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Texture-based differences in eating rate influence energy intake for minimally processed and ultra-processed meals

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ABSTRACT

Background: Consumption of ultra-processed foods has been linked with higher energy intakes. Food texture is known to influence eating rate (ER) and energy intake to satiation, yet it remains unclear whether food texture influences energy intakes from minimally processed and ultra-processed meals.

Objectives: We examined the independent and combined effects of food texture and degree of processing on ad libitum food intake. We also investigated whether differences in energy intake during lunch influenced postmeal feelings of satiety and later food intake.

Methods: In this crossover study, 50 healthy-weight participants [$n = 50$ (24 men); mean ± SD age: 24.4 ± 3.1 y; BMI: 21.3 ± 1.9 kg/m^2] consumed 4 ad libitum lunch meals consisting of "soft minimally processed," "hard minimally processed," "soft ultra-processed," and "hard ultra-processed" components. Meals were matched for total energy served, with some variation in meal energy density (±0.20 kcal/g). Ad libitum food intake (kcal and g) was measured and ER derived using behavioral coding of videos. Subsequent food intake was self-reported by food diary.

Results: There was a main effect of food texture on intake, whereby "hard minimally processed" and "hard ultra-processed" meals were consumed slower overall, produced a 21% and 26% reduction in food weight (g) and energy (kcal) consumed, respectively. Intakes were higher for "soft ultra-processed" and "soft minimally processed" meals ($P < 0.001$), after correcting for meal pleasantness. The effect of texture on food weight consumed was not influenced by processing levels (weight of food: texture*processing-effect, $P = 0.376$), but the effect of food texture on energy intake was (energy consumed: texture*processing-effect, $P = 0.015$). The least energy was consumed from the "hard minimally processed" meal (482.9 kcal; 95% CI: 431.9, 531.0 kcal) and the most from the "soft ultra-processed" meal (789.4 kcal; 95% CI: 725.9, 852.8 kcal; Δ=↓~300 kcal). Energy intake was lowest when harder texture was combined with the "minimally processed" meals. Total energy intake across the day varied directly with energy intakes of the test meals (Δ15%, $P < 0.001$).

Conclusions: Findings suggest that food texture–based differences in ER and meal energy density contribute to observed differences in energy intake between minimally processed and ultra-processed meals. This trial was registered at clinicaltrials.gov as NCT04589221. *Am J Clin Nutr* 2022;116:244–254.

Keywords: texture, eating rate, energy density, NOVA food processing, ad libitum energy intake

Introduction

Ultra-processed foods have been defined by the NOVA classification system as "industrial formulations of processed

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Supplemental Figure 1 and Supplemental Table 1 are available from the "Supplementary data" link in the online posting of the article and from the same link in the online table of contents at https://academic.oup.com/ajcn/.

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Abbreviations used: EIR, energy intake rate; ER, eating rate; iAUC, incremental area under the curve; IRB, Institutional Review Board; RISE-Q, Reasons Individuals Stop Eating Questionnaire; SQ, satiety quotient; VAS, visual analog scale.

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food substances (i.e., oils, fats, sugars, starch, protein isolates) that contain little or no whole food, and typically include flavorings, colorings, emulsifiers and other cosmetic additives" (1). Numerous association studies have linked diets high in ultra-processed foods with higher risk of obesity (2, 3) and with other cardiometabolic health risks (4–6). A recent inpatient metabolic ward feeding study demonstrated that consuming ultra-processed diet for 2 consecutive weeks led to an increase of >500 kcal in daily energy intake compared with a similar period consuming a minimally processed diet. These sustained differences in daily energy intakes led to weight gain on the ultra-processed diet and weight loss on the minimally processed diet (7). Importantly, the meals in the ultra-processed diet were higher in energy density and consumed at a 50% faster energy intake rate (EIR; kcal/min) than meals in the minimally processed diet (7). This suggests that a combination of faster eating rate (ER) and higher energy density (kcal/g) may be one of the mechanisms by which ultra-processed food consumption promotes higher sustained energy intakes. Comparisons of energy intake from foods classified as ultra-processed are likely to also depend on differences in energy density, and the presence of softer textures and rapid ERs often associated with foods in this category. As such, observed differences in energy intake between minimally processed and ultra-processed diets may be attributed to differences in a food's texture, oral processing, and energy density, which are often themselves a consequence of food processing.

Cumulative empirical evidence has demonstrated that eating at a slower rate can reduce ad libitum energy intakes (8). A reduced bite size with increased chews per bite and a longer oral exposure time has been shown to lower food intake (9, 10), whether manipulated through verbal instructions to chew for longer, within-meal prompts to slow consumption, or by changing the textural properties of the food being consumed (8). Texture-led changes to ER have been shown to effectively moderate eating speed, as people adapt their oral processing behaviors in response to the structural properties of a food being consumed (11). For example, a soft/thin and less chewy food can be consumed at a faster rate than harder-textured, chewy, less lubricated, and more viscous foods (12–14). Variations in these textures are found within the food environment (12, 13, 15–17), where the most obvious distinction lies between foods of different forms from liquids to semisolids and solids (18).

Several ad libitum studies have successfully demonstrated that food texture modification can reduce eating speed and overall energy intake, without an associated reduction in postmeal satisfaction (19–21). Previous findings show that a food's sensory properties and eating speed contribute to dietary energy intakes (22), and the rate of energy intake (kcal/min) has been shown to vary widely among foods, from minimally processed to processed and ultra-processed categories (23). It remains unclear whether changes in food texture and ER can influence energy intake differently in minimally processed and ultra-processed meals. Food texture–based differences in ER have been suggested as a possible mechanism for the observed differences in energy intake between minimally processed and ultra-processed diets in a randomized controlled trial (23, 24). No study has yet tested whether food texture will influence energy intake from meals that independently differ in both texture and their degree of food processing.

The current study examined the independent and combined effects of food texture and degree of processing on ER, EIR, and ad libitum food intake. We also investigated whether differences in energy intake during lunch influenced postmeal ratings of satiety and later food intake.

Methods

Study design

In a randomized crossover 2 × 2 repeated-measures design, participants attended 4 lunchtime sessions to assess the independent and combined effects of food texture (harder and softer) and degree of processing (minimally processed and ultra-processed) on ER (g/min), EIR (kcal/min), and ad libitum food intake (measured in both g and kcal). Participants also rated their postmeal appetite and subsequent food intake after each of the test meals. The 4 test meals consisted of meal components chosen to represent soft or hard textures from both minimally processed and ultra-processed categories, as defined by the NOVA classification (1) (see **Supplemental Figure 1** and **Supplemental Table 1**).

The primary outcome of the study (NCT04589221) was a comparison of ER (g/min), EIR (kcal/min), and ad libitum food intakes (g and kcal) after consumption of each of the 4 test meals. The secondary outcome was a comparison of the sensory ratings, postmeal appetite ratings, and later food intake after each of the 4 test meals.

Participants

A priori power calculation was used to determine a sample size adequate to test the main effects and interaction across the 4 meals. The article of Bolhuis et al. (19) was used to estimate the effect of a similar texture manipulation on ER and energy intake. In that study, a 32% reduction in ER led to a significant (13%) reduction in energy intake, using a repeated-measures design. We predicted that the texture manipulation (which was designed to be matched across processing levels) would drive differences in intake over the processing level. Based on this, we conducted a power calculation in G*Power version 3.1.9.2 (Heinrich-Heine-Universität Düsseldorf) to estimate the sample required to test a similar magnitude of difference in ER on energy intake across the 4 conditions at 80% power, using a repeated-measures design and $\alpha = 0.05$. This suggested a minimum of 23 participants would be required, which we raised to a recruitment target of 50 to account for dropouts and the unknown effect of processing level in this context.

Fifty healthy participants (52% women) with a mean age of 24.4 y were recruited from the general public in Singapore through advertisement, and from a participant database (see **Table 1** for general characteristics of participants). To conceal the main focus of the study, participants were informed that the study aimed to investigate how sensory properties of commonly consumed foods influence eating behavior. Participants were recruited to have a BMI in the healthy range (18.5–24.9 kg/m^2), were not pregnant, without allergies or aversions to any of the test foods, with no underlying eating difficulties, with low dietary restraint (25), and none of the participants were currently trying to lose weight or using

TABLE 1 General characteristics of participants[1]

	Men ($n = 24$)	Women ($n = 26$)
Age, y	24.5 ± 2.9	24.4 ± 3.4
Body weight, kg	66.4 ± 7.8	54.0 ± 4.2
BMI, kg/m^2	22.2 ± 2.0	20.5 ± 1.4
Body fat, %	27.6 ± 3.3	27.6 ± 3.3
Dietary restraint score (0–8)[2]	3.3 ± 1.3	4.0 ± 1.4

[1] $n = 50$. Values are means ± SDs.

[2] Measured with the revised Three-Factor Eating Questionnaire-18 (25), where 0 represents no dietary restraint, and 8 represents highest dietary restraint.

medication known to affect appetite or energy metabolism. Written consent was obtained from all the participants before the study. This study was approved by the Agency for Science, Technology and Research Institutional Review Board (IRB), Singapore (IRB reference: 2019-084) and conducted in accordance with the Declaration of Helsinki on research involving human participants.

Experimental procedure

Participants were screened for their eligibility which included anthropometric measurements, body weight and height (Seca 763 digital scale), and percentage of body fat (bioelectrical impedance analysis, Tanita BC-418). Eligible participants were invited to attend 4 ad libitum lunch meal sessions across nonconsecutive test days at the Clinical Nutrition Research Centre. Each test day followed the same procedure and was separated by a minimum of 7 d.

Participants refrained from strenuous physical activities and were instructed to fast for a minimum of 10 h from the evening before each test session, which was confirmed verbally with research staff the morning of each test day (08:00–09:00). To equilibrate premeal appetite, participants were provided with a standardized breakfast and mid-morning drink, which they were instructed to consume at 4 and 2 h before their ad libitum lunchtime session, respectively.

Participants returned for lunch at the same time for each of the 4 meals (12:00–13:00), and were provided with an ad libitum portion of each meal and 250 mL of water. Participants began by completing a first set of appetite ratings, and were instructed to rate their hunger, fullness, desire to eat, and prospective intake on a 0- to 100-mm visual analog scale (VAS), anchored by "Not at all" (0) to "Extremely" (100). All ratings were presented in a randomized order. Participants were instructed to taste the meal and complete ratings of pleasantness for each meal component, overall meal pleasantness, and perceived intensity for overall flavor, salty, chewy, springy, and firmness. Sensory attribute ratings were captured using the same 0- to 100-mm VAS line scale as for the appetite ratings. After the sensory and pleasantness ratings, participants were allocated 20 min and instructed to complete their meal in their normal way until they felt comfortably full. Participants were then instructed to report their reasons for stopping eating using the newly developed Reasons Individuals Stop Eating Questionnaire (RISE-Q) (26), right after their meal. Those who finished their portions were free to request another, although no participant requested a second portion. The total weight of the test meal and water consumed was recorded to the nearest 0.01 g using a Sartorius balance.

Participants rated their appetite immediately after their meal, and then repeated these ratings online with their mobile phone every 15 min for the next 90 min. During this 90-min period, participants refrained from eating or drinking anything except water. Participants were also instructed to keep a food diary to record any of their subsequent meal intakes for the rest of the test day. All returned diet records were checked for accuracy and completeness and were keyed in by a trained researcher using Food-Works 10.0 software (Food-Works Professional, Xyris Software Pty Ltd).

Test meals

Foods selected for inclusion in the test meals were chosen for being familiar and regularly consumed in Singapore, and were selected from a Singaporean FFQ, which represents >95% of daily energy intake in Singaporean adults (27). The standardized breakfast consisted of orange juice (Marigold: 350 mL), a packet of nut-chocolate oat cookies (Munchy's Oat Krunch Crackers: 26 g), and a muesli bar (Uncle Toby's strawberry-flavored yoghurt tops: 24 g), for a total of 356.9 kcal. Participants received a mid-morning drink (124 kcal) of malt chocolate milk (Nestle Milo: 200 mL). Both breakfast and mid-morning drink provided women 28% and men 22% of their respective daily energy intake requirements, based on the recommendations from the Health Promotion Board, Singapore (28).

The test lunch meals consisted of "soft minimally processed," "hard minimally processed," "soft ultra-processed," and "hard ultra-processed" meal components. Supplemental Figure 1 shows the 4 ad libitum test meals that varied in terms of food textures (soft compared with hard) and degree of NOVA processing (minimally processed compared with ultra-processed). All meal components were chosen to reflect a wide range of savory-tasting foods that differed in their degree of processing and included potatoes, grains, fish, chicken, fruits, vegetables, sauces, and dairy products (Supplemental Table 1). Based on the NOVA classification, minimally processed meals were defined as meals that have been subjected to minimal or no processing, whereas ultra-processed meals were defined as industrial formulations of processed food substances (oils, fats, sugars, starch, protein isolates) that contained flavorings, colorings, preservatives, emulsifiers, or other cosmetic additives (1). The 4 test meals were matched for energy from macronutrients, although there were differences in the energy density of each meal (±0.2 kcal/g), total weight (g), and overall energy content (kcal) served (Supplemental Figure 1). Pilot testing was completed to ensure meal components were hedonically acceptable and familiar, and efforts were made to match test meals for palatability of meal components and overall liking. The energy density for each meal component was calculated from the food composition database of the Singapore Health Promotion Board (28) and the USDA National Nutrient Database for Standard Reference (29).

All ad libitum test meals were prepared fresh on the morning of each test day using standardized cooking procedures in order to achieve realistic, consistent, and reproducible texture manipulations. Each meal was served warm at 50–60°C, with a fork and a glass of water (250 mL), and

TABLE 2 Sensory ratings (0–100) of the 4 test meals[1]

	Soft-textured		Hard-textured		Main effect of type of test meals, P value
	Minimally processed	Ultra-processed	Minimally processed	Ultra-processed	
Meal pleasantness	66.3 ± 2.7^a	68.4 ± 2.4^a	35.8 ± 3.3^b	75.0 ± 2.8^a	<0.001
Meal component pleasantness					
Carbohydrate	38.9 ± 3.3^b	37.8 ± 3.4^b	32.6 ± 3.8^b	61.3 ± 3.6^a	<0.001
Vegetable	53.2 ± 3.5^a	50.8 ± 3.7^a	40.1 ± 4.0^b	49.4 ± 3.6^a	0.028
Protein	63.3 ± 3.2^b	75.5 ± 2.4^a	28.3 ± 3.1^c	78.4 ± 2.4^a	<0.001
Fruit	76.1 ± 2.1^a	43.0 ± 3.7^b	78.5 ± 2.3^a	49.4 ± 3.7^b	<0.001
Dairy	45.1 ± 4.3^b	73.4 ± 3.4^a	53.7 ± 3.9^b	82.5 ± 2.1^a	<0.001
Sauce	$52.4 \pm 4.2^{b,c}$	62.4 ± 3.2^b	49.6 ± 4.1^c	73.2 ± 3.4^a	<0.001
Overall firmness[2]	24.9 ± 2.0^a	25.1 ± 1.5^a	59.5 ± 2.4^b	53.7 ± 2.5^b	<0.001
Overall chewiness[2]	27.0 ± 2.1^a	28.6 ± 1.4^a	52.3 ± 2.6^b	53.2 ± 2.4^b	<0.001
Overall springiness[2]	22.0 ± 2.5^a	$24.8 \pm 2.3^{a,b}$	$30.3 \pm 2.6^{b,c}$	32.8 ± 2.3^c	0.001

[1] $n = 50$ (24 men). Values are means ± SEMs. Means in a row without a common superscript letter differ, $P < 0.05$ with Bonferroni adjustments for multiple comparisons.

[2] Averaged values from the 4 main meal components (carbohydrate, protein, vegetable, and fruit) in each test meal.

participants were provided with salt and pepper to season their meal.

Oral processing characteristics

Oral processing behaviors were quantified using behavioral coding analysis of video recordings of each participant consuming each test meal, using a method described previously (30). Behavioral coding was completed by trained researchers and validated in line with previously described standards (12). Data collection was completed in individual booths equipped with a tablet (Microsoft Surface Go Lte 128GB 8GB) with webcam (Logitech HDc310) positioned to capture participants' eating behaviors during consumption. Participants were unable to view the video of themselves during consumption. A series of predefined oral processing behaviors were quantified with a predefined behavioral coding scheme and videos were annotated using specialized software (ELAN version 4.9.1; Max Planck Institute for Psycholinguistics, The Language Archive) (31). Behavioral coding recorded the frequency of bites, chews, and swallows and the duration of food in mouth (oral exposure time in s). Measured oral processing behaviors were related back to total weight and energy of food consumed to derive meal ER (g/min) and EIR (kcal/min).

Statistical analysis

Descriptive statistics were reported as mean ± SEM, unless otherwise indicated. The assumptions of the statistical model were verified before data analysis. These assumptions included distribution and homogeneity of the residuals, independence of the data points, independence of the random effects from the covariates, linearity of the relation between predictor and response, and absence of measurement error in the predictor. The estimated mean values of each derived oral processing behavior, food intake (g and kcal), and sensory and appetite ratings from a total of 50 participants were reported for each meal. No missing data were reported in the current study.

Repeated-measures linear mixed models were used to examine the independent and combined effects of food texture (soft compared with hard; within-subject) and degree of processing (minimally processed compared with ultra-processed; within-subject) on outcome variables, including ER (g/min), EIR (kcal/min), and overall food and energy intake (g and kcal). In these models food texture, degree of processing, and their interactions were added as fixed factors. Unstructured correlation with homogeneous variance was used as the covariance structure because no constraints were imposed on the correlation pattern. An additional covariate, participants' rating of overall meal pleasantness, was adjusted for in the models where overall meal intakes (g and kcal) were the outcome variables; whereas, the pleasantness of the individual meal components was adjusted for in the models where intakes of individual meal components (g and kcal) were the outcomes. Post hoc Bonferroni adjustments were used to compare means.

Average sensory and appetite ratings were reported per meal and in the case of appetite at each time point. Similar repeated-measures linear mixed models were used to examine the independent and combined effects of food texture (soft compared with hard; within-subject) and degree of processing (minimally processed compared with ultra-processed; within-subject) on sensory and appetite ratings. Appetite ratings were controlled for their baseline measures and participants' sex (men compared with women; between-subject). An additional within-subject variable of time (prelunch to 90 min postlunch) was added to the analysis model of appetite. The incremental area under the curve (iAUC) was also calculated for each appetite sensation (i.e., hunger, fullness, desire to eat, and prospective intake) from time point 0 min (prelunch) to 90 min postlunch using the trapezoidal rule (32, 33), ignoring the area beneath the baseline. Mean satiety quotient (SQ; mm/kcal) for each of the 4 appetite sensations was also calculated by subtracting the average appetite response at the postmeal VAS from the fasting response (mm) and dividing it by the total energy consumed from a test meal (kcal), which was then multiplied by 100 (34). SQ is a marker of the satiating capacity of a meal/food per unit of energy consumed (kcal); a higher SQ for each appetite sensation indicates a greater satiating capacity. Repeated-measures linear mixed models were used to test for differences in the iAUC and SQ of appetite sensations between test meals. All repeated-measures linear mixed models were executed using an unstructured covariance structure with homogeneous variance and Bonferroni post hoc adjustments.

All statistical analyses were performed using IBM SPSS for Windows version 26.0 (IBM) and P values < 0.05 were considered statically significant.

Results

Hedonic and sensory characteristics

Table 2 summarizes the mean sensory and hedonic ratings of the 4 test meals. In line with the texture manipulation, the soft-textured meals were rated as significantly less firm ($P < 0.001$), less chewy ($P < 0.001$), and less springy ($P = 0.03$) than the hard versions for foods classified as minimally processed and ultra-processed. Three of the test meals had similar ratings for meal pleasantness, and the "hard minimally processed" test meal had significantly lower ratings for meal pleasantness than the other meals.

Oral processing characteristics

Figure 1 presents the mean ER and EIR of each test meal. There was a main effect of food texture ($F = 282.76$; $P < 0.001$) on ER, such that both "soft minimally processed" and "soft-ultra-processed" meals were consumed at a significantly faster rate than the hard versions ($P < 0.001$), which led to an overall 35% difference in ER between the hard- and soft-textured meals. There was a significant processing effect on ER ($F = 20.83$; $P < 0.001$). As reported in Figure 1, the "soft ultra-processed" meal was consumed fastest (52.3 g/min; 95% CI: 47.6, 57.0 g/min), followed by the "soft minimally processed" meal (45.9 g/min; 95% CI: 42.6, 49.3 g/min), with similar ERs reported for the "hard minimally processed" (30.3 g/min; 95% CI: 27.6, 33.0 g/min) and "hard ultra-processed" meals (33.4 g/min; 95% CI: 30.7, 36.2 g/min; $P = 0.077$). Food texture accounted for the observed differences in ER, and differences in degree of food processing contributed to differences in ER between the soft-textured meals, although the interaction term was not statistically significant (texture*processing-effect, $F = 3.75$; $P = 0.059$).

There were significant main effects of food texture ($F = 387.37$; $P < 0.001$) and degree of processing ($F = 98.82$; $P < 0.001$) on EIR, but no significant interaction (texture*processing-effect, $F = 0.03$; $P = 0.954$). Both "soft minimally processed" (53.5 kcal/min; 95% CI: 49.5, 57.4 kcal/min) and "soft ultra-processed" meals (66.6 kcal/min; 95% CI: 60.7, 72.6 kcal/min) had a significantly higher EIR than the "hard minimally processed" (29.7 kcal/min; 95% CI: 26.8, 32.7 kcal/min) and "hard-ultra-processed" meals (43.0 kcal/min; 95% CI: 39.5, 46.6 kcal/min; $P < 0.001$). EIR was significantly higher for both ultra-processed meals ($P < 0.001$), with an overall increase of 24% between the ultra-processed and minimally processed meals. Energy density was higher for the

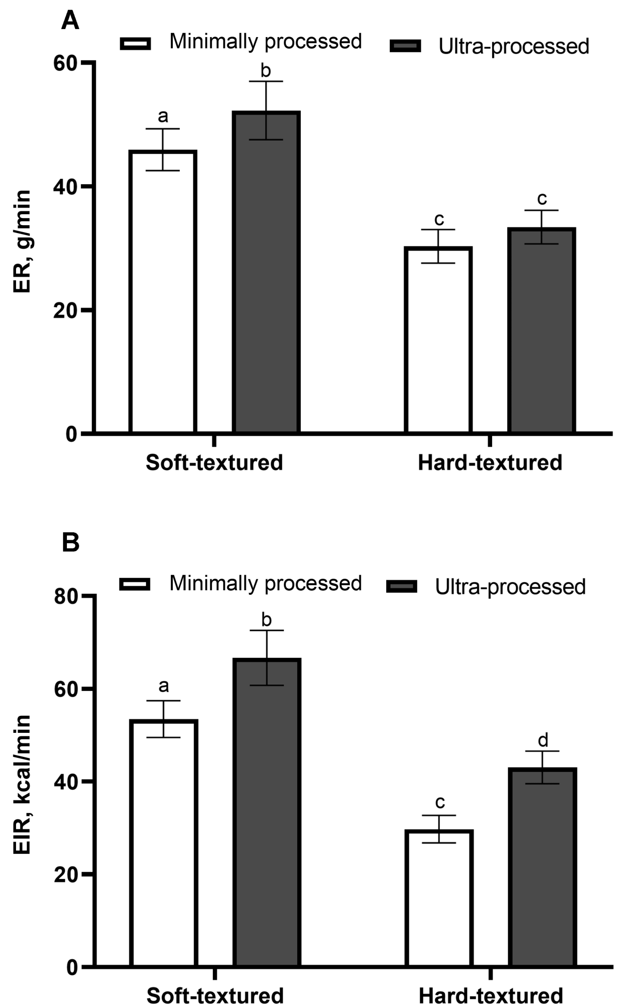

FIGURE 1 ER (A) and EIR (B) of the 4 test meals. Values are mean (95% CI), $n = 50$ (24 men), repeated-measures linear mixed models. Within each graph, bars without a common letter differ (Bonferroni post hoc test, $P < 0.001$; ER: texture*processing-effect, $P = 0.059$; EIR: texture*processing-effect, $P = 0.954$). EIR, energy intake rate; ER, eating rate.

ultra-processed meals, and both meal texture and degree of food processing accounted for the differences in EIR overall.

Food and energy intake at ad libitum lunch

Figure 2 depicts the mean intakes of the 4 test meals (g and kcal), after controlling for differences in meal pleasantness. There was a main effect of food texture ($F = 227.34$; $P < 0.001$) such that participants consumed significantly less of the hard-textured meals (482.1 g; 95% CI: 447.0, 517.3 g) than the soft-textured meals (621.2 g; 95% CI: 575.7, 666.7 g), whereas a relatively small effect of meal pleasantness ($F = 4.24$; $P = 0.042$) was observed. There was no significant effect of degree of food processing on the amount (g) of food consumed ($F = 0.36$; $P = 0.549$), and degree of processing did not interact with meal texture to influence intake ($F = 0.79$; $P = 0.376$). Participants consumed significantly less energy from the harder meals (555.6 kcal; 95% CI: 510, 601.2 kcal) than from the softer meals (756.5 kcal; 95% CI: 699.4, 813.6 kcal; $P < 0.001$), with

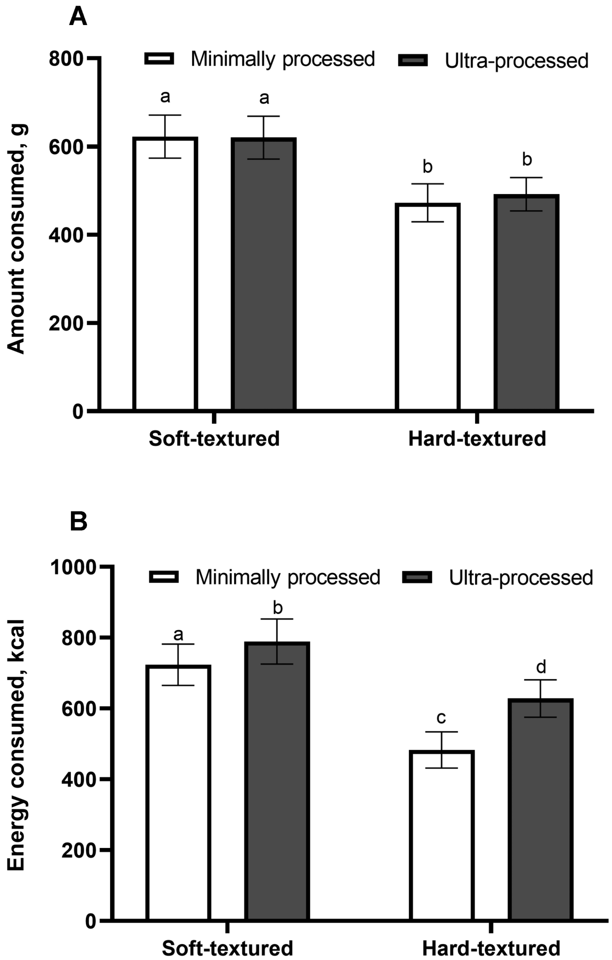

FIGURE 2 Intake of meals as weight (A) and energy (B) consumed across the 4 test meals, controlling for rated meal pleasantness. Values are mean (95% CI), $n = 50$ (24 men), repeated-measures linear mixed models. Within each graph, bars without a common letter differ ($P < 0.05$), with Bonferroni adjustment (weight of foods consumed: texture*processing-effect, $P = 0.376$; energy consumed: texture*processing-effect, $P = 0.015$).

a 26% reduction in ad libitum energy intake (texture effect, $F = 214.14$; $P < 0.001$). The least energy was consumed from the "hard minimally processed" meal (482.9 kcal; 95% CI: 431.9, 531.0 kcal) with a decrease of 300 kcal compared with the "soft ultra-processed" meal (789.4 kcal; 95% CI: 725.9, 852.8 kcal). There was a significant main effect of food processing on energy intake ($F = 39.93$; $P < 0.001$) such that participants consumed more energy from the soft and hard versions of the ultra-processed meals than from the soft and hard versions of the minimally processed meals (texture*processing-effect, $F = 6.27$; $P = 0.015$). Ad libitum energy intake was lowest when a combination of both harder-texture and lower–energy density minimally processed foods were consumed within a meal, and this effect persisted after controlling for meal pleasantness (pleasantness-effect, $F = 9.93$; $P = 0.002$). Importantly, the differences in food (g) and energy (kcal) intakes were not different when individual intakes were adjusted for differences in rated meal pleasantness. In addition, results from the RISE-Q showed that the predominant reason for stopping eating was self-reported to be fullness (physical satisfaction), and this did not differ across each of the 4 meals (data not shown).

Across the test meals there were 6 meal components that had the same commodity that was presented in $\geq$2 forms. For example, potatoes were presented as instant potato mash or as waffle fries in the ultra-processed meals. This enabled a comparison of the intake of individual meal components across different textures and degrees of food processing. Figure 3 shows the weight and energy consumed for different forms of similar meal components, after controlling for their respective rated pleasantness. Among the 6 meal components, the protein element in each meal was the most consumed (g) (texture*processing-effect, $F = 0.89$; $P = 0.350$). An equivalent weight of carbohydrate was consumed across 3 test meals, the exception being the hard ultra-processed meal (texture*processing-effect, $F = 4.90$; $P = 0.031$). The vegetable component was less consumed (g) in hard-textured meals than in the soft-textured meals (texture-effect, $F = 152.22$; $P < 0.001$). Energy from protein was the most consumed for both soft minimally processed and soft ultra-processed meals (texture-effect, $F = 212.92$; $P < 0.001$). Energy consumed from carbohydrate in both hard-textured meals was higher than energy from carbohydrate in both soft meals (texture-effect, $F = 86.11$; $P < 0.001$). The vegetable component contributed more to energy consumed for the ultra-processed meals than for the minimally processed meals (processing-effect, $F = 143.27$; $P < 0.001$).

Postmeal energy intake

Figure 4 shows the total energy consumed during the remainder of each test meal day. Daily energy intake across each of the 4 test days varied directly in proportion to the differences in energy intake at the lunchtime test meal ($\Delta_{kcal} = 15\%$; $P < 0.001$). The observed total daily energy intake was lower during the "hard minimally processed" condition (1800.3 kcal/d; 95% CI: 1651.0, 1949.5 kcal/d) than during the "soft ultra-processed" condition (2029.2 kcal/d; 95% CI: 1897.5, 2160.8 kcal/d). There was no significant interaction between food texture and degree of processing ($F = 0.24$; $P = 0.625$). Despite large differences in energy intake at lunch (i.e., $\Delta_{kcal} = 300$), participants did not compensate at subsequent meals within the same day ($P = 0.964$).

Changes in rated appetite and postmeal satiety

Figure 5 shows the changes in rated hunger, fullness, desire to eat, and prospective intake over 90 min across the 4 test meals, after correcting for the baseline ratings and participants' sex. There was a significant effect of time on the 3 rated appetite sensations (all, $P < 0.001$), with similar prelunch appetite ratings, decreasing immediately after lunch, and gradually increasing from 15 to 90 min postconsumption for all 4 meals. The opposite pattern was observed in rated fullness (time-effect, $P < 0.001$). Consistent differences in appetite over time were observed between the different test meals, and were associated with differences in the energy consumed for each ad libitum meal, although the interactions between food texture, processing level, and time on 3 of the 4 appetite sensations were not statistically significant (hunger: texture*processing*time-effect, $F = 0.73$; $P = 0.65$; prospective intake: texture*processing*time-effect,

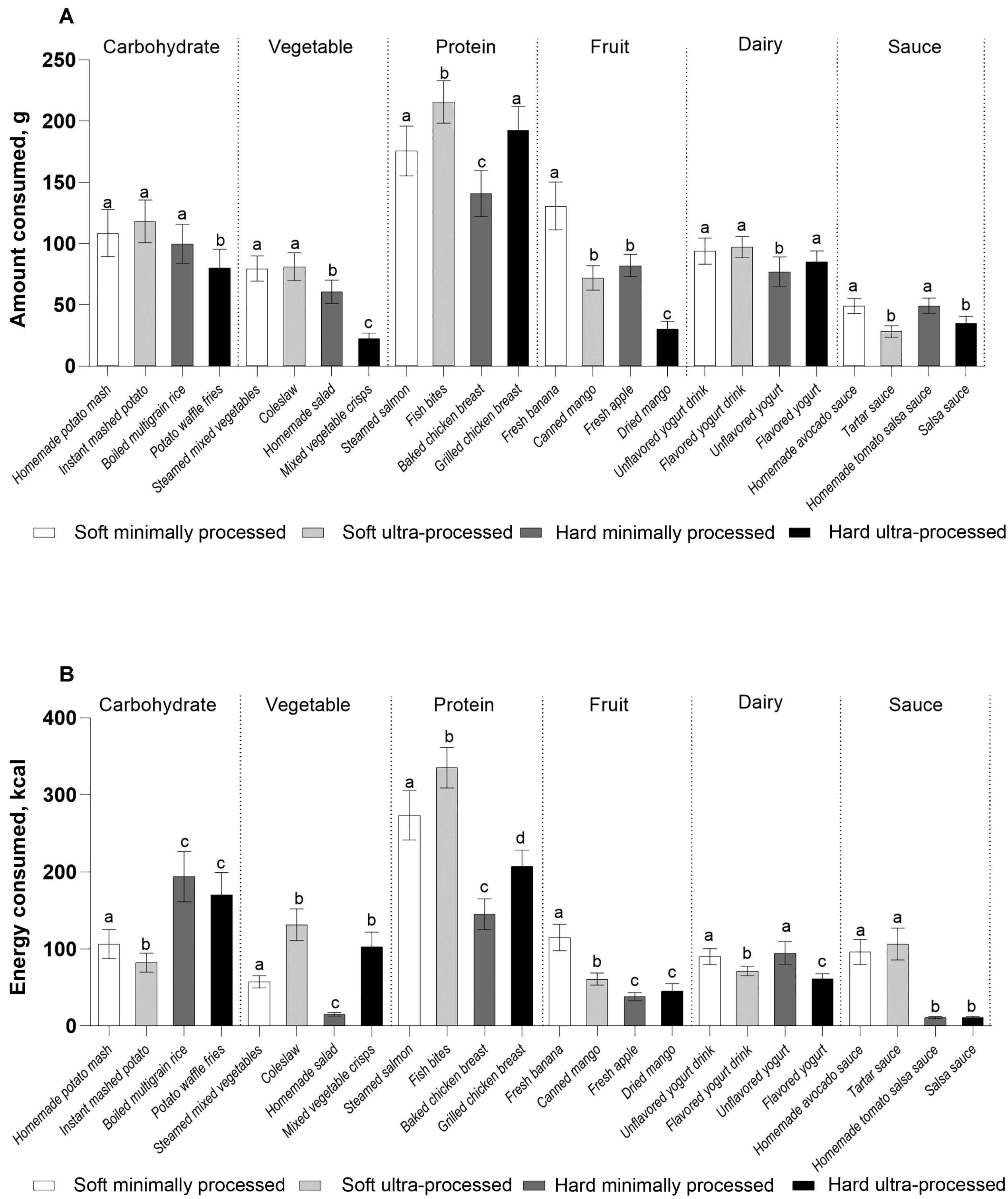

FIGURE 3 Intake of meal components as weight (A) and energy (B) consumed across the 24 meal components in the 4 test meals, controlling for their respective rated meal component pleasantness. Values are mean (95% CI), $n = 50$ (24 men), repeated-measures linear mixed models (carbohydrate: weight of foods consumed: texture*processing-effect, $P = 0.031$; energy consumed: texture*processing-effect, $P = 0.985$; vegetable: weight of foods consumed: texture*processing-effect, $P < 0.001$; energy consumed: texture*processing-effect, $P = 0.289$; protein: weight of foods consumed: texture*processing-effect, $P = 0.350$; energy consumed: texture*processing-effect, $P = 0.994$; fruit: weight of foods consumed: texture*processing-effect, $P = 0.414$; energy consumed: texture*processing-effect, $P < 0.001$; dairy: weight of foods consumed: texture*processing-effect, $P = 0.508$; energy consumed: texture*processing-effect, $P = 0.053$; sauce: weight of foods consumed: texture*processing-effect, $P = 0.053$; energy consumed: texture*processing-effect, $P = 0.228$). Within each component of each graph, bars without a common letter differ ($P < 0.05$), with Bonferroni adjustment.

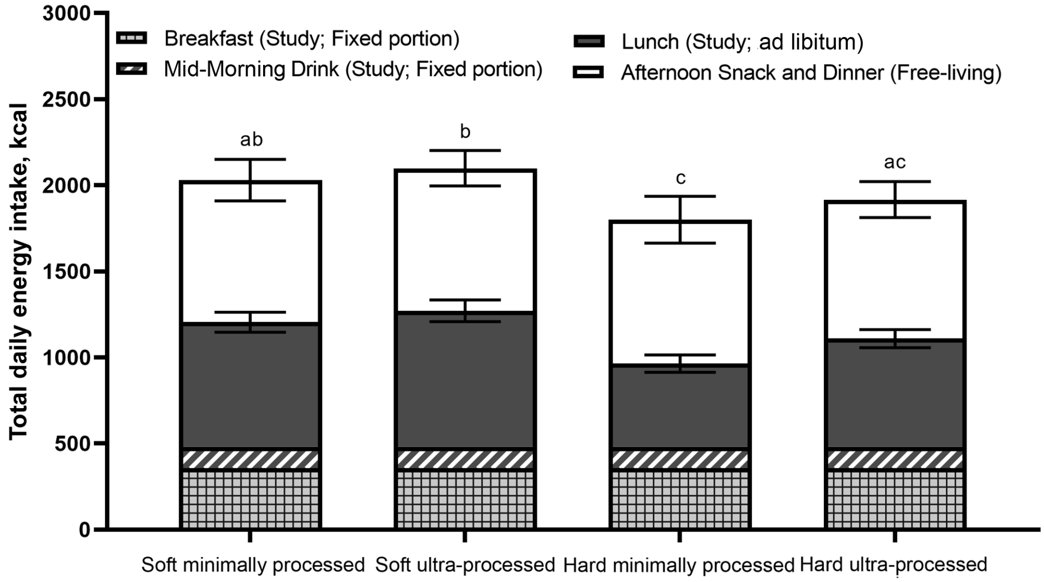

FIGURE 4 Total energy intake across each test day, controlling for rated meal pleasantness. Values are mean (95% CI), $n = 50$ (24 men), repeated-measures linear mixed models. Bars without a common letter differ ($P < 0.05$), with Bonferroni adjustment (texture*processing-effect, $P = 0.625$).

$F = 0.82$; $P = 0.58$; fullness: texture*processing*time-effect, $F = 1.77$; $P = 0.17$; desire to eat: texture*processing*time-effect, $F = 3.39$; $P = 0.025$). The lower postmeal ratings for fullness for the "hard minimally processed" meal were associated with lower amounts of energy consumed. Similarly, there were no significant differences in postmeal $iAUC_{90}$ values of appetite sensations across the test meals, except for the $iAUC_{90}$ value of fullness (**Table 3**). The $iAUC_{90}$ value of fullness showed that both hard and soft ultra-processed meals were more filling than the hard minimally processed meals, and were associated with greater amounts of energy consumed during the 2 ultra-processed meals. The mean SQs (i.e., satiating capacity of a meal per unit energy consumed; mm/kcal) for hunger, fullness, desire to eat, and prospective intake did not differ across the 4 meal conditions (Table 3), suggesting all meals were equally satiating calorie for calorie.

Discussion

We tested the independent and combined effects of food processing and food texture on ad libitum food and energy intakes to better understand the potential reasons for higher energy intakes from ultra-processed meals observed previously (7). Results showed that meal texture, rather than processing level, accounted for differences in the amount of food (g) consumed within an ad libitum test meal, whereas meal texture and the higher energy density of ultra-processed meals accounted for observed differences in energy intake (kcal). Energy intake was lowest in the minimally processed harder-textured condition, and highest in the soft-textured ultra-processed condition. Although intake was higher for the softer meals, all meals were rated as equally satiating postconsumption, with no energy compensation for missing or additional energy at subsequent meals. These findings suggest that texture and energy density in combination were driving differences in food and energy intake across meals that differed in their degree of food processing. Softer texture influenced intakes for both minimally processed and ultra-processed meals, although the size of effect was not equivalent across both sets of meals. Differences in meal energy intake at lunch were not adjusted for in later food intake, suggesting differences in texture and energy density had a stronger effect on satiation than on satiety.

The soft ultra-processed meal was consumed at the fastest rate and to the greatest extent, whereas the ERs (g/min) of the hard versions of the minimally processed and ultra-processed meals were very similar. This aligns with previous research identifying food texture as a major driver of a food's ER, where foods that are softer in texture require fewer chews per bite and are consumed at a faster rate (35). For example, ER was observed to be 32% lower for a lunch of harder foods than for a similar meal comprising softer foods (19). The ER of composite foods can be reduced by between 29% and 33% when increasing the hardness level of a food (i.e., from bread to cracker) (36). The current study demonstrates that both food texture and degree of processing as defined by the NOVA classification had a significant impact on the rate of energy intake (kcal/min), which was higher for the ultra-processed meals. A higher energy density has previously been associated with both higher acute energy intake and higher cardiometabolic risk (37). Recent comparisons of the EIRs for a wide range of foods that differed in their degree of processing highlight that reported increases in energy intake associated with increased consumption of ultra-processed diets may be attributed to underlying differences in a food's ER and energy density (23). If it can be demonstrated that a higher EIR is the mechanism by which ultra-processed foods promote greater energy intakes, it creates new opportunities to reformulate foods to have both lower energy density and more challenging food textures that require longer oral processing and reduce eating speed to better regulate energy intake, while maintaining a food's sensory appeal and postmeal satisfaction. Promoting the consumption

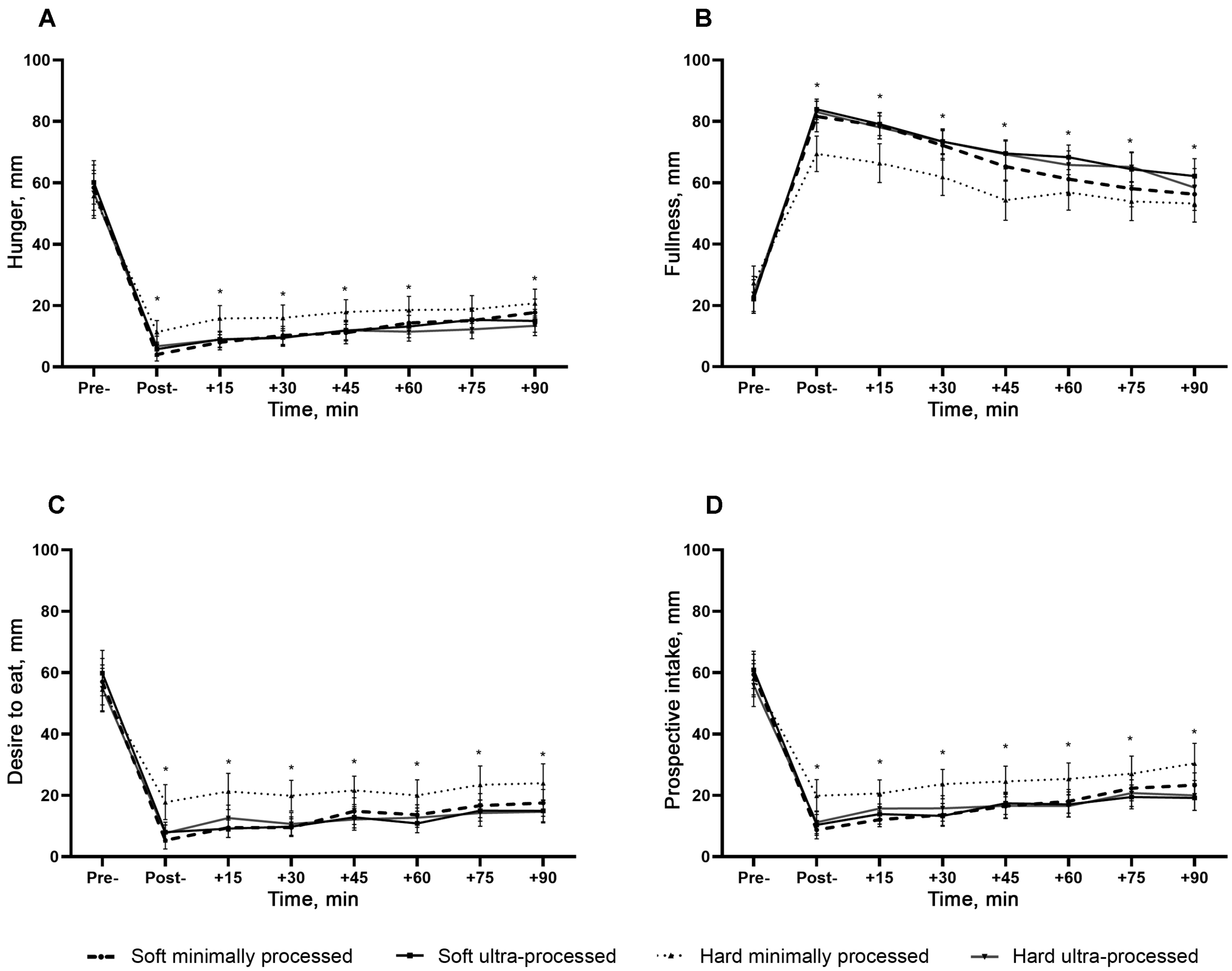

FIGURE 5 Changes in rated hunger (A), fullness (B), desire to eat (C), and prospective intake (D) from before lunch to after lunch and during subsequent 15-min intervals for 90 min postlunch, controlling for the baseline ratings and participants' sex. The 4 test meals varied in texture and processing levels. Values are mean (95% CI), $n = 50$ (24 men), repeated-measures linear mixed models (hunger: texture*processing*time-effect, $P = 0.65$; fullness: texture*processing*time-effect, $P = 0.17$; desire to eat: texture*processing*time-effect, $P = 0.025$; prospective intake: texture*processing*time-effect, $P = 0.58$). *Significant difference between test meals at these time points, $P < 0.05$.

of harder minimally processed foods that have lower energy density offers an approach to reduce the risk of excessive energy intakes.

The "hard ultra-processed" meal was consumed 2 times slower than the "soft ultra-processed" meal, and was associated with 16%–25% reductions in food and energy intakes. This aligns with previous findings where, across a number of studies, texture-based reductions in ER of 20% supported a decrease of between 10% and 13% in ad libitum energy intakes (38). The implication is that ultra-processed diets may not always promote increased energy intake (39), if enhanced food texture is combined with reductions in energy density to support reduced intake. Participants in the current study consumed a similar weight (g) of food within the same texture condition (hard compared with soft), and this was observed for both the minimally processed and ultra-processed versions of the soft- and hard-textured meals. Energy intake increased in line with the higher energy density of both the soft and hard versions of the ultra-processed meals. Taken together, these results highlight that texture and energy density had a consistent impact on ad libitum food and energy intake, and have both an independent and a combined effect on total energy consumed to fullness across minimally processed and ultra-processed meals.

The present study suggests that consistent increases in energy intake from diets composed of ultra-processed meals (7) may be driven by the softer textures and higher energy density often associated with ultra-processed foods. Several putative mechanisms by which ultra-processed foods affect energy intake have been previously suggested, including that ultra-processed foods are "hyper-palatable" and promote hedonic overeating (40). Meal pleasantness did not significantly influence intake differences observed in the current study, although the "hard minimally processed" meal had significantly lower rated pleasantness than the other meals. This finding highlights that although it is possible to influence meal ER and reduce the risk of overconsumption, challenges remain in understanding how to

TABLE 3 $iAUC_{90}$ and SQ for appetite sensations of the 4 test meals[1]

	Soft-textured		Hard-textured		Main effect of type of test meals, P value
	Minimally processed	Ultra-processed	Minimally processed	Ultra-processed	
$iAUC_{90}$, mm × min					
Hunger	12.4 ± 8.7	4.8 ± 3.2	14.6 ± 8.3	12.7 ± 9.3	0.561
Fullness	3661.8 ± 304.9^{a,b,c}	4243.7 ± 264.2^{a,c}	2913.5 ± 294.0^{b}	4072.5 ± 289.7^{c}	<0.001
Desire to eat	11.7 ± 10.6	8.0 ± 6.0	29.3 ± 12.5	6.8 ± 5.1	0.102
Prospective intake	0.9 ± 0.6	8.4 ± 8.2	44.6 ± 25.4	29.2 ± 16.2	0.184
SQ, mm/kcal					
Hunger	5.7 ± 0.6	6.0 ± 0.6	8.2 ± 1.1	7.4 ± 0.7	0.082
Fullness	− 4.4 ± 0.5	− 5.3 ± 0.5	− 5.4 ± 1.0	− 5.7 ± 0.7	0.602
Desire to eat	5.4 ± 0.6	6.0 ± 0.6	6.5 ± 0.9	6.8 ± 0.7	0.510
Prospective intake	4.9 ± 0.5	5.5 ± 0.5	6.6 ± 1.0	6.0 ± 0.7	0.363

[1] $n = 50$ (24 men). Values are means ± SEMs. Means in a row without a common superscript letter differ, $P < 0.05$ with Bonferroni adjustments for multiple comparisons. $iAUC_{90}$, 90-min postmeal incremental area under the curve; SQ, satiety quotient.

modify these meal properties while still maintaining the sensory appeal.

Calorie for calorie, there was no observed difference in subjective appetite ratings or subsequent food intake behavior across the test meals, despite large differences in the energy consumed within each meal. This preliminary finding is in line with the previous randomized controlled trial which also demonstrated no differences in postmeal satiety, despite large and sustained increases in intake from the ultra-processed diet (7). Findings suggest that texture and energy density are likely to affect energy consumed to satiation (15, 19, 21, 41–43), rather than postmeal satiety (1). Further controlled studies are needed to specifically test whether the postmeal satiety derived from minimally processed and ultra-processed meals differs when meals are consumed as a fixed portion of energy, rather than consumed ad libitum.

A strength of this study is the controlled nature of data collection and the use of realistic, everyday composite meals that varied in the texture of meal components. Despite differences in rated pleasantness, when this was included as a covariate it did not significantly change the overall differences in food (g) or energy (kcal) intakes observed. Findings from the RISE-Q also highlighted that the main reason participants gave for concluding the meal was fullness (physical satisfaction) across the 4 meals. A lower meal pleasantness rating for the "hard minimally processed" meal also reflects a realistic outcome, and highlights that although results consistently show it is possible to reduce ER and energy intake by changing a food's texture, it is challenging to implement changes in food texture without also affecting a food's sensory appeal.

The test meals were matched for energy served, but there were residual differences in meal energy density (±0.2 kcal/g) and, as a result, the total weight of food served ad libitum to participants. These differences are mainly attributed to the high energy density of some of the ultra-processed meal components, which had higher sugar, fat, and sodium content. The current trial focused on acute (24-h) differences in intake in response to a controlled test lunch of unprocessed and ultra-processed foods, and all meals were consumed in a controlled laboratory-based setting. Future studies should extend these findings further to include a longer observation and normal food intake behavior in a home setting. In an effort to focus the comparison on the properties of the foods served, the current study recruited normal-weight healthy adult participants, and findings cannot be generalized to a wider population. Future research should examine whether similar effects of texture and processing are observed across a broader population.

Our findings demonstrate that food texture accounted for observed differences in the amount (g) of food consumed across minimally processed and ultra-processed diets, and texture and degree of processing (energy density) accounted for observed differences in energy intake. These findings suggest it may be possible to reformulate foods to enhance their texture, slow eating speed, and reduce energy density to support reduced energy intake from ultra-processed foods, while also promoting the consumption of harder minimally processed foods. Future studies should test whether food texture and energy density manipulations can be combined to reduce energy intakes over an extended period of time to better regulate energy intakes.

The authors' responsibilities were as follows—CGF, KM, and PST: designed the research; AJL, ATG, JR, and JYMC: conducted the research and curated the data; PST: analyzed the data; PST and CGF: wrote the paper and had primary responsibility for the final content; and all authors: read, edited, and approved the final manuscript. The authors report no conflicts of interest.

Data Availability

Data described in the article, code book, and analytic code are not publicly available but are available upon request pending (e.g. application and approval, payment etc.).

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