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"From vibration to sensation: decoding tactile perception of skincare formulations using force plate"

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1. Introduction

Tactile perception plays a key role in how consumers evaluate skincare products. Beyond efficacy, creams and lotions are judged by "skinfeel" attributes like spreadability, greasiness, thickness, and stickiness, factors crucial to product acceptance [1]. These sensations stem from tactile interactions between the formulation, skin, and fingers. As the product is applied, mechanoreceptors detect changes in friction, pressure, and vibration, generating dynamic perceptions that evolve with absorption or film formation [2].

To address the demand for objective and reproducible methods of evaluating tactile characteristics, researchers have developed instrumental approaches simulating touch, with tribological analysis proving especially useful for quantifying frictional forces under controlled conditions. Nacht et al. demonstrated that skin friction measurements correlate with perceived greasiness and smoothness [3], while Nakano et al. combined tribological and vibrational data with neural networks to predict complex descriptors like velvetiness and adhesion [4].

However, traditional tribometers often use simplified geometries and static conditions that fail to reflect realistic finger motions, leading to the development of force plate systems. A force plate simultaneously records both normal (vertical) and lateral forces generated during circular or spreading finger movements as the product is applied, creating a detailed interaction profile or "fingerprint". Guest et al. showed that frictional and vibrational data from force plates can predict key tactile sensations, especially in the after-feel stage [5]. A major strength of force plate is the ability to trace the temporal progression of tactile interactions.

Unlike static friction or viscosity readings, force plate outputs reflect how physical behaviour shifts as the product is spread, dries or absorbs. This dynamic perspective is essential for understanding sensory responses that emerge during or after application. They also enable the study of interactions between parameters such as application speed, pressure (load) and tactile perception.

This study investigates the correlation between physical signals acquired via a 6-axis force plate and tactile perception of sixteen skincare formulations. The formulations, characterised by diverse rheological and sensory properties, were assessed in vivo by a calibrated sensory panel. Physical measurements were obtained by recording the mechanical and vibrational responses generated as participants spread the formulations with their fingertips over an artificial silicone skin surface mounted on the force plate. Recorded variables included friction, vibration signals across different frequency bands, application speed and derived variables such as intercept values, the logarithm of speed and the logarithm of the applied normal force (Fz).

Finally, the robustness of predictive models was evaluated using seven new oil-in-water (O/W) emulsions. Predicted tactile attributes were compared to those obtained from expert sensory panel evaluations. By focusing on realistic, time-resolved measurable data, this study supports the development of reliable, quantitative tools for decoding tactile perception and offers new insights for optimising skincare sensory experiences.

2. Materials and Methods

2.1. Products and attributes

Sixteen skincare products, referred to as "F-Codes," were selected to represent a diverse range of sensory and textural characteristics commonly found in commercial cosmetic formulations. Each product was assigned a unique internal code, beginning with the letter "F" followed by three digits. The selection encompasses a wide variety of formulation types and rheological profiles, including an aqueous clay gel (F100), a pure oil blend (F101), multiple oil-in-water emulsions (F103, F104, F105, F107, F108, F388, F581, F584), water-in-oil emulsions (F583, F585, F700, F715), as well as a petroleum jelly (F106) and a jelly oil (F717). This diversity ensures comprehensive coverage of physical behaviours and tactile sensations relevant for tribological analysis.

This study specifically focused on predicting three key sensory attributes: spreadability, thickness, and stickiness. Spreadability was defined as the ease of moving the product over the skin during the first three rubs. Thickness referred to the perceived thickness of the product between the fingertip and the skin during the first twelve rubs (rub-out phase). Stickiness described the degree to which the fingertip adhered to the treated skin during the after-feel phase. These attributes were selected based on a previous principal component analysis (PCA) performed on 30 F-Code formulations, highlighting their importance in characterising the sensory experience of skincare products. Moreover, these attributes were considered particularly suitable for instrumental measurement, thus enhancing their applicability for the current research.

