scientific reports

OPEN

Predicting human tactile smoothness/roughness perception from multidimensional mechanical properties of synthetic fibers using machine learning

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Accurately predicting human perception of tactile roughness remains challenging because previous models often used limited mechanical properties, small sample sizes, and insufficient validation methods. To address these limitations, we developed a predictive model integrating multidimensional mechanical properties and subjective evaluations of tactile perception, using 50 commercially available synthetic fiber samples, including polyester, spandex, nylon, and their blends. Twelve mechanical properties were measured across four categories: geometric roughness, frictional force, hardness, and tensile strength. Tactile perception of smoothness/roughness was evaluated by 37 participants using a 5-point scale, with lower values indicating smoother textures and higher values indicating rougher textures. Correlation analysis identified kinetic friction coefficient (KF, ρ = -0.67), arithmetic mean roughness (Ra, ρ = 0.44), mean width of profile elements (RSm, ρ = 0.42), maximum load (ML, ρ = -0.41), and root mean square slope (Rdq, ρ = 0.31) as key predictors. Among six regression models, Gaussian process regression showed the highest predictive accuracy (cross-validated R^2 = 0.71). Comparisons between non-cross-validated and cross-validated results revealed substantial performance drops in cross-validation, underscoring the risk of performance overestimation without rigorous validation. The proposed framework provides a robust, generalizable approach applicable to broader tactile dimensions, benefiting material evaluation, product development, and haptic technologies.

Keywords Tactile perception, Smoothness/roughness perception, Mechanical properties, Regression model

Tactile perception refers to the subjective sensation formed by integrating information received through receptors distributed across the skin. This perception includes tactile attributes such as smoothness/roughness, softness/hardness, coldness/warmth, and springiness/stiffness. These tactile attributes play essential roles not only in evaluating material comfort, but also in shaping user experience across a wide range of domains, including consumer products, virtual reality, robotics, and rehabilitation[1–3]. Smoothness/roughness is particularly influential in how users judge surface quality and usability in both daily interactions and specialized applications. Therefore, developing reliable methods for evaluating smoothness/roughness is crucial for quality control, material development, and consumer satisfaction across industries.

Given this importance, researchers have proposed various quantitative methods to evaluate smoothness/roughness based on surface mechanical properties, ranging from surface friction measurements to advanced analyses of nanoscale microstructures. Recent studies have achieved remarkable spatial resolutions (10 nm–1 μm) using sophisticated measurement techniques for surface smoothness/roughness measurement[4,5]. However,

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these quantitative mechanical measurements alone cannot fully capture human perceptions of smoothness/roughness[6,7] because such perception involves subjective interpretations influenced by multisensory integration, context, and individual variability. Consequently, integrating quantitative mechanical measurements with subjective evaluations of smoothness/roughness is increasingly recognized as essential.

Early studies primarily explored relationships between perceived smoothness or roughness and individual mechanical properties, such as surface geometry or frictional force. More recent research emphasizes that tactile perception arises from the complex interactions among multiple mechanical factors, including surface topography, height variation, spacing patterns, and material composition[8]. Multiparameter modeling approaches have consistently outperformed single-feature methods, showing significant improvements in predictive performance (R^2) of approximately 0.20 to 0.35[8,9]. These findings highlight the necessity of multidimensional approaches that comprehensively integrate geometric properties (e.g., surface height and spacing), contact-related properties (e.g., friction and hardness), and intrinsic material properties for accurate tactile perception modeling.

While multidimensional approaches are essential, achieving a balance between experimental control and practical relevance is equally important. Most previous studies used artificially manufactured samples via 3D printing or lithography to ensure precise control. Although these studies reported high predictive accuracy (classification accuracies and regression R^2 values ranging from approximately 0.75 to 0.89), their generalizability to real-world materials, influenced by multiple uncontrolled factors, remains limited[10–12]. Artificial samples typically simplify complex real-world textures by varying only a few parameters, insufficiently capturing the intricate interplay among mechanical factors. To overcome this limitation, it is necessary to investigate perception using realistic materials that naturally embody diverse mechanical interactions.

As research increasingly emphasizes linking mechanical properties to human tactile perception using real-world samples, developing predictive models with practical generalizability has become crucial. Achieving this involves multidimensional feature integration coupled with rigorous validation. Cross-validation, particularly, ensures models accurately predict tactile responses for unseen materials. Recent studies by Lee et al. and James et al. illustrated that neglecting proper cross-validation procedures leads to inflated accuracy, dramatically reducing predictive reliability on new data[13,14]. Although previous tactile studies reported high performance (R^2 values of 0.72–0.92), many evaluated their models using the same datasets used for training, limiting their applicability[10,12,15]. To ensure reliable and transferable outcomes, predictive tactile models must incorporate robust cross-validation procedures.

This study aims to develop a predictive model for human smoothness/roughness perception based on multiple mechanical properties of fiber materials, making three significant contributions to tactile perception research. First, we systematically selected nine representative mechanical features from an initial set of twelve through multicollinearity analysis, enabling comprehensive yet non-redundant characterization of fiber surfaces. This approach represents a methodological improvement compared to earlier studies that typically considered fewer parameters without systematic feature selection. Second, we used 50 diverse synthetic fibers commonly encountered in daily life, including polyester, spandex, nylon, and their composites. This sample size significantly expands upon the relatively small number of samples (typically 10–20) used in earlier research. Third, we rigorously evaluated model performance through fivefold cross-validation, addressing previous limitations of studies reporting high predictive accuracy without independent validation. Utilizing these selected features, we developed and evaluated six regression models, determining the most effective approach for predicting smoothness/roughness perception. Our approach provides a robust and transferable framework for modeling tactile perception, with potential applications in material evaluation, product development, and haptic technology design, and it has the potential to be extended to other tactile dimensions such as softness, hardness, and thermal sensations. Furthermore, recent studies have reported a closed loop from afferent tactile signals generated by object-skin contact to active human behavior[16]. Our study may provide a foundation for predicting human motor responses.

