NutriLoop: A Cellular Aging-Aware Dietary Feedback Framework via Inflammation and Telomere Association

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Abstract

Understanding the link between everyday dietary behavior and long-term biological aging is critical for designing personalized health feedback systems. Most existing dietary feedback tools focus on calorie or macronutrient tracking, overlooking deeper physiological impacts such as chronic inflammation and biological aging. In this work, we analyze data from 2,412 participants in the NHANES 1999–2002 cohort and confirm a significant negative association between the Dietary Inflammatory Index (DII) and telomere length (TL), a biomarker of cellular aging. Building on this insight, we propose NutriLoop, a cellular aging-aware dietary feedback framework that integrates real-time dietary inflammation estimation with long-term biological feedback. NutriLoop introduces a closed-loop feedback model that leverages fast-changing signals (DII) and slow-changing biomarkers (TL) to promote aging-aware eating behavior. We conducted an online survey (N=100) to evaluate users' perceptions of this framework, finding strong acceptance of the dual-timescale feedback concept and design rationale. Our work demonstrates how data-driven insights can inform feedback architectures in ubiquitous health systems and opens new opportunities for integrating long-term cellular aging biomarkers into everyday dietary monitoring.

CCS Concepts

• **Human-centered computing → HCI theory, concepts and models**.

Keywords

Dietary feedback, aging-aware systems, inflammation, telomere length, ubiquitous health, mobile sensing

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1 Introduction

Maintaining a healthy diet is one of the most impactful lifestyle factors influencing long-term well-being [11]. While existing mobile health applications and wearable-integrated systems [5] have made significant progress in providing dietary feedback, most of these tools focus on short-term nutritional goals such as calorie counting, macronutrient balancing, or weight management. These systems often overlook the deeper physiological consequences of dietary habits, particularly the role of chronic inflammation and its association with biological aging.

Emerging research in nutritional epidemiology suggests that certain dietary patterns can induce or mitigate systemic inflammation, which in turn influences cellular aging processes [9]. However, such long-term physiological indicators are rarely incorporated into current feedback systems, which predominantly rely on fast-changing, easily measurable metrics (*e.g.*, calorie). This disconnect limits the ability of existing dietary technologies to support aging-aware health interventions or promote sustained behavior change.

To address this gap, we first investigate the population-level relationship between dietary inflammation and biological aging by analyzing data from 2,412 participants in the National Health and Nutrition Examination Survey (NHANES) 1999–2002 cohort [14]. Our analysis confirms a significant negative association between the Dietary Inflammatory Index (DII, a composite score reflecting the pro- or anti-inflammatory potential of one's diet) and telomere length (TL, a widely recognized biomarker of cellular aging). This empirical evidence suggests that individuals with more pro-inflammatory diets may experience accelerated cellular aging, reinforcing the need for dietary feedback systems that go beyond surface-level nutritional metrics.

Building on this insight, we propose NutriLoop, a cellular aging-aware dietary feedback framework that integrates fast-changing dietary signals (*e.g.*, food type) with slow-changing physiological biomarkers (*e.g.*, telomere length). As shown in Fig. 1, NutriLoop captures everyday food intake through lightweight multimodal inputs, computes real-time DII scores, and conceptualizes long-term feedback through telomere-based aging trajectories. Personalized diet feedback is provided by Large Language Models (LLMs) accompanied by immediate visualizations of daily inflammation levels and dietary trends, as well as periodic summaries that reflect cumulative aging-related risks. By introducing a closed-loop architecture that spans both behavioral and biological timescales, NutriLoop aims to support more meaningful and sustainable dietary behavior change.