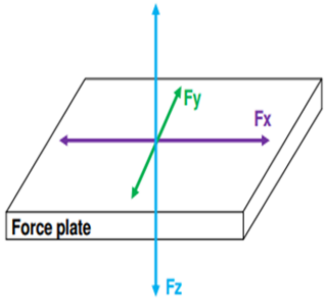
2.2. Force plate testing panel

A panel of six trained assessors (panellists AA, UI, DD, RP, FE, and MC) participated in the force plate measurements. The panel included individuals of different ethnic backgrounds (Caucasian, African, and Indian) and varying skin types, aged between 25 and 45 years. This diversity was intentionally introduced to account for inter-individual variability in touch behaviour and to improve the robustness of the predictive modelling.

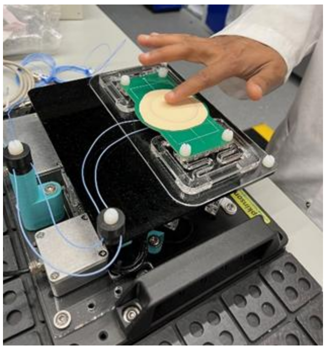
The testing method consisted of evaluating eight F-Code products per session, with each panellist performing three repetitions across multiple sessions. Sessions were scheduled over two weeks to prevent finger fatigue. Furthermore, four panellists (AA, RP, UI, MC) evaluated seven additional oil-in-water (O/W) formulations to validate the robustness of the predictive model.

2.3. Force plate instrumentation and protocol

Instrumental measurements were conducted using a custom-developed 6-axis force plate with integrated vibration measurement capabilities (Hopkinson Research). This device incorporated two PCB Piezotronics Model 352A24 accelerometers, measuring vibrations along the X and Z axes. Forces (Fx, Fy, Fz) and torques (Tx, Ty, Tz) were recorded simultaneously, enabling comprehensive capture of interactions across all three spatial dimensions, as shown in Figure 1a.



(**a**)



(**b**)

Figure 1. Force plate setup and measurement principles. (a) Schematic diagram illustrating the measured force components: Fz (vertical load), Fx and Fy (horizontal forces). (b) Photograph of the experimental setup showing the silicone skin fixed at the centre of the stage and the panellist performing the circular spreading motion with the index finger.

Measurements were performed on a silicone substrate (Silicone Skin L7350), selected due to its surface properties resembling human skin, although it does not mimic skin absorption characteristics. A printed circle (5 cm diameter) was marked on this substrate, matching the sensory evaluation area, as shown in Figure 1b. The silicone substrate was firmly attached to the force plate stage using a precise arrangement of three adhesive tapes to ensure stability: RS Components 913-9526 (pink tape), RS Components 399-9515 (double-sided tape), and RS Components 832-6307 (green masking tape).

For each measurement, a fixed volume of the skincare formulation was deposited accurately at the centre of the marked area. Panellists then spread the formulation using the index finger of their dominant hand, employing controlled circular movements closely aligned with the sensory panel protocol. To minimise external vibrations and background noise, the force plate was placed upon a specialised rubber mat.

Initial instrumental optimisation was carried out prior to full-scale measurements, focusing on critical parameters such as the applied load, speed of finger movement, measurement procedure, and the exact sample quantity. Preliminary correlation analyses were conducted, to validate and refine these instrumental settings, ensuring that measurement conditions closely replicated real sensory evaluation scenarios before proceeding with the comprehensive panellist testing. The optimal method selected involved tactile evaluation using a 50 µL sample applied with a bare finger under controlled spreading conditions (0.2–1 N load, 70–160 mm/s speed), following a time-segmented protocol comprising a 6-second initial spreading phase and three 75-second rubbing intervals, designed to capture sensory-relevant mechanical changes over time.

