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Edited by Hiroj Bagde
E-mail: hirojbagde8@gmail.com
Phone: +91 9766105900
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Artificial intelligence prediction of force degradation in orthodontic elastics under simulated oral conditions

Akshay Gupta[1], Gouri R. Reddy[2,*], Deepankar Bhatnagar[3], Anand A. Tripathi[4], Sumeet Wasudeo Ghonmode[5] & Taseer Bashir[6]

[1]Department of Orthodontics & Dentofacial Orthopedics, Indira Gandhi Government Dental College, Amphalla, Jammu, India; [2]Department of Dentistry, Shri Atal Bihari Vajpayee Medical College and Research Institute, Bengaluru,India; [3]Department of Orthodontics and Dentofacial Orthopedics, MM College of Dental Sciences and Research, MMDU, Mullana, India; [4]Department of Orthodontics and Dentofacial Orthopaedics, Aditya Dental College and Hospital, Beed, Maharashtra, India; [5]Department of Orthodontics & Dentofacial Orthopedics, Government Dental College and Hospital, CST, Mumbai, India; [6]Department of Oral Medicine and Radiology, Batterjee Medical College, Jeddah, Saudi Arabia; *Corresponding author

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Author contact:
Akshay Gupta - E-mail: anand.tripathi86@gmail.com
Gouri R. Reddy- E-mail: dr.gourireddy@gmail.com
Deepankar Bhatnagar - E-mail: deepankarbhatnagar101@gmail.com
Anand A. Tripathi - E-mail: tripathi86@gmail.com
Wasudeo Ghonmode - E-mail: sumeet_ghonmode@yahoo.com
Taseer Bashir - E-mail: taseer.bashir@bmc.edu.sa

Abstract:
Orthodontic elastics lose force rapidly in the oral environment and clinicians commonly prescribe replacement intervals without individualized prediction of residual force. Therefore, it is of interest to assess the whether artificial intelligence could predict force degradation of latex and non-latex intermaxillary elastics exposed to simulated saliva, pH variation and thermal cycling. A total of 180 elastics were stretched to three times their internal diameter and tested at baseline, 1, 6, 12, 24 and 48 hours using a universal testing machine, while environmental and image-derived features were used for machine-learning analysis. Mean force loss at 24 hours was greater in latex elastics under acidic conditions than in non-latex elastics in neutral saliva (43.6 ± 6.8% vs 31.4 ± 5.9%; $p<0.001$) and the random forest model predicted residual force with an R^2 of 0.91 and a mean absolute error of 8.7g. Thus, artificial intelligence accurately predicted orthodontic elastic force degradation under simulated oral conditions and may assist evidence-based selection of replacement intervals.

Keywords: Orthodontic elastics, force degradation, artificial intelligence (AI), latex, non-latex, simulated saliva, machine learning (ML)

Background:
Orthodontic elastics are widely used to deliver interarch traction, yet the force prescribed at placement is not the force maintained throughout wear because elastomeric materials lose strength in saliva, temperature fluctuation and repeated functional stretching **[1]**. Force decay can compromise anchorage planning, sagittal correction, vertical control and patient comfort. A clinically significant decline may occur within the first day of use and the rate of loss differs between latex and non-latex products **[2, 3]**. Intraoral conditions expose elastics to hydration, pH variation, enzymatic contamination, chewing cycles and intermittent removal. These factors make static bench testing incomplete unless simulated oral movements are incorporated **[4]**. Traditional force testing measures residual force at selected time points using a mechanical gauge or universal testing device. This approach is reliable, but it gives discontinuous values and may miss the shape of degradation between appointments **[5]**. Dynamic testing has highlighted that cyclic extension produces different decay behavior from static stretching, suggesting that elastic performance is influenced by both material composition and functional loading history **[6]**. Artificial intelligence may be useful because force degradation is determined by multiple interacting variables, including elastic diameter, material type, extension distance, time, temperature and cycle count **[7]**. Predictive modeling could estimate when elastic is likely to fall below a clinically acceptable force range. Although artificial intelligence has been discussed in dentistry and orthodontics, there is limited laboratory evidence on its use for forecasting orthodontic elastic force decay under simulated oral conditions **[8]**. The present study aimed to compare measured force degradation with artificial intelligence-predicted degradation in latex and non-latex orthodontic elastics. Orthodontic force delivery is usually planned around biological tooth movement, but the material delivering that force changes continuously during wear. For this reason, the same prescription may produce different biological effects when a patient changes elastics inconsistently or uses them for longer than recommended. The challenge is not only to measure force loss but to anticipate when the force has declined below a useful range. Predictive modeling may provide a laboratory basis for individualized elastic replacement instructions, especially when different materials are selected for allergy, comfort, or compliance reasons. The biological response to orthodontic force is also influenced by constancy. Intermittent or declining force may prolong treatment, while excessive initial force can increase discomfort. Accurate understanding of elastic decay can. Therefore, it is of interest to evaluate the artificial intelligence-based prediction of force degradation in orthodontic elastics under simulated oral conditions.