Methods

Material preparation

In this study, 50 synthetic fibers commonly used in practical applications were selected for experimental analysis. The fiber samples were classified into single-component and composite groups. The single-component group consisted of 30 samples of 100% polyester and 2 samples of 100% nylon. The composite group included 18 blended samples: polyester-based (9 polyester/spandex, 2 polyester/polyurethane combinations) and nylon-based blends (5 nylon/spandex, 2 nylon/polyurethane combinations). These fiber types were chosen to reflect materials frequently encountered in textile and apparel products, enabling the development of a practically relevant model for predicting tactile smoothness/roughness perception.

Polyester, representing approximately 70% of the global fiber market, was primarily selected due to its significant market share, durability, cost-effectiveness, and widespread industrial and consumer applications[17]. Nylon and synthetic blends were also included because of their common use in functional and everyday clothing, offering diverse tactile and mechanical characteristics such as variations in friction, elasticity, and surface texture. The inclusion of blended materials particularly enhances the model's applicability, reflecting the complexity of real-world tactile experiences.

Mechanical property measurement

Human tactile smoothness/roughness perception arises from the integration of various stimuli detected by mechanoreceptors in the skin during surface contact. To accurately model this complex perceptual process, we measured 12 mechanical properties across four categories that comprehensively characterize fiber surfaces: First, two frictional properties of the samples were assessed using standardized testing methods. Although these tests may not fully replicate finger-surface interactions, they allow objective comparisons among materials and have been validated as reliable predictors of tactile perception in numerous studies[18]. Second, geometric roughness properties were evaluated through seven parameters defined in the ISO 4287 standard. It specifies profile-based geometric smoothness/roughness, including Ra, Rq, Rz, Rsk, Rku, and RSm, providing a standardized framework for quantifying surface micro-geometry. It is commonly applied in conjunction with ISO 4288, which defines measurement and filtering procedures to ensure comparability across instruments and laboratories[19]. Third, Shore hardness was measured to account for the influence of material hardness on tactile sensation. Hardness has been demonstrated by Yeo et al. (2017) to significantly impact tactile feedback during contact[20]. Lastly, two tensile properties, including strength and extensibility, were examined to reflect material deformation under tactile interaction forces. These mechanical attributes significantly contribute to tactile experiences in textile perception[21]. The twelve selected properties collectively represent diverse aspects of tactile interactions between human skin and fiber surfaces. This multidimensional approach effectively captures the complex microstructure characteristics that cannot be adequately represented by a single roughness parameter[22]. Each property was measured 10 times per sample, and mean values were calculated to ensure measurement reliability.

Friction force measurement

The frictional characteristics of the fiber samples were quantified by measuring the static (SF) and kinetic friction (KF) coefficients using a friction coefficient tester (QMESYS, Korea)[23]. Measurement conditions included a load cell of 1.0 kgf, movement speed of 200.0 mm/min, and friction weight of 200.0 g. Friction force was measured by securing each fiber sample to the friction element. The SF coefficient was recorded at the initiation of movement, while the KF coefficient was measured during constant velocity motion.

Geometric smoothness/roughness measurement

Geometric smoothness/roughness of the fiber samples was measured using an Alpha-Step IQ surface profiler (KLA Tencor, USA)[24]. Measurement parameters included a sampling rate of 200 Hz, scan length of 5.0 mm, and scan speed of 0.1 mm/sec. Seven parameters were extracted from the profiles based on ISO 4287 standard: arithmetic mean roughness (Ra), root mean square roughness (Rq), maximum height of the profile (Rz), mean width of the profile elements (RSm), skewness of the profile (Rsk), kurtosis of the profile (Rku), and root mean square slope (Rdq).

Hardness measurement

Shore hardness (SH) of fiber samples was measured using an HT-6510 hardness testers (REED Instruments, USA)[25]. The tester was mounted on a support stand, and SH was measured at multiple points on each fiber sample to obtain representative hardness values.

Tensile strength measurement

Maximum load (ML) and elongation at break (EB) of the fiber samples were measured using Instron tensile testing machine (Instron, USA)[26]. Measurements were conducted at a tensile speed of 100.0 mm/min. ML represents the peak force that fibers withstand before breaking, while EB is expressed as the percentage of extended length relative to initial length at rupture, quantitatively evaluating the strength and extensibility of each fiber sample.

Tactile perception evaluation

Participants

The experiment was conducted with 37 healthy adult volunteers (23 males and 14 females; mean age: 24.1 ± 2.6 years). Participants had no mental or physical disorders, nor any history of sensory nerve damage. The study protocol was approved by the Institutional Review Board of Korea University (IRB-2024-0163). All processes were conducted in accordance with the relevant guidelines and regulations, including the principles outlined in the Declaration of Helsinki. Before the experiment, participants were informed about the study objectives, procedures, and necessary precautions, after which they provided informed consent. Appropriate compensation was provided upon completion of the experiment.

Experimental procedure

The tactile smoothness/roughness perception experiment was conducted using 50 fiber samples. Participants' hands were thoroughly cleaned prior to evaluation to eliminate interference from foreign substances or perspiration. Detailed instructions on the evaluation method were provided, and participants practiced with sample materials until they were comfortable with the procedure. All fiber samples were stored under identical environmental conditions and presented in random order.

To minimize perceptual variations, tactile perception was assessed using only the distal phalanx of the right index finger[27]. Participants moved their index finger horizontally across each fiber sample, ensuring consistent tactile stimulation and reliable assessments. Participants classified each sample on a 5-level scale, with lower values indicating smoother textures and higher values indicating rougher textures. This 5-point classification scheme is consistent with established practices in tactile research, effectively capturing meaningful differences in human tactile perception with optimal sensitivity and minimal complexity[28,29]. The use of this approach ensured a balanced distribution of samples across perception levels (Fig. 1), providing adequate statistical power and reducing potential bias during regression analyses, particularly within the cross-validation procedure for assessing predictive model generalizability. The responses from all 37 participants were averaged for each fiber sample to derive representative tactile perception values, which were subsequently used for modeling the correlation between human tactile perception and physical properties.

