

ChewTect: Designing Temporal Food Texture via Computational Molding

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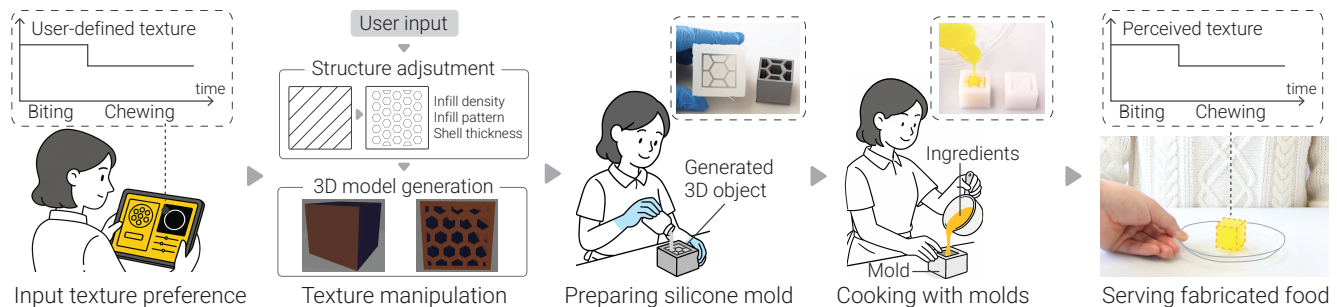


Figure 1: Overview of ChewTect: A System for Structure-Based Temporal Texture Design. Users specify their desired texture level for the first bite and the chewing experience through a user interface. Based on this input, ChewTect adjusts internal structure parameters of the food, such as infill density, infill pattern, and shell thickness (i.e., material thickness), to generate a customized 3D model. A silicone mold is then fabricated and used in conventional cooking workflows. The resulting food matches the desired texture experience.

Abstract

Food texture plays a crucial role in the overall sensory experience and the functional properties of food, evolving dynamically from the first bite to the final chew. Traditional methods for modifying food texture, such as adjusting cooking parameters, often compromise other key attributes, including cooking appearance and nutritional value, whereas existing computational approaches largely treat texture as a static, monolithic attribute. This paper presents a computational method that modulates the internal structure of food to design temporal food texture experiences. Our method generates a silicone mold based on the desired food texture experience. This approach decouples textural properties from visual and amount attributes, enabling independent tuning of sensory factors during different oral processing stages. We characterize the relationship between internal structure and temporal texture perception, specifically finding that infill pattern and shell thickness control the bite and

chewing phases, respectively. We present an interactive design interface that allows users to create food items tailored to specific temporal food textures.

CCS Concepts

• **Human-centered computing** → **Interaction techniques.**

Keywords

Digital gastronomy, Digital Food Fabrication, Temporal texture of food, FoodHCI

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1 Introduction

Food texture is central not only to the enjoyment of eating but also to health and accessibility, influencing whether meals are satisfying, nutritious, and even safe to consume for populations such as older adults with dysphagia [1, 60]. Similar to taste and flavor, texture



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is perceived dynamically through oral processing: the first bite conveys an immediate impression (e.g., hardness), while subsequent chewing refines this perception through continued interaction [61]. Designing texture experiences across these distinct temporal stages, i.e., the stage of oral processing of food from the first bite to the moment of swallowing, is therefore vital for ensuring both safe consumption and satisfying sensory experiences.

Traditionally, food texture has been modulated by adjusting cooking parameters such as cooking time or ingredient combinations [6, 44, 63, 65]. However, these methods face two key limitations. First, modifications to texture often alter other attributes, such as appearance or nutritional profile, making it difficult to control them independently. For example, altering sugar content in gummy candies changes not only hardness but also caloric intake, taste, and appearance [62], potentially leading to undesired eating experiences. Second, existing methods often lack reproducibility, relying heavily on trial-and-error practices and culinary expertise.

Beyond cooking-based methods, researchers have investigated the relationship between the mechanical structures of food and their associated sensory profiles, showing that structural modifications can modulate both mechanical properties and perceived texture [10, 12, 19, 25, 28, 32]. Yet, our sensory understanding of food during oral processing (i.e., biting and chewing) remains limited. Consequently, computational approaches that treat temporal texture perception as a programmable, independently controllable design attribute have not been systematically explored.

In this paper, we introduce *ChewTect*, a computational design system for temporal food texture design. *ChewTect* enables users to specify desired texture levels for the first bite and subsequent chewing through an interactive interface. The system then automatically computes internal structures, such as infill patterns, density, and shell thickness, and generates molds that realize the target texture without altering other key properties such as appearance or caloric content. We refer to the shell thickness as the thickness of materials that are being prepared for each of the infill patterns. By adopting a cooking-with-molding workflow rather than direct food printing, *ChewTect* aligns with traditional cooking practices [74], avoids reliance on specialized food-compatible printers, and enables efficient batch production.

The design of our *ChewTect* is informed by a perception study aimed at understanding how variations in internal structure, within a given food shape and material, affect perceived texture. The study design was inspired by prior work on food perception and illusion [27], but our work focuses deeper on the food experience that transitions from the first bite to the final chew. We recruited 27 participants who consumed a series of food samples and evaluated their sensory experiences through questionnaires and EMG-based jaw movement analysis. Results show that overall perceived hardness and springiness can be modulated by infill density, and that first-bite hardness and chewing hardness can be independently decoupled and controlled by tuning infill pattern and shell thickness. These insights informed both a computational model for textural control and the design of an interactive interface.

To summarize, our contributions are computational method for food design systems that allow users to create food items tailored to specific texture targets during two specific oral processing stages: first biting and subsequent chewing (Section 3). In particular, our

sensory studies found that modulating internal structure, such as infill patterns, infill density, and pattern thickness, affects how users perceive different temporal texture dynamics (Section 4). Based on these results, we developed an end-to-end fabrication interfaces that automatically adjust internal structures based on target food textures (Section 5).

2 Related Work

Our work is related to the research areas of food texture design, digital gastronomy in HCI, and digital food fabrication.

2.1 Computational Approaches to Texture Design

Texture is a defining characteristic of the culinary experience, determining not only enjoyment but also safety and swallowability [51]. With the advent of digital fabrication, researchers have begun to treat texture as a programmable design element [21, 66]. Early approaches in 3D food printing demonstrated that tuning printing parameters, such as infill density, pattern, layer height, nozzle diameter, and printing speed, allows for the modulation of mechanical properties of food, affecting the perceived texture [9, 10, 24, 28, 32, 73]. Chen et al. [5], for example, showed that increasing the infill density of 3D printed pumpkin-based snacks reduced their crispness. While these researchers successfully established static texture control by tuning the food structure for a single, monolithic attribute such as “overall hardness”, they often overlook the temporal dynamics of eating. Food science research emphasizes that texture perception is an evolving process: the mechanics of the first bite differ significantly from the bolus formation during chewing [61].

Current 3D food printing methods typically rely on mechanical analysis (e.g., compression testing) to validate their designs [50]. While effective for characterizing the initial fracture (first bite), these static tests fail to capture the dynamic transformation of the food structure during mastication, such as chewing hardness. Although several studies have begun to incorporate sensory evaluation into the loop [3, 25], such as mapping 3D printed chocolate structures to perceived texture, they predominantly focus on optimizing global texture scores rather than enabling the independent design of these temporal stages.

