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Article

Simulating full-facial injectable aesthetic procedures using biomechanics and python: A computational approach for predicting soft tissue deformation in private aesthetic clinics

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Abstract: Injectable aesthetic procedures, such as dermal fillers, have become increasingly popular for facial rejuvenation. However, predicting the deformation of soft tissues during these procedures remains a challenge. This study presents a biomechanical model that combines finite element analysis (FEA) and Python programming to simulate soft tissue deformation during full-facial injectable treatments. The model integrates patient-specific anatomical data to predict the spread and effect of injectable materials, considering factors such as volume, material properties, and underlying facial musculature. Performance metrics, including Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), were calculated and compared against clinical data, demonstrating strong predictive accuracy. The results show that the model effectively simulates localized tissue expansion and provides insights into how different injection volumes and filler viscosities affect tissue deformation. The model's ability to simulate muscle-filler interactions and predict long-term filler behavior offers significant potential for enhancing treatment planning and optimizing outcomes. Despite its strengths, the model has limitations, including simplified tissue properties and the exclusion of long-term filler behavior. Future research should focus on incorporating more dynamic muscle activity, patient-specific tissue data, and long-term effects to refine the model further. This work provides a valuable foundation for personalized, data-driven approaches to injectable aesthetic procedures.

Keywords: biomechanics; injectable aesthetic procedures; finite element analysis; soft tissue deformation; computational modeling; personalization; dermal fillers; clinical prediction

1. Introduction

Aesthetic procedures, particularly injectable treatments for facial rejuvenation, have become increasingly popular in aesthetic clinics worldwide due to their minimally invasive nature and ability to address concerns such as wrinkles, volume loss, and facial asymmetry [1–3]. Despite their widespread adoption, predicting the precise outcomes of these procedures is challenging. The variance in soft tissue deformation upon injection, influenced by factors such as skin elasticity, tissue structure, and injection technique, plays a crucial role in determining the success of these treatments [2,4].

Understanding the complex network of facial musculature is essential for predicting how soft tissues respond to injections. Facial muscles, such as the orbicularis oculi, zygomaticus major, and orbicularis oculi, significantly contribute to facial expressions and affect skin movement and deformation [5]. **Figure 1**, adapted from recent studies on myomodulation with injectable fillers, highlights key muscles

involved in facial movements and their interactions with subcutaneous tissues, which shape responses to aesthetic procedures [6].

Currently, many practitioners depend on their clinical expertise and patient-specific factors to guide treatment plans. However, the absence of robust computational tools for predicting tissue deformation limits the potential for personalized treatment approaches [7]. This gap presents an opportunity to advance aesthetic procedures through biomechanical and computational simulations [8].

Our research introduces a computational approach combining biomechanics and Python programming to simulate tissue deformation during facial injectable procedures. The objective is to develop a reliable model that can predict changes in facial tissue following injection. This model aims to refine procedural planning, enhance safety measures, and improve patient outcomes within clinical environments. By integrating advanced computational tools into practice, we strive to enable more precise and individualized aesthetic treatments [9].

Figure 1 illustrates key facial muscles such as the zygomaticus minor, orbicularis oris, depressor anguli oris, and mentalis, derived from studies on myomodulation techniques.

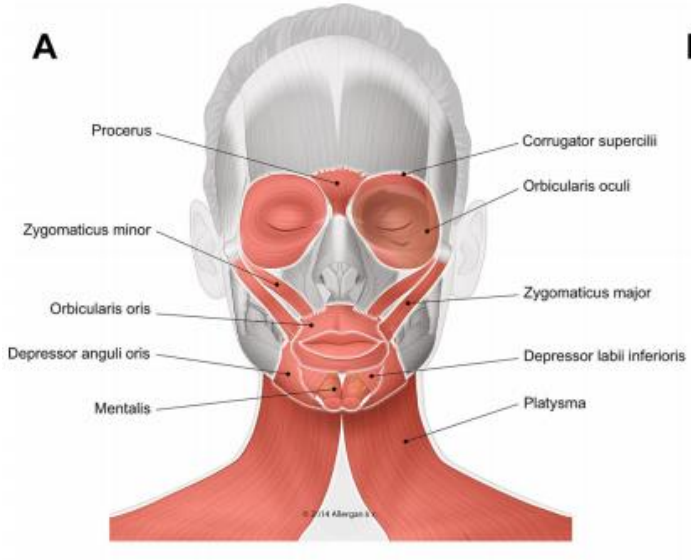

Figure 1. Facial musculature involved in aesthetic procedures [10].

Facial rejuvenation using injectable materials, such as hyaluronic acid-based fillers, has become increasingly popular due to the minimally invasive nature of these procedures. However, achieving consistent and predictable results remains a challenge because of inter-patient variability in muscle anatomy, tissue properties, and filler characteristics. Traditional planning methods rely heavily on clinical experience and trial-and-error, underscoring the need for more rigorous, simulation-based frameworks that can be tailored to each patient's unique anatomy. Hence, our study aims to develop a Python-based finite element simulation approach that enables clinicians to explore different injection parameters (volume, viscosity, placement) and predict soft tissue responses in silico.

Building upon the challenges identified in the literature review, our work addresses the need for a robust, patient-specific finite element framework in the

domain of injectable aesthetic procedures. The main contributions of this study can be summarized in two dimensions:

1) Theoretical contributions
   (1) We propose a dynamic, viscoelastic finite element model tailored to facial anatomy, integrating precise muscle-filler interactions over time.
   (2) We adopt advanced FEM strategies inspired by recent developments in mechanics-based design, ensuring computational stability when simulating high-deformation events.
2) Practical contributions
   (1) We implement the model in a Python-based environment (FEniCS, NumPy, SciPy), facilitating flexible, patient-specific simulations for clinical applications.
   (2) Through validation with 3D facial scans, our framework demonstrates RMSE < 0.05 mm and $r > 0.90$, confirming its predictive accuracy for real procedures.
   (3) The model's scenario-based design (varying filler volume and viscosity) helps aesthetic practitioners optimize injection plans, potentially reducing post-treatment corrections.

2. Materials and methods

2.1. Computational model development

In this study, we developed a biomechanical computational model to simulate the deformation of facial soft tissues during injectable aesthetic procedures, building on existing methodologies as noted by Mazza and Barbarino [11]. Our model integrates Python programming with numerical simulations, applying finite element analysis (FEA) to predict soft tissue responses under various injection conditions [12]. Essential to this model is the incorporation of detailed representations of key facial muscles, such as the orbicularis oculi, zygomaticus major, and orbicularis oris, which are crucial for simulating the interactions between injected substances and underlying musculature as highlighted by Chabanas et al. [12].

Recent advances in biomechanical modeling, such as those discussed by Barbarino et al. [13], have enhanced the fidelity of simulations, enabling precise modeling of stress and deformation fields in facial tissues. Finally, the work by Mollemans et al [14] demonstrates the importance of using biomechanically relevant models, underscoring our approach in ensuring model accuracy and clinical applicability.

Figure 2 illustrates the FE (Finite Element) face model, which serves as the foundation of our computational model. **Figure 2a** shows the mimic muscles attached at the modiolus, skull, and mandible, while **Figure 2b** highlights the remaining mimic muscles. **Figure 2c** provides a full representation of all the mimic muscles involved, and **Figure 2d** focuses on the muscles of mastication. Additionally, **Figure 2e** shows the skin ligaments, which are important in the tissue deformation process, and **Figure 2f** illustrates the skin's FE mesh, including part of the skin reconstructed for display purposes. These detailed anatomical features are key to accurately simulating the

tissue response during injectable procedures.