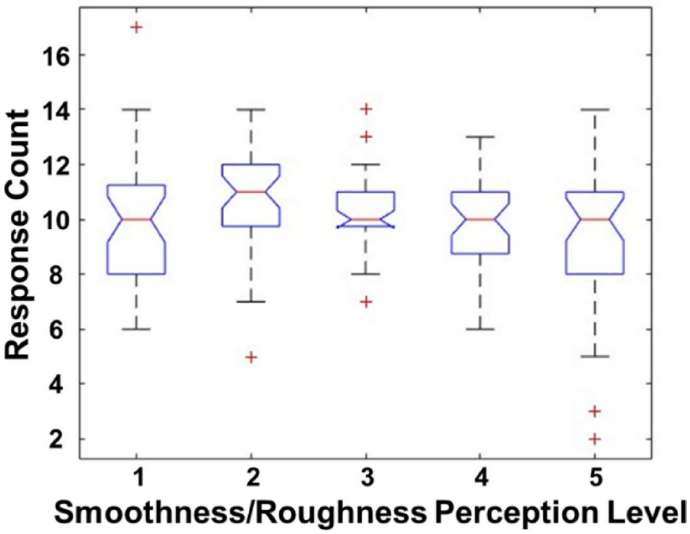

Fig. 1. Distribution of samples across smoothness/roughness perception levels. The boxplot illustrates the number of participant responses for each perception level. Lower values indicate smoother textures, while higher values indicate rougher textures.

	Mechanical properties											
	SF (a.u.)	KF (a.u.)	Ra (μm)	Rq (μm)	Rz (μm)	RSm (μm)	Rsk (a.u.)	Rku (a.u.)	Rdq (μm)	SH (a.u.)	ML (N)	EB (%)
Min	0.12	0.13	5.23	6.36	25.58	0.16	-0.68	1.62	19.12	49.43	0.05	4.95
Max	0.67	0.70	39.53	43.85	148.47	0.75	0.36	3.83	60.43	83.38	0.39	93.44
Mean	0.37	0.38	18.10	21.82	86.72	0.33	-0.07	2.69	46.78	71.17	0.17	34.07
Std	0.13	0.13	8.32	9.32	31.68	0.12	0.25	0.46	9.22	8.38	0.08	21.8

Table 1. Summary of statistical results for each mechanical property before z-score normalization.

Data analysis and modeling

Data preprocessing

All analyses were performed in MATLAB R2023b (version 10; The MathWorks, Natick, MA, USA). The mechanical properties possess varying units and ranges, complicating their direct comparison in smoothness/roughness perception prediction models. For instance, Ra is measured in micrometers (μm), two friction coefficients (SF and KF) are dimensionless values, and SH uses a scale from 0–100 (Table 1). Such scale discrepancies may cause disproportionate influence of certain features or underestimation of important ones during model training. To resolve this issue, each mechanical property was normalized using standard scores (z-scores)[30], calculated as follows:

$$Z = \frac{X - \mu}{\sigma} \tag{1}$$

where Z is the standardized value, X represents the original data value, μ is the mean of the respective feature, and σ is the standard deviation of the feature. Within each cross-validation fold, the μ and σ were estimated using only the training set. These statistics were then applied to compute the z-scores for both the training and the held-out test data, thereby preventing data leakage. This normalization transforms all mechanical properties into distributions with a mean of 0 and a standard deviation of 1, facilitating direct feature comparison. Normalized data enhances the accuracy of feature importance assessment and improves the convergence and stability of machine learning algorithms.

Multicollinearity analysis

Addressing multicollinearity among independent variables is essential for accurate and reliable regression modeling. Multicollinearity occurs when independent variables exhibit high correlations, potentially destabilizing regression coefficients and complicating model interpretation. Specifically, including highly correlated variables together makes it difficult to assess their distinct effects, which can negatively impact model performance[18]. To identify multicollinearity issues, Variance Inflation Factor (VIF) analysis was conducted on the initial 12 mechanical properties. A VIF value exceeding 10 generally indicates severe multicollinearity[27]. The VIF was computed within each cross-validation fold using only the training split, and the resulting values were aggregated across folds. We report the VIF as the mean ± standard deviation. The analysis identified severe multicollinearity in SF (192.93 ± 86.18), KF (188.89 ± 85.18), Ra (1306.40 ± 256.88), and Rq (2355.20 ± 495.13), Rz (249.12 ± 86.18), while acceptable VIF values were observed for Rsk (1.67 ± 0.09), Rdq (3.23 ± 0.24), RSm (2.69 ± 0.27), Rku (5.19 ± 1.75), SH (1.83 ± 0.17), EB (1.41 ± 0.13), and ML (2.02 ± 0.15).

Geometric smoothness/roughness parameters Ra, Rq, and Rz showed particularly high intercorrelations (ρ > 0.95), as all represent surface height deviations similarly. Among these, Ra—the arithmetic mean roughness—is widely recognized and thus selected as the representative parameter[22]. Similarly, friction parameters SF and KF were highly correlated (ρ > 0.99). KF was selected as the representative parameter due to its closer relationship with tactile perception, as it directly reflects resistance experienced during finger movement at constant speed. During tactile exploration, participants primarily perceive dynamic frictional properties, making KF more relevant than SF[13]. Following this feature selection, nine properties were retained: KF, Ra, RSm, Rsk, Rku, Rdq, SH, ML, and EB. These features exhibit acceptable VIF levels and comprehensively represent essential mechanical properties for robust tactile perception prediction modeling (Fig. 2).