To evaluate the feasibility and user acceptance of this framework, we conducted an online survey (N=100) presenting the NutriLoop concept, its feedback mechanisms, and representative interface

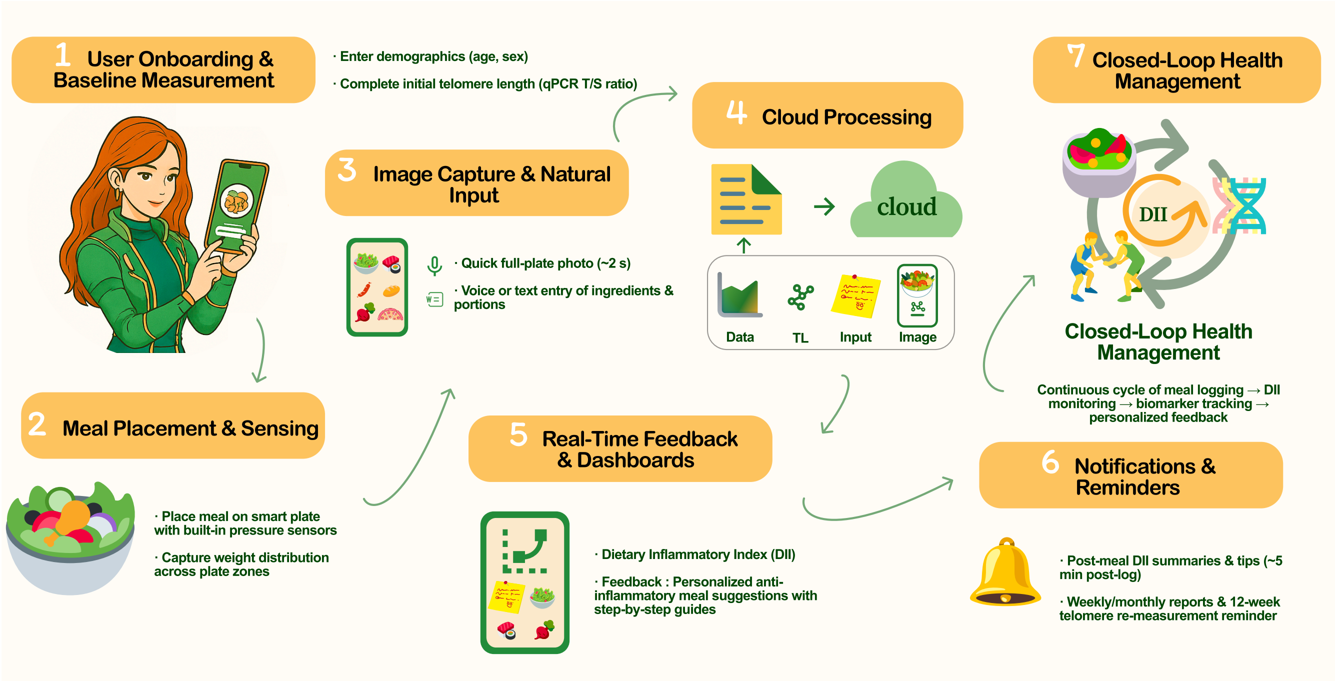

Figure 1: Nutriloop system workflow.

designs. The responses revealed strong user interest in cellular aging-aware dietary feedback, high perceived usefulness of combining immediate and long-term health signals, and support for the system's design rationale, especially for female users. By combining empirical findings with user feedback, this work lays the groundwork for the future implementation of aging-aware dietary feedback systems grounded in both scientific insight and user needs. In summary, this paper makes the following contributions:

- We conduct a large-scale population analysis (N=2,412) linking dietary inflammation (DII) and cellular aging (TL), providing evidence for integrating inflammation metrics into long-term dietary feedback.
- We propose NutriLoop, a personalized dietary feedback framework that introduces a dual-timescale feedback model combining fast-changing dietary inputs and slow-changing cellular aging markers.
- We outline design principles for future ubiquitous systems that incorporate long-term health signals into everyday behavior feedback, and validate the conceptual framework through an online survey (N=100), demonstrating its perceived value and user acceptance.

The remainder of this paper is structured as follows. Section 2 reviews related work on dietary sensing and aging-aware feedback systems. Section 3 presents our population-scale data analysis. Section 4 introduces the NutriLoop framework design. Section 5 describes the online survey and its results. Section 6 discusses limitation and future directions, and Section 7 concludes the paper.