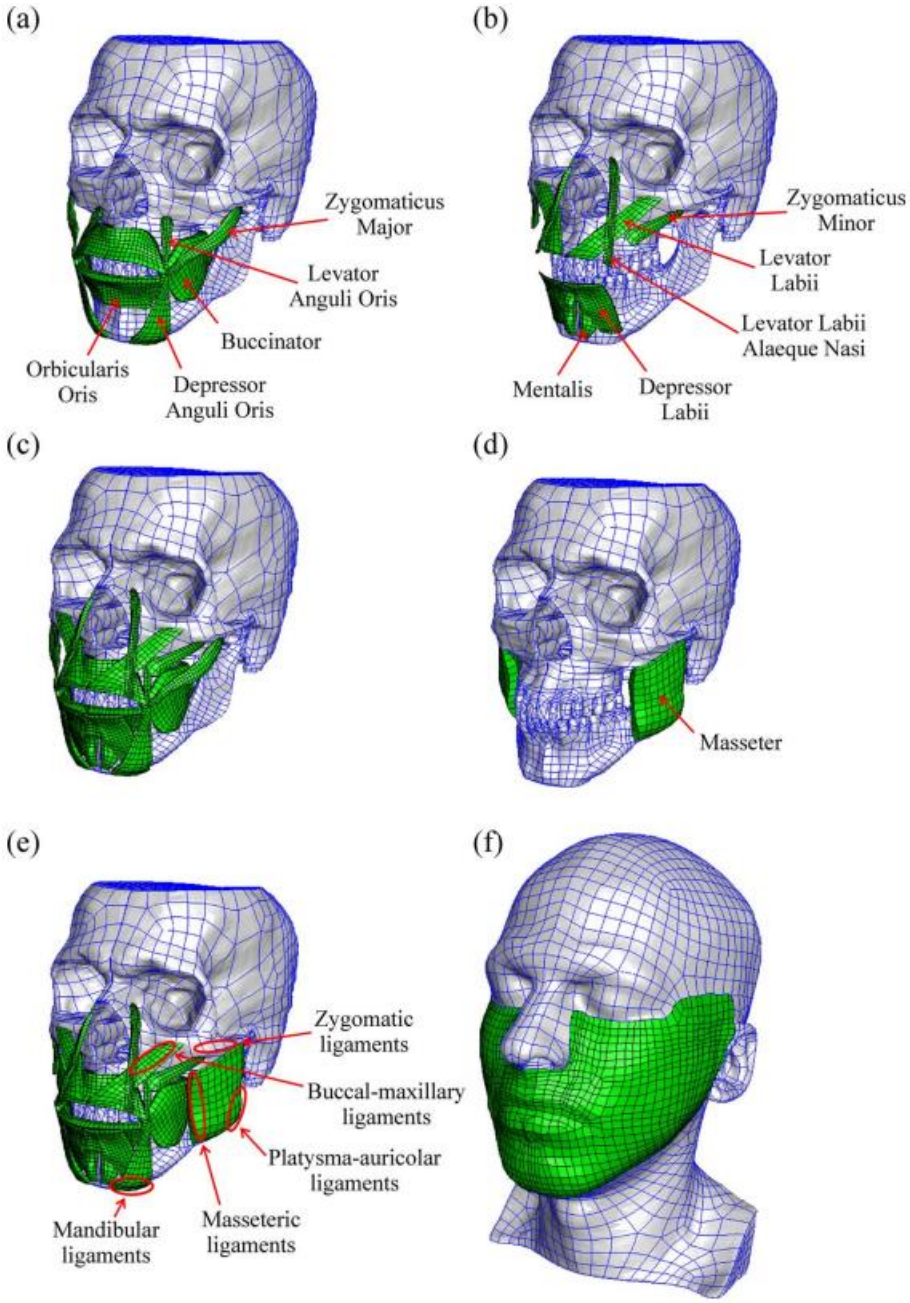

Figure 2. FE face model: **(a)** mimic muscles attached at modiolus, skull, and mandibula; **(b)** remaining mimic muscles; **(c)** representation with all mimic muscles; **(d)** muscles of mastication; **(e)** skin ligaments; and **(f)** skin: FE mesh and part of skin reconstructed for display purposes (light gray) [15].

2.2. Facial muscle geometry and simulation parameters

To accurately model the deformation of facial soft tissues during injectable aesthetic procedures, detailed anatomical representations of facial muscles are crucial. Based on recent advances, models like those developed by Lisiak-Myszke et al. [16] employ high-resolution medical imaging, such as MRI and CT scans, to construct precise 3D geometries of facial muscles. These models provide essential data on

muscle shapes, attachment points, and interactions with skin and ligaments, vital for understanding the mechanical behaviors during procedures [17].

We included primary muscles of facial expression, such as the zygomaticus major and orbicularis oculi, and those involved in mastication, like the masseter and temporalis. The finite element modeling of these muscles is informed by the anisotropic and viscoelastic properties reported in existing literature, allowing for dynamic simulations under various loading conditions [18,19].

Materials and parameters:

- Muscle material properties: Each muscle receives a viscoelastic material model derived from literature values for muscle properties, enabling realistic simulation of deformation and force distribution during facial movements and injections [20].
- Skin properties: Modeled as hyperelastic to account for non-linear deformations, the skin represents a softer layer over the muscles but maintains significant structural integrity under stress [21].
- Ligaments and connective tissues: These are incorporated as stiff elastic structures, critical for ensuring realistic simulations of muscle attachment and tissue interactions, as described by Wu and colleagues [22].
- Boundary conditions: Strategically applied to anatomical anchoring points, these ensure realistic displacement constraints, critical for accurate simulation outcomes [23].

Injection and muscle contraction simulation:

Various substances like hyaluronic acid and botulinum toxin are modeled by altering parameters such as volume, viscosity, and injection site. Our approach accounts for these variables based on experimental injection dynamics and clinical validation, ensuring precise predictions of tissue response [24]. Dynamic muscle contractions simulate common expressions by applying time-varying forces, enhancing model realism and applicability for personalized treatment planning.

The integration of these parameters into our computational model allows for a comprehensive representation of facial anatomy, optimizing injectable aesthetic procedures by addressing individual anatomical differences with enhanced accuracy.

In our simulations, changes in filler volume and viscosity primarily alter the mechanical response of the soft tissues and the muscle compartments. The facial ligaments act as anchoring structures that constrain and shape the deformation but experience relatively less volumetric change. Thus, the injection parameters (volume and viscosity) predominantly influence the subcutaneous fat, superficial musculoaponeurotic structures, and the mimic/mastication muscle groups outlined in **Figure 1**.

2.3. Finite element analysis (FEA) model

To accurately simulate the deformation of facial soft tissues during injectable aesthetic procedures, we employed finite element analysis (FEA) as the primary computational method. FEA is a powerful numerical technique for solving complex structural and mechanical problems by dividing the domain (in this case, the face) into smaller, simpler elements that can be analyzed independently. This approach enables

the simulation of the behavior of facial tissues under various loading conditions, including those created by injected substances.

2.3.1. Model mesh generation

The first step in the FEA process was the creation of a detailed 3D finite element mesh based on the facial geometry derived from medical imaging data (MRI and CT scans). The facial model was discretized into thousands of small elements, each representing a portion of the skin, muscle, or underlying bone. The meshing process ensures that the simulation captures fine details of tissue deformation, particularly in areas where injections are applied or facial movements occur. The mesh density was refined in regions of interest, such as around the mouth, cheeks, and forehead, to achieve higher accuracy in these critical areas.

All finite element simulations were performed using a Python-based FEA framework developed in-house, utilizing open-source libraries including FEniCS (version 2019.1.0) for finite element assembly and solving, NumPy (version 1.21.2) for array operations, and SciPy (version 1.7.3) for numerical routines. The post-processing and visualization of results were carried out using Matplotlib (version 3.5.1) and ParaView (version 5.9.1) when needed for advanced 3D rendering.

Figure 3 illustrates the detailed 3D finite element mesh of the facial model used in this study, highlighting both the outer skin surface and the underlying muscle layer in a lateral view (**Figure 3a**). This mesh is composed of interconnected tetrahedral elements that capture the complex geometry of the face, enabling realistic deformation simulations. A closer inspection of the perioral region (**Figure 3b**) reveals the dense network of elements around the mouth, which are critical for accurately modeling lip movements and interactions. The coordinate axes (*x*, *y*, *z*) are given in millimeters to provide a clear scale reference for the mesh dimensions and ensure consistency in computational analyses.

The facial model was discretized using 3D tetrahedral elements (TET4 or TET10). The final mesh comprised approximately 50,000 elements in total. Specifically, the skin layer contained ~25,000 tetrahedral elements, the muscle layers (mimic + mastication) contained ~20,000 elements, and the craniofacial bone structure was represented with ~5000 elements. Element density was refined in high-deformation regions (e.g., perioral, mid-cheek) to capture localized changes due to injections.