Regression model construction and validation

Six regression models were utilized to analyze the relationship between fiber mechanical properties and smoothness/roughness perception: linear (fitlm), Gaussian process (fitrgp), support vector (fitrsvm), random forest (TreeBagger), gradient boosting (fitrensemble), and neural network (trainNetwork) regression. All models were run using default settings; however, when mandatory inputs were required, we set the number of trees in the Random Forest to 100 and specified a three-layer neural network with 10 nodes per layer. Model performance and generalization capability were evaluated through fivefold cross-validation[5]. For all regression models, model fitting and hyperparameter tuning were performed strictly within each training fold of the cross-validation. The dataset (N = 50) was randomly partitioned into five subsets, with four subsets (N = 40) used for training and the remaining subset (N = 10) used for validation. Optimal parameters were determined solely by using the training data through an internal grid search procedure. The trained model was then evaluated on the corresponding held-out test fold, ensuring that no information from the test data influenced model selection or training. This approach effectively prevents data leakage and provides an unbiased estimate of model performance. This procedure was repeated five times, allowing each subset to serve once as a validation set, thereby utilizing all data evenly in the evaluation. The predictive performance was assessed using the coefficient of determination (R^2), which indicates how effectively a model explains variance in the data, ranging from 0 to 1, with values closer to 1 representing higher accuracy. The R^2 was calculated as follows:

$$\mathrm{R}^2 = 1 - \frac{SSR}{SST} \tag{2}$$

where SST (Sum of Squares Total) and SSR (Sum of Squares Residual) are defined as:

$$SST = \sum (y_i - \overline{y})^2 \tag{3}$$

$$SSR = \sum (\hat{y}_i - y_i)^2 \tag{4}$$

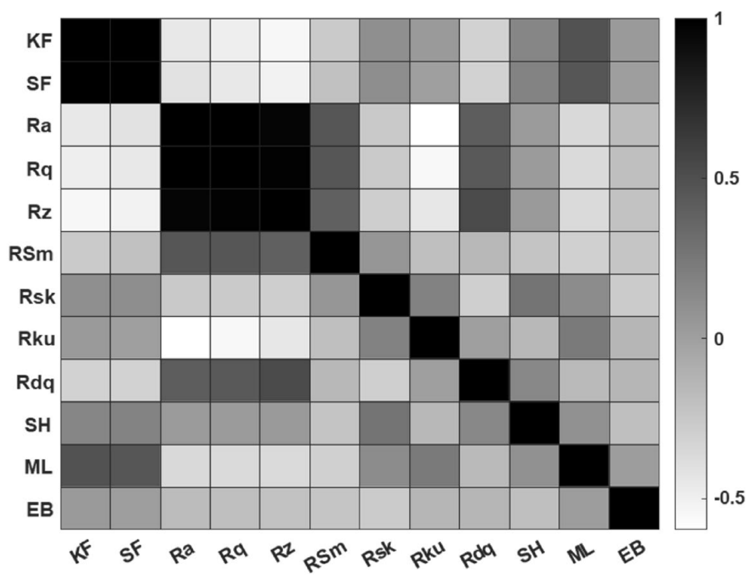

Fig. 2. Correlation matrix of mechanical properties illustrating multicollinearity. Among highly correlated parameters, KF was selected over SF, and Ra was chosen among Ra, Rq, and Rz as representative features.

Here, y_i represents the actual values, $\overline{y}$ is the mean of the actual values, and $\widehat{y_i}$ represents the predicted values.

In this study, model performance was evaluated using two methods: first, a single evaluation by training and testing on the entire dataset (non-cross-validation), and second, using fivefold cross-validation. This dual approach detects potential overestimation of performance when models are evaluated on training data alone, providing a more accurate estimate of generalization capability. The single evaluation method aligns with previous tactile perception research, facilitating direct comparisons, but it does not reliably reflect performance on unseen samples—an essential factor in practical applications such as material design and quality control. Therefore, we report both single evaluation results for consistency with prior work and cross-validation results to better represent expected performance on novel samples. Comparing these two evaluation methods also helps identify potential overestimation of model performance and enhances understanding of model generalizability.

To optimize predictive performance, a feature selection process was implemented. After identifying the nine features with acceptable VIF values, we systematically evaluated each regression model across all possible feature combinations using fivefold cross-validation. This procedure identified the optimal set of features that maximized predictive performance for each regression technique. Additionally, we analyzed the frequency of feature selection across all optimal models to identify mechanical properties consistently recognized as important predictors of smoothness/roughness perception. Consequently, because the non-cross-validation setting was performed only once for all samples, we report only the accuracy without a standard deviation. In contrast, for fivefold cross-validation, both accuracy and standard deviation were computed across folds and are reported together.

Results

Correlation between mechanical properties and smoothness/roughness perception

Figure 3 presents scatter plots illustrating Pearson correlations and false discovery rate (FDR)-adjusted two-sided p-values between each of the nine normalized mechanical properties and smoothness/roughness perception. Among the measured properties, KF demonstrated the strongest negative correlation (ρ = -0.67, p = 0.00). Ra and RSm showed moderate positive correlations (ρ = 0.44, p = 0.01 and ρ = 0.42, p = 0.01, respectively), while ML exhibited a moderate negative correlation (ρ = -0.41, p = 0.01). Rdq displayed a relatively weak positive correlation (ρ = 0.31, p = 0.05), and EB showed a weak negative correlation (ρ = -0.26, p = 0.10). Rku demonstrated a weak correlation (ρ = 0.17, p = 0.30). Notably, SH (ρ = -0.09, p = 0.60) and Rsk (ρ = 0.01, p = 0.94) showed negligible correlation with smoothness/roughness perception.