This gap presents the opportunity for temporal texture design, a framework that allows designers to computationally create the “First bite” and “Chewing” experiences. Unlike prior work that correlates structure with a single texture value, *ChewTect* aims to decouple these phases, providing a design space in which the timeline of sensation can be intentionally authored.

2.2 Expanding the Dimensions of Food Interaction in HCI

Food and dining, as essential (inter)personal experiences that everyone engages with daily, have been drawing attention in the HCI community [16, 43]. Research in this space can be broadly categorized into two approaches: augmenting the external dining context and fabricating the food’s physical properties.

Several studies have focused on modifying the external environment or the user’s sensory organs to alter perception without

changing the food itself. For example, projection mapping has been used to alter the appearance of food directly on the table [30, 53], while head-mounted displays overlay visual textures to modulate flavor perception [46, 47]. Beyond vision, researchers have employed cross-modal stimuli to trick the senses [2, 47, 58] such as using electrical stimulation to simulate taste [35, 45, 57] or modifying auditory feedback to alter perceived crispness [72]. Texture, in particular, has often relied on these external interventions, such as Electrical Muscle Stimulation (EMS) to simulate chewing resistance [48] or mechanical skin deformation to mimic the sensation during swallowing [42]. While effective for virtual experiences, these approaches require specific hardware, limiting their practicality for everyday dining.

In parallel with augmentation, researchers have investigated ways to directly design the food itself. For example, digital fabrication has enabled the customization of food form [20, 23, 43, 68, 71], color [14], and shape-changing behaviors, e.g., triggered by heat or dehydration [64, 68, 69]. Taste has also been computationally arranged through, e.g., computational molding [74], liquid mixing [7, 8, 33, 34, 59]. However, the computational food design of texture remains underexplored. Perhaps the closest works to ours are the FoodFab system [27] and Ishii's work on bubble-embedded food customization [19]. In FoodFab, the internal structure of biscuits is manipulated to influence mastication duration while maintaining appearance and caloric content. Different from our ChewTect, their primary goal was to alter perceived satiety, rather than to focus on designing the food textures. In Ishii's work, the embedded air pockets, although they alter food texture, also change the food's reflectance, thus unintentionally affecting its visual appearance. ChewTect advances this design space by establishing temporal texture, specifically decoupling the first bite from the chewing phase, as a programmable dimension. Additionally, our structure-based molding approach enables this control without requiring external devices ("programming the eater") or compromising visual aesthetics.

2.3 Food Fabrication Approaches

Much of the research discussed in the previous sections on direct food customization has been enabled by various fabrication approaches. This section briefly reviews these digital food fabrication methods.

Generally speaking, digital food fabrication can be categorized into three types of methods: additive, subtractive, and formative. A variety of materials and fabrication systems have been proposed to leverage the layer-wise 3D printing paradigm for food customization. For example, paste extruders have been widely used to make cookies, chocolates, jelly, and even cakes [19, 20, 27, 36, 40, 49, 69]. Robotic arms [37] have also been used for additive food fabrication, providing precise control. One limitation of such fabrication methods, beyond the accessibility issues due to the often higher cost of food-grade printing systems, is the limited range of materials that can be used. To date, most food printing systems can only work with pastes that have suitable rheological properties.

Subtractive manufacturing is another type of approach used for food modification. For example, previous work has investigated the use of CO₂ lasers for food preparation or to harness the high

energy of a laser beam to control the cooking temperatures [13, 17]. CNC-based machines have been explored for shaping food into custom forms through subtractive milling [43, 70].

One final group of food fabrication approaches is formative fabrication, or food molding. Compared to the previous two methods, food molding often involves more manual labor during the preparation phase, as it requires the creation of custom molds, for example, using food-safe silicone, and manually injecting food materials. However, food molding has its own advantages. It does not require expensive hardware, and with a single mold, one can produce unlimited customized food items, with the added potential to explore different food materials. This fulfills a unique need that other fabrication methods often struggle to meet. As a result, several food fabrication studies have adopted food molding approaches [23, 25, 54, 74] or using customized stamps [23, 38, 64]. For example, Digital Konditorei [74] created various taste structures and combinations of food materials using modular silicone molds, while Lee et al. [25] generated varying textures by stacking chocolate plates with molded patterns.

Given the low cost and flexibility of food molding, all examples in this paper use this approach. However, since our system also generates 3D food models directly, it remains compatible with and easily extendable to direct 3D food printing.

3 ChewTect: System Overview

ChewTect is an end-to-end computational food system that tailors food textures, specifically the perceived hardness and springiness during the first bite and subsequent chewing, based on the user's preferred eating experience. It achieves this by adjusting internal food structures while maintaining compatibility with user-defined visual and nutritional goals. The system generates the silicone mold that is in line with the designed food structure, and allows the user to freely cook the food with molding. This level of texture customization enables the creation of novel eating experiences as well as functional foods tailored to specific oral processing needs.

As one example, consider a user preparing food for an elderly resident in a care facility. With ChewTect, they can design a gummy that provides a firm first bite to stimulate jaw muscle engagement [52], while ensuring a soft chewing texture for easier mastication and safer swallowing [55]. As another example, imagine a restaurant seeking to create engaging dining experiences. Here, the chef could craft a plate of beautifully decorated desserts that look similar at first glance, yet offer distinct chewing experiences. Some are soft, others are much firmer, and a few may surprise diners with a completely different first bite and evolving texture. It's a culinary play on the famous line from *Forrest Gump*: "...life was like a box of chocolates. You never know what you're gonna get."

ChewTect utilizes computationally designed silicone molds to achieve the desired internal structures, allowing seamless integration into conventional cooking recipes and techniques. This approach is especially valuable when specific texture profiles must be reproduced consistently (e.g., in restaurants or standardized care meals). System-wise, ChewTect comprises three main components: an interactive user interface for specifying the desired texture, a parameter calculator that determines structural settings such as biting and chewing hardness based on user input, and a 3D model

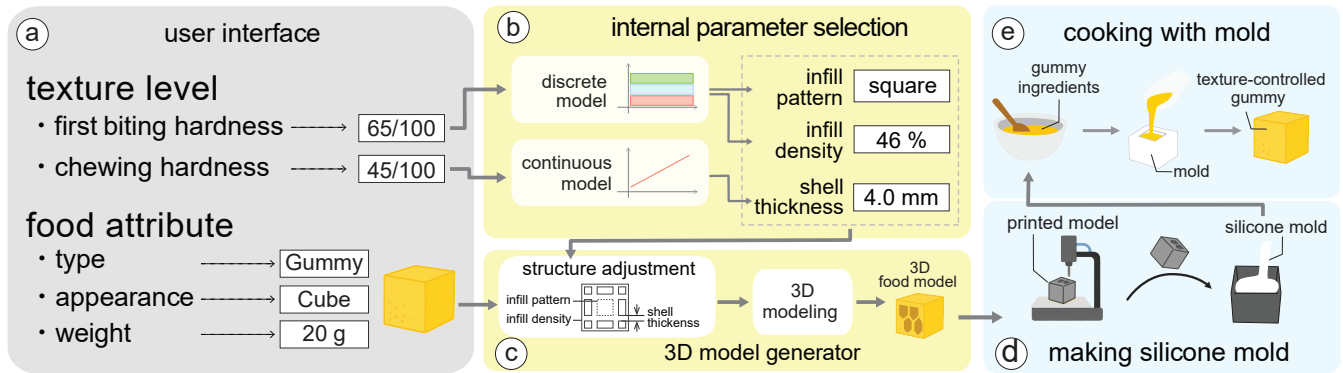


Figure 2: System overview: (a) user inputs their preferred food, such as type, appearance, and amount. Moreover, they can input the preferred texture levels, such as biting and chewing hardness. (b) The preference is then processed through the computational models that compute the internal structure, such as infill pattern, infill density, and shell thickness. Then, (c) our system automatically adjusts the structure of food and creates a negative 3D model for mold. (d) The 3D model of the mold is 3D printed and creates a final silicone mold, and (e) used as a cooking tool.

generator that creates food models, empowered with computed internal structures for silicone mold fabrication. These components are followed by the mold fabrication and cooking steps.