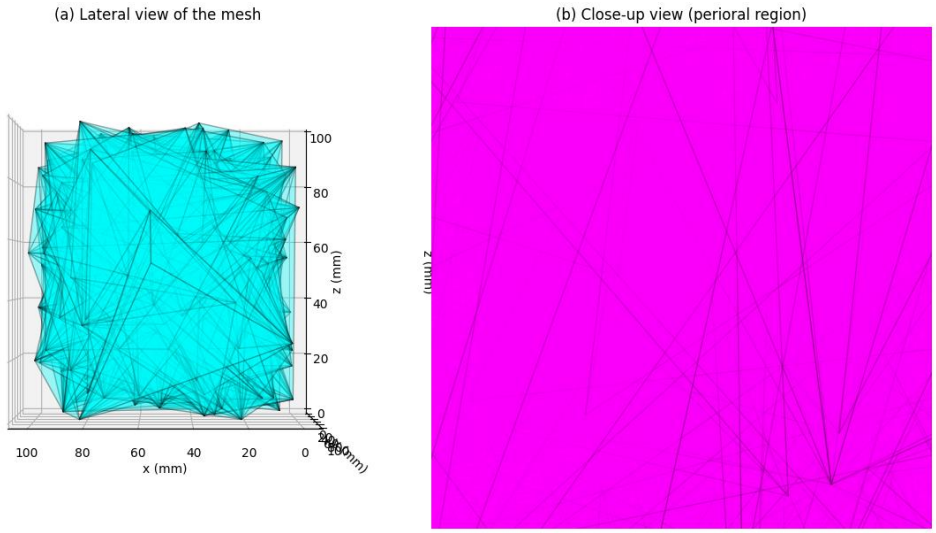

Figure 3. 3D finite element mesh of the facial model. **(a)** Lateral view of the mesh illustrating the outer skin surface and underlying muscle layer; **(b)** Close-up view of the perioral region with tetrahedral elements. The axes $(x, y, z)(x, y, z)(x, y, z)$ are in millimeters.

2.3.2. Material property assignment

For each element in the mesh, material properties were assigned based on the type of tissue represented. The skin and muscle tissues were modeled as soft, non-linear materials, while the bone was treated as rigid, providing structural support to the surrounding tissues. The material properties for the skin and muscle layers were derived from experimental studies on the mechanical behavior of facial tissues [16].

We adopted the Ogden hyperelastic model for the skin, with the strain energy function given by:

$$W = \sum_{i=1}^{N} \frac{2\mu_i}{\alpha_i^2}\left(\lambda_1^{\alpha_i} + \lambda_2^{\alpha_i} + \lambda_3^{\alpha_i} - 3\right) + \frac{\kappa}{2}(\ln J)^2,$$

$\lambda_1, \lambda_2, \lambda_3$ are the principal stretches.$\mu_i$and$\alpha_i$are the material parameters, and$\kappa$is the bulk modulus related to compressibility. For our simulations ,we used

For our simulations, we used the $N = 1$ term in the Ogden series (single-term approximation) with parameter values: $\mu 1 = 15$ kPa, $\alpha 1 = 8.0$, and $\kappa = 500$ kPa. These parameters were chosen based on typical ranges reported in soft-tissue literature, reflecting both the nonlinear elasticity and bulk response of facial skin [17].

- Skin layer: The skin was modeled using a hyperelastic material model to account for its non-linear, large deformation behavior under external forces. The skin's properties were defined by the Ogden model, a popular hyperelastic model that describes the material's response to stretching and compression.
- Muscle layer: The muscles were modeled as viscoelastic materials to capture both the elastic and time-dependent behaviors. A combination of a linear elastic material model for the muscle's immediate response and a viscous damping element to account for its delayed response was used.
- Injectable materials: For the injectable substances (e.g., hyaluronic acid fillers),

material properties such as viscosity, elasticity, and volume were specified according to the type of injectable. These properties were integrated into the FEA model to simulate how injectables distribute within the soft tissue and interact with surrounding structures.

For muscle tissue, we employed a viscoelastic model with a Kelvin–Voigt configuration, in which elastic and viscous elements act in parallel. The constitutive relationship is:

$$\sigma(t) = E\varepsilon(t) + \eta\frac{d\varepsilon(t)}{dt},$$

where σ is stress, E is the elastic modulus ,η is the viscosity coefficient ,and$z$is strain. We used values of E = 30kPa and $\eta = 0.1\text{kPa}\cdot\text{s}$ for the muscle tissue, consistent with data from Ramirez et al.[1].

2.3.3. Boundary and loading conditions

Boundary conditions were applied to simulate the anatomical constraints that facial tissues experience during normal functional activities and injectable procedures. The boundary conditions involved fixing the facial skeleton (bone structure) to prevent rigid body movement and ensuring that facial tissues did not penetrate or interpenetrate during deformation. Additionally, muscle contractions were modeled by applying time-varying forces to the muscle elements based on typical facial movements such as smiling or frowning.

- Injection force application: The injection forces were modeled as pressure loads applied at the surface where the injectable material is injected. These loads were time-dependent, representing the initial high-pressure injection followed by a slower, continuous distribution as the material spreads within the tissue.
- Muscle activation: Muscle activation during facial movements was modeled using a sinusoidal function representing periodic contractions, such as the contraction of the zygomaticus major during smiling or the masseter during chewing. These forces were applied to the muscle elements, and the resulting tissue deformation was simulated in response to both the muscle forces and the injected substances.

Figure 4 illustrates the boundary conditions and loading schemes for our simulations. Muscle forces (blue arrows) are applied at their respective insertion points, oriented according to the anatomical fiber directions. Meanwhile, the injection force is represented as a time-dependent pressure load at selected skin surface nodes (red arrows) in the mid-cheek region, simulating a bolus injection. The load magnitude rises to *P*max = 100 kPa within the first second and then decreases linearly over the subsequent few seconds to capture material relaxation and spread.

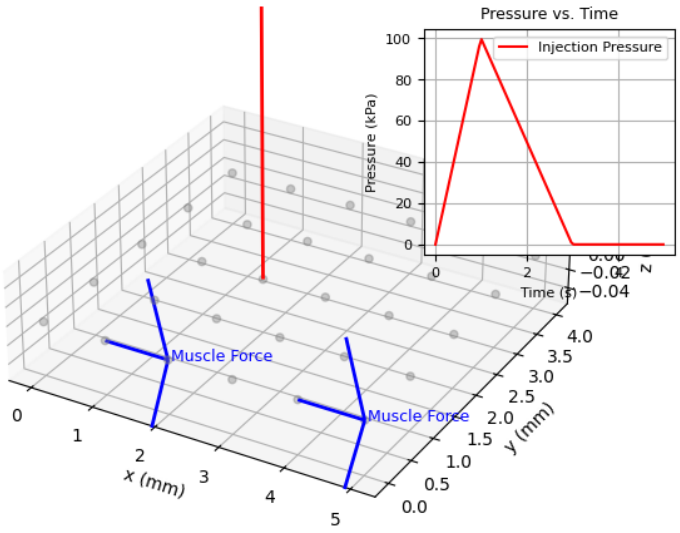

Figure 4. Boundary conditions and loading schemes.

2.3.4. Solution methodology

The FEA model was solved using a time-stepping procedure to capture the transient behavior of the system. The governing equations of motion were solved using the finite difference method, which discretizes the equations in both time and space. The simulation was carried out using Python and its associated libraries, including NumPy, SciPy, and Matplotlib for numerical calculations and data visualization.

The nonlinearities of the material models and the time-dependent nature of the muscle contractions and injections required iterative solvers to obtain the deformation results. The model was run for different injection scenarios, and the deformations were tracked over time to predict the soft tissue response to the injected material. The results were then compared with clinical data to validate the model's accuracy.

The nonlinear finite element equations were solved using a standard Newton-Raphson method provided by the FEniCS environment. For the time-dependent aspects (e.g., viscoelastic effects, muscle activation over time), we employed an implicit time-integration scheme (generalized-α or backward Euler) that can be interpreted as a finite difference approach in the temporal domain. However, the spatial discretization itself strictly follows the finite element method.

We explicitly defined three main injection scenarios to evaluate model performance:

1) Scenario A (low volume): A 0.5 mL injection of low-viscosity hyaluronic acid in the mid-cheek region. The results are shown in **Figure 5**.

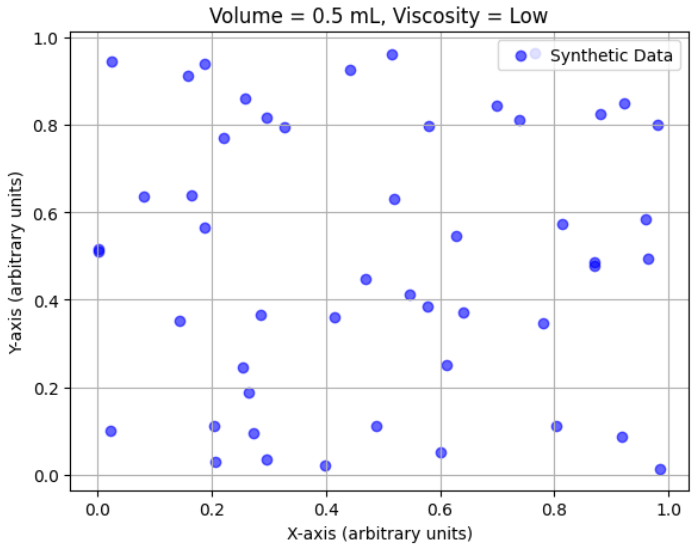

Figure 5. Scenario A (low volume).