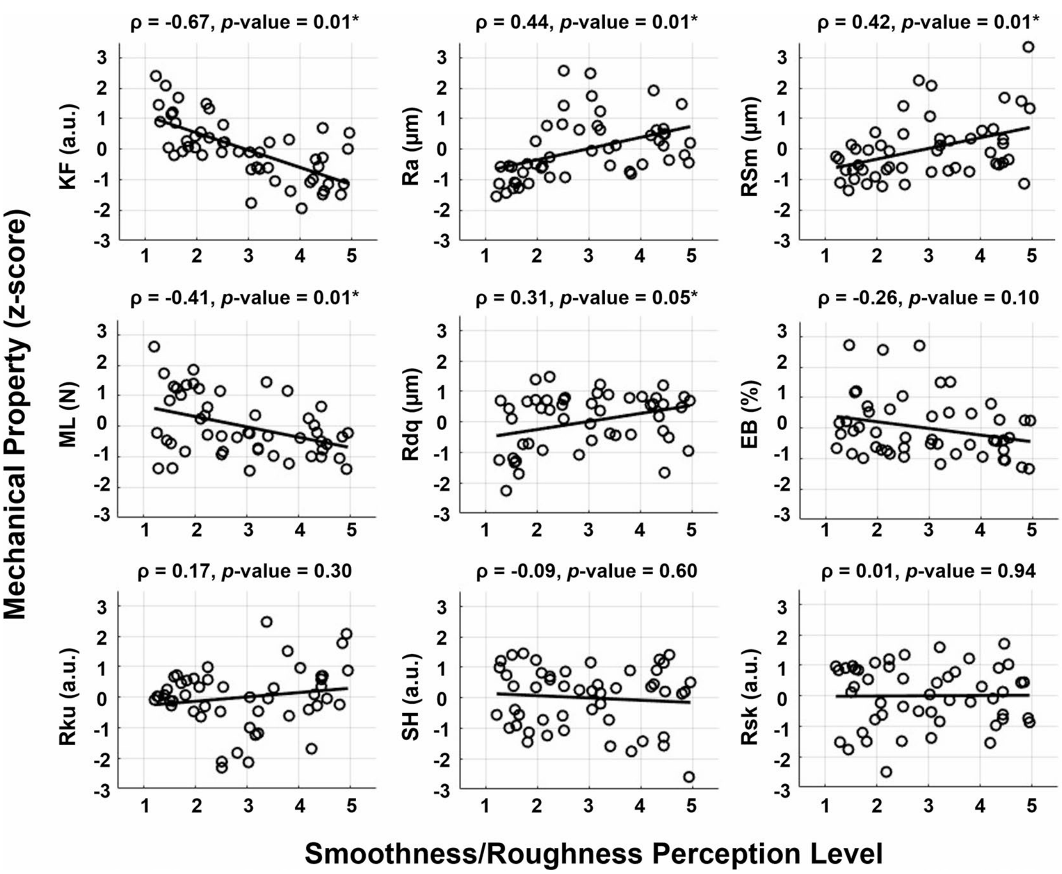

Fig. 3. Pearson correlation between each of the nine normalized mechanical properties and smoothness/roughness perception.

Regression analysis results

The predictive performance of six different regression models for smoothness/roughness perception was evaluated by comparing non-cross-validation and fivefold cross-validation results. In the non-cross-validation, the gradient boosting and neural network models demonstrated the highest explanatory power (both $R^2 = 1.00$), followed by the Gaussian process regression ($R^2 = 0.94$). Random forest ($R^2 = 0.81$), linear regression ($R^2 = 0.68$), and support vector regression ($R^2 = 0.66$) showed comparatively lower performance levels (Fig. 4).

However, the fivefold cross-validation results revealed substantially different performance patterns (Fig. 5). Both the gradient boosting and neural network models, which had perfect performance in the non-cross-validation evaluation, showed notable performance drops to $R^2 = 0.44$ and $R^2 = 0.18$, respectively. Instead, Gaussian process regression demonstrated the highest performance ($R^2 = 0.61 \pm 0.14$), followed by support vector regression ($R^2 = 0.52 \pm 0.10$), and linear regression ($R^2 = 0.52 \pm 0.07$). Gradient boosting regression ($R^2 = 0.44 \pm 0.15$) and random forest ($R^2 = 0.42 \pm 0.15$) regression exhibited moderate performance. These performance differences between non-cross-validation and cross-validation results indicate potential performance overestimation in some models, particularly in gradient boosting, neural network models, and random forest. Analyzing the performance differences in detail, the linear regression ($R^2 = 0.68 \rightarrow 0.52$) and support vector regression models ($R^2 = 0.66 \rightarrow 0.52$) displayed relatively minor differences non-cross-validation and cross-validation, suggesting stable predictive capabilities. Gaussian process regression consistently maintained strong performance relative to other models, both non-cross-validation and cross-validation ($R^2 = 0.94 \rightarrow 0.61$), despite exhibiting a notable performance drop between these conditions.

To improve the prediction performance of the regression models, a feature selection approach was implemented. Performance was systematically evaluated for all possible combinations of the nine features selected after the multicollinearity analysis to determine the optimal set for each model. The Gaussian process regression model achieved the highest predictive performance ($R^2 = 0.73 \pm 0.13$) with six features (KF, Ra, RSm, Rsk, Rku, and ML). Linear regression and support vector regression also exhibited strong predictive performance ($R^2 = 0.59 \pm 0.08$ and $R^2 = 0.60 \pm 0.08$, respectively) using the same six-feature set. The random forest regression yielded an R^2 of 0.55 ± 0.21 with five features (KF, RSm, Rsk, Rku, and Rdq), while the gradient boosting model achieved $R^2 = 0.57 \pm 0.16$ using a different set of five features (KF, Ra, Rsk, Rku, and ML). Neural network regression showed the lowest optimal performance ($R^2 = 0.43 \pm 0.23$) using only three features (KF, Rku, and SH) (Fig. 6). To provide a comprehensive comparison of model performance, Table 2 presents the results of three evaluation scenarios: no cross-validation, fivefold cross-validation without feature selection, and fivefold cross-validation with optimal feature selection.