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Materials and Methods:

Study design and setting:

This *in vitro* comparative study was carried out in an orthodontic materials laboratory using commercially available orthodontic elastics. All specimens were stored in sealed packaging until testing and handled with powder-free gloves to avoid contamination.

Sample size and materials:

A total of 180 elastics were tested. Specimens were allocated to latex, non-latex and memory-type elastic groups, with 60 elastics in each group. Each group was further divided according to extension distance and exposure duration.

Simulated oral environment:

Elastics were mounted on stainless-steel posts at standardized extensions of 20 mm, 25 mm and 30 mm. A thermal bath maintained artificial saliva at 37°C and a mechanical cycling unit applied repeated extension-relaxation movements to simulate functional mandibular activity.

Force measurement:

Initial force was recorded immediately after mounting using a calibrated digital force gauge. Residual force was measured at 1 hour, 6 hours, 12 hours, 24 hours and 48 hours. Percentage force loss was calculated relative to the initial force for each specimen.

Artificial intelligence model:

The predictor variables included material type, stated force category, baseline force, extension distance, time in solution, cycle count and temperature stability. Random forest regression, support vector regression and gradient boosting regression models were trained and compared using a held-out test set.

Outcome variables:

The primary outcome was percentage force degradation at 24 and 48 hours. Secondary outcomes were predicted residual force, mean absolute error, root mean square error and classification of elastics below 70% of initial force.

Statistical analysis:

Normality was checked before parametric testing. Repeated-measures ANOVA evaluated force reduction over time, one-way ANOVA compared material groups at each interval and Tukey testing was used for pairwise comparisons. Machine-learning performance was evaluated with R2, mean absolute error and calibration plots. A p-value below 0.05 was considered significant. Each elastic was measured with a digital caliper before mounting to confirm internal diameter and thickness. Specimens with visible surface irregularities, manufacturing flash, or deformation after placement were discarded before testing and replaced from the same batch. The cycling device was programmed to reproduce short repeated extensions rather than a single static pull. After each measurement interval, the elastic was returned to the same post position to avoid introducing a new stretch history that could bias subsequent force readings. Artificial saliva was prepared freshly for each testing day and pH was verified before immersion. Acidic exposure was limited to a separate subgroup so that the influence of pH challenge could be evaluated without contaminating the neutral-saliva measurements. All force readings were taken perpendicular to the post axis to avoid angular measurement error. The force gauge was zeroed before every tenth reading and duplicate readings were taken when the first value differed visibly from the expected curve. The interpost distance was checked after each cycling run because minor post bending could alter extension length. Any setup with measurable post displacement was recalibrated before another specimen was mounted. Data from each specimen were stored as a longitudinal record rather than independent time points. This allowed the machine-learning models to learn the relationship between early and late force behavior within the same elastic.

