Uncovering Snackification, from Motivations to Behavior: An Analysis of Dutch Millennials Using Mobile Food Diaries

ZIHAO WANG, Idiap Research Institute, Martigny, Switzerland & EPFL, Lausanne, Switzerland
LAKMAL MEEGAHAPOLA, ETH Zurich, Zurich, Switzerland
MARIELLE TAMARA DE VAAL, Wageningen University, Wageningen, Netherlands
DANIEL GATICA-PEREZ, Idiap Research Institute, Martigny, Switzerland & EPFL, Lausanne, Switzerland

The shift from structured meals to frequent snacking, often referred to as "snackification", introduces new challenges for mobile health interventions targeting dietary well-being. While mobile Ecological Momentary Assessments (mEMA) enable real-time data collection via food diaries, they often overlook the underlying drivers of snack choices, such as situational motivations (e.g., appetite, socializing) and contextual factors (e.g., location, time). This gap in understanding limits the ability to design personalized and context-aware interventions, which are essential for promoting healthier eating behaviors in real-world settings. To address this gap, we analyzed a longitudinal dataset of 14,312 in-situ self-reports, focused exclusively on snacking and collected over one year from 264 Dutch Millennials. Using association rule mining and machine learning models, we systematically examined two key snack attributes: snack groups and nutritiousness, in relation to multi-dimensional contextual and motivation factors. Our findings reveal associations between specific motivations and snack choices, such as alcoholic beverages aligning with the motivation of sociability (lift = 4.180), and nutritious snacks associating with the motivation of health (lift = 1.926). Notably, dietary motivations emerged as the strongest predictor of snack nutritiousness (nutritious vs. non-nutritious), with machine learning models achieving AUROC scores of ≈0.8 via contextual and motivation features. SHAP (SHapley Additive exPlanations) analysis further confirmed that health-related motivations favor nutritious snack consumption, while hedonic ones promote non-nutritious choices. Overall, this study highlights the crucial role of dietary motivations in snack selection and offers practical insights for public health initiatives and mobile food diary design.

CCS Concepts: • **Human-centered computing → Empirical studies in ubiquitous and mobile computing**; • **Applied computing → Health informatics**; • **Social and professional topics →** *Cultural characteristics.*

Additional Key Words and Phrases: machine learning, association rule mining, nutrition science, snacking behavior, self-reports, ecological momentary assessments, eating behavior, food consumption

1 Introduction

The individual food consumption has drawn increasing attention with respect to its impact on the environment, public health, and economy [119]. Understanding food consumption is not only fundamental for healthy personal eating practices, but also informs data-driven food production and retail strategies. However, the development of technology and economy has significantly changed individual eating habits by stimulating the shift from meals to snacks [20]. It is inevitable that more people are beginning to consume snacks in place of or outside meals frequently, especially in developed countries [124]. For example, in Sweden, the number of meals decreased

Authors' Contact Information: Zihao Wang, Idiap Research Institute, Martigny, Switzerland & EPFL, Lausanne, Switzerland, zwang@idiap.ch; Lakmal Meegahapola, ETH Zurich, Zurich, Switzerland, lmeegahapola@ethz.ch; Marielle Tamara De Vaal, Wageningen University, Wageningen, Netherlands, marielle.devaal@wur.nl; Daniel Gatica-Perez, Idiap Research Institute, Martigny, Switzerland & EPFL, Lausanne, Switzerland, gatica@idiap.ch.

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significantly in the last century [35], while also in the United States, people tend to have less time to prepare or enjoy meals, which leads to skipping meals or increasing snack intake [31, 32]. This transformation of dietary habits is also known as the "snackification" trend [62]. Although snacking is considered by some studies to be unhealthy and associated with weight gain and adiposity [87, 97], other research suggests that this association is unclear [67] or may even be considered healthy [12, 49].

Individuals may exhibit different dietary behaviors when consuming meals vs. snacks, shaped by both internal and external factors [14, 74, 82, 125]. Dietary behavior is influenced by a wide range of contextual variables, including time, location, social setting, weather, and physical or mental state [16, 68, 85], which also help distinguish snack consumption from meals. For example, snacks are typically consumed less frequently in social contexts and more rapidly than meals [14, 126]. However, the conceptual boundaries between meals and snacks remain fluid, varying with individual perception, cultural norms, and disciplinary definitions [49, 90, 122]. Physiological factors such as stimulus and satiety prior to food intake are also proved to play a key role in differentiating meals and snacks [77]. While nutrition science has examined the motivations and health implications of snacking [49], and ubiquitous computing has focused on detecting dietary behavior through wearable sensors [10, 11, 15], relatively few studies have examined snacking behavior explicitly using mobile food diaries. When such tools are used, snacks are often aggregated with meals in the analysis [10, 58], rather than studied separately as in [14]. Given that both contextual [14, 82, 85] and motivation [49, 95, 96] factors strongly influence snacking behavior, treating snacks as a distinct analytical category offers significant value. In addition, methodologies from ubiquitous computing can be effectively applied to investigate the unique characteristics of snacking, provided that both contextual and non-contextual determinants are taken into account.