Analysis of the frequency at which each mechanical property appeared in optimal feature combinations across the six regression models revealed that KF and Rku were the most frequently selected, each appearing in all six models. Rsk was selected five times, while Ra, RSm, and ML were each included four times. Conversely,

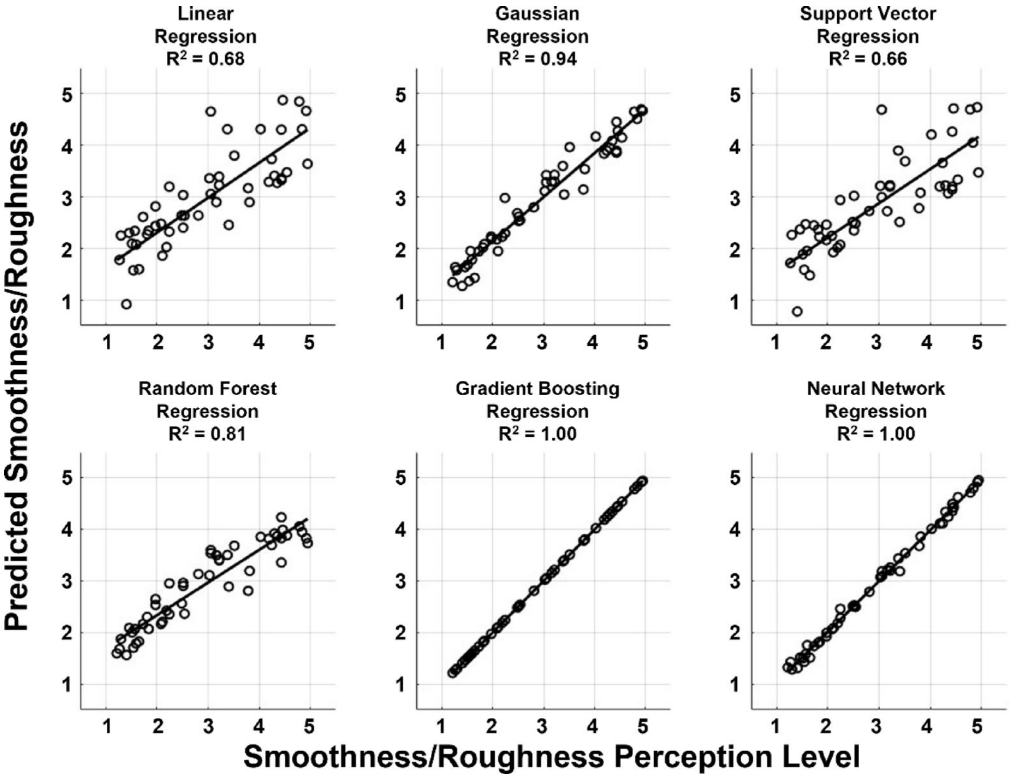

Fig. 4. Comparison of regression model performance for predicting smoothness/roughness perception using non-cross-validated results (entire dataset for training and testing).

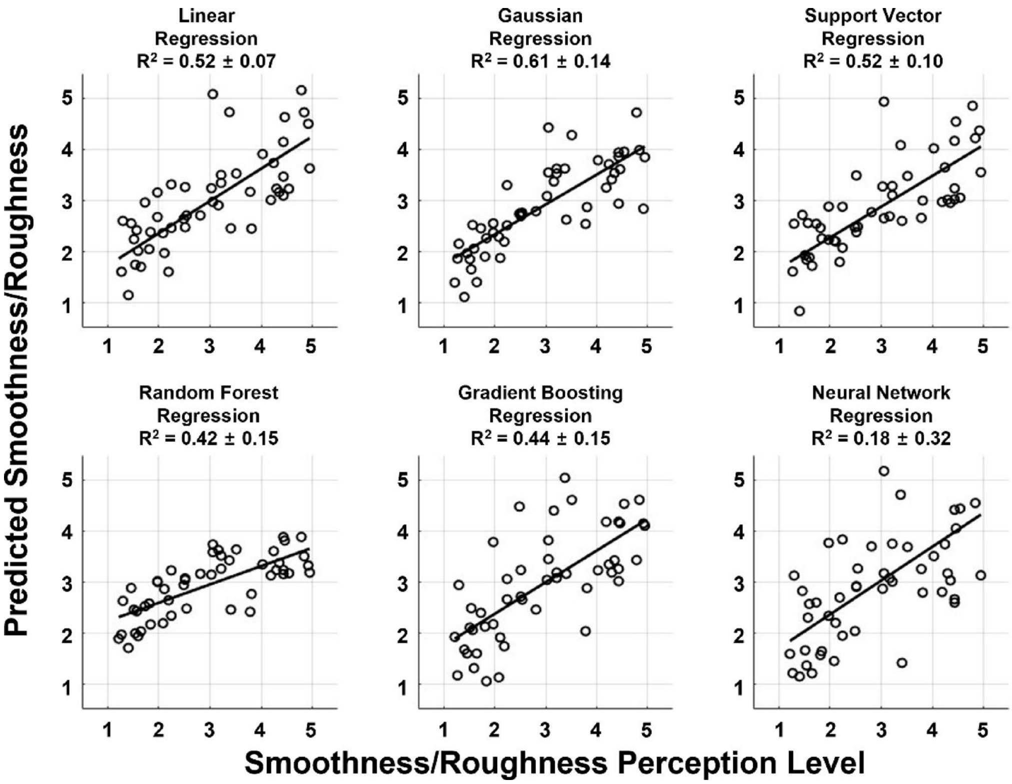

Fig. 5. Comparison of regression model performance for predicting smoothness/roughness perception using cross-validated results.

SH and Rdq were selected only once each, and notably, EB was not included in any optimal feature combinations (Fig. 7).

Discussion

This study developed a predictive model for human smoothness/roughness perception by integrating multiple measurable mechanical properties with subjective evaluations. Unlike earlier approaches that relied on limited features or artificial samples, our model emphasizes both dimensional richness and practical realism. By leveraging a diverse set of 50 commercially available synthetic fibers, we evaluated tactile perception under conditions that closely resemble real-world material interactions. Although fibers served as our experimental platform, the methodology can be broadly applied to a wide range of tactile materials and use cases.