3.1 Workflow: From Design to Fabrication

We describe the step-by-step workflow for authoring temporal food textures using ChewTect, as illustrated in Fig. 2 and further demonstrated in the supplementary video.

Select the Texture Level and Food Properties. To begin, users select the desired texture levels for the food via the user interface. For example, they may specify a hardness of 65% for the first bite and 45% for subsequent chewing. In addition to these temporal texture targets, users can specify common food parameters such as food type, shape, and quantity.

Structural Parameter Mapping. The mapping engine, grounded in our sensory studies (see Section 4 and Section 5), translates the texture targets into the simple digital fabrication parameters such as internal structural parameters, including infill pattern, infill density, and shell thickness. For example, ChewTect may select a thinner structural pattern or reduce the infill density if the user prefers a softer chewing sensation. These parameters are then passed to the 3D model generator.

3D Model Generator. Using the computed structural parameters and specific visual appearance, the generator creates the 3D food models for fabrication. While our primary workflow generates mold negatives for casting, the underlying computational model is fabrication-agnostic. For instance, users with access to 3D food printers can utilize the same generated geometries to print texture-controlled food items directly.

Cooking with Silicone Molds. Once the silicone molds are fabricated, users can produce foods with the designed temporal textures using general cooking methods. Since the molding approach is generally faster than 3D food printing and compatible with a wide

range of culinary processes, such as heating and cooling, we prioritize this approach in our pipeline. Moreover, the molds are reusable, and thus a sustainable approach, allowing users to explore different food materials while maintaining the same internal structure.

Presentation of Texture-controlled Food. Finally, the texture-controlled food is presented for consumption. As shown in Fig. 3, the resulting food item delivers the designed temporal narrative, exhibiting the specific programmed resistance during the first bite and the subsequent chewing phase.

3.2 Internal Structure Parameters

The food internal structure parameters, which are referred to as the infill patterns, infill density, and shell thickness, have been used to program the temporal food textures (Fig. 4).

- **Infill pattern**, which defines the geometric shape of internal voids (e.g., honeycomb, triangle, square).
- **Infill density**, which determines the ratio of filled to unfilled space within the structure.
- **Shell thickness**, which controls the thickness of the structural walls, i.e., how thick any thin food materials is.

We chose these parameters for three main reasons. First, prior studies have shown that variations in infill patterns and infill density significantly influence texture perception [10, 32]. Second, changes to the internal structure have minimal impact on the food's visual appearance [27, 40], allowing independent texture control without altering visual cues. Third, recent work in additive manufacturing has found that the thickness of the infill pattern directly affects the perceived hardness [41], which we believe also generalizes to food applications. Additionally, these approaches do not require external devices such as electrical muscle stimulation (EMS) [48], making them more practical for daily use.

Based on our user study (see Section 4 for details), we designed ChewTect to use an infill pattern to control hardness during a first bite, and shell thickness to modulate hardness during chewing.



Figure 3: Eating scene showing oral processing of a texture-controlled food. The first bite is designed to provide higher hardness (65%), followed by a softer chewing hardness (45%).

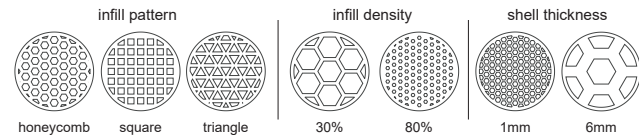


Figure 4: Visual representation of the three internal structure parameters used in ChewTect. Left: Infill patterns, honeycomb, square, and triangle, used to shape the internal void geometry. Middle: Infill density levels (30% and 80%) determine the proportion of filled vs. unfilled space. Right: shell thickness (1 mm and 6 mm) controls the thickness of the structural walls.

Infill density is used to fine-tune both hardness and springiness throughout the eating process.

3.3 Example Walkthrough with ChewTect

To demonstrate how ChewTect can be integrated into general cooking workflows, we present an example application involving mold preparation and food fabrication using a cube-shaped gummy. We specified the cube dimensions as 30mm × 30mm × 30mm and generated the mold negative using the ChewTect user interface.

Preparation of Silicone Molds. The mold negative was printed using an off-the-shelf 3D printer (Ultimaker 3, Ultimaker). To fabricate the silicone mold, we cast food-safe classified silicone (HTV-4000, Engraving Japan) into the printed negative (Fig. 5 a). The silicone was left to cure at 23 °C for approximately three hours (Fig. 5 b). For improved durability and easier demolding, a vacuum chamber has been used to remove remaining air during casting.

Cooking Procedure with ChewTect: Gummy. Gummies were used to demonstrate a sample of texture-controlled food created using a silicone mold (for exploration of additional food materials and shapes, see Section 6). The gummy base was prepared by mixing water, sugar, and gelatin and heating the mixture in a microwave until fully liquefied. Optional additives, including food coloring, flavoring, and citric acid, were used to enhance the sensory properties of the gummies. The liquid mixture was then poured into the silicone molds and allowed to cool in a refrigerator for at least 20 minutes (Fig. 5 c). As a result of the molding process, one side of the sample remains open and visible. To conceal the internal structure, this open side was sealed by placing it onto a thin layer of the same food. Alternatively, the open side can be sealed using edible glues such as syrup or egg whites. This treatment effectively

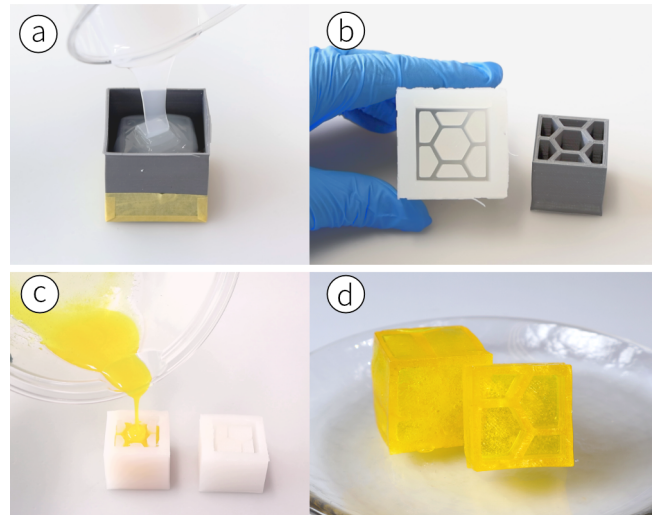


Figure 5: Workflow of food fabrication using ChewTect. (a) Pouring food-safe silicone into a 3D-printed negative mold. (b) Completed silicone mold with internal structures and the original 3D-printed negative. (c) Casting the gummy mixture into the mold. (d) Final food samples with embedded internal structures after demolding.

hides the internal pattern, even at low infill densities and avoids the overhang-related issues commonly found in conventional 3D food printing methods [22, 40]. This approach enables the gummy to be readily served using conventional cooking steps without requiring special equipment (Fig. 5 d).