Mobile apps have increasingly become valuable tools for dietary data collection [9, 34], offering real-time alternatives to paper-based methods. As health and dietary apps proliferate, researchers have recognized their value in capturing detailed, long-term information on individual behaviors while minimizing participant burden [34]. Consequently, mobile apps can generate large-scale dietary data, leading to richer insights into participants' dietary patterns within real-world contexts [76]. These applications also improve participant compliance and data accuracy, and lower the costs of dietary assessments [14, 76]. However, commercial apps, such as MyFitnessPal [33] and Samsung Health [104], often fall short in research settings, given their commercial focus, proprietary data storage, privacy issues, and limited transparency [5, 30, 36, 65]. Additionally, these applications do not allow researchers to collect information on external factors influencing food consumption, such as physical contexts or motivations behind dietary choices. Some well-designed research apps, such as [55], are highly sophisticated, requiring participants to have a high level of technological proficiency. However, they lack data on dietary motivations and do not specifically focus on snacking, making them less suitable for studying snacking patterns.

In light of these considerations, further research is essential for understanding the role of motivations in snack selection, particularly why individuals opt for certain snacks in specific contexts and under diverse triggers. Mobile food diaries designed explicitly for this present an ideal platform, enabling the collection of both comprehensive contextual features and subjective motivation data essential for untangling the complex decision-making processes in snacking. Given the prevalence of snacking behavior in the Netherlands [43], especially among Millennials (born between 1980–2000) [127], we focus our study on Dutch Millennial consumers. This demographic is also known for its greater engagement with digital tools, making it a suitable population for examining snacking behavior via mobile food diaries. Drawing on mobile food diary logs collected through a customized mobile application [71], we obtained a recent longitudinal dataset from the authors of the FOODLOOP study [28]. [1] This dataset includes both contextual factors and motivations for each snacking episode, thereby addressing the lack of motivation-oriented data required to explain how snack nutritiousness and product choices tie back

[1]Details about the FOODLOOP data can be found at https://www.wur.nl/nl/onderzoek-resultaten/leerstoelgroepen/agrotechnologie-en-voedselwetenschappen/levensmiddelentechnologie/food-quality-and-design-1/foodloop/het-foodloop-onderzoek.htm.

Table 1. Terminology and definitions used in the paper

Term	Description
Snack	One food or beverage product consumed outside of what is considered (part of) one of the three traditional main meals (breakfast, lunch and dinner) [20, 114]
Snacking	The consumption of the snack
Snacking episode	One unique snack consumed by one participant for a unique combination of motivations, in a unique combination of physical, social and temporal contexts
Snacking behavior	The totality of snacking episodes of all users
Food Choice Motives (FCM)	The 20 motivations for consumption of the snacks, adapted from [100], including liking, habit, hunger and thirstiness, health, convenience, pleasure, traditional eating, natural concerns, sociability, variety seeking, visual appeal, weight concerns, affect regulation, social norms, social image, choice limitation, appetite, food freshness, food waste, price
User-Hybrid Approach	An approach based on Stratified-K-Fold cross validation [47], where machine learning models are trained simply by sampling some subsets from the whole dataset as the test set, while the remaining cases constitute the training set, without considering individual users. However, the percentage of samples for each class is preserved as much as possible in the test set
User-Agnostic Approach	An approach based on Leave-One-Out, Group-K-Fold and Stratified-Group-K-Fold cross validations [47], where machine learning models are trained on the data of a set of users, and tested on the data of other user(s) not seen in the training set. The term "agnostic" refers to that the model could be applied to new or unknown users
Leave-One-Out (LOO)	Machine learning models are trained on the data of a set of users, and tested on the data of one user not seen in the training set
Group-K-Fold (GKF)	Machine learning models are trained on the data of a set of users, and tested on the data of another set of users not seen in the training set
Stratified-Group-K-Fold (SGKF)	Machine learning models are trained on the data of a set of users, and tested on the data of another set of users not seen in the training set while attempting to preserve the percentage of samples for each class as much as possible in the test set. This approach is thus important for multi-class classification

to personal motivations. To this end, our analysis aims to understand the distinctive drivers behind snacking and to investigate how contextual and motivation factors interact, offering insights that can guide the design of personalized, context-aware mobile interventions for healthier dietary habits. Following the terminology defined in Table 1, our work incorporates both classic contextual factors and participants' motivations for each snacking episode, which were systematically analyzed to address the following research questions:

- **RQ1:** What would a statistical analysis (mixed-effects model) reveal about how Dutch Millennials' motivations and contextual factors influence their snack choices (snack groups and nutritiousness)?
- **RQ2:** What frequent and interpretable association patterns can be extracted between specific motivations and snack choices (snack groups and nutritiousness)?
- **RQ3:** Can the snack choices (snack groups and nutritiousness) be inferred through motivation and other (non-)contextual features from only self-reported data, captured via a mobile food diary? Which features are the most significant in these inference tasks?