2 Related Work

Existing dietary monitoring technologies predominantly rely on manual or semi-automated input, including food diaries [15], barcode scanning or photo logging [12]. While effective in short-term tracking, these methods often demand significant user engagement, leading to low adherence and reporting bias. To address this, researchers have explored automated solutions using multimodal sensing, such as computer vision [7], wrist- or ear-worn motion sensors [6], smart utensils and weight-based systems. These approaches improve accuracy and reduce reliance on self-reporting, but often introduce trade-offs in terms of cost, wearability, and power consumption.

Short-term biomarkers, such as heart rate [1], blood glucose [8], and step count, are also widely used in wearable interventions to prompt immediate behavioral adjustments. These signals respond quickly to behavioral changes and are well-suited for short-term interventions. However, they fail to capture the cumulative physiological impact of lifestyle habits. In contrast, slow-moving biomarkers like telomere length or DNA methylation age are rarely incorporated into interactive systems, and their potential for supporting sustained behavioral change remains largely untapped.

Recent efforts have explored inflammation-related dietary assessment, including the use of the Dietary Inflammatory Index (DII) to quantify the inflammatory potential of food intake [10]. However, to date, no system integrates multimodal dietary perception, real-time DII visualization, and telomere-based feedback into a unified closed-loop architecture. NutriLoop bridges this gap by continuously monitoring dietary inflammation and exposing the dynamic link between anti-inflammatory dietary patterns and aging through telomere-informed feedback. By connecting short-term dietary behavior with long-term biological consequences, NutriLoop aims to sustain user motivation and support healthy dietary decisions through a dual-timescale feedback framework.

3 Population Analysis of Dietary Inflammation and Cellular Aging

3.1 Dietary Inflammation and Cellular Aging

Dietary patterns play a critical role in shaping long-term health outcomes, not only by affecting metabolic indicators like weight and blood glucose, but also by influencing chronic inflammation, which is an underlying factor in aging and age-related diseases [9]. Telomere length (TL), a biomarker reflecting cellular aging and replicative potential, has been increasingly used in large-scale population studies to quantify long-term biological changes [14]. Meanwhile, the Dietary Inflammatory Index (DII) has emerged as a validated metric for assessing the inflammatory potential of an individual's diet. While both markers have been studied independently, their combined use in interactive health systems remains limited. In this section, we perform a population-scale analysis to examine the statistical relationship between DII and TL, with the goal of grounding the design of an aging-aware dietary feedback framework.

3.2 Dataset and Preprocessing

This study used data from the 1999–2002 cycles of the National Health and Nutrition Examination Survey (NHANES), with an initial sample of 7,839 participants who had measured telomere length (TELOMEAN) [14]. We excluded individuals with missing data on key covariates (*e.g.*, age, sex, BMI, lifestyle factors, white blood cell count, and chronic disease diagnoses) and outliers based on the following thresholds: white blood cell count $\geq 10 \times 10^9$/L, BMI <12 or >35 kg/m^2, age ≤40 years, telomere length <0.5 or >1.55, or history of malignancy. This resulted in 2,577 eligible participants. After excluding 165 participants with a total Dietary Inflammatory Index (DII) score of zero, the final analytic sample comprised 2,412 individuals. All data processing and statistical analyses were performed in R (version 4.3.4). As shown in Table 1, baseline characteristics were summarized using the `gtsummary` package and compared across telomere length tertiles (TELO_Q: Q1 shortest, Q2 middle, Q3 longest) using the Kruskal–Wallis test for continuous variables and Pearson's chi-square test for categorical variables.