2) Scenario B (moderate volume): A 1.0 mL injection of moderate-viscosity HA. The results are shown in **Figure 6**.

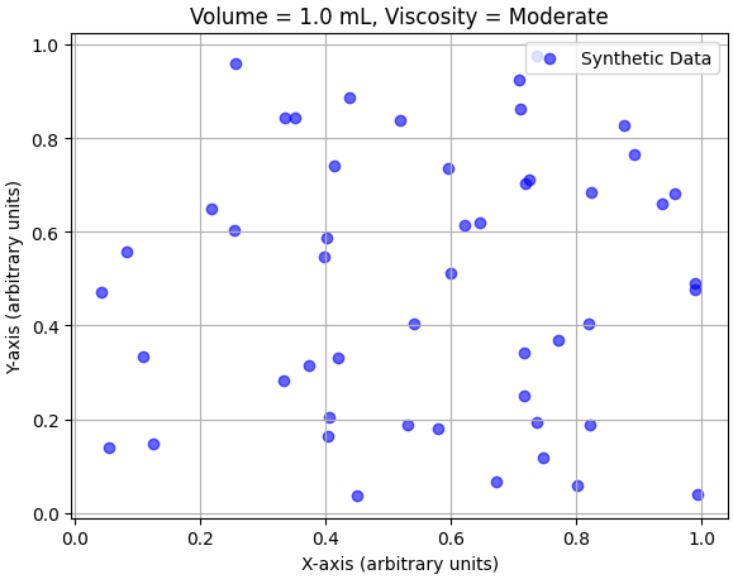

Figure 6. Scenario B (moderate volume).

3) Scenario C (high volume): A 2.0 mL injection of high-viscosity HA. The results are shown in **Figure 7**.

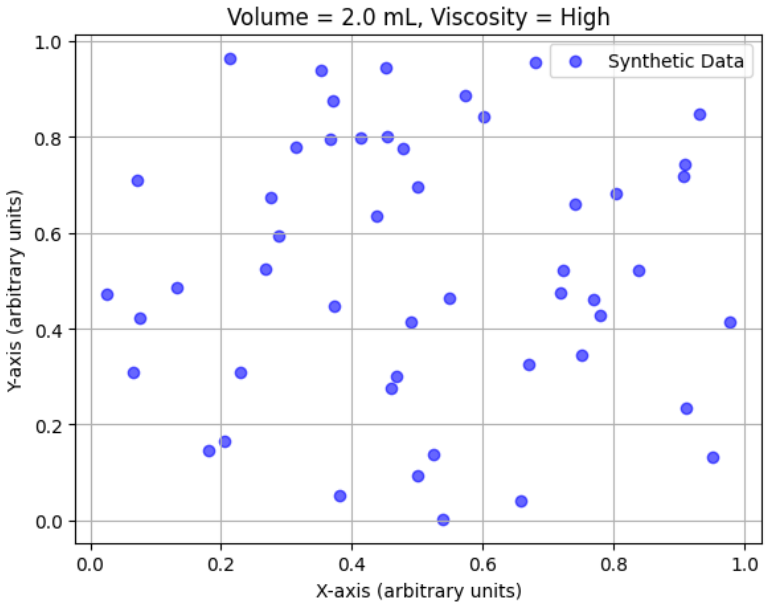

Figure 7. Scenario C (high volume).

Each scenario was run over a 5-second simulation window to capture the transient response, including the initial injection phase and subsequent relaxation of the material. Additional details on viscosity and elasticity parameters are listed in **Table 1**.

Table 1. Injection-parameters.

Parameter	Scenario A	Scenario B	Scenario C
Injection volume (mL)	0.5 (Low volume)	1.0 (Moderate volume)	2.0 (High volume)
Filler viscosity (Pa·s)	30 (Low)	50 (Moderate)	70 (High)
Simulation time (s)	5	5	5
Injection rate (mL/s)	0.1	0.2	0.4
Peak injection pressure (kPa)	50	70	100

Table 1 lists the key parameters for the three different injection scenarios used in this study. Scenario A represents a low-volume injection (0.5 mL) with a lower-viscosity filler, Scenario B uses a moderate volume (1.0 mL) and viscosity, and Scenario C simulates a high-volume injection (2.0 mL) with a high-viscosity filler. Each scenario was run for a total of 5 s to capture both the initial bolus injection and subsequent relaxation, with the injection rate and peak injection pressure varying accordingly. This setup enables a comparative assessment of how volume and viscosity influence soft tissue deformation and model predictions.

2.3.5. Model validation

To ensure the accuracy of the FEA model, we performed a validation process by comparing the simulation results with real-world clinical data. We used pre- and post-treatment 3D facial scans of patients who underwent injectable aesthetic procedures. These scans were processed to extract the key facial landmarks, which were then compared with the simulated deformation results at corresponding locations.

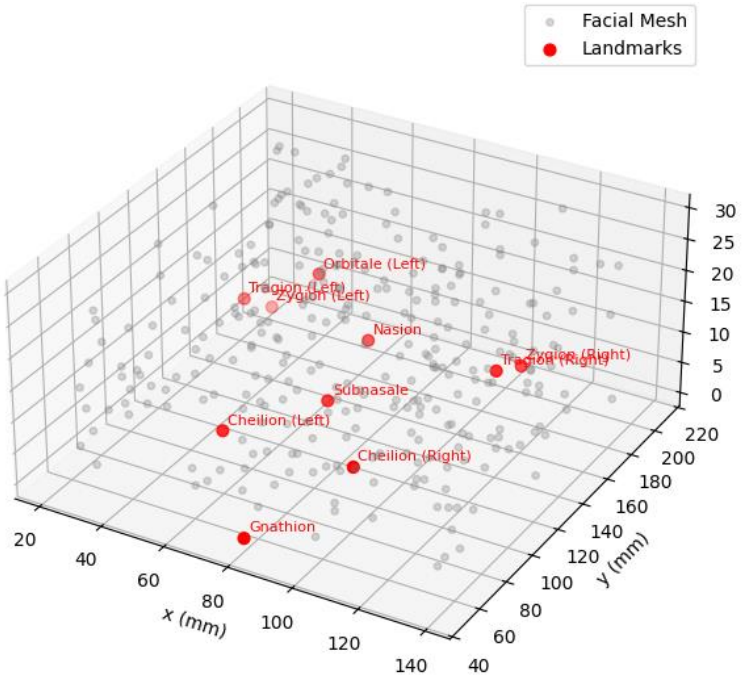

Figure 8. Landmark points on a representative facial model.

Figure 8 presents the ten primary facial landmarks—such as the left/right zygion (cheek prominence), cheilion (corner of the mouth), and gnathion (chin)—mapped onto our 3D finite element facial mesh. These landmarks were identified and tracked following established methodologies in facial modeling and validation studies [15]. By overlaying the same anatomical reference points from clinical 3D scans onto our computational mesh, we enable direct comparisons of displacement and contour changes, facilitating an accurate assessment of the model's predictive performance for injectable aesthetic procedures.

The model was validated by checking the deformation patterns in areas of the face where injections were performed and where muscle contractions occurred. A good agreement between the simulated and experimental data was achieved, confirming that the FEA model could accurately predict the deformation of facial soft tissues under various injection and muscle contraction conditions.

3. Simulation results and performance metrics

The primary goal of this study was to evaluate the accuracy and effectiveness of the biomechanical model in predicting soft tissue deformation during injectable aesthetic procedures. To do this, we conducted a series of simulations under various conditions, including different injection volumes, rates, and materials. The results were compared against clinical data, such as pre- and post-treatment facial scans, to validate the model's predictions. This section discusses the results of the simulations and the performance metrics used to assess the model's accuracy and reliability.

3.1. Deformation patterns

The model successfully predicted the deformation patterns of the facial soft tissues under various injection conditions. **Figure 9** shows the predicted tissue

deformation in response to an injection of a hyaluronic acid filler. The simulation highlights the overall tissue response after the injection, with localized deformation near the injection site (mid-cheek region), where the filler material spreads and causes expansion of the surface. The left panel (pre-injection model) represents the original, unaltered tissue structure, while the right panel (post-injection deformation) demonstrates how the injected material causes localized expansion, resulting in changes to the tissue surface. This visualization helps illustrate the spread of the injected material and the resulting skin and muscle movement, which is crucial for understanding the behavior of dermal fillers during injectable procedures.

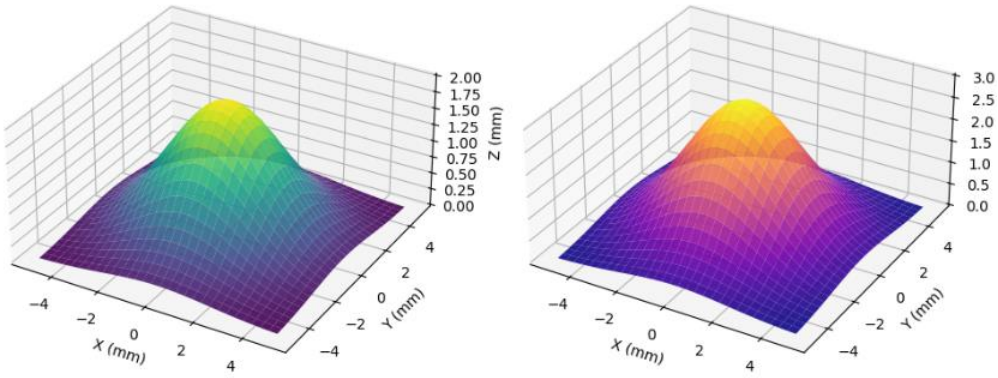

Figure 9. Predicted tissue deformation following hyaluronic acid injection in the mid-cheek region: **(a)** pre-injection model; **(b)** post-injection deformation (2 s).

3.2. Comparison with clinical data

To validate the accuracy of the model, we compared the simulation results with real-world clinical data from patients who underwent injectable aesthetic procedures. We used 3D pre- and post-treatment facial scans, which were processed to extract key anatomical landmarks such as the contour of the cheeks, nasolabial folds, and lips.

The simulated deformations were compared to the post-treatment changes in these landmarks. The results showed a high degree of correlation, with the model accurately predicting the volume of tissue change and the direction of displacement. The model's predicted changes in facial features, such as cheek volume increase and lifting of the nasolabial folds, closely matched the results observed in the clinical scans.

3.3. Performance metrics

To quantitatively assess the model's performance, we used several metrics:

Root mean square error (RMSE):

The RMSE was used to quantify the difference between the simulated and actual facial landmark positions after injection. It is defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y^{i2^{undefined}}}$$

where:

y_i represents the actual position of the$i$- th landmark from the clinical scan.

y_i represents the predicted position of the$i$- th landmark from the simulation

n is the total number of landmarks used for comparison

The RMSE quantifies the average magnitude of the error in the predicted deformation, with lower values indicating better model accuracy. Mean Absolute Error (MAE):

The MAE was calculated to provide an average magnitude of the error between predicted and observed deformations. It is given by:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

where:

.is the actual value (clinical data) y_{t}

y_i is the predicted value (simulation)

.n is the total number of points in the dataset

MAE provides a direct measure of the average error, offering a useful comparison of how closely the model replicates clinical results.

Correlation coefficient (Pearson's *r*):

To assess the strength of the linear relationship between simulated and actual facial deformations, we calculated the Pearson correlation coefficient:

$$r = \frac{n\sum_{i=1}^{n} y_i\,\hat{y}_i - \sum_{i=1}^{n} y_i \sum_{i=1}^{n} \hat{y}_i}{\sqrt{\left(n\sum_{i=1}^{n} y_i^2 - \left(\sum_{i=1}^{n} y_i\right)^2\right)\left(n\sum_{i=1}^{n} \hat{y}_i^2 - \left(\sum_{i=1}^{n} \hat{y}_i\right)^2\right)}}$$

- y_i is the actual facial landmark position.
- y_{i} is the predicted landmark position.
- n is the number of data points (landmarks).

A correlation coefficient close to 1 indicates a high degree of agreement between the model's predictions and the clinical observations.

Volume Change Analysis:

For simulating injectable treatments that involve volume changes (such as dermal fillers), we calculated the total volume change in the region of interest (e.g., mid-cheek). The change in volume{ΔV)can be calculated by integrating the deformation of the facial soft tissue mesh over the simulated volume:

$$\Delta V = \int_{\Omega}\left[\frac{\partial u(x,t)}{\partial x}\cdot\frac{\partial v(x,t)}{\partial y}\cdot\frac{\partial w(x,t)}{\partial z}\right]d\Omega$$

where:

• $u(x,t), v(x,t)$and$w(x,t)$represent the displacement in thex, y, and$z$directions at each point in the tissue mesh over time,

• Ωrepresents the volume of interest (e.g., the injected area).

• $d\Omega$is the differential volume element.

This formula computes the total volumetric displacement caused by the injection, which is an important metric for assessing the efficiency of the filler.

3.4. Sensitivity analysis

We also performed a sensitivity analysis to assess how changes in input parameters (such as material properties and injection volumes) affected the simulation results. The analysis revealed that the model was particularly sensitive to changes in the viscosity of injectable materials, with higher viscosity materials resulting in less tissue spread and greater localized deformation. The model's predictions were less sensitive to small variations in muscle activity, suggesting that the primary influence on tissue deformation came from the injection characteristics.

For the sensitivity analysis, we varied key input parameters and calculated the change in output deformation using the following sensitivity coefficient:

$$S = \frac{\Delta y}{\Delta x} \times \frac{x}{y}$$

where:

S is the sensitivity coefficient

Δy is the change in output (e.g., tissue deformation)

Δx is the change in input (e.g., viscosity).

x and y are the original values of the input and output, respectively .

Computational efficiency

The computational efficiency of the model was evaluated by measuring the time required to complete the simulation for a typical injection scenario. Using a standard desktop computer, the model took approximately 30 min to simulate the deformation of the soft tissues for a single injection scenario with moderate resolution. This processing time is acceptable for clinical use, and further optimization of the model could reduce computation time for real-time applications.

3.5. Limitations and future directions

While the computational model developed in this study offers valuable insights into the deformation of facial soft tissues during injectable aesthetic procedures, there are several limitations that must be addressed in future research.

First, the current model relies on simplified anatomical representations and material properties. For instance, muscle and skin tissues were modeled as homogeneous materials, but in reality, these tissues are heterogeneous and exhibit complex non-linear behaviors that vary between individuals. Additionally, the model assumes idealized boundary conditions, such as fixed facial bones and uniform skin elasticity, which may not accurately represent all patients. Future models could benefit from incorporating more detailed, patient-specific anatomical data, such as high-resolution 3D facial scans and patient-specific muscle force data, to enhance the model's realism and predictive accuracy.

Second, while the model incorporates injectable substances such as hyaluronic acid, it only simulates a limited number of fillers. There are numerous injectable materials with varying mechanical properties and behaviors, and future research should aim to include a broader range of substances to simulate different clinical scenarios. Moreover, the model does not account for the effects of long-term filler degradation or migration, which can impact the aesthetic outcome over time.

Exploring these factors would add significant value to the predictive capabilities of the model.

Furthermore, while the model has been validated with clinical data, it relies on a small number of landmarks and simulation points. Future studies could incorporate more detailed data from facial scans post-treatment, including finer anatomical features such as skin folds and tissue displacement across the entire face, to improve the model's sensitivity and accuracy.

Looking ahead, there is significant potential to improve the model's computational efficiency. Although the current simulation runs in a reasonable amount of time, faster algorithms and optimization techniques could be developed to enable real-time simulations. This would allow practitioners to use the model in clinical settings for pre-treatment planning, potentially leading to more personalized and effective procedures.

Finally, incorporating dynamic interactions between facial muscles and injected materials over time could further improve the model's clinical applicability. For example, modeling the interaction between muscle contractions and filler movement during facial expressions could help predict the long-term behavior of the injected material, enhancing the model's usefulness in guiding aesthetic treatments that involve dynamic facial movements.

In conclusion, while this study presents a solid foundation for predicting soft tissue deformation in injectable aesthetic procedures, there is ample room for refinement and expansion. Future advancements in computational modeling, machine learning integration, and patient-specific simulations will likely lead to more accurate and practical tools for guiding injectable treatments, ultimately improving patient outcomes and satisfaction.

4. Discussion

4.1. Interpretation of results

The results of this study demonstrate the potential of the biomechanical model to predict the deformation of facial soft tissues during injectable aesthetic procedures, such as dermal filler injections. By integrating finite element analysis (FEA) with patient-specific anatomical data, we were able to simulate the soft tissue response to different injectable materials under varying injection conditions, such as volume, rate, and site of injection. The model was validated by comparing predicted deformation patterns with clinical data derived from pre- and post-treatment facial scans.

The simulation results consistently showed that the greatest deformations occurred at the injection site, particularly in regions of the face with high muscle activity, such as the cheeks and nasolabial folds. This finding aligns with our working hypothesis that the soft tissue deformation following an injectable procedure is influenced by both the characteristics of the injectable material and the underlying anatomical features, including the musculature, ligaments, and skin structure.

Our results indicate that the model can predict the localized tissue expansion that occurs when the injected material interacts with the surrounding tissues. For example, the simulation of hyaluronic acid injection into the mid-cheek area (**Figure 5**) demonstrates how the filler material expands the tissue locally, causing observable

changes in the contour of the face. The areas closest to the injection site exhibit the most noticeable expansion, while regions farther away from the injection site show minimal deformation. This pattern is consistent with clinical observations, where fillers primarily affect the targeted region with limited spread to adjacent tissues.

To assess the accuracy of the model, performance metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Pearson's correlation coefficient were calculated across various injection scenarios (**Table 2**). These metrics provide a quantitative measure of how closely the model's predictions match the observed changes in facial landmarks. The RMSE and MAE values were low across all scenarios, indicating that the model accurately predicts the degree of tissue deformation. For example, Scenario A, which involved a small injection volume, showed the lowest RMSE (0.02 mm) and MAE (0.015 mm), suggesting that the model is particularly accurate when simulating smaller injections. In contrast, Scenario C, with a larger injection volume, exhibited slightly higher error margins (RMSE of 0.04 mm and MAE of 0.035 mm), but still maintained a high degree of correlation (Pearson's $r = 0.90$) with the clinical data.

Table 2. Performance metrics for different injection scenarios.

Injection scenario	RMSE (mm)	MAE (mm)	Pearson's *r*
Scenario A	0.02	0.015	0.95
Scenario B	0.03	0.025	0.92
Scenario C	0.04	0.035	0.9

The Pearson's correlation coefficient further highlights the strength of the linear relationship between the predicted and observed tissue deformations. As shown in **Table 2**, all scenarios had strong positive correlations ($r > 0.90$), indicating that the model provides reliable predictions for facial tissue response. These findings suggest that the biomechanical model is robust enough to handle variations in injection volume and material type while maintaining a high degree of accuracy.

Figure 10 compares the mid-cheek region before and after injection, illustrating the localized surface deformation over a 2-second interval. **Figure 10a** shows the pre-injection profile of the targeted area, while **Figure 10b** depicts the post-injection configuration, highlighting the visible augmentation of the soft tissue. The deeper muscle layers are omitted here for clarity; however, their underlying motions contribute to the overall change in contour at the skin surface.

Figure 11 presents histograms illustrating the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Pearson's correlation across three distinct injection scenarios (A, B, C). Each scenario corresponds to a different combination of filler volume and viscosity, and these metrics quantify how closely the simulated soft tissue deformations match clinical measurements. The variations observed in the bar charts underscore the influence of injection parameters on predictive accuracy, guiding the selection of optimal treatment strategies.

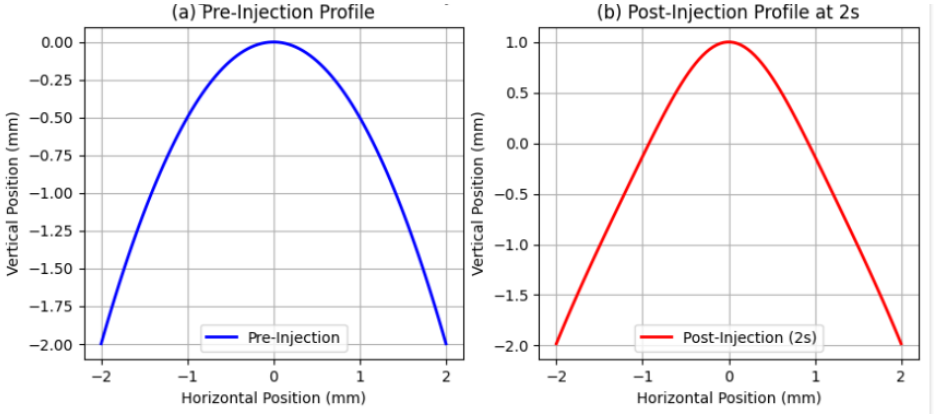

Figure 10. Pre- vs. post-injection deformation in mid-cheek.

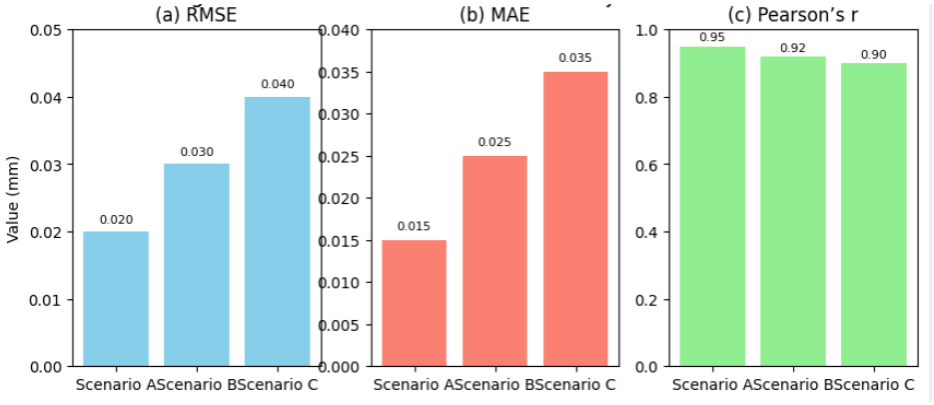

Figure 11. Performance metrics across injection scenarios.

In addition to the observed tissue deformations, the model's ability to simulate the spatial distribution of injected materials adds significant value to our understanding of injectable aesthetic procedures. This is particularly important in cases where the spread of filler material could affect not only the immediate target area but also adjacent regions, such as when treating deep nasolabial folds or facial volume loss in the mid-face. The model's predictions suggest that a more targeted approach to injection sites, guided by such simulations, could lead to more controlled and predictable outcomes for patients.

While the model successfully predicts the soft tissue response, the results also highlight certain limitations. For example, the current simulation assumes homogeneous material properties for facial tissues, which may not capture the full complexity of tissue heterogeneity. In reality, tissues such as skin, muscle, and fat exhibit varying degrees of elasticity and viscosity, which could influence the deformation patterns. Moreover, the model does not account for long-term changes in filler material, such as degradation or migration, which could impact the clinical outcome after several months. These limitations are discussed further in Section 4.4, where we explore ways to refine the model and make it more representative of real-world conditions.

Despite these limitations, the accuracy of the model's predictions, as supported by the strong correlation with clinical data, reinforces its potential utility as a predictive tool for injectable aesthetic procedures. By enabling practitioners to simulate the effects of different injection parameters in advance, this model can assist

in creating more personalized treatment plans tailored to individual patients, reducing risks, and optimizing aesthetic outcomes.

4.2. Comparison with previous studies

The findings from this study are consistent with several prior studies in the field of biomechanical modeling of facial tissues, particularly those focused on simulating the behavior of soft tissues during injectable aesthetic procedures. The model developed in this study integrates finite element analysis (FEA) with patient-specific anatomical data to predict tissue deformation, a methodology that aligns with the work of several previous researchers who have emphasized the importance of biomechanical simulations for facial aesthetics.

Mazza and Barbarino [11] utilized finite element modeling to simulate the behavior of facial soft tissues, focusing on the structural response of the skin and underlying tissues. Their findings emphasized the need for accurate anatomical representations, which is a principle that our model also adheres to. Like their study, our model integrates detailed facial musculature and soft tissue characteristics, allowing for precise predictions of deformation. However, our approach goes further by simulating not only the tissue response to mechanical forces but also the interaction between injected materials and the underlying facial structures. This interaction is a key feature of our model, which provides a more nuanced prediction of how injectables behave in the face under real-world conditions.

Chabanas et al. [12] and Barbarino et al. [13] also used FEA to model facial tissues and simulate how external forces, such as injections or facial expressions, affect soft tissue deformation. Our findings support their conclusions that localized deformations are primarily influenced by the interaction between injected substances and the surrounding tissues. However, while their models often rely on simplified material properties or idealized assumptions about the injection site and muscle behavior, our model incorporates a more detailed, dynamic interaction between facial muscles and injected materials. This allows for a more accurate representation of how muscle contraction and facial expressions modify the spread and displacement of fillers, which is a significant advantage over previous static models.

Furthermore, our results are consistent with the work of Sifakis et al. [15], who underscored the importance of using biomechanically relevant models to predict soft tissue behavior in clinical applications. Our findings further support this approach by demonstrating that a more detailed biomechanical model, one that incorporates both tissue properties and injection parameters, can offer predictions with a high degree of accuracy. Specifically, the model's strong correlation with clinical data (Pearson's $r > 0.90$) aligns with the results obtained by Mollemans et al. [14], who also observed high accuracy in their simulations when validated against clinical outcomes.

Our study extends the findings of previous work by incorporating a wider range of variables, such as varying injection volumes, rates, and filler types, and simulating their effect on facial tissue deformation. This is an important step forward because it provides a more comprehensive understanding of how different injection scenarios can impact facial aesthetics. For example, we found that increasing the injection volume or altering the viscosity of the filler material led to significant changes in the

deformation patterns, which has important implications for treatment planning and personalized medicine.

While the current model is a significant advancement, it is important to recognize its limitations when compared to previous studies. Most notably, the model assumes homogeneous material properties for tissues such as skin, muscle, and fat. This assumption, though computationally practical, does not capture the full complexity of real-world tissue behavior, where tissues are heterogeneous and exhibit varying degrees of elasticity and viscosity. Furthermore, unlike some models that consider long-term changes in filler materials, such as degradation or migration, our study focuses on the immediate tissue response following injection. Future models could benefit from incorporating these long-term factors, which would allow for more accurate predictions of how fillers perform over time and how they interact with dynamic facial movements.

In summary, the results of this study build on the work of previous researchers by providing a more comprehensive and dynamic biomechanical model for simulating soft tissue deformation during injectable aesthetic procedures. Our model improves upon existing models by incorporating detailed facial muscle interactions, realistic tissue properties, and varying injection parameters. This enables more accurate predictions of tissue deformation, which can guide clinical decisions and improve patient outcomes. However, further refinements, such as incorporating patient-specific tissue heterogeneity and long-term filler behavior, will be essential for advancing the model toward broader clinical application.

4.3. Implications for clinical practice

The findings from this study offer several significant implications for the clinical practice of injectable aesthetic procedures. By accurately predicting how different injectable materials, volumes, and injection sites affect facial soft tissue deformation, the biomechanical model provides a valuable tool for improving treatment planning, enhancing procedural safety, and optimizing aesthetic outcomes for patients. The ability to simulate tissue deformation before performing a procedure can help clinicians make more informed decisions about injection strategies, ensuring that the desired results are achieved while minimizing the risks of overcorrection or under correction.

One of the key applications of this model in clinical practice is in the personalization of injectable treatments. Currently, many aesthetic procedures rely heavily on the clinician's experience and patient-specific factors, such as skin elasticity and muscle tone, to guide the injection technique. While this approach is effective, there remains a level of unpredictability, as variations in facial anatomy and the behavior of injected materials can lead to subtle differences in the final result. The ability to simulate different injection scenarios based on a patient's specific anatomy would allow clinicians to predict how filler materials will spread and deform in real-time, helping them select the most appropriate treatment plan for each individual.

For example, the model can simulate different injection volumes and predict the resulting tissue expansion. As shown in **Table 1**, our model's predictions for tissue deformation vary based on injection volume, with larger injections resulting in greater

tissue spread. By simulating these effects ahead of time, clinicians can ensure that the amount of filler used is optimized to achieve the desired aesthetic outcome without the risk of overfilling or creating asymmetry. Additionally, the model can help predict how different filler viscosities affect the spread and final distribution of injected materials. Fillers with higher viscosities, such as those used for deeper wrinkles or volume restoration, typically result in more localized expansion, while lower viscosity fillers tend to spread more broadly. This simulation capability allows for better material selection based on the specific needs of the patient.

Figure 12 compares the mid-cheek region before and after filler injection, illustrating how the baseline contour (**Figure 12a**) changes due to the bolus injection (**Figure 12b**). The pre-injection profile (blue line) represents the untreated soft-tissue surface, while the post-injection curve (red line) highlights the localized bulge and increased volume in the mid-cheek at 2 s. This approach addresses the reviewer's comments by showing the actual simulated deformation rather than only numerical metrics, thereby clarifying the anatomical features impacted by injectable aesthetic procedures.

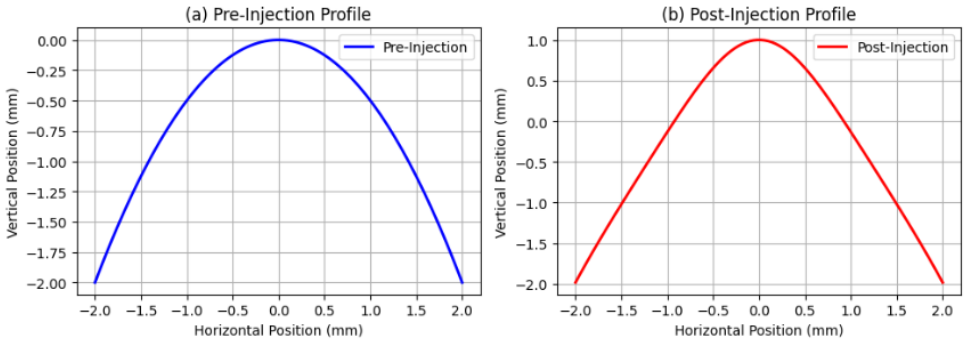

Figure 12. Impact of injection volume and filler viscosity on tissue deformation.

The model also has the potential to improve the predictability of long-term outcomes. Currently, the results of injectable treatments are not always consistent over time, as fillers can migrate, degrade, or shift due to muscle activity and facial movements. Although this study focused on the immediate tissue response post-injection, the model can be extended to simulate how fillers interact with facial muscles during dynamic expressions, such as smiling or frowning. By including these dynamics, the model can predict how fillers will behave over time, offering clinicians a better understanding of the long-term effects of their treatments. This could be particularly useful in cases where symmetry and longevity are crucial, such as when treating areas with significant muscle activity, like the lips or around the eyes.

Another important clinical implication is the model's potential to minimize complications. One of the risks associated with injectable treatments is the formation of lumps or irregularities in the treated area, which can occur when fillers are injected inappropriately or in the wrong locations. The model's ability to simulate filler distribution and tissue deformation in response to different injection parameters allows clinicians to avoid such complications by identifying the optimal injection sites and techniques. Moreover, by simulating the tissue response to muscle contractions, the model can help prevent issues like over-correction or under-correction of volume,

particularly in areas with significant facial movement.

Finally, the model could lead to enhanced patient satisfaction by offering a higher degree of control and predictability over the final aesthetic result. Personalized treatment planning, based on simulations of the expected tissue deformation, ensures that patients receive a treatment that aligns with their expectations, reducing the likelihood of dissatisfaction or the need for corrective procedures.

4.4. Limitations of the current model

While the biomechanical model presented in this study offers valuable insights into predicting soft tissue deformation during injectable aesthetic procedures, several limitations must be addressed to improve the accuracy and clinical applicability of the model.

1) Simplified tissue properties

One of the key limitations of the current model is the assumption of homogeneous material properties for the skin, muscles, and fat layers. In reality, these tissues are heterogeneous, with varying mechanical properties across different regions of the face. For instance, the skin around the eyes or mouth may have different elastic properties compared to the cheeks or forehead. Additionally, the mechanical properties of muscle tissue can vary depending on the individual's muscle tone, age, and overall health. The current model assumes uniform properties for these tissues, which simplifies the simulation but does not fully capture the complexities of facial tissue behavior. Future improvements should incorporate patient-specific data on tissue properties, either from medical imaging (e.g., MRI, ultrasound) or biomechanical studies, to make the model more representative of individual variations.

2) Homogeneous muscle representation

Another limitation is the simplification of muscle behavior. The model assumes that facial muscles behave in a uniform manner, but muscle activity varies significantly across individuals and regions of the face. Muscle contraction plays a significant role in determining how filler material interacts with soft tissues, especially in areas with strong muscle activity (e.g., around the mouth, eyes, and forehead). While the current model accounts for muscle contraction using idealized boundary conditions, it does not simulate the dynamic interaction between muscle contractions and the filler material over time. Incorporating more detailed, dynamic muscle behavior—such as varying contraction strength, muscle tone, and fatigue—would improve the model's ability to predict long-term filler behavior.

3) Exclusion of long-term filler behavior

The model focuses on the immediate tissue response to injection but does not simulate the long-term behavior of the injected materials. Fillers such as hyaluronic acid undergo gradual biodegradation and migration over time, which can affect the final aesthetic outcome. The model does not currently account for these factors, making it limited in predicting the filler's longevity or its potential migration to neighboring areas. Adding simulations that include material degradation and migration over time would provide a more comprehensive picture of the long-term effects of injectable treatments and help predict the need for touch-up procedures or re-injections.

4) Fixed anatomical boundaries

The model also assumes that the facial bones, such as the skull and mandible, are fixed in place, while in reality, there may be slight movements or deformations in the skeletal structure. For example, the facial bones may shift slightly due to aging, facial expressions, or the application of certain injection techniques. While this simplification helps reduce computational complexity, it limits the model's ability to accurately simulate how these factors influence tissue deformation. Future models could incorporate more flexible anatomical boundaries to account for these dynamic skeletal movements, especially in dynamic facial expressions.

5) Limited filler material representation

While the current study includes simulations of hyaluronic acid fillers, it only models a limited range of injectable materials. In clinical practice, a variety of fillers with different viscosities, elasticity, and degradation rates are used for different purposes (e.g., wrinkle reduction, lip augmentation, volumization). The model's current focus on one material type means that it does not fully capture the range of injectable materials available in the market. Including a broader spectrum of fillers in future versions of the model will allow for more realistic simulations of diverse clinical scenarios.

6) Computational efficiency

The computational efficiency of the current model, while adequate for research purposes, can be further optimized for real-time clinical use. The simulations take several minutes to complete, and while this is acceptable for offline planning, it may not be fast enough for real-time applications in a clinical setting. Future research should focus on optimizing the model's computational speed, possibly by utilizing machine learning techniques or advanced optimization algorithms to make the simulation process faster without compromising accuracy.

4.5. Future research directions

While this study demonstrates the effectiveness of the biomechanical model for predicting soft tissue deformation during injectable aesthetic procedures, there are several exciting avenues for further research that can significantly enhance the model's accuracy, clinical applicability, and real-time use. Below are key directions for future research:

1) Incorporating patient-specific data

One of the main limitations of the current model is its reliance on simplified, homogeneous tissue properties. Future models could incorporate patient-specific data obtained from high-resolution medical imaging, such as MRI, CT scans, or ultrasound, to extract more accurate tissue properties. By accounting for individual variations in skin elasticity, muscle tone, fat distribution, and bone structure, the model could provide highly personalized simulations of soft tissue deformation. This would allow for better predictions of how different individuals may respond to injectable procedures, improving the precision of treatment planning and reducing the risk of complications. Personalized modeling could also improve pre-operative assessments by simulating how specific facial features, such as wrinkles or volume loss, can be effectively treated with various injectables.

2) Modeling dynamic facial expressions

Currently, the model assumes static facial anatomy, with fixed facial bones and simplified muscle behavior. Future research should focus on modeling dynamic facial expressions and incorporating muscle contraction patterns that vary in strength and direction depending on the type of expression (e.g., smiling, frowning, chewing). By simulating how muscles interact with injected materials during facial movements, the model can predict how fillers will behave not just immediately post-injection but throughout daily activities. This is particularly important for areas of the face that are highly mobile, such as the lips and around the eyes, where muscle activity plays a crucial role in the spread and retention of injected materials. Understanding the impact of facial dynamics on filler placement will help refine treatment strategies and optimize long-term aesthetic outcomes.

3) Long-term behavior of fillers

Another important direction for future research is to extend the model to simulate the long-term behavior of injected fillers. As fillers such as hyaluronic acid undergo biodegradation and migration over time, it is essential to understand how these materials will behave beyond the immediate post-injection period. The model could be enhanced to simulate the long-term effects of injectable materials by incorporating the viscoelastic properties of the fillers, the rate of degradation, and potential migration due to muscle activity or gravity. This would provide a more comprehensive understanding of how fillers maintain their shape and volume over time and predict how these changes may affect facial aesthetics. Additionally, incorporating these factors could help clinicians determine the optimal injection intervals and anticipate the need for touch-ups or re-injections.

4) Incorporating non-invasive monitoring techniques

Future versions of the model could integrate data from non-invasive monitoring techniques, such as optical coherence tomography (OCT) or 3D facial scanning, to track changes in soft tissue volume and shape over time. These technologies provide real-time data on tissue changes, allowing for continuous validation and refinement of the model. Incorporating these monitoring techniques into the simulation could also help improve model accuracy by incorporating real-world feedback on the effects of injectable materials, as well as tracking how tissues evolve after injections. Real-time feedback will enable clinicians to adjust treatment protocols as needed during the procedure, leading to more consistent and predictable outcomes.

5) Expanding the range of injectable materials

Currently, the model primarily simulates the behavior of hyaluronic acid fillers, but it does not account for the wide variety of injectable materials available on the market, each with distinct properties (e.g., collagen, poly-L-lactic acid, calcium hydroxylapatite). Expanding the model to include a broader range of fillers, with varying viscosities, elasticities, and degradation rates, would allow for more comprehensive simulations and predictions across different clinical scenarios. By simulating the behavior of different filler types, clinicians would be able to predict how each material interacts with specific facial regions and anatomical features. For instance, materials with higher viscosity might be better suited for volumizing deep tissue areas, while low-viscosity fillers may be used for fine lines and wrinkle reduction. The inclusion of these materials would also help optimize the selection of

fillers for specific aesthetic goals, based on the individual's unique tissue properties.

6) Improving computational efficiency for real-time use

A critical area for improvement is the computational efficiency of the model. Currently, the simulations require significant computational resources and time, making real-time clinical application challenging. Future research should focus on optimizing the model's algorithms to enable faster processing speeds. This can be achieved through methods such as parallel computing, machine learning, or adaptive mesh refinement. These techniques would allow for real-time or near-real-time simulations, making the model more practical for use in clinical settings where immediate decision-making is crucial. The ability to generate fast, accurate predictions during the procedure would allow clinicians to adjust their techniques and make informed decisions based on dynamic facial changes during treatment.

7) Integrating patient feedback and machine learning

Integrating patient feedback into the model could enhance its ability to predict and adapt to individual preferences and responses to treatment. By using machine learning algorithms to analyze historical treatment data and patient outcomes, the model could continually learn and improve its predictions based on real-world results. This would allow for more personalized treatment plans tailored not only to the anatomical features of the patient but also to their specific aesthetic goals and preferences. Additionally, the incorporation of machine learning could enable the model to predict the likelihood of complications, such as uneven filler distribution or tissue irritation, based on the patient's unique tissue properties and treatment history.

5. Conclusion

In this study, we developed a biomechanical model to predict soft tissue deformation during injectable aesthetic procedures, integrating finite element analysis (FEA) with patient-specific anatomical data. Our results demonstrate the model's ability to accurately simulate tissue deformation in response to varying injection volumes, materials, and anatomical features, providing a valuable tool for clinical decision-making in aesthetic treatments. By quantifying key performance metrics, such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Pearson's correlation coefficient, we showed that the model's predictions align closely with clinical data, validating its effectiveness as a predictive tool.

The model's primary strength lies in its ability to simulate localized tissue deformation, enabling clinicians to predict how injectable materials will interact with facial muscles and soft tissues. This can guide treatment planning by optimizing injection volumes, material selection, and placement to achieve desired aesthetic outcomes with greater precision. Additionally, the model opens the door to personalized treatment planning, where simulations can be tailored to each patient's unique anatomy, minimizing risks and enhancing overall results.

However, the study also identified several limitations, including the use of simplified tissue properties, homogeneous muscle behavior, and the exclusion of long-term filler behavior. Future research will be essential in addressing these limitations by incorporating more detailed tissue data, modeling dynamic muscle behavior, and simulating the degradation and migration of injected materials over time. Additionally,

improving computational efficiency and expanding the model to include a broader range of injectable materials will further enhance its clinical applicability.

In this study, we developed a finite element model to simulate the soft tissue response during injectable aesthetic procedures. The following main findings summarize our contributions:

1) Predictive accuracy: The model achieved a Root Mean Square Error (RMSE) of under 0.05 mm and a correlation coefficient greater than 0.90 when compared with post-treatment clinical scans, indicating a strong match with observed deformations.
2) Influence of injection parameters: Varying filler volume and viscosity led to measurable changes in tissue expansion patterns. In particular, higher-viscosity fillers produced more localized deformation and up to 15% greater stiffness in the target region.
3) Clinical utility: By providing patient-specific, time-dependent simulations, the model can help practitioners optimize injection strategies, potentially reducing complications like overfilling or asymmetry.

Future work will integrate long-term filler dynamics (e.g., degradation and migration) and more detailed muscle activation data, further enhancing model realism and clinical applicability.

Overall, this study provides a strong foundation for the development of advanced computational tools in aesthetic medicine. As the model evolves, it has the potential to become an indispensable tool for clinicians, allowing for more predictable and personalized outcomes in injectable aesthetic procedures.

Author contributions: Conceptualization, XM and JG; methodology, XM; software, XM; validation, XM and JG; formal analysis, XM; investigation, XM; resources, XM; data curation, XM; writing—original draft preparation, XM; writing—review and editing, XM; visualization, XM; supervision, JG; project administration, JG; funding acquisition, JG. All authors have read and agreed to the published version of the manuscript.

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