We addressed the above questions by making the following contributions:

- **Contribution 1:** We conducted a statistical analysis on a dataset collected across one year from 264 Dutch Millennials (born between 1980–2000), which contains over 14K self-reports and external weather data corresponding to each snacking episode. The statistical analysis conducted through mixed-effects models indicated that motivation features (including health, habit, pleasure, convenience, etc.) outperformed the other features in discerning both 10-class snack groups and 2-class nutritiousness (i.e., nutritious vs. non-nutritious), with higher t-statistics than the other features (i.e., demographic, contextual, and weather features). These findings highlight the importance of motivation data collection via mobile food diaries. Researchers and developers can leverage longitudinal self-reported and motivation-aware data to enhance dietary behavior modeling, towards mobile food diary apps that adapt to real-world consumption patterns.

- **Contribution 2:** We used association rule mining to discover the specific association patterns between consumers' motivations and their snack choices. The results revealed some significant associations, such as the pair of alcoholic beverages and the motivation of sociability, and nutritious snacks and the motivation of health. These results demonstrate behavioral patterns between different motivations and corresponding snack choices, and also reveal a temporal shift in these patterns from the morning to the evening/night. Our study shows how association rule mining, as a pattern discovery method, can be integrated into mobile food diaries to provide personalized recommendations and intervention strategies.
- **Contribution 3:** We used different approaches when implementing both multi-class (for snack groups) and binary classification tasks (for nutritiousness) on the longitudinal data. By testing different feature group combinations, we achieved reasonable model performance with the LightGBM classifier and Stratified-Group-K-Fold approach when using only motivation and contextual features. SHAP analysis further highlighted that motivation features are of predominant importance in inferring both snack groups and nutritiousness. This analysis demonstrated a link between health-related motivations and nutritious snacks, as well as between hedonic motivations and non-nutritious snacks. Hence, this work provides insights into feature selection and explainability techniques for dietary behavior modeling in mobile food diaries. The results suggest the potential to reduce the burden of manual food labeling in mobile dietary tracking applications. Furthermore, the use of SHAP-based interpretability in inference models offers a transparent framework for personalized recommendation in mobile health interventions.

To provide a comprehensive understanding of snacking behavior, our analysis is structured as a sequential progression, from statistical explorations to co-occurrence pattern discovery and predictive validation. We first employed mixed-effects models (RQ1) to explore multi-dimensional characteristics of snacking behavior, and identify the statistically significant factors to distinguish snack choices while accounting for individual user variability. Then, building on these significant features, especially motivations, we applied association rule mining (RQ2) to uncover how motivation features and snack choices co-occur overall and within specific temporal contexts. After the co-occurrence patterns were revealed, we validated the importance of motivation features by utilizing a machine learning methodology (RQ3) that integrates all (non-)contextual features into a classification model. By assessing predictive performance and utilizing SHAP-based interpretability, this final stage reinforces the importance of dietary motivations and ensures the robustness of our findings across different analytical methods. Taken together, this approach bridges the gap between statistical significance and predictability, offering a foundation for mobile food diary design that emphasizes transparency.

2 Background and Related Work

2.1 The Trend of Snackification

Food consumption is a fundamental aspect of daily life and plays a crucial role in the modern world. However, with the rapid transformation of society, economy, and technology, food choices are no longer limited to monotonous options. Instead, consumers select foods and dietary styles based on different physical, social, and temporal contexts [19]. For instance, individuals with demanding or restrictive jobs tend to consume more fast food or skip meals [31], whereas those eating in social settings spend more time dining and consume more energy [51]. Additionally, the access to food has become more flexible and varied, making traditional meal structures less rigid. The conventional structure of three meals per day is gradually being replaced by more dynamic eating patterns. In this context, the term "snackification" has emerged to describe the global trend of shifting from traditional meals to snacks. Many developed and developing countries, including the United States [32], United Kingdom [87, 126], Sweden [72], France [103], and China [124], have witnessed a significant rise in snack consumption as meal replacements over the past few decades. Moreover, this trend affects people of all ages, including children [114] and adults [32, 97]. Despite its widespread prevalence and integration into daily life, the definition of "snack" and "snacking" remains varied and dynamic [49]. Previous literature has presented different conceptualizations: some studies define snacking as the consumption of food within a certain timeframe outside main meals, focusing on timing and duration [27, 97], while others classify snacks based on food type and nutritional content [39, 50, 114]. Furthermore, the perception of snacks also varies among consumers, who may consider factors such as nutrition, context, portion size, and personal preferences when defining what constitutes a snack [26, 40, 125]. These perceptions ultimately influence food choices and intake behaviors [49, 90].

