital fabrics need to be verifiably accurate in terms of mechanical behavior. Systematic evaluation procedures to compare and improve fabric digitization methods can favor this endeavor.

In this work, we have discussed different accuracy evaluation approaches, and we propose the use of the Cusick drape test to measure the accuracy of a digital fabric and compare fabric digitization methods. We have introduced an ad-hoc device-based digitization pipeline to serve as reference and we have conducted a comprehensive study including other six commercially available device-based and metadata-based digitization methods. For the study we have gathered a dataset of real fabrics with their corresponding Cusick drape test. We have then digitized all fabrics in the dataset with the evaluated methods, and ran the corresponding digital Cusick drape tests.

Our analysis shows that, while more ad-hoc digitization methods yield better results on average, metadata-based solutions can already offer competitive digitizations for a fraction of the cost, time and logistics requirements. They already offer

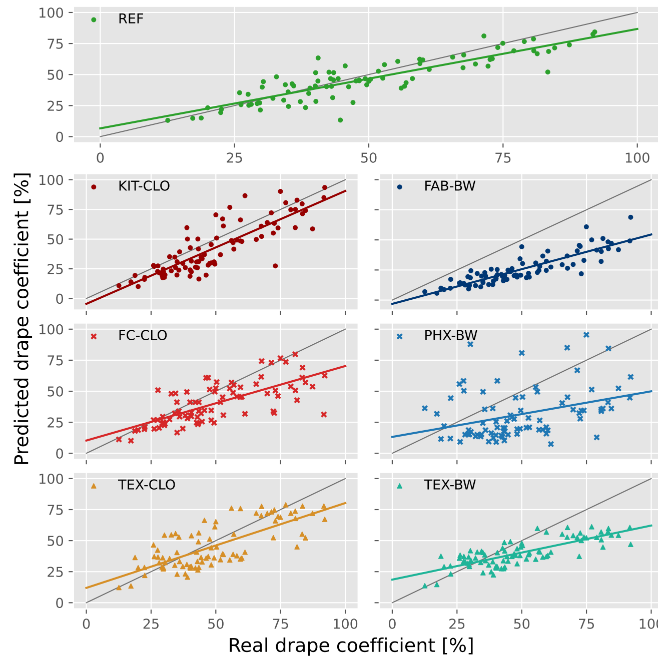

Fig. 7. Actual versus Predicted plots for the drape coefficients. The x axis represents the real drape coefficients of all the fabrics in the dataset, and the y axis represents the corresponding digital drape coefficients for a given digitization method. Each plot also shows the regression line (thick, in color), and the perfect fit line (thin, in grey).

comparable and sometimes even better results for low density fabrics.

Our study also shows that current commercial fabric simulators tend to produce more isotropic drapes than their real counterparts, independently of the digitization method used. Recent approaches in the research literature address this problem directly by targeting the locking problem and using more complex bending models that better replicate the non-linear behavior of fabric [30], [26], but to our knowledge, have not yet made their way into commercial products.

We also provide the collected dataset as a contribution, including the metadata of the fabrics (density, thickness, structure, composition), their real drape metrics, and all digitizations with their corresponding digital drape metrics, so that it can be used to evaluate and compare additional digitization methods or future evolutions of existing methods. For more details, see Section 1 of the Supplementary Document.

Our study leverages the most informative metrics derived from the Cusick drape test, quantitatively characterizing fabric drape [62]. However, this test alone is not capable of capturing other relevant mechanical behaviors, such as non-linear stretch deformation in compression fabrics or frictional properties. There are in fact other standardized tests [75], [76] and more novel setups [24] that can easily target some of these relevant behaviors and that are also easy to adapt to a virtual setting. Our ICC analysis also suggests that an additional test designed to evaluate fabric anisotropy could complement the Cusick test, as the DU metric shows only moderate reliability. Recent efforts in the computer graphics community also aim to evaluate the mechanical models together with the simulators

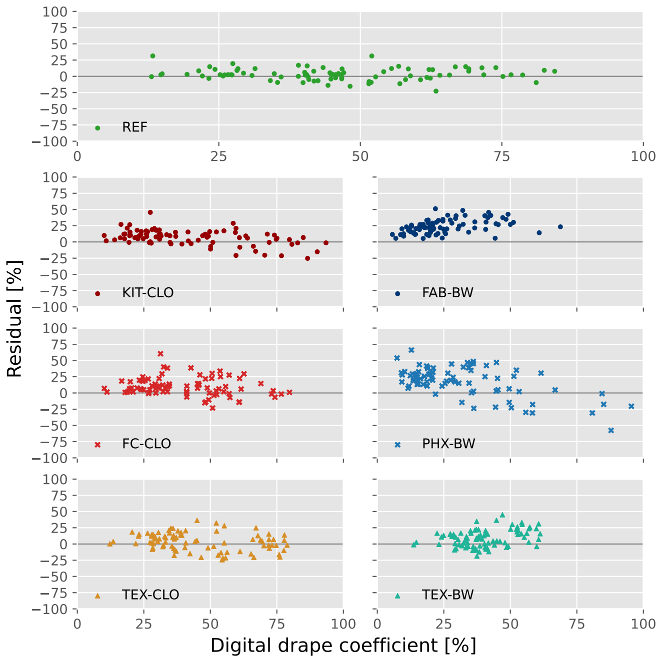

Fig. 8. Residual plots for the drape coefficients. The x axis represents the digital drape coefficients of all the fabrics in the dataset, and the y axis represents the residuals (difference between the real drape coefficients and their corresponding digital drape coefficients) for a given digitization method. Each plot also shows the perfect fit line (y=0, in grey).

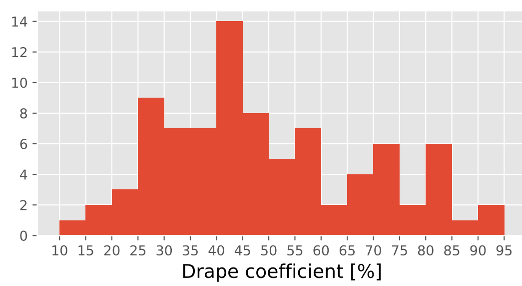

Fig. 9. Histogram of real drape coefficients for all fabrics in our dataset, showing a skew towards lower values. The x axis is the drape coefficient.

[77], including fabric bending models [26]. We believe that these can complement the Cusick drape test, forming a sort of virtual lab test set to evaluate the digital fabric properties most relevant to the apparel industry.

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