4 Sensory Perceptual Study

We conducted a user study to obtain a computational model that maps internal structure parameters to perceived food textures, examining how variations in structure influence texture perception. Specifically, we measured perceived hardness and springiness of gummy at two stages of oral processing: the first bite and subsequent chewing. As we mentioned earlier, the structural parameters tested in this study included infill pattern, infill density, and shell thickness. Additionally, we examined how structural variations affect other sensory factors, such as perceived sweetness and chewing duration. This study protocol was approved by the Ethical Review Committee (No. R6-E-51) of the institution, and informed consent was obtained from all participants.

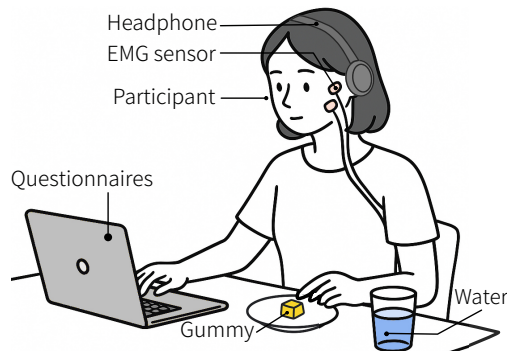


Figure 6: Experimental setup. Participants were seated at a table with a gummy sample and a glass of water. An EMG sensor was attached to their masseter muscle to record chewing activity. After consuming the sample, participants reported their perceived texture using a questionnaire on a laptop.

4.1 Experimental Setup

The experimental setup is illustrated in Fig. 6. Participants were seated comfortably at a desk, and the room temperature was maintained at a constant 24 °C to ensure a controlled testing environment.

Food Preparation. Gummies were selected as the experimental food samples due to their inherent textural variability. We used the same cube shape (30mm × 30mm × 30mm) as mentioned in Section 3.3, and prepared silicone molds and gummy accordingly. The gummy base was formulated using water, sugar, gelatin, and citric acid in a ratio of 1:1:0.2:0.05. A small amount of yellow food coloring and orange-flavored oil was also added to enhance visual and sensory appeal, but does not affect the eating process. Before molding, the gummy mixture was weighed using a precision scale (Latuna, KINGJIM), ensuring accuracy within ±0.1 g of the target. Gummies were prepared one day before the experiment, refrigerated overnight to solidify, and stored under refrigeration until the experiment.

Data Collection: Questionnaire. Participants’ sensory experiences were assessed using a structured questionnaire, consisting of first bite hardness, first bite springiness, chewing hardness, chewing springiness, and sweetness. The questionnaire was designed to evaluate perceived texture across two distinct phases of oral processing: the first bite and subsequent chewing, following methodologies established in prior work [61]. Items such as first bite hardness, first bite springiness, and chewing effort were adapted from existing sensory evaluation protocols [15]. Additional questions, including sweetness, were added to capture a broader range of sensory impressions during chewing. Each item was rated on a 7-point Likert scale. After consuming each gummy sample, participants completed the questionnaire on a laptop in front of them.

Data Collection: Electromyography (EMG). To understand the chewing behavior, we utilize an EMG sensor (IWS940-DEV, Tokyo Devices) attached to the participants’ masseter muscles. Chewing duration was assessed by trimming the start and the end of

chewing based on the signal activity. Before the experiment, participants confirmed the correspondence between their chewing motions and the real-time EMG signal visualization. This visualization was shown only during calibration and was hidden during actual data collection. To promote consistent chewing across trials, participants followed auditory beeps delivered at 1.4 Hz through noise-canceling headphones (Soundcore Life Q30, Anker). This frequency was empirically selected based on typical human chewing rates.

4.2 Participants and Experimental Methods

27 participants (20 male, 7 female; aged 18–34 years) from five different countries voluntarily took part in the study. All participants received detailed instructions regarding the experimental procedure and provided informed consent in advance. Prior to the experimental trials, participants underwent sensory calibration. They chewed commercial gummy (HARIBO Goldbears) with the same taste to establish baseline perceptions of hardness and springiness, and tasted a 10% sugar solution as a reference for sweetness.

The experiment tested 11 structural conditions, created by varying 5 infill density (0%, 25%, 50%, 75%, 100%), 3 infill pattern (honeycomb, triangle, square), and 3 shell thickness (2mm, 3mm, 6mm), as shown in Table 1. To isolate the effect of each parameter, only one was varied at a time while keeping the others constant (e.g., thickness trials used 50% infill and honeycomb pattern). In the condition I, J, and K, the shell thickness has been varied by adjusting the void size so that the thickness changes while the total weight is constant. Note that the 0% and 100% infill conditions do not contain internal structures, so their outcomes are independent of infill pattern and shell thickness. Redundant conditions were removed, resulting in nine unique samples per participant. The order of experimental conditions was randomized to mitigate order effects.

During each trial, the designated gummy sample was placed in front of the participant, who picked it up from the far edge and inserted it into their mouth. They were instructed to bite one-third of the sample with their incisors (first bite phase), then chew the piece (chewing phase). Any remaining portion was discarded. Participants completed the questionnaire immediately after each trial. To prevent flavor carry-over, participants rinsed their mouths with water between samples.

4.3 Results

We analyzed the data using one-way repeated-measures ANOVAs. When ANOVA tests revealed significant main effects ($p < .05$), we conducted pairwise comparisons using paired t -tests on estimated marginal means, with p -values adjusted by Holm’s method to control for multiple comparisons. Where Mauchly’s test indicated sphericity violations, Greenhouse–Geisser corrections were applied; these corrections did not change any statistical conclusions.

4.3.1 Result of infill density. Repeated-measures ANOVAs revealed significant main effects of infill density on first-bite hardness [$F(4, 104) = 81.93, p < .01, \text{partial } \eta^2 = .77$], first-bite springiness [$F(4, 104) = 26.86, p < .01, \text{partial } \eta^2 = .52$], chewing hardness [$F(4, 104) = 47.08, p < .01, \text{partial } \eta^2 = .65$], chewing springiness [$F(4, 104) = 17.43, p < .01, \text{partial } \eta^2 = .41$], and chewing effort [$F(4, 104) = 34.23, p < .01, \text{partial } \eta^2 = .58$]. No significant effects were observed

Table 1: Experimental conditions used in the user study. In the infill pattern row, H, T, and S denote honeycomb, triangle, and square patterns, respectively. All samples shared the same external dimensions (30mm × 30mm × 30mm).

	A	B	C	D	E	F	G	H	I	J	K
Infill density (%)	0	25	50	75	100	50	50	50	50	50	50
Infill pattern (mm)	N/A	H	H	H	N/A	H	T	S	H	H	H
Total weight (g)	10	15	20	25	30	20	20	20	20	20	20

for sweetness perception. Holm-corrected pairwise comparisons are summarized in Table 2. Fig. 7 (a) and Fig. 8 (a) present box plots for the first bite and chewing hardness. Other texture-related variables, including first-bite springiness, chewing springiness, and chewing effort, showed an increasing trend similar to hardness perception. No such trend was found for sweetness perception. Significant differences were found across most condition pairs for both first and chewing hardness, including adjacent levels such as 25% vs. 50% and 50% vs. 75%.

4.3.2 Results of infill pattern. ANOVA showed significant effects of infill pattern on first bite hardness [$F(2, 75) = 20.25, p < .01$, partial $\eta^2 = .48$]. No significant effects were observed for chewing hardness or other dependent variables. Holm-corrected pairwise comparisons for first bite hardness showed significant differences (Fig. 7 b) between triangle and honeycomb ($p < .01$), honeycomb and square ($p < .05$), and triangle and square ($p < .01$).

4.3.3 Results of shell thickness. ANOVA revealed significant effects of shell thickness on chewing hardness [$F(2, 75) = 10.26, p < .01$, partial $\eta^2 = .29$], but not on first bite hardness or other dependent variables. Holm-corrected pairwise comparisons revealed a significant difference in chewing hardness (Fig. 8 b) between 2 mm and 3 mm ($p < .01$), and 2 mm and 6 mm ($p < .01$). Significant differences are marked with asterisks.

4.3.4 Results of EMG signals. We performed an ANOVA on integrated EMG activity during the biting and chewing sequence. The raw EMG signals were first rectified, then normalized per participant using min-max scaling across all trials (i.e., each value transformed to the range [0,1] based on that participant's overall maximum and minimum). The normalized signals were then integrated over the biting phase to obtain the total biting activity. For integrated biting EMG, significant effects were found for infill density [$F(4, 125) = 12.73, p < .01$, partial $\eta^2 = .33$] and infill pattern [$F(2, 75) = 7.06, p < .01$, partial $\eta^2 = .24$], but not for shell thickness [$F(2, 75) = 0.32, p > .05$] (Fig. 7 c, d). Holm-corrected pairwise comparisons revealed significant differences between various infill densities, with lower densities (0% and 25%) showing significantly different biting work compared to higher densities (75% and 100%). For the infill pattern, a significant difference was found between triangle and square patterns ($p < .01$) and triangle and honeycomb patterns ($p < .01$). The results show similar trends to the sensory reports for biting hardness.

For chewing sequence time, significant effects were observed for infill density [$F(4, 125) = 7.29, p < .01$, partial $\eta^2 = .41$] and shell thickness [$F(2, 75) = 3.85, p < .05$, partial $\eta^2 = .26$], but not for infill pattern [$F(2, 75) = 0.11, p > .05$] (Fig. 8 c, d). Post-hoc

analyses showed that lower infill densities (0% and 25%) required significantly shorter chewing times compared to higher densities (75% and 100%). For shell thickness, the 6 mm thickness required significantly longer chewing time compared to 3 mm ($p < .01$) and 2 mm thickness ($p < .01$). The results show similar trends to the sensory reports for chewing hardness.

4.4 Summary

The results demonstrate that infill density effectively modulates perceived hardness and springiness in the first bite and subsequent chewing. As infill density increased, participants experienced a harder and more springy texture, which required a more significant chewing effort. These findings are consistent with prior work on infill density and perceived hardness [28], further refining our understanding of how hardness and springiness are perceived across sequential stages of oral processing. Our results further suggest that both attributes can be simultaneously modulated by adjusting the infill density.

Our results also suggest that infill pattern and shell thickness enable stage-specific modulation of oral texture perception. In particular, the square structure produced the highest perceived hardness during the first bite, followed by honeycomb, while the triangle resulted in the softest experience. We hypothesize that this difference arises from the distinct mechanical resistance each pattern provides during the first bite. In terms of chewing-phase texture, thicker structural supports (6 mm) significantly increased perceived hardness compared to thinner ones (2 mm). Unlike the prior work that showed the correlation between food structure and sweetness [3], our result did not show any effects across all conditions. We assume that the chilled gummy in our experiments may have affected sweetness perception, making it difficult for participants to detect differences in sweetness. Further study should clarify if sweetness also alters depending on the structure parameters, using different temperature ranges.

Prior work in texture analysis using food having different material compositions showed that the more biting power and number of chewing cycles lead to more overall sensory hardness [56]. Our EMG-based results also align with these findings, which further confirms that first biting hardness correlates with required biting power and chewing hardness perception correlates with the chewing time (which is related to chewing cycles, as we controlled chewing behavior through headphones) when using foods having variable internal structure. These objective data provide quantitative evidence that validates our subjective sensory reports, demonstrating that participants' perceptual assessments of texture hardness are reliably reflected in measurable physiological responses during mastication.

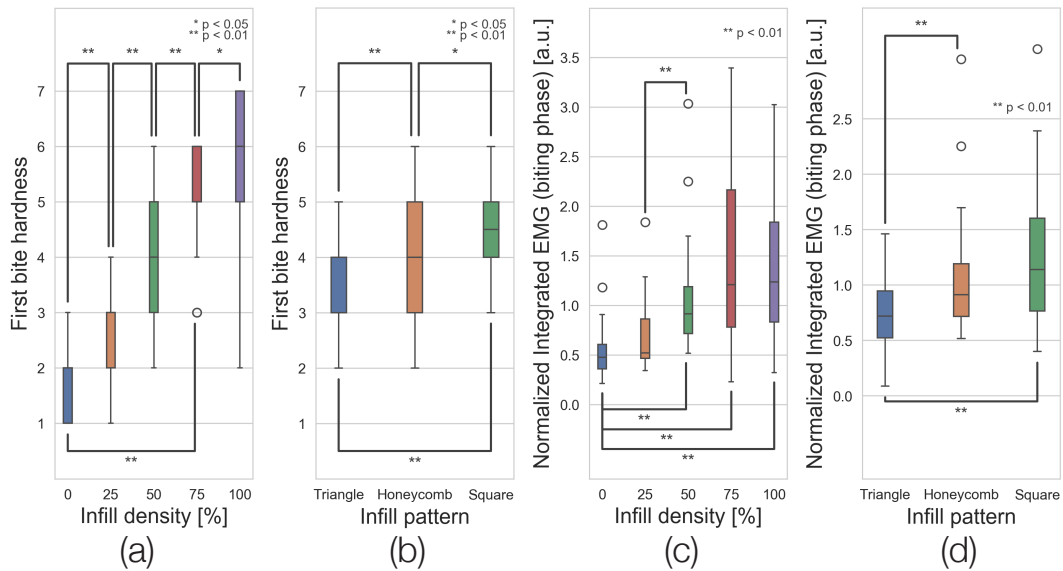


Figure 7: Perceptual and behavioral effects of varying infill density and pattern on texture evaluation. Significant differences are selectively marked with asterisks to minimize visual clutter. For clarity, annotations are shown only between adjacent or every-other conditions where full pairwise marking would otherwise overlap. (a) First bite hardness across infill densities. (b) First bite hardness across infill patterns. (c) Normalized integrated EMG during the biting phase across infill densities. (d) Normalized integrated EMG during the biting phase across infill patterns.

These findings provide a foundation for the development of computational models that predict and generate desired textures independently of nutritional content, ingredient choice, or visual appearance.

5 Computational Model and User Interface

5.1 Computational Model

We developed two computational models to achieve the desired first bite and subsequent chewing hardness based on the experimental results. The models use infill density, infill patterns, and shell thickness as controllers for hardness. We then integrate the models into the user interface, which allows users to generate molds and fabricate food textures as they desire directly. To integrate the sensory evaluation data into our computational model, we linearly rescaled the 7-point Likert scores to a 0.0–1.0 range using min-max normalization, where 1 corresponds to 0.0 and 7 corresponds to 1.0.

Infill Pattern: Discrete Selection. Experimental results indicated that the perceived first bite hardness can be effectively controlled by tuning infill density and selecting the infill pattern. To model these corresponding parameters, we first fitted a linear regression to the hardness scores from the honeycomb pattern, using infill densities of 25%, 50%, and 75%, along with the two boundary conditions at 0% and 100%. Since the results for 0% and 100% infill densities are consistent across all infill patterns, we used these common endpoints to construct quadratic interpolation functions for the

triangle and square patterns. The resulting formulas are:

$$\text{Honeycomb: } H_{\text{First bite}} = 0.681D_{\text{Infill}} + 0.137$$

$$\text{Triangle: } H_{\text{First bite}} = 0.384D_{\text{Infill}}^2 + 0.269D_{\text{Infill}} + 0.141$$

$$\text{Square: } H_{\text{First bite}} = -0.512D_{\text{Infill}}^2 + 1.166D_{\text{Infill}} + 0.141$$

where $H_{\text{First bite}}$ represents the first bite hardness, and D_{Infill} denotes the infill density. $H_{\text{First bite}}$ and D_{Infill} are scaled from 0.0 to 1.0 ($R^2 = 0.98$ for honeycomb model). The corresponding graphs are also shown in Fig. 9 (a). These models predict first-bite hardness for each infill pattern based on the infill density derived from the user-specified food per portion. In other words, our models can control temporal texture through infill patterns and their corresponding densities.

Shell Thickness: Continuous Model. Further analysis of experimental data indicates that subsequent chewing hardness can be effectively controlled through continuous adjustment of the shell thickness. We have found that this correspondence is clearly seen using a linear regression model, which is described as follows:

$$H_{\text{chewing}} = 0.0216L_{\text{shell thickness}} + 0.584D_{\text{infill}} + 0.093$$

where H_{chewing} represents the subsequent chewing hardness, and $L_{\text{shell thickness}}$ indicates the thickness of the infill pattern measured in millimeters ($R^2 = 0.94$). The corresponding graphs are also shown in Fig. 9 (b). This linear model enables continuous adjustments to achieve targeted chewing hardness.

Model Generalizability. In terms of generalizability, we evaluated our models using the leave-one-participant-out cross-validation (LOPOCV) method on the dataset of 27 participants. In each fold,

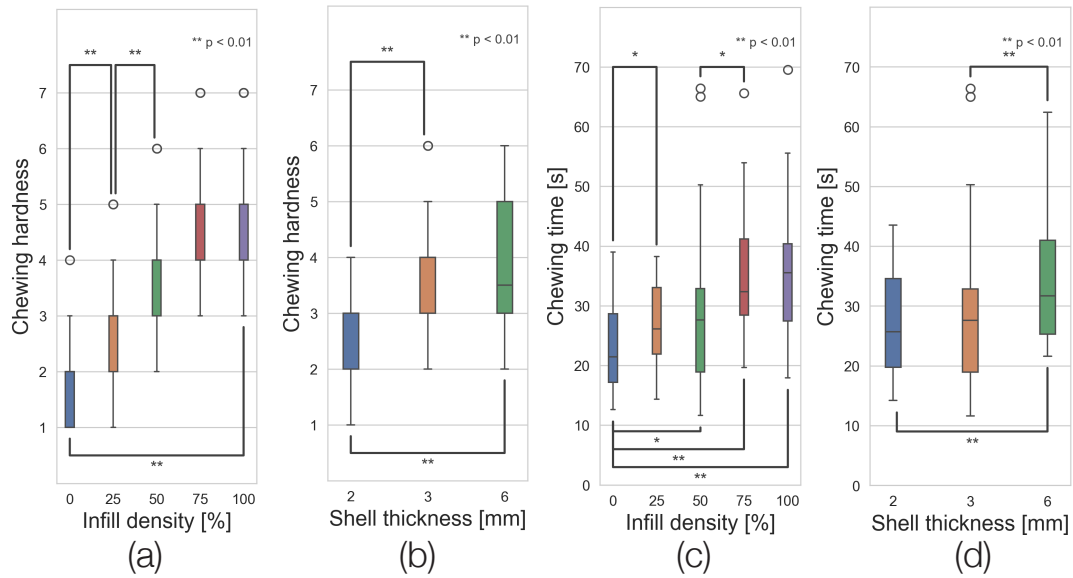


Figure 8: Perceptual and behavioral effects of varying infill density and shell thickness on texture evaluation. Significant differences are selectively marked with asterisks to minimize visual clutter. For clarity, annotations are shown only between adjacent or every-other conditions where full pairwise marking would otherwise overlap. (a) Chewing hardness across infill densities. (b) Chewing hardness across shell thickness. (c) Chewing time across infill densities. (d) Chewing time across shell thickness.

Table 2: Holm-corrected pairwise comparisons for infill density across dependent variables. “n.s.” denotes non-significant differences ($p \geq .05$).

Comparison	First bite Hardness	Chewing Hardness	First bite Springiness	Chewing Springiness	Chewing Effort
0% vs. 25%	< .05	< .05	< .01	< .05	n.s.
0% vs. 50%	< .01	< .01	< .01	< .01	< .01
0% vs. 75%	< .01	< .01	< .01	< .01	< .01
0% vs. 100%	< .01	< .01	< .01	< .01	< .01
25% vs. 50%	< .01	< .01	< .01	< .01	< .01
25% vs. 75%	< .01	< .01	< .01	< .05	< .01
25% vs. 100%	< .01	< .01	< .01	< .01	< .01
50% vs. 75%	< .01	n.s.	< .05	n.s.	n.s.
50% vs. 100%	< .01	n.s.	< .01	n.s.	n.s.
75% vs. 100%	< .05	n.s.	n.s.	n.s.	n.s.

all data from one participant were held out as the test set, while the model was trained on the remaining 26 participants. The trained model was then used to predict the perceived texture ratings of the held-out participant. This procedure was repeated until each participant had served as the test set once, and the predictive performance was averaged *across folds*.

Across folds, the model for first-bite hardness achieved an RMSE of 1.01 on the 7-point hardness scale, with an R^2 of 0.70 and a Spearman’s ρ of 0.67. The model for chewing hardness (plane fit) achieved an RMSE of 1.09, with an R^2 of 0.43 and a Spearman’s ρ of 0.62.

These results indicate that the models capture systematic relationships between internal structural parameters and perceived texture. While inter-individual variability limits perfect prediction, the models explain around 70% of the variance in first-bite hardness and 43% in chewing hardness, and preserve the relative ordering of texture levels across unseen participants ($\rho \approx 0.6$). This makes them suitable as fast, first-stage predictors for practical temporal texture design, while also providing a foundation for future adaptive refinement through online optimization in Section 6.

Example Result of Computational Model. We created a mold for our computational models to generate food with different texture

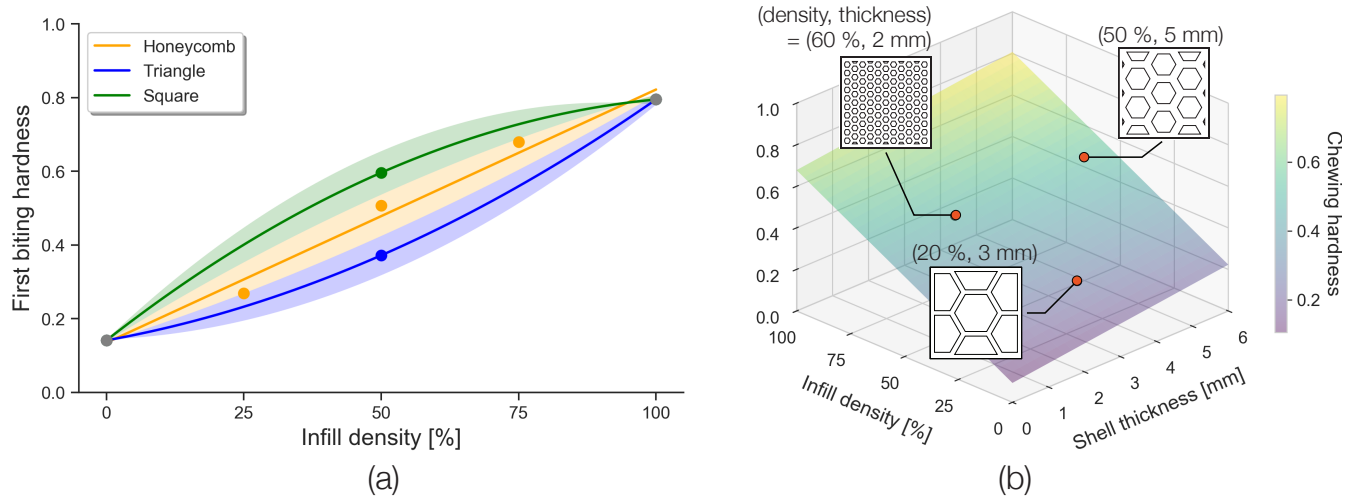


Figure 9: Computational models. (a) A computational model representing the relationship between infill density and perceived first bite hardness for different infill patterns. The shaded regions indicate interpolation areas between data points, where the region boundaries are determined based on proximity to the corresponding fitted curves. (b) A computational model representing the relationship between infill density, pattern thickness, and perceived chewing hardness.

parameters. For instance, food A was generated with a first bite hardness of 55/100 and a chewing hardness of 60/100. The infill density, infill pattern, and shell thickness were calculated as 70%, triangle, and 4.4 mm, respectively. Similarly, food B was designed with a first bite hardness of 45/100 and a chewing hardness of 40/100. Its infill density, infill pattern, and shell thickness were calculated as 43%, triangle, and 2.5 mm, respectively.

Since infill density is an overlapping valid parameter in both computational models for the first bite and chewing hardness. Therefore, it is currently impossible to generate food with a very high first bite hardness combined with a very low chewing hardness, as such combinations fall outside the tunable parameter space shown in Fig. 9.

5.1.1 User Interface. Putting all together, we developed a user interface that integrates our computational models, as shown in Fig. 10. At the top, a display window shows a preview of the food shape's top view, which is loaded via the *Load SVG File* button (Fig. 10 a). A drop-down menu labeled *Type* allows users to select the food type (e.g., gummy, etc.), and a slider labeled *Weight* sets the desired weight (Fig. 10 b). Further down, two sliders labeled *First Bite Hardness* and *Chewing Hardness* enable users to specify their preferred texture levels (Fig. 10 c). When the *Generate 3D Model* button is pressed, the system computes suitable internal structural parameters and a corresponding 3D model is then automatically generated, incorporating both the calculated internal structure (Fig. 10 d) and the selected external shape (Fig. 10 e). Once the model is generated, users can save it via the *Save* button and export it for fabrication with an off-the-shelf digital fabrication tool. Examples of designs generated with this interface, including various geometries and textural targets, are presented in Fig. 5, Fig. 11, and Fig. 12.

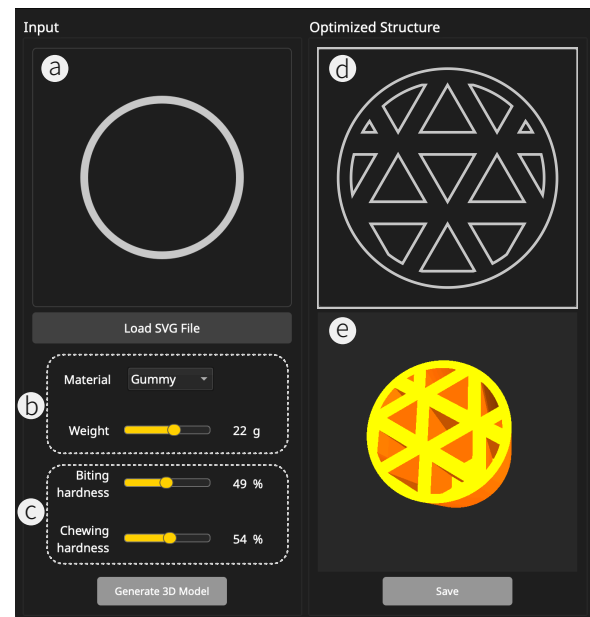


Figure 10: ChewTect user interface for designing temporal textures. (a) The user loads a 2D shape (e.g., SVG file) as input geometry. (b) Material and target weight are selected from the dropdown and slider, respectively. (c) Users specify desired texture levels for biting and chewing hardness. (d) The system optimizes an internal structure that satisfies the input conditions. (e) A 3D preview of the printable gummy model is generated for export.

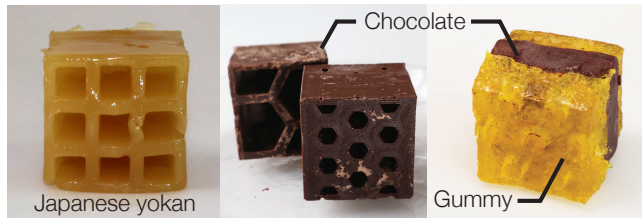


Figure 11: Examples of food materials supported by our molding technique, including Japanese yōkan (a traditional firm jelly), chocolate, and a multimaterial sample combining gummy and chocolate.

6 Discussion, Limitations and Future Perspective

We now reflect on the limitations of our work and discuss how they may be addressed in future research.

Food Material Diversity. Our empirical study is currently limited to gummy cubes, but ChewTect also supports other food types. Fig. 11 shows fabricated examples of yōkan (a traditional Japanese firm jelly made from agar), chocolate, and a multi-material gummy–chocolate composite, all produced with our computational model and silicone molds. While we have not yet validated the specific perceptual curves for these ingredients, prior food science literature suggests that elastic matrices follow similar perceptual trends [11], implying our model can generalize, especially to viscoelastic foods, after a baseline calibration. However, brittle materials (such as chocolate or biscuits) with the infill structures exhibit distinct fracture mechanics that would differ from the flow behavior of gelatin. Applying ChewTect to these materials may require fundamentally different structural unit cells designed to control crack propagation rather than bulk deformation. Moreover, our current approach relies on mold-compatible food materials, which may limit the types of food that are difficult to demold, such as those with highly porous structures. The future study should ensure a range of available food materials compatible with our approach.

Complex 3D Geometries. While we use gummy cubes as a walk-through example throughout our paper, our system supports molded foods in diverse shapes. As shown in Fig. 12 (a), ChewTect accommodates general 2.5D food shapes, such as circles, hearts, and flowers. Moreover, ChewTect supports fully 3D objects with complex topologies, such as a famous Stanford Bunny (Fig. 12 b), by decomposing the shape into simpler components. This decomposition enables the generation of a continuous internal structure. Although the capability to fabricate such objects is supported, detailed control of texture variations within these complex shapes remains a topic for future work.

Silicone Mold versus 3D Food Printing. Compared to existing fabrication methods, particularly extrusion-based 3D food printing [39], our silicone mold approach may have limited fabrication resolution, but it has strong potential for rapid fabrication and mass production. Additionally, the 3D food printing approach could enable automated processing and remove the burden of demolding. However, 3D food

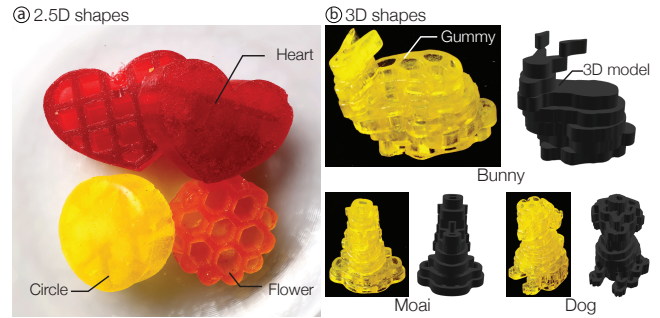


Figure 12: Additional food shapes produced using our molding technique. (a) Examples of 2.5D shapes include circles, hearts, and flower motifs. (b) Examples of 3D shapes include bunny, Moai, and dog models.

printing may be underexplored with new materials, and that molding approach can be used with a wider range of food materials, e.g., less viscous ones, which may not be possible with 3D food printing. While our work could generalize to a 3D food printing approach, we explored the silicone mold approach because it is easier to manipulate food texture and reduces the operational time. Our investigation into the 3D food printing approach will be in the body of future work.

Expanding the Dynamic Range. First-bite and chewing hardness varied systematically with infill density, pattern, and shell thickness. In contrast, perceptual differences in springiness were observed only for infill density, and springiness appeared less responsive to changes in the other parameters (infill pattern and shell thickness) than to changes in infill density. As a potential direction, we explored metamaterial-inspired designs [18, 29], as illustrated in Fig. 13, which enable directional deformation and nonlinear responses such as auxetic behavior. These demonstrations suggest that such designs could expand the range of perceptually distinguishable textures, opening the possibility of more diverse and nuanced experiences.

Multidimensional Texture Complexity. Our current model focuses on hardness and springiness, which are dominant mechanical properties for gelatin-based foods. However, the full texture experience includes complex temporal phenomena, such as crumbliness, adhesiveness, and melting rate (e.g., in chocolate), which should be incorporated into our geometric library to induce these specific fracture behaviors (e.g., creating shattering structures for brittle foods).

Biting Orientation. In the study, participants were instructed to grasp the cube-shaped gummy with two fingers and bring it to their mouth in a horizontal orientation to ensure consistency. For real-world usage, shape affordance can guide biting orientation. Anisotropic shapes such as sticks or chocolates shaped like a triangular prism (e.g., Toblerone, Mondelez International) may naturally promote directional biting. Although precise control of food orientation during chewing is challenging, our design utilizes infill density and shell thickness, features that are relatively unaffected by intraoral rotation. Supported by the fact that people typically

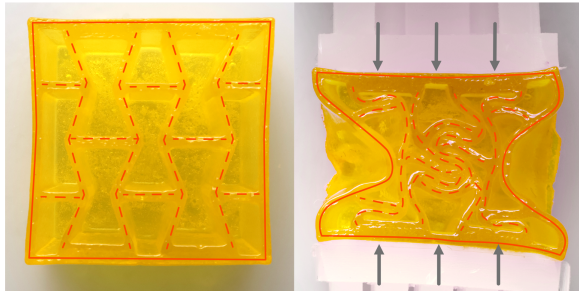


Figure 13: Metamaterial-inspired internal design enables directional deformation via re-entrant honeycomb structures. (left) Undeformed sample. (right) Under vertical compression (gray arrows), the structure exhibits a negative Poisson's ratio, resulting in lateral contraction in response to axial force.

bite the largest portion first and gradually form a bolus [4], our design and chewing habits help maintain a consistent texture despite some rotation.

Hygiene and Reusability. While silicone molding enables reusability, utilizing complex internal negatives (e.g., dense structures) presents challenges for thorough cleaning and sterilization between uses. Residue from previous batches could lead to flavor transfer or bacterial growth. Future iterations of ChewTect could explore sacrificial molding (using food-safe soluble supports) to ensure long-term hygiene in professional culinary settings.

Fabrication Latency for the Mold Preparation. Silicone molds can take several hours to fully cure, depending on their size. This may create a bottleneck for users seeking rapid customization, particularly in scenarios that require immediate or quick-turnaround production. To mitigate this, we explored a patch-based molding technique (Fig. 14) where pre-cured, reusable patches are combined to form variable internal structures, offering a potential pathway toward faster iteration. While still exploratory, this approach suggests a direction for reducing preparation time, and future work will investigate more efficient alternatives (e.g., [31, 67]).

Participant Diversity. The sensory evaluations in our study involved a relatively small, homogeneous participant group, which may limit the generalizability of the perceptual findings. Expanding future studies to include more extensive and more diverse participant pools (e.g., varying in age, gender, and cultural background) would enhance the robustness of our results, refine computational models for texture perception, and ensure broader applicability.

Towards Personalized Design Models. Finally, our deterministic models provide immediate, reasonable mappings from structure to perception, but their generalization to unseen participants was more modest ($R^2 = 0.70$ for first-bite, 0.43 for chewing), reflecting inter-individual variability. This variability reinforces the need for personalized design models rather than static automation. To address this, we explored a Bayesian optimization framework that leverages transfer learning to tune the model to a specific user with just three to four sample bites [26]. Future iterations of ChewTect

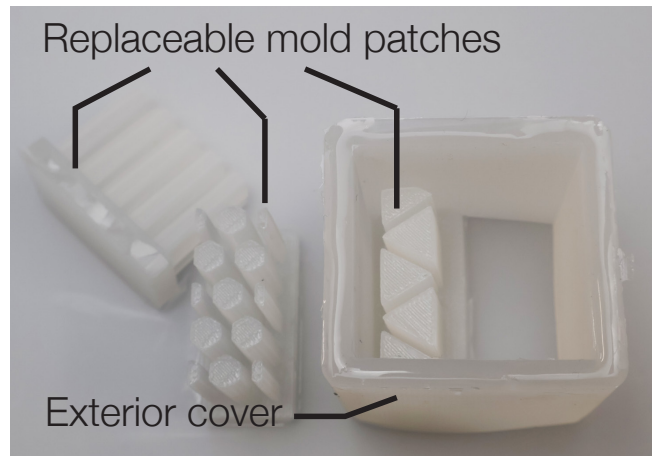


Figure 14: Replaceable mold patch mechanism, consisting of an exterior cover and interchangeable mold patches for fabricating different food textures and shapes.

could incorporate this “calibration loop,” allowing the system to learn the designer’s (or eater’s) specific oral physiology to maximize prediction accuracy. Ultimately, this adaptive framework for temporal texture design broadens the scope of digital gastronomy, facilitating applications ranging from narrative gastronomy to safe, texture-modified meals.

7 Conclusion

This paper presented *ChewTect*, a computational molding method to author programmable temporal texture experiences by modulating the internal structure of food. Our approach decouples textural properties from visual and caloric attributes, enabling independent tuning of sensory factors such as hardness and springiness. We characterized the relationship between internal geometry and oral perception, establishing a design space to ensure the perceptual differences arising from controlled variations in internal structure. Through our interactive interface and fabrication walkthrough, we demonstrated how this workflow empowers designers to craft novel eating experiences from functional foods for healthcare to narrative desserts for gastronomy. *ChewTect* expands the boundaries of Digital Gastronomy by transforming food texture from a static material property into a dynamic, programmable design dimension.

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