Bisogni et al. [16] outlined eight interacting dimensions that characterize everyday eating: food type, time, social setting, physical condition, mental condition, activities, location, and recurrence. The study emphasizes the importance of considering these dimensions to gain a deeper understanding of food consumption. With the trend of snackification, these dimensions continue to play a crucial role in defining snacking behaviors [72], influencing snack choices and consumption patterns in multiple ways. For instance, snacking is often driven by hedonic motivations and distracted contextual factors [49, 108] and is associated with the consumption of specific types of food that differ from traditional meals [67, 90]. Additionally, snacking behaviors exhibit personalized characteristics based on physiological factors [77, 83], motivations and perceptions [49, 90], time [14], location [117], and social environment [105]. Cultural factors also play a significant role in shaping consumers' snacking habits and perceptions, both at interpersonal and international levels. For example, in France, the concept of "goûter" refers to an afternoon snack traditionally perceived as a structured meal component, whereas individuals from other cultural backgrounds might categorize it as a general snacking behavior [103]. Overall, although the boundaries between meals and snacks are becoming increasingly blurred due to the global snackification trend, food and contextual factors continue to shape the nature of snacks and snacking behaviors, alongside consumers' motivations and perceptions.

2.2 Nutrition Science Perspective on Snacking

The health implications of snacking remain highly debated [84], largely due to the lack of a clear definition of snacks and the multiple criteria used to evaluate their impact. Negative perspectives on snacking are often associated with overeating, weight gain, and diabetes, as higher snacking frequency has been linked to energy imbalance [97], poor dietary quality, and increased adiposity [87]. However, some studies have found this association to be unclear [46, 67] or even inverse, suggesting that snacking may not necessarily contribute to negative health outcomes, or even favor more positive health outcomes [12, 49]. Additionally, individuals with higher body weight may have already altered their diets in an effort to lose weight, leading to misleading conclusions about the effects of snacking [84]. While snacking can contribute to overeating [90], it does not always indicate poor dietary habits. For instance, snacking can increase fruit and vegetable intake [117], as well as boost consumption of whole grains and fiber, which are beneficial for health [17]. Furthermore, in response to growing health concerns, retailers are increasingly marketing healthier snack options, as the way food is categorized (snack vs. meal) can have a greater influence on consumption behavior than simply labeling it as healthy or unhealthy [90].

Consumers' psychological states, including emotions and motivations, also influence food choices and eating behaviors. Research suggests that consuming nutritious snacks is associated with lower levels of anxiety, depression, and emotional distress compared to consuming non-nutritious snacks [109]. Additionally, the perception of overeating can influence subsequent snack choices [101]. In terms of motivations, hedonic and hunger-driven motivations are positively associated with higher snacking frequency and overeating [12, 27, 52], whereas health-related motivations are linked to increased consumption of nutritious foods [70, 89]. A notable example is [96], which utilized the Eating Motivation Survey (TEMS) [100] to evaluate Food Choice Motives (FCM). The findings indicated that health-motivated individuals consumed more nutritious foods like cereals, while pleasure-driven consumers preferred sweets and other less healthy options. However, despite the growing body of research on nutrition and motivation, most studies focus on general food consumption, with limited attention paid exclusively to snacking behaviors.

2.3 Mobile Technologies for Dietary Behavior Monitoring

The widespread adoption of smartphones and mobile devices has increased their potential in dietary research and behavior monitoring [7, 14, 45, 55, 81]. This advancement has enabled researchers to develop mobile food diaries, which assist individuals in logging dietary data. Generally, two main techniques are used in mobile food diaries to capture dietary data [60, 80]: passive sensing and self-reports. Passive sensing refers to the automated collection of personal, environmental, and crowd-based data through embedded sensors in smartphones and wearables (e.g., accelerometers, proximity sensors, GPS) and user-device interactions (e.g., phone calls, app usage, screen-on time), requiring little to no user effort during data collection [25, 80]. Passive sensing has been shown to be effective in characterizing eating events by capturing contextualized information [14, 80] and detecting dietary behaviors [82, 99, 115, 128].