The present research offers three primary methodological contributions. First, by systematically selecting nine representative mechanical properties from friction, surface geometry, hardness, and tensile strength through multicollinearity analysis, the model effectively represented diverse factors influencing tactile perception. This multidimensional approach significantly improved both predictive accuracy and interpretability compared to earlier studies that relied on fewer properties[6,31]. Second, the use of 50 commercially available synthetic fibers, including polyester, nylon, and spandex blends, provided enhanced material diversity and realism compared to prior studies using artificially constructed stimuli[11,12]. Third, implementing a rigorous fivefold cross-validation procedure ensured robust evaluation of model generalizability, addressing the inflated performance reported by studies lacking independent validation[11,15].

Cross-validation results revealed substantial performance discrepancies across regression models, highlighting the critical risk of performance overestimation in modeling tactile perception. Specifically, gradient boosting regression and neural network regression showed perfect performance in non-cross-validation (R^2 = 1.00) but showed notable declines to R^2 = 0.44 ± 0.15 and R^2 = 0.18 ± 0.32, respectively, after cross-validation. These findings demonstrate that previous research without proper validation may have significantly overestimated prediction accuracy[25,30]. Conversely, Gaussian process regression consistently maintained strong performance (R^2 = 0.73 ± 0.13), suggesting superior reliability for practical applications. Linear regression and support vector regression also showed stable predictive capacity across validations, further underscoring the value of cross-validation in ensuring model generalization.

Correlation analysis and systematic feature selection revealed complex interactions among mechanical properties underlying tactile smoothness/roughness perception. Kinetic friction (KF) exhibited the strongest individual correlation (ρ = -0.67, p < 0.05), aligning with previous research emphasizing the importance of friction in tactile evaluations[6,18]. Additionally, surface geometry (Ra and RSm) and tensile strength (ML) demonstrated moderate but meaningful correlations ($\rho \approx 0.4$, p < 0.05). Notably, although Rku individually exhibited a relatively weak correlation (ρ = 0.17, p = 0.30), its universal selection across all six models highlights

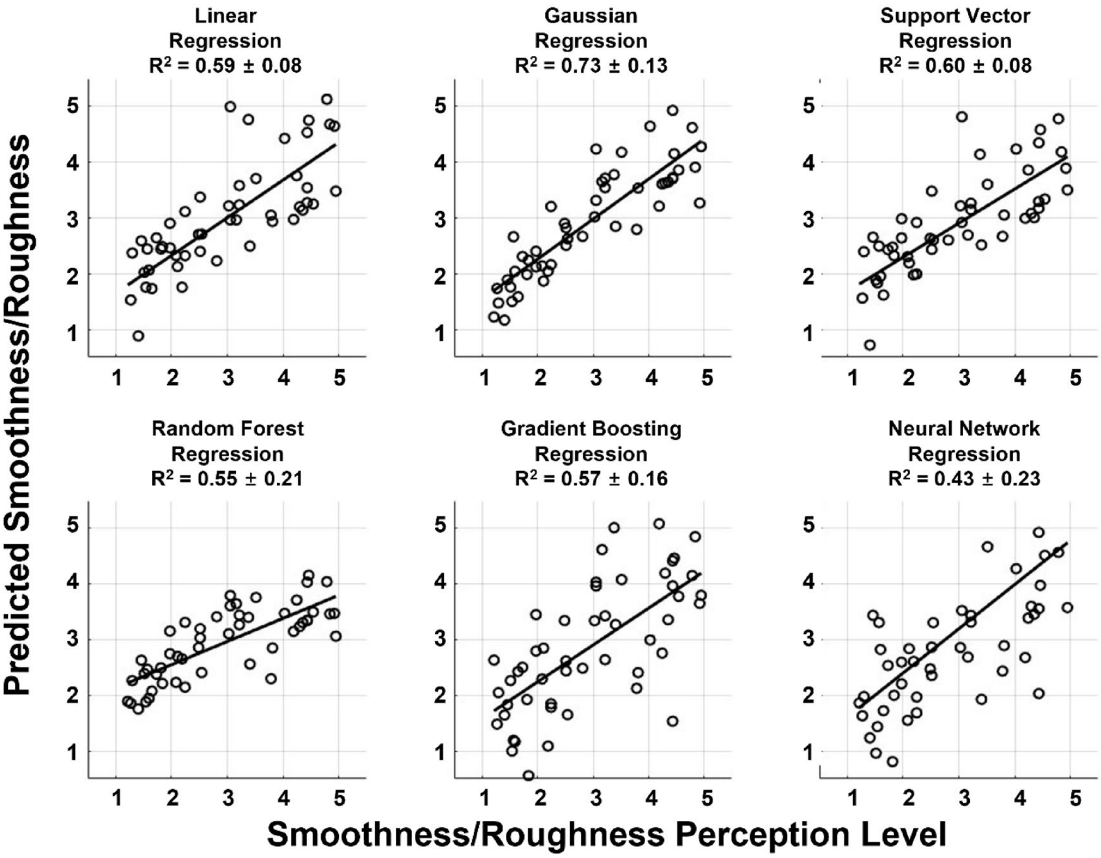

Fig. 6. Optimal performance of regression models after feature selection using fivefold cross-validation.

		Regression model (mean ± std)					
		Linear	**Gaussian process**	**Support vector**	**Random forest**	**Gradient boosting**	**Neural network**
Regression strategy	Non-CV	0.68	0.94	0.66	0.81	1.00	1.00
	fivefold CV with all features	0.52 ± 0.07	0.61 ± 0.14	0.52 ± 0.10	0.42 ± 0.15	0.44 ± 0.15	0.18 ± 0.32
	fivefold CV with optimal features	0.59 ± 0.08	0.73 ± 0.13	0.60 ± 0.08	0.55 ± 0.21	0.57 ± 0.16	0.43 ± 0.23

Table 2. Comparison of regression model performance with and without cross-validation and feature optimization.

its critical importance within multivariate contexts. Similarly, skewness (Rsk), despite showing negligible individual correlation (ρ = 0.01, p = 0.94), was selected in five models. These results indicate that even when individual surface features appear statistically insignificant on their own, they can meaningfully contribute to perceptual prediction when considered jointly with other properties. This suggests that subtle aspects of surface shape and profile distribution, such as asymmetry and peakedness, play a significant role in the integration of tactile information. These findings reinforce the perspective that tactile perception arises from the interaction of multiple mechanical characteristics, rather than being driven by any single factor alone[8].

Several limitations of this study should be noted. First, the study exclusively investigated synthetic fibers, which may limit applicability to natural fibers with differing structural properties. Although our dataset comprised only synthetic fibers, many natural fibers share similar weave or knit architectures, suggesting that the mechanical descriptors used in this study could be transferable with appropriate recalibration. Second, while participant sample size (n = 37) was larger than that of previous tactile studies, broader demographic diversity could further enhance model generalizability. Third, the standardized evaluation protocol (horizontal finger movement using only the distal phalanx) may not fully represent diverse tactile exploration behaviors typical in everyday material interactions. This limitation is important because haptic exploration varies in direction, normal force, speed, and ambient conditions, each of which can influence perceived roughness. Additionally, individual variations in tactile sensitivity were not explicitly modeled, potentially influencing perceptual assessments.

Future research could address these limitations by expanding the sample set to include natural fibers. In particular, the fabric set will be diversified by incorporating natural and nonuniform materials, such as silk

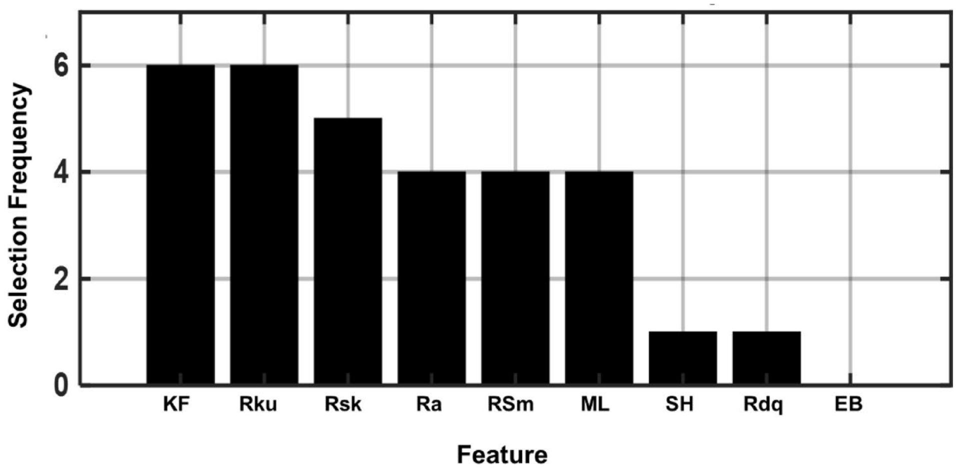

Fig. 7. Frequency of mechanical properties selected in optimal feature combinations across the six regression models.

and leather, to verify the model's applicability and maintain predictive accuracy across different fabric types. Future experiments will incorporate multidirectional strokes, controlled normal force levels, and varied velocity profiles, along with simultaneous recording of force, velocity, and temperature to more accurately represent active tactile behavior. To enhance demographic diversity, we will recruit participants across different ages, occupations, and hand characteristics. We will also evaluate tactile sensitivity and skin condition, which may vary with demographic factors, and examine how these variables, combined with mechanical properties, shape tactile experience. Wei et al. provide convergent evidence that afferent tactile signals, including friction-related dynamics, are closely linked to efferent motor responses[16]. Although our study focuses on tactile perception, consistent with this perspective, the changes in contact mechanics driven by friction (notably KF measured during ongoing contact) and surface variability parameters (Ra, Rsm, and Rsk) in our data appear not only perceptually salient but also relevant for motor control. Building on these findings, future research could explicitly integrate our perceptual features with motor responses to investigate how tactile experience influences grip stabilization and action strategies. Moreover, the proposed modeling framework could be expanded to encompass additional tactile attributes, such as softness, hardness, and thermal perception. It could also be adapted for applications involving wearable haptics, virtual materials, and human–robot interfaces. Our approach contributes toward the broader goal of developing generalizable tactile models applicable across diverse industries and material categories.

Data availability

This study is based on data collected independently by the authors, specifically questionnaire responses from 37 participants and mechanical property data extracted from 50 synthetic fiber samples. The data are not publicly available but can be obtained upon reasonable request from the corresponding author, Han-Jeong Hwang (hwanghj@korea.ac.kr), or the first author, Hyung-Tak Lee (htlee@korea.ac.kr).

Received: 4 July 2025; Accepted: 28 October 2025
Published online: 27 November 2025

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Acknowledgements

This work was partly supported by the National Research Foundation (NRF) funded by the Korean government (MSIT) (No. RS-2023-00302489, 35%) and by Institute of Information & Communications Technology Planning & Evaluation(IITP)-ITRC(Information Technology Research Center) grant funded by the Korea government (MSIT) (IITP-2025-RS-2023-00258971, 20%; No. RS-2025-25441996, Development of a Virtual Tactile Signal Generation Platform Technology Based on Multimodal Vision–Tactile Integrated AGI, 25%) and by Institute of Information & communications Technology Planning & Evaluation (IITP) grant funded by the Korea government(MSIT) (No.RS-2025-02263277, 20%).

Author contributions

H.-T.L., J.-Y.K., and K.B. contributed equally to this work and share first authorship. They were primarily responsible for designing the experiment, analyzing the data, developing the regression models, and writing the initial draft of the manuscript. K.K. contributed to the implementation of data collection and assisted in generating figures. S.C. and H.-J.H., as corresponding authors, supervised the entire research process and provided essential guidance throughout the study. All authors had full access to and responsibility for all aspects of the study.

Declarations

Competing interests

The authors declare no competing interests.

Ethical approval

The study was approved by the Institutional Review Board of Korea University (IRB-2024-0163). Before the experiment, participants were informed about the study objectives, procedures, and necessary precautions, after which they provided informed consent. Appropriate compensation was provided upon completion of the experiment.

Additional information

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