3.3 Modeling Approach

To assess the relationship between DII and telomere length, we first performed univariable linear regression analyses to evaluate the association between each Dietary Inflammatory Index (DII) metric and telomere length (TELOMEAN). Telomere length (TL) was measured by quantitative PCR (qPCR), comparing the amplification of telomeric repeats to that of a single-copy reference gene (S) to derive a T/S ratio [13].

$$\text{Telomere length (kbp)} = \frac{3{,}274 + 2{,}413 \times (\text{T/S})}{1{,}000} \tag{1}$$

We then fitted multivariable linear regression models adjusting for potential confounders: age, sex, BMI, education level, marital

Table 1: Baseline Characteristics of Participants According to Telomere Length Tertiles

Variable	Overall N = 2,412[1]	Q1 N = 804[1]	Q2 N = 804[1]	Q3 N = 804[1]	p-value[2]
Overall DII	0.67 ± 1.53	0.90 ± 1.51	0.59 ± 1.54	0.54 ± 1.53	<0.001
Gender					0.13
Male	1,283 (53%)	444 (55%)	434 (54%)	405 (50%)	
Female	1,129 (47%)	360 (45%)	370 (46%)	399 (50%)	
Age (year)	60 ± 13	65 ± 13	60 ± 12	55 ± 11	<0.001
Race					0.064
Mexican American	558 (23%)	198 (25%)	186 (23%)	174 (22%)	
Other Hispanic	118 (4.9%)	34 (4.2%)	35 (4.4%)	49 (6.1%)	
Non-Hispanic White	1,305 (54%)	451 (56%)	440 (55%)	414 (51%)	
Non-Hispanic Black	364 (15%)	104 (13%)	118 (15%)	142 (18%)	
Other	67 (2.8%)	17 (2.1%)	25 (3.1%)	25 (3.1%)	
Education Level					<0.001
<9th Grade	454 (19%)	191 (24%)	144 (18%)	119 (15%)	
9–11th Grade	406 (17%)	137 (17%)	136 (17%)	133 (17%)	
High School Grad	536 (22%)	176 (22%)	177 (22%)	183 (23%)	
Some College/AA Degree	520 (22%)	160 (20%)	178 (22%)	182 (23%)	
College Graduate or above	496 (21%)	140 (17%)	169 (21%)	187 (23%)	
Marital Status					<0.001
Married	1,578 (65%)	521 (65%)	527 (66%)	530 (66%)	
Widowed	303 (13%)	138 (17%)	95 (12%)	70 (8.7%)	
Divorced	266 (11%)	84 (10%)	90 (11%)	92 (11%)	
Separated	62 (2.6%)	12 (1.5%)	25 (3.1%)	25 (3.1%)	
Never married	128 (5.3%)	30 (3.7%)	36 (4.5%)	62 (7.7%)	
Living with partner	75 (3.1%)	19 (2.4%)	31 (3.9%)	25 (3.1%)	
BMI (kg/m^2)	27.1 ± 3.9	27.3 ± 3.8	27.0 ± 4.0	26.9 ± 4.0	0.2
Smoking					0.12
Yes	1,266 (52%)	416 (52%)	445 (55%)	405 (50%)	
No	1,146 (48%)	388 (48%)	359 (45%)	399 (50%)	
Alcohol Use					0.4
Yes	1,654 (69%)	538 (67%)	561 (70%)	555 (69%)	
No	758 (31%)	266 (33%)	243 (30%)	249 (31%)	
Family Poverty Income Ratio	2.86 ± 1.61	2.68 ± 1.62	2.87 ± 1.58	3.04 ± 1.62	<0.001
Hypertension					0.095
Yes	879 (36%)	311 (39%)	298 (37%)	270 (34%)	
No	1,533 (64%)	493 (61%)	506 (63%)	534 (66%)	
Diabetes					0.4
Yes	274 (11%)	101 (13%)	88 (11%)	85 (11%)	
No	2,138 (89%)	703 (87%)	716 (89%)	719 (89%)	
White Blood Cell Count (SI)	6.67 ± 1.48	6.75 ± 1.45	6.66 ± 1.49	6.60 ± 1.50	0.11
Lymphocyte Percent (%)	30 ± 8	30 ± 8	30 ± 8	31 ± 8	0.003
Monocyte Percent (%)	8.45 ± 2.21	8.64 ± 2.19	8.42 ± 2.19	8.30 ± 2.24	<0.001
Eosinophils Percent (%)	2.92 ± 2.10	2.97 ± 2.15	2.90 ± 2.24	2.89 ± 1.90	0.3
Basophils Percent (%)	0.66 ± 0.37	0.63 ± 0.37	0.65 ± 0.36	0.70 ± 0.36	<0.001