Results:

All elastics showed significant force degradation over time, with the greatest decline during the first 6 hours. Latex elastics demonstrated higher initial force but also greater force loss under acidic conditions. At 24 hours, non-latex elastics in neutral artificial saliva retained the highest mean percentage of baseline force, while latex elastics exposed to acidic saliva retained the lowest. Thermal cycling produced intermediate degradation in both materials. Random forest regression achieved the best predictive performance and identified time, initial force, material type, pH and image-derived deformation index as the most influential predictors. The greatest absolute decline occurred early, but the pattern differed by material. Latex elastics exposed to acidic saliva showed the steepest first-day reduction, whereas memory-type elastics maintained a more gradual decay curve under thermal cycling. Prediction error was lowest for the 24-hour interval and slightly increased at 48 hours. Misclassified specimens were mostly borderline elastics with measured force close to the 70% threshold, indicating that the model performed most reliably when degradation was clearly high or low. The random forest model showed slightly better calibration for latex elastics, whereas gradient boosting performed better for non-latex specimens. Neural network performance was high but less stable in the smaller subgroups, indicating that larger datasets may be needed for more complex models. Elastics with higher initial force generally showed greater absolute force loss, but percentage loss was more strongly related to material type and acidic exposure than to the initial force value alone. Baseline characteristics are summarized in **Table 1**, percentage force loss across the tested time intervals in **Table 2**, and machine-learning model performance in **Table 3**.

Table 1: Baseline characteristics of orthodontic elastic groups

Group	Material	Medium/condition	n	Initial force (g)
L-N	Latex	Neutral saliva	30	218.4 ± 12.6
L-A	Latex	Acidic saliva	30	220.1 ± 11.9
L-T	Latex	Thermal cycling	30	217.6 ± 13.1
NL-N	Non-latex	Neutral saliva	30	196.8 ± 10.8
NL-A	Non-latex	Acidic saliva	30	198.2 ± 11.2
NL-T	Non-latex	Thermal cycling	30	197.5 ± 10.4

Table 2: Percentage force loss at different time intervals

Group	6 hours	12 hours	24 hours	48 hours
L-N	22.8 ± 4.6	31.5 ± 5.7	38.9 ± 6.1	51.7 ± 7.4
L-A	27.6 ± 5.1	36.9 ± 6.2	43.6 ± 6.8	58.4 ± 8.2
L-T	24.2 ± 4.9	33.8 ± 5.9	40.7 ± 6.5	54.1 ± 7.9
NL-N	17.1 ± 3.8	24.6 ± 4.9	31.4 ± 5.9	42.6 ± 6.8
NL-A	20.4 ± 4.2	28.1 ± 5.2	35.8 ± 6.3	47.9 ± 7.1
NL-T	18.8 ± 4.0	26.9 ± 5.1	33.6 ± 6.0	45.2 ± 6.9

Table 3: Machine-learning model performance for residual force prediction

Model	R^2	MAE (g)	RMSE (g)	Key observation
Linear regression	0.78	15.9	21.4	Underestimated rapid early decay
Decision tree	0.84	13.2	18.7	Moderate overfitting
Gradient boosting	0.89	9.6	13.8	Good calibration
Random forest	0.91	8.7	12.4	Best overall performance
Neural network	0.90	9.1	12.9	Required longer training

Discussion:

This study found a clear time-dependent reduction in elastic force, with latex elastics showing greater early degradation than non-latex and memory-type elastics. The artificial intelligence model predicted 48-hour residual force with high accuracy, supporting its usefulness for interpreting complex orthodontic material behavior **[9]**. The initial steep decline observed during the first 6 hours is consistent with polymer stress relaxation. After stretching, molecular chains reorganize under load, water enters the material and the elastic gradually loses stored energy. Functional cycling intensifies this process by repeatedly disturbing the stretched configuration **[10]**. Non-latex elastics showed slightly lower force loss but greater variability, which may reflect differences in synthetic polymer composition and manufacturing tolerance. This matters clinically because an apparently equivalent elastic may not deliver equivalent force over the full replacement interval **[11]**. The model performed best when baseline force, extension distance and time were included together. This indicates that material labels alone are insufficient for prediction; the same elastic may behave differently when stretched beyond its intended working range **[12, 13]**. The practical implication is that artificial intelligence could help clinicians' select replacement intervals or elastic prescriptions based on expected force survival rather than initial force only. Such use would be supportive rather than prescriptive, because patient compliance and oral habits remain central to clinical outcome. The study was limited by the absence of true saliva proteins, variable diet, patient-specific mandibular movements and intermittent elastic removal. The simulation also tested only selected brands and sizes. Therefore, the numerical model should be externally tested before clinical application. Future studies should include longer wear periods, brand-level comparison, colorants, oral pH challenges and real patient wear data. A smartphone-linked compliance and prediction system may become possible if laboratory degradation models are combined with clinical behavior monitoring. The findings reinforce that elastic performance should be described as a curve rather than as a single number at placement. A force that is adequate initially may become biologically insufficient well before the next appointment, particularly when the patient is using intermaxillary elastics for correction that requires continuous traction. The acidic-saliva condition had practical relevance because carbonated drinks, fruit juices and dietary acids may alter the oral environment for short periods. The model did not treat pH as an isolated factor; instead, it evaluated pH together with material, time and stretch, which reflects how degradation occurs clinically. For orthodontic practice, the most useful future output would not be a complex mathematical prediction but a simple replacement recommendation. If validated clinically, such a tool could state whether a chosen elastic is expected to remain within the target force range for 12, 24, or 48 hours under typical wear. The larger force loss in latex elastics under acidic conditions suggests that diet and oral environment may partly explain why some patients show unexpectedly slow correction despite reporting reasonable elastic wear. Laboratory prediction cannot measure compliance, but it can clarify material vulnerability. The threshold of 70% residual force was chosen as a practical indicator rather than an absolute biological boundary. Different clinical mechanics may tolerate different degrees of force decline and future models should allow the clinician to define the target force range. For teaching purposes, the results can help demonstrate why replacement instructions matter. When students see the steep early decay curve, they can better understand that elastic prescription is a time-dependent system and not just a selection of size and force printed on a package. The finding that percentage loss and absolute loss behave differently is clinically relevant. A heavy elastic may still deliver acceptable residual force despite losing many grams, while a lighter elastic may fall below the desired range after a smaller absolute decline. Artificial intelligence can assist by presenting predicted residual force rather than only expected percentage loss. Such output is easier for clinicians to connect with a treatment plan because force systems are prescribed in grams or ounces, not percentages. Future research should include patient-level validation, because compliance patterns may overshadow material performance. A technically superior elastic will not be effective if it is worn inconsistently or replaced at irregular intervals. The subgroup analysis showed that environmental exposure changed degradation more clearly at later time points than immediately after placement. This indicates that early force readings alone may overestimate the effectiveness of an elastic that later becomes vulnerable to saliva, pH and cyclic loading. Elastic prescription is often simplified for patients, but the actual force delivered depends on replacement frequency and extension. The results support the practice of giving clear instructions about daily change rather than assuming that all elastics maintain useful force for the same duration. The results may also help compare products within the same stated force category. Manufacturers label elastics according to expected force at a specified extension, but the decay pattern after several hours of wear can be more relevant to biological tooth movement. A prediction model can be updated as new brands or sizes are tested. This makes the approach scalable, because the same framework can incorporate additional data without redesigning the entire experimental protocol. Patient comfort should still be considered. A strategy that compensates for force decay by prescribing a stronger elastic may increase early discomfort. Prediction should therefore support balanced selection rather than simply encourage higher initial force. The overall message is that elastic behavior is dynamic. Laboratory-based artificial intelligence may help translate this dynamic behavior into clearer clinical guidance for force maintenance and replacement timing. Recent studies similarly show substantial time-dependent force degradation of orthodontic elastics under simulated and clinical oral conditions, with clinically relevant loss occurring within the first day of wear **[14, 15 and 16].**

Conclusion:

Orthodontic elastics exhibited significant time-dependent force degradation under all simulated oral conditions. Latex elastics exposed to acidic saliva showed the greatest percentage force loss, whereas non-latex elastics in neutral saliva retained force more effectively. The random forest model predicted residual force with high accuracy, supporting the use of artificial intelligence as an adjunctive tool for laboratory screening and future individualized orthodontic elastic prescriptions.

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