In contrast, self-reports require proactive user engagement, capturing detailed information about daily behaviors, eating contexts, and perceptions. Self-reports are particularly essential for collecting data on food consumption, social context, and psychological states, which passive sensing alone cannot fully capture [106]. The most common methods for collecting self-reported data include structured questionnaires and Ecological Momentary Assessments (EMA) [107]. Traditional questionnaires require users to answer multiple-choice or yes/no questions to document their eating behaviors and contexts. Before technological advancements, EMA was conducted using paper-based methods. However, with the rise of ubiquitous smartphones, real-time, mobile-based Ecological Momentary Assessments (mEMA) have emerged as a seamless, real-time alternative [9]. There are two main sampling approaches for collecting mEMA data: signal-contingent sampling, which prompts participants at fixed or random times throughout the day to complete an mEMA survey and record their dietary behavior during a specific period [29]; and event-contingent sampling, which requires participants to complete an mEMA immediately after an eating event occurs [69]. Event-contingent mEMA can be integrated with passive sensing, allowing the system to automatically notify participants when eating is detected, prompting them to record additional contextual details [29].

Although traditional 24-hour dietary recalls and food frequency questionnaires (FFQs) are widely used, they are highly memory-dependent, which can be burdensome for participants, and prone to recall bias and misreporting [29, 98]. mEMA, in contrast, can provide higher temporal resolution and allow for dynamic behavioral insights by offering real-time dietary tracking and reducing memory-based inaccuracies. It thus has been validated as a more accurate and reliable method for monitoring real-time behavior [9]. Additionally, mEMA holds promise for detecting nutrition-related problems and improving dietary assessments [9]. Despite its widespread use in food consumption behavior research, mEMA remains underutilized in the study of snacking behaviors, presenting significant opportunities for future research. Moreover, while passive sensing can detect eating events and provide valuable contextual information, we opted not to use it because it lacks the granularity required to differentiate between snack types, assess their nutritional quality, or indicate subjective factors [4, 23]. Furthermore, most commonly used research-based dietary tracking apps primarily rely on self-reported food logging rather than passive sensing [14, 102]. Given our focus on analyzing snack categories and nutritiousness, we leveraged self-reported food logs within a mobile food diary, which provide a more precise and structured way to collect detailed dietary information. This approach aligns with conventional dietary assessment methods and ensures compatibility with existing research-oriented mobile food diary applications.

Despite the increasing prevalence of snacking in daily life, many existing studies utilizing mEMA (or similar mobile food diaries) fail to exclusively focus on snacking behavior. For instance, Biel et al. [14] developed a research-focused mobile food diary application that collected data on both meal and snacking behaviors, while the study primarily identified general dietary patterns, leaving snacking behavior relatively underexplored [41]. Similarly, recent food diaries incorporating image recognition, such as [24, 102], tend to conflate snacks with meals, further obscuring a detailed understanding of snacking habits. Moreover, beyond contextual factors, understanding the specific motivations behind snacking is essential for researching snacking behavior, as these motivations differ from those associated with regular meals [49] and can be effectively captured through mobile surveys [96, 100]. However, many existing studies remain short-term or cross-sectional, limiting their ability to track behavioral trends over time [14, 80, 116], and large-scale, longitudinal research on snacking behavior remains scarce. To address these gaps, we leveraged a research-focused mobile food diary dataset comprising over 14K+ in-situ self-reports collected across one year. This approach enables more robust, longitudinal insights into snacking choices and motivations within varied contexts, providing a deeper understanding of snacking behavior beyond prior research limitations.

3 Dataset Overview

3.1 Data Collection

To characterize broader behavioral insights related to snacking consumption, including the influence of context, product, and consumer-specific factors, the FOODLOOP project collected longitudinal food and beverage consumption data from a cohort of Dutch Millennials participating in an app-based study [28]. We obtained the dataset used in the original paper [28]. Participants were recruited through social media platforms and the Netherlands Nutrition Centre (Voedingscentrum) using the snowball sampling technique. Before the app-based study, a pre-study questionnaire was distributed to participants. This questionnaire served two purposes: (1) participant selection, and (2) collecting baseline data on socio-demographic characteristics and lifestyle factors. From a total of 798 potential participants who completed the questionnaire, 534 were deemed eligible based on five specific inclusion criteria. Eligible participants were required to be born between 1980 and 2000, reside in the Netherlands, and possess Dutch language proficiency. Additionally, they had to consume snacks regularly and were not following medically supervised diets or suffering from eating disorders such as anorexia or bulimia. Following the selection process, 398 participants provided informed consent and commenced the diary study by accessing the smartphone application.