[1]Mean ± SD; n (%)
[2]Kruskal-Wallis rank sum test; Pearson's Chi-squared test

status, smoking status, poverty income ratio, diabetes, hypertension, and lymphocyte percentage. Additionally, stratified multivariable regressions were conducted within each telomere tertile (Q1–Q3), adjusting for the same covariates, to determine whether the DII–telomere length relationship varied by telomere length subgroup. All tests were two-tailed, with $p < 0.05$ considered statistically significant.

3.4 Key Findings

Figure 2 shows the relationship between 33 DII components and biological aging (*i.e.*, telomere length). Beta coefficients β represent the estimated change in telomere length per unit increase in each dietary component, while p-values p indicate the statistical significance of these associations. We can observe that higher overall DII scores (*i.e.*, more pro-inflammatory diets) were significantly associated with shorter telomere length in both univariable ($\beta = -0.02$, $p < 0.001$) and multivariable models ($\beta = -0.02$, $p < 0.001$), underscoring the detrimental impact of chronic dietary inflammation on cellular aging.

We further extended the analysis to individual DII components. Several pro-inflammatory factors, such as saturated fat, cholesterol, and total energy intake, were linked to reduced telomere length, while anti-inflammatory components, such as fiber, magnesium, and various vitamins (A, B6, C, E), were positively associated with telomere preservation, even after controlling for demographic and lifestyle confounders. The consistency in effect size and direction

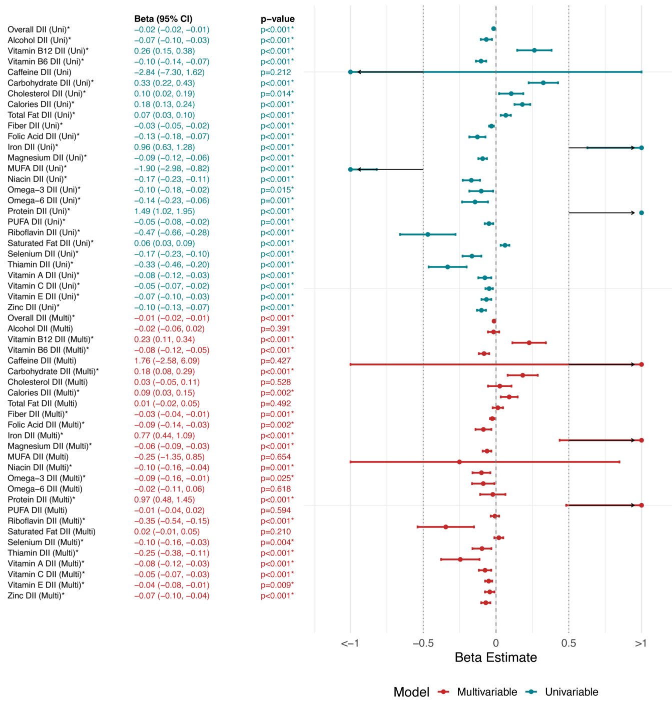

Figure 2: Multivariable/Univariable Linear Regression between key dietary Components and the telomere length.

across uni- and multivariable regressions reinforces the robustness of these associations.

To explore population-level heterogeneity, we selected six representative DII components (Overall DII, Fiber, Vitamin A, Thiamin, Riboflavin, and Magnesium) for stratified analysis across telomere length tertiles (Q1–Q3) (Figure 3). These components were chosen for their statistical significance, biological relevance, and diversity across the inflammatory spectrum. The results reveal that diet–telomere associations were most pronounced in the longest telomere group (Q3), suggesting that individuals with initially healthier aging profiles may be more responsive to diet-induced inflammation. These findings highlight dietary inflammation as a modifiable risk factor for biological aging and inform the design of personalized, aging-aware feedback systems.