2.4. Physical parameters derived from tactile measurements

To characterise the physical properties associated with finger-silicone skin interactions, raw data collected during rubbing phases were analysed using friction and vibration-based measures. The selection of these parameters was based on their sensitivity to changes in load and speed, as well as their relevance to the perceptual attributes. The friction-related measures assess the resistance experienced by the finger during movement, while the vibration-related measures capture the dynamic responses of the system within specific frequency bands, reflecting surface texture and film behaviour.

The raw data was pre-processed using a block-averaging frequency of 20 Hz, and analysed either in a blocked approach (each rubbing interval treated separately) or an unblocked approach (combined intervals). For each interval, friction coefficients were predicted at four key conditions combining high/low load and high/low speed. Additionally, slopes from regression models: LogFzSlope and LogSpeedSlope were extracted to quantify the dependency of the friction or vibration responses on load and speed, respectively.

The friction-related parameters, detailed in Table 2, reflect the mechanical interaction between the finger and surface, capturing both static conditions and trends. The vibration-related parameters were derived from the squared acceleration filtered into defined frequency bands (e.g., 15.6 Hz, 125 Hz, 500 Hz, 1000 Hz), chosen to reflect perceptual vibratory sensitivity relevant to touch. These parameters include predicted values at different touch conditions. Such measures are critical to establishing a robust link between instrumental measurements and perceived sensory attributes.

Table 1. Friction-related measures

No.	Measure Description	Touch Speed (cm/s)	Indenting Load (N)
1	Slope of log(friction coefficient) vs log(indenting load) (LogFzSlope)	Various	Various
2	Slope of log(friction coefficient) vs log(touch speed) (LogSpeedSlope)	Various	Various
3	Predicted friction coefficient at low speed & low load	Low	Low
4	Predicted friction coefficient at high speed & low load	High	Low
5	Predicted friction coefficient at low speed & high load	Low	High
6	Predicted friction coefficient at high speed & high load	High	High

2.5. Statistical analysis

All statistical analyses were conducted using XLSTAT software (version 2023.1.4). The software was employed to analyse sensory panel data, perform analysis of variance (ANOVA), investigate correlations between instrumental measurements and sensory attributes, and develop predictive models. Pearson correlation coefficients (rp) were used to assess relationships between instrumental and sensory data, with values above 0.6 indicating moderate to strong correlations. Linear regression, combined with a stepwise approach, was used to build models based on R^2 and MSE. The best models were validated using seven in-house formulations, with sensory differences under 10 points considered non-significant.

3. Results

3.1. Panel Analysis

A statistical panel analysis was conducted using the XLSTAT “Panel Analysis” tool to evaluate both the consistency of panellist measurements and the ability to discriminate between product formulations (F-Codes). The model assessed several effects and interactions across dimensions (product, panellist, session), using the equation: Y = P + A + S + P*A + P*S + A*S, where P = Product, A = Assessor, S = Session. Interaction terms reflect how responses vary based on combinations of these factors. The model was run with random assessor and session effects, which was appropriate given that panellists were not experts and greater variability in repeatability was expected.

For a robust panel, a significant product effect (P) indicates effective discrimination, while non-significant effects for assessor, session and interactions suggest consistent evaluations. The analysis focused on the first rubbing interval, identified as the most relevant for capturing product behaviour. Table 3 summarises significance levels (Pr > F) for the descriptor Coeff LogFzSlope, derived from friction measurements.

Table 2. Sum of squares analysis for the variable Coeff Log Fz Slope across the full dataset. Statistically significant effects (Pr > F < 0.05) are indicated in bold, highlighting key factors and interactions contributing to product discrimination.

Factor	Pr > F
F-Code	**<0.0001**
Panellist	**<0.0001**
Session	0.406
F-Code*Panellist	**0.001**
F-Code*Session	0.758
Panellist*Session	**0.010**

The F-Code effect was statistically significant, validating the methodology's ability to discriminate between products. The panellist effect was also significant, reflecting expected variability in individual application techniques. Meaningful interactions between F-Code and panellist, and between panellist and session, suggested that perception differed among individuals and consistency across sessions was limited. One panellist (FE) tested all 16 F-Codes in a single session, unlike others who were split across two. Removing FE rendered the Panellist*Session interaction non-significant, highlighting the influence of session structure. Nevertheless, FE was retained due to strong individual correlations and valuable contribution to dataset variability.

3.2. Filtering instrumental parameters

The analysis also focused on identifying which instrumental parameters were most effective in discriminating between products. A significance threshold of 0.1 was used to filter the results. Friction-related descriptors, such as Coeff LogFzSlope, consistently showed significant differences between F-Codes. In contrast, many vibrational descriptors, particularly those corresponding to lower frequency bands (15.625 to 62.5 Hz), were not significant and were therefore excluded from further consideration. This suggests that the higher frequency vibrational signals and friction data hold the greatest potential for predictive modelling.

3.3. Correlation analysis and implications for sensory prediction

To determine if instrumental data could predict sensory attributes, correlation analyses were conducted between instrumental parameters and sensory scores, using individual repetitions to maintain data fidelity and capture variability. Among the different intervals, the first 75-

second rubbing interval consistently showed the strongest correlations, particularly for spreadability and thickness since these attributes are most noticeable during initial application when the product is still moist. Correlations significantly declined in the second and third intervals, often falling below a Pearson coefficient of 0.4, likely due to product absorption and reduced tactile perception. A similar trend appeared for afterfeel attributes. Additionally, combining all intervals into a single, unsegmented dataset weakened the overall correlations, confirming the advantage of isolating and analysing the first interval independently.

Based on this, the first interval was selected for model development. Variables were chosen for their consistent correlation with key sensory attributes. The final set comprised four friction-related "Coeff Predicted" variables and the slope parameter Coeff LogFzSlope, which proved robust across panellists. Although vibrational parameters generally showed weaker correlations, one squared acceleration on the X-axis at 250 Hz was well correlated (Pearson coefficient > 0.6) with sensory attributes such as thickness during rub-out, and stickiness during afterfeel, as shown in Table 6. Its relevance may stem from how sticky formulations alter vibrational response and resonance during high-frequency, thereby encoding tactile sensations like stickiness into the vibrational signal.

Table 3. Pearson correlation coefficients between selected instrumental variables and key sensory attributes used for model development. Bold values indicate statistically significant correlations (p-value < 0.05).

		Friction-related measures					Vibration-related measures
Variables		**Coeff Log-FzSlope**	**Coeff Log-Speed-Slope**	**Coeff Pre-dicted At-Low-Load-Low-Speed**	**Coeff Pre-dicted At high Load Low-Speed**	**Coeff Pre-dicted AtLow Load High-Speed**	**Squared Accelera-tion on the X-axis at 250 Hz (m/s2)^2 Log-Speed-Slope**
Rub-out	Spreadability	**0.724**	**-0.610**	**-0.231**	**-0.662**	**-0.373**	**-0.594**
	Thickness	**-0.728**	**0.586**	**0.214**	**0.673**	**0.385**	**0.614**
After-feel	Stickiness	**-0.541**	**0.429**	**0.140**	**0.542**	**0.300**	**0.624**

3.4. Predictive model development

To build the model, linear regression was selected for its ability to identify direct relationships between instrumental and sensory data. A stepwise regression method was used to iteratively add or remove variables, ensuring both optimal performance and interpretability. Two key metrics were used to evaluate model quality: the R-squared value (R^2), which reflects predictive accuracy, and the mean squared error (MSE), which measures the average deviation between predicted and observed values. Prior to modelling, all variables were standardised to ensure comparability.

The six selected variables were tested to determine their effectiveness in predicting sensory attributes. To refine the model, multicollinearity was assessed to avoid redundancy among inputs. Coeff LogFzSlope was identified as a strong predictor due to its low correlation with other variables. Conversely, the Coeff Predicted parameters were strongly intercorrelated, as they are derived from the same calculation set. Among them, Coeff Predicted at Low Load High Speed was chosen for its relevance and good correlation with the target attributes.

The selected vibrational parameter, squared acceleration on the X-axis at 250 Hz, exhibited low correlation with the other input variables, allowing its inclusion without introducing redundancy. As it originates from a distinct measurement approach, it provides complementary information to the friction data. While friction data captures the dynamics of contact force during rubbing, vibration data reflects the response of the force plate to those interactions. Incorporating both types of data broadens the model's analytical scope and improves its ability to capture different aspects of product behaviour. An interaction effect between Coeff LogFzSlope and Coeff Predicted at High Load Low Speed was introduced, as these two variables were not strongly correlated and thus contributed complementary information. Their combination improved the model's predictive performance without compromising its stability. The final model therefore included Coeff LogFzSlope, Coeff Predicted at Low Load High Speed, their interaction effect, and the vibrational parameter. Together, these variables formed the foundation of the regression equations presented in Table 4.

Table 4. Final predictive equations derived from reduced variable linear regression using finger sensor data, generated by XLSTAT with the stepwise method. Abbreviations: Hi = high load or speed, Lo = low load or speed.

Sensory Attribute	Equation generated from final linear regression
Spreadability R^2 : 0.704 MSE : 0.301	Spreadability = -0.019 + (0.55*Coeff LogFzSlope) - (0.25*Coeff PredictedAtLoLoadHiSpeed) - (0.17* Squared_ACCEL_X_250Hz_(m/s2)^2 LogSpeedSlope) + (0.30*(Coeff LogFzSlope*Coeff PredictedAtHiLoadLoSpeed))
Thickness R^2 : 0.694 MSE : 0.312	Thickness = 0.012 - (0.52*Coeff LogFzSlope) + (0.27*Coeff PredictedAtLoLoadHiSpeed) + (0.19* Squared_ACCEL_X_250Hz_(m/s2)^2 LogSpeedSlope) - (0.19*(Coeff LogFzSlope*Coeff PredictedAtHiLoadLoSpeed))
Stickiness R^2 : 0.496 MSE : 0.513	Stickiness = 0.11 - (0.30*Coeff LogFzSlope) + (0.14*Coeff PredictedAtLoLoadHiSpeed) + (0.39* Squared_ACCEL_X_250Hz_(m/s2)^2 LogSpeedSlope) - (0.17*(Coeff LogFzSlope*Coeff PredictedAtHiLoadLoSpeed))

The model demonstrated strong performance for attributes evaluated during the rub-out phase, with R^2 values ranging from 0.694 to 0.704 and consistently low mean squared errors. Coeff LogFzSlope emerged as the most influential predictor among all variables. In contrast, the model's ability to predict stickiness measured during the after-feel phase was more limited, with a lower R^2 value of 0.496. This result is not surprising, as after-feel occurs once the product has been absorbed, a condition not accurately replicated by the non-absorbent silicone substrate used in instrumental testing. None of the friction-related variables showed strong individual correlations with stickiness, and although one vibrational parameter exhibited moderate association, it was not sufficient to support a reliable prediction. Despite their low individual correlations, some friction parameters were still selected in the final equation, as stepwise regression evaluates their added value in the context of all other predictors. Overall, these findings highlight that instrumental measurements are more effective at capturing product behaviour during the application phase than after absorption.

3.5. Validation of the model

Sensory data inherently exhibit a certain degree of variability, making it unrealistic to expect a predictive model to perfectly match the average scores across multiple panellists. A more practical and meaningful reference point is whether the model can predict values within ±10 points of the sensory score, an interval considered both perceptible and significant in sensory evaluation.

The O/W emulsions used for model validation introduce an additional challenge due to their narrow sensory range. As they are based on the same formulation with only minor differences in emulsifier composition, their sensory profiles are extremely close. Validating the model on such minimally differentiated samples provides a rigorous test of its sensitivity, particularly its ability to detect and quantify subtle yet meaningful differences in perceived product performance.

Table 5. Actual vs. predicted spreadability and thickness values using final linear regression equation.

O/W emulsion reference	**Spreadability**			**Thickness**		
	Actual	Predicted	Difference	Actual	Predicted	Difference
DA569	53.23	54.76	-1.53	30.30	39.35	-9.05
DA566	51.05	55.87	-4.82	35.03	36.65	-1.62
DA568	69.65	54.65	15.00	22.38	38.91	-16.53
DA565	63.58	58.75	4.83	24.70	34.45	-9.75
DA570	55.13	55.28	-0.15	31.18	36.86	-5.69
DA567	55.85	56.14	-0.29	34.85	36.87	-2.02
DA571	63.00	60.94	2.06	26.42	32.73	-6.31

As shown in Table 5, the predictive model accurately estimated both spreadability and thickness for six out of seven samples. For these six, differences remained within ±5 for spreadability and ±10 for thickness, well within the acceptable range. These results are consistent with the R^2 values of 0.704 for spreadability and 0.694 for thickness, supporting the model’s reliability. In contrast, sample DA568 showed significant deviations, with a 15-point error for spreadability and 16.53 for thickness. Notably, DA568's sensory data came from a different batch than the one used for model calibration, likely introducing variability that the model could not capture. Further discussions suggested possible reproducibility issues with this formulation, including batch-to-batch variation. Rather than reflecting a model limitation, this highlights its sensitivity to formulation inconsistencies.

For stickiness, predictions were inaccurate for two samples, DA568 and DA569. While the differences (6.67 and 8.74) remained within the ±10 target, the narrow scale of stickiness across samples means even moderate deviations are perceptible from a sensory standpoint. For the remaining five samples, differences between predicted and actual values were smaller and acceptable, indicating that the model performed reliably across most of the dataset. A tendency to overestimate stickiness values was also observed, suggesting a possible bias in the model. Stickiness remains a key sensory attribute and a central target for in-vitro prediction. Although the current equation does not fully capture stickiness across all samples, it should not be dismissed. Instead, it highlights the need for a complementary approach. Combining this model with additional analytical techniques, such as texture analysis, rheology, or tribology, could improve predictive accuracy by forming a more robust, multi-parameter strategy.

4. Discussion

The results of this study support the working hypothesis that a force plate-based in-vitro method can predict key sensory attributes of skincare emulsions, particularly spreadability and thickness. These findings are consistent with previous research demonstrating the value of physical instrumentation in approximating sensory evaluations conducted by expert panels. The strong correlations observed with R^2 values above 0.7 highlight the potential of this approach to reduce reliance on human panels during early formulation screening. The misprediction of DA568, attributed to batch variation, also underscores the model's value as a diagnostic tool capable of flagging formulation inconsistencies, offering promise not only for prediction but also for quality control.

By contrast, the lower correlation for stickiness suggests that after-feel attributes may be less compatible with this method due to differences in evaluation phases and product behaviour on silicone skin. This points to the need for complementary techniques such as rheology, tribology, or texture analysis when addressing more complex sensory properties. The narrow range of formulations used also limited validation, indicating that expanding the dataset with more diverse emulsions is a necessary next step. Future work should also focus on developing a shorter protocol based on the most predictive rubbing intervals and exploring robotic systems for automated testing. Automating the method would not only enhance reproducibility and minimise operator variability, but also offer the potential for more routine testing by avoiding panel fatigue and enabling early prediction of ingredient performance even in the absence of toxicological data.

5. Conclusion

This study successfully developed and tested a force plate-based method for predicting sensory attributes of O/W emulsions. The generated predictive equations demonstrated strong performance for spreadability and thickness, with minimal error and high correlation to panel data. Although stickiness was less accurately predicted, the model still showed moderate reliability and could be enhanced through integration with complementary techniques. The consistent misprediction of sample DA568, due to batch variability, revealed the model's potential to detect unstable formulations, a valuable feature for early-stage screening. Overall, this approach offers a promising, objective, and time-efficient alternative to traditional sensory evaluation, with strong potential for further optimisation and automation in future research.

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