Participants recorded all food and beverage consumption using signal-contingent active mEMA, following a 24-hour digital, 2-hour phased recall dietary diary approach. This method, based on the principles of smartphone-based behavioral assessment, was designed to capture snacking behavior in real-world settings. Participants were required to document their daily food and beverage consumption (including product type, portion size, and consumption occasion label) in the Traqq (WUR) smartphone application [71]. Additionally, for food and beverage consumption labeled as snacking occasions, participants provided information on motivations, physical context, social context, and temporal context (Table 2) through seamlessly integrated Qualtrics questionnaires. Each participant was asked to log their food and beverage intake in Traqq for 12 non-consecutive days, evenly distributed across four seasons over one year (2022–2023) [56]. The specific documentation days for each participant were randomly assigned using an automated sampling scheme. This scheme ensures that the days were non-consecutive, contained two weekdays and one weekend day, and took place within the two most representative months for a particular season. This strategy aligns with previous research which proves that three non-consecutive days of records can ideally estimate dietary intake [8, 53, 56] and balance user acceptance and seasonality. On each assigned day, all participants received nine prompts (phased recall) to report their consumption after each designated time window, following a consistent temporal structure across all study days. During the data collection process, 264 (66.33%) out of 398 participants completed all four data collection periods, thereby completing the study and constituting the cohort of the dataset. Some users missed several days of

Table 2. Key features in the dataset

Dimension	Feature name	Description	Type (# classes)	Classes / Ranges
Product (Target Variables)	Snack group	The group that the consumed product is categorized in	Categorical (10)	Non-alcoholic beverages | Fruit | Bread and cereals | Dairy products and substitutes | Confectionery and ice cream | Savory snacks | Alcoholic beverages | Cookies, bars and pastries | Meat, poultry, fish, eggs and substitutes | Vegetables and legumes
	Nutritiousness	Whether the consumed product is nutritious	Categorical (2)	Nutritious | Non-nutritious
Context (CONT)	Location	In what location participants were during their eating moment	Categorical (10)	At home | At work/study location | On visitation | On the go | On vacation | Outing | Sportsactivity | Hospitality establishment | Healthcare facility | Other
	Social environment	Who were present during participants' eating moment	Categorical (15)	Alone | With partner and child(ren) | With friends | With partner | With co-inhabitants | With partner and friends | With family | With child(ren) | With strangers | With studymates | With acquaintances | With colleagues | Mix | With partner and family | Other
	Day part	The part of the day within which the product was consumed	Categorical (3)	Afternoon | Evening/night | Morning
	Day type	The type of day on which the product was consumed	Categorical (2)	Week | Weekend
	Time window	The time period within which the product was consumed	Categorical (9)	6-8 | 8-10 | 10-12 | 12-14 | 14-16 | 16-18 | 18-20 | 20-22 | 22-6
	Season	The season within which the product was consumed	Categorical (4)	Spring | Summer | Autumn | Winter
	Consumption occasion	The way participants define the eating moment the consumed product belongs to	Categorical (5)	In-between meals | Replacement of lunch | Replacement of breakfast | Replacement of dinner | Other
Motivation (MOTI)	Food Choice Motives (FCM)	The motivations for consumption of the product (20 features in total). For the full list, please refer to Table 1.	Ordinal (1–3, Treated as Numeric)	No (1) | Somewhat (2) | Yes (3)
Demography (DEMO)	Age	The age of the participant	Numeric	22 – 42
	BMI	The body mass index of the participant	Numeric	15.82 – 42.16
	Sex	The sex of the participant	Categorical (2)	Male | Female
	Education group	The type of educational group, with the demarcation set at higher vocational education	Categorical (2)	Lower educated | Higher educated
	Living situation	Whether the household is shared with other people, and the relation to these people	Categorical (6)	Living with parent(s)/sibling(s) | Living with roommates | Living with partner | Living with partner and child(ren) | Single | Living with child(ren)
	Urbanity	The level of urbanity of the municipality the participant lives in, based on the zip code of the address	Categorical (5)	High urbanity | No urbanity | Very high urbanity | Low urbanity | Moderate urbanity
	Act scale	Activity level of the participant	Categorical (3)	Norm-active | Semi-active | Inactive
Weather (WEA)	Temperature	Air temperature at 2 meters above ground	Numeric	-3.35 – 34.25
	Humidity	Relative humidity at 2 meters above ground	Numeric	31.21 – 100
	Precipitation	Total precipitation sum of the preceding hour	Numeric	0 – 3.6
	Wind speed	Wind speed at 10 meters above ground	Numeric	0.51 – 47.85
	Sunshine duration	Number of seconds of sunshine of the preceding hour per hour	Numeric	0 – 3600

documentation because they did not consume any snacks on those days. While underreporting cannot be ruled out, this is a well-known characteristic of mobile food diary studies and is on par with existing literature.