4 NutriLoop Framework Design

Based on our population-level findings that dietary inflammation is negatively associated with telomere length, we designed NutriLoop, an aging-aware dietary feedback framework that integrates fast-changing dietary behavior with slow-changing cellular aging. As illustrated in Fig. 1, NutriLoop adopts a closed-loop architecture comprising seven key modules, forming a closed-loop architecture that connects user input, cloud-based analysis, and personalized feedback:

(1) **User Onboarding & Baseline Measurement**. NutriLoop begins by collecting basic demographic information (age, sex, etc.) and an initial telomere length measurement (*e.g.*, via qPCR T/S ratio), which serves as a long-term aging baseline.
(2) **Meal Placement & Sensing**. Users place meals on a smart plate embedded with pressure sensors to estimate portion size and weight distribution across different food zones.
(3) **Image Capture & Natural Input**. The system supports multimodal input, including quick full-plate photos and voice or text entry of meal ingredients and quantities. This step balances automation and user control.
(4) **Cloud Processing**. All raw data are validated locally and then uploaded to the cloud to estimate the meal’s Dietary Inflammatory Index (DII). Image capture and preprocessing are optimized to complete within 2 seconds to ensure a smooth logging experience [3]. The smart plate communicates with the mobile app over Wi-Fi, and the app interacts with backend microservices via RESTful APIs. The backend consists of modular services for ingredient recognition, nutrient and DII computation, user data management, and notifications. All logs, including dietary entries, DII scores, and telomere measurements (*i.e.*, the user’s cellular age), are stored in an encrypted time-series database to ensure privacy and auditability [2].
(5) **Real-Time Feedback & Dashboards**. NutriLoop provides users three main dashboards: 1) DII Dashboard displays intraday and multi-day inflammation levels with a color-coded bar and trend line. 2) Recipe Recommendations dynamically suggest three anti-inflammatory recipes based on the user’s cellular age and real-time DII score to provide step-by-step text and animated cooking guides generated by LLMs. 3) Telomere Dashboard presents baseline vs. follow-up T/S ratios in an interactive line chart with hoverable data points, allowing users to visually track slow-moving biomarker changes. As telomere length changes gradually over time (typically about 3 months) [4], we propose a 12-week interval for qPCR-based reassessment to provide meaningful updates on cellular aging within the NutriLoop feedback cycle.
(6) **Notifications & Reminders**. To promote sustained engagement, NutriLoop uses lightweight nudges to help maintain engagement, including post-meal DII summaries (5 min after logging), weekly reports, and periodic reminders for telomere re-measurement.
(7) **Closed-Loop Health Management**. All components form a continuous loop, reinforcing dietary decisions through real-time inflammation tracking and long-term physiological anchoring. This design supports sustainable behavior change by helping users connect daily choices with biological aging trajectories.

This modular design enables scalable deployment and flexible integration with existing health platforms. By combining low-burden sensing, rapid cloud computation, and motivating feedback, these components form a dual-timescale closed-loop feedback system, designed to promote sustainable dietary behavior change by connecting everyday actions to long-term biological consequences.

5 User Perception of Aging-Aware Feedback

5.1 Survey Design

To evaluate the perceived usefulness, clarity, and motivational potential of aging-aware dietary feedback, we conducted a structured

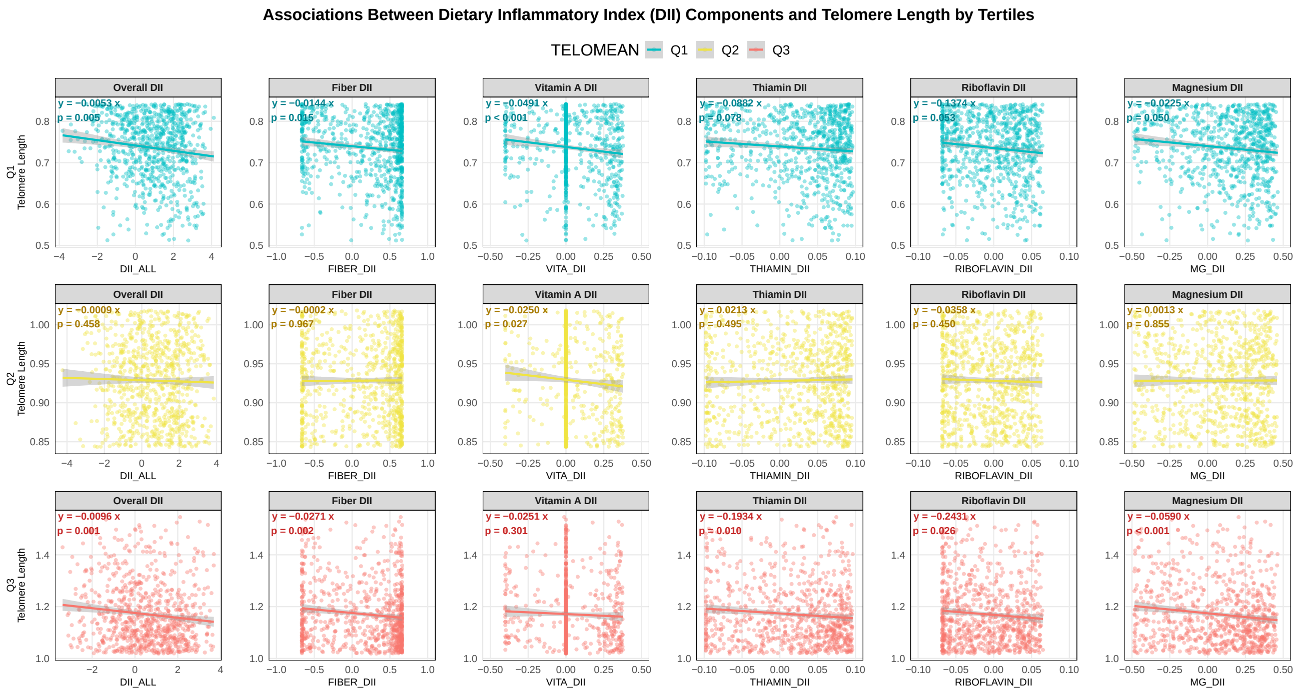

Figure 3: Associations Between Six Representative DII Components and Telomere Length by Tertiles.

online survey. The goal was to understand how users respond to different feedback, particularly those grounded in biological aging indicators, and whether such feedback could enhance long-term engagement with dietary tracking. The 17-item questionnaire was organized into six modules:

- Demographics (3 items): gender, age, overall health status.
- Usage Habits (3 items): frequency of system use, average meals logged per day, preferred logging method.
- Awareness and Acceptance (3 items, 1–5 scale): familiarity with anti-inflammatory diets,acceptance of DII-based recipe suggestions,acceptance of telomere feedback prompts.
- Intention modules (2 items, 1–5 scale): intention to use the system frequently in the upcoming week, and level of concern about the relationship between diet and aging.
- Feature Importance (4 items, 1–5 scale): importance ratings for multimodal input, real-time DII dashboard, personalized anti-inflammatory recipes, and context-aware notifications.
- Interaction Preferences & Privacy (2 items): preferred feedback channels, and willingness to provide biological samples for telomere testing and to use the system long term.

The survey is conducted via Google Forms, distributed through convenience and snowball sampling on WhatsApp and Messenger. All participants provided informed consent, and no identifiable data were stored.

5.2 Key Findings and Insights

We collected 100 valid responses (65 female, 33 male, 2 unspecified). The findings reveal several key insights into how users perceive and respond to aging-aware feedback.

Item	Female (n=60)	Male (n=30)
Use intention (mean ± SD)	4.2 ± 0.7	3.5 ± 0.9
Concern about diet & aging (%)	75%	50%
Telomere feedback acceptance (%)	70%	40%
Sample-provision willingness (mean ± SD)	4.0 ± 1.0	3.2 ± 1.2

Table 2: NutriLoop feature acceptance and user intentions.

- **Intentions and Concerns.** As shown in Table 2, female participants expressed significantly higher use intention (M = 4.2 vs. 3.5) and willingness to provide biological samples (M = 4.0 vs. 3.2) compared to males. They also reported greater concern about diet-aging relationships (75% vs. 50%) and stronger acceptance of telomere-based feedback (70% vs. 40%). These findings suggest that gender plays a notable role in the perception of aging-aware dietary systems, highlighting the need for personalized engagement strategies.
- **Logging Habits.** Participants logged on average 2.4 meals per day (mean 2.4, SD = 0.9); the most common methods were photo (52%), manual entry (30%), and voice (12%).
- **Awareness and acceptance.** 42% of respondents had heard of anti-inflammatory diets to some extent, 23% were very familiar with them, and 35% had never heard of them. Participants demonstrated greater acceptance of DII-based recipe suggestions (58%) compared to telomere feedback prompts (45%), suggesting that users are more receptive to actionable, food-related guidance than to abstract physiological metrics.
- **Intention Modules.** 72% of participants indicated that they would use the system twice a day and would be willing to use it long term, provided that the feedback was perceived as meaningful, actionable, and non-intrusive.

- **Feature Importance.** Women rated multimodal input (4.5 vs. 3.0), the real-time DII dashboard (3.9 vs. 2.2), and personalized anti-inflammatory recipe suggestions (4.6 vs. 3.0) higher than men, reflecting their stronger demand for these core features.
- **Feedback Channels and Privacy.** 58% preferred in-app notifications, 25% chose smartwatches, and 12% chose SMS/email. Regarding data privacy and biological sampling, 61% of participants expressed willingness to provide biological samples for telomere testing if sufficient privacy protections were ensured.

These findings highlight users' interest in anti-inflammatory diets and biological aging awareness, offering valuable insights for informing future feature design and prioritization in our aging-aware dietary feedback systems.

6 Limitation and Future Work

While this work introduces NutriLoop as a novel aging-aware dietary feedback framework grounded in population data and user perceptions, we have not yet implemented the full system. Our contributions primarily lie in the formulation of the design concept, empirical validation of the underlying dietary-aging relationship, and a user-centered exploration of feedback acceptability. Translating this framework into a deployable, end-to-end system presents several implementation challenges. First, the current study does not evaluate long-term user adherence or physiological outcomes, limiting insights into real-world behavioral impact. Second, the framework relies on laboratory-based telomere testing (*e.g.*, qPCR), which introduces logistical and financial barriers that may hinder adoption at scale. Third, the food recognition pipeline remains in a prototype stage and requires further development to handle culturally diverse and compositionally complex meals.

To address these limitations, future work should include longitudinal field deployments to establish the framework's practical efficacy, the integration of low-cost telomere measurement alternatives (e.g., saliva assays or finger-prick kits), and the enhancement of food recognition models using expanded, representative datasets. Further directions include embedding adaptive recommendations and social engagement features to improve motivation, and broadening the physiological feedback scope to include additional aging-related biomarkers such as DNA methylation or inflammatory cytokines. These efforts will enable NutriLoop to evolve into a scalable and generalizable platform for aging-aware dietary guidance.

7 Conclusion

We propose NutriLoop, a personalized dietary feedback framework that integrates short-term dietary signals with long-term cellular aging markers. Through population-scale analysis, we demonstrate a significant association between the Dietary Inflammatory Index (DII) and telomere length, providing a physiological basis for aging-aware interventions. Building on these findings, we propose a closed-loop system that delivers dual-timescale feedback, and validate its perceived value through user surveys. Our results highlight the potential of incorporating aging biomarkers into everyday dietary guidance and offer a foundation for future deployable health technologies.

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