In the final dataset, each record represents a snack consumed by a participant and contains essential information about the snack itself, the context in which it was consumed, and the personal characteristics of the participant. The consumption of each product is considered a distinct snacking episode in the data collection process. Given the potential influence of weather factors on dietary behavior [54, 86], we further extracted real-time weather data using the historical weather API from the Open Meteo platform [92]. The weather data was then merged with the original dataset, aligning records based on the start time of each time window and the corresponding date. This integration resulted in a final dataset incorporating both snack consumption details and real-time weather conditions. Table 2 summarizes the key features captured in the dataset for each snacking episode.

The key features in the dataset are categorized into five dimensions: product, context, motivation, demography, and weather. Most key features are categorical, while age, BMI, and weather features are numeric. Notably, Food Choice Motives (FCM) represent motivations for consumption and consist of 20 distinct features, each reflecting a specific motivation. The FCM framework used in this study is adapted from The Eating Motivation Survey (TEMS) [100], with modifications and improvements from [95] and [123]. For each FCM, participants were required to indicate whether they were motivated by that factor when consuming a snack, using a three-point ranking scale: 1 (No), 2 (Somewhat), 3 (Yes). These ordinal variables were also treated as numeric in the subsequent experiments. Each consumed product was mapped to the Dutch Food Composition Database (NEVO) [37] using a unique NEVO code, and categorized into 10 snack groups based on the NEVO coding system and the Dutch National Food Consumption Survey [38]. The nutritiousness label (nutritious vs. non-nutritious) was assigned on a per-product basis, following the Netherlands Nutrition Center's "Wheel of Five" (Schijf van Vijf) guidelines [121], which define a balanced dietary pattern to promote health and adequate nutrient intake. Specifically, each food or beverage item (identified via NEVO code) was mapped to a binary nutritiousness label (nutritious vs. non-nutritious) according to whether it aligns with the Center's recommendations for healthy eating.

Table 3 provides a summary of the dataset. For consistency, the 264 participants are referred to as "users" throughout the text. The dataset contains 14,312 records, representing the total number of snacking episodes, and spans 2,987 user-days across four seasons. Among the 264 users, 179 documented dietary records for all 12 assigned days, while the remaining participants missed at least one day, because they did not consume any snacks on those days. On average, users recorded 11.31 days (SD = 1.35) of dietary data. In terms of consumed snacks, the dataset includes 9,148 food (solid) records and 5,164 beverage (liquid) records. Of these, 6,629 snacks were categorized as nutritious, while 7,683 were classified as non-nutritious.

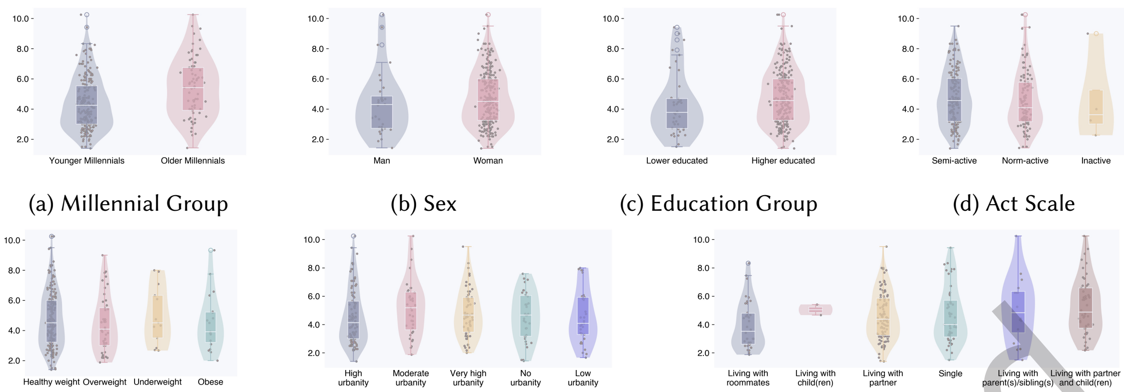
Table 3. A summary of the dataset

	Records	**Users**	**User-days**	**Solid / Liquid**	**Nutritious / Non-nutritious**
# items	14,312	264	2,987	9,148 / 5,164	6,629 / 7,683

3.2 Statistics of Key Features

3.2.1 Demographic Features. The individual demographic survey was conducted separately from food diaries and serves as a static feature group for the same user throughout the entire data collection period. To quantify individual snacking behavior, we compute the Personal Daily Snacking Frequency (PDSF) by dividing the total number of snacking episodes per user by the number of days on which they documented snack consumption, considering specific criteria (e.g., a given context). Figure 1 presents box plots illustrating the distribution of PDSF among users from different demographic groups. Notably, users from different demographic groups generally tend to display discrepancy in snacking frequency. For example, older Millennials tended to consume snacks more often per day compared to younger Millennials, while women and individuals with higher education levels exhibit higher daily snacking frequencies. In terms of physical condition, overweight, obese, and inactive individuals show a lower frequency of daily snacking episodes. Regarding urbanity and living situations, users living with family (including parent(s), sibling(s), and children) or in a higher urbanity tended to consume more daily snacks than those living alone or with roommates, or those living in a lower urbanity.

3.2.2 Motivation Features. For each snacking episode, FCM is evaluated using a three-point ranking scale: 1 (No), 2 (Somewhat), 3 (Yes). While all motivation scores were retained as numeric features in this study, a score of 3 was used to indicate that a specific motivation was strongly applicable to a given snacking episode for interpretability. Figure 2 displays the mean value of each FCM across the dataset. 87% of snacking episodes were motivated by liking, resulting in the highest mean value (AVG = 2.85, SD = 0.40). Additionally, 75% of snacking episodes were driven by the motivation of appetite, which is a hedonic status indicating that people just want to eat or drink (AVG = 2.70, SD = 0.57). Natural concerns were the least considered motivation for snacking, with only 2% involvement in the entire dataset (AVG = 1.05, SD = 0.28). The results suggest that most snacking behavior in this study was triggered by liking and hedonic factors, whereas some motivations such as social and natural concerns are less influential.



(a) Millennial Group (b) Sex (c) Education Group (d) Act Scale

(e) BMI Group (f) Urbanity (g) Living Situation

Fig. 1. Distribution of PDSF among users from different demographic groups

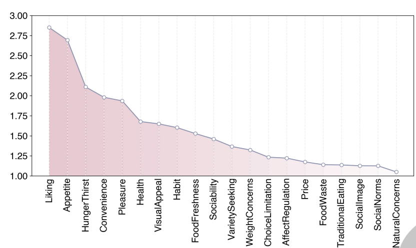


Fig. 2. Mean value of 20 FCM (Motivations)

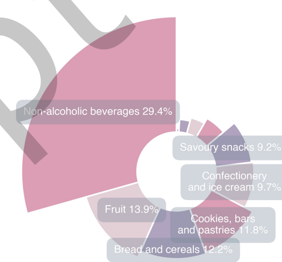
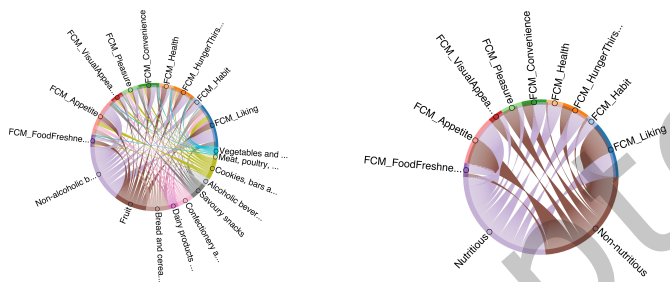


Fig. 3. Frequency distribution of snack groups

3.2.3 Product Features. Regarding the frequency distribution of snack group, Figure 3 shows that non-alcoholic beverages predominate in snacking episodes, accounting for 29% of the total frequency, followed by fruit (14%) and bread and cereals (12%). In terms of temporal contexts, the variation across different seasons is less pronounced than differences by day type and day part. It is especially noteworthy that non-alcoholic beverages were more frequently consumed in the morning, while alcoholic beverages were more commonly consumed in the weekend. The frequency discrepancies within location and social environment are similar, except that fruit was more often consumed outside while savory snacks were more frequently consumed at home. As shown in Figure 4a, the chord diagram is generated to demonstrate the co-occurrence between each snack group and motivations (with mean value > 1.5). It can be inferred that the co-occurrence pairs are diverse, indicating that the consumption of specific snack groups could be driven by multiple motivations, while no salient associations were discovered between pairwise snack group and motivation, except that non-alcoholic beverages were more often connected with the motivation of appetite and liking, mainly due to their relative high frequencies across the whole dataset.

Despite most motivation features averaging around 1, some motivations show noteworthy difference in nutritiousness. For instance, when users lacked the motivation of habit (FCM_Habit = 1), nutritious snacks were consumed less frequently (19%) than non-nutritious snacks (40%), which is similar to health (FCM_Health) (48% vs. 13%) and food freshness (FCM_FoodFreshness) (44% vs. 25%). In contrast, users triggered by pleasure consumed non-nutritious snacks more frequently (24%) than nutritious ones (8%). In terms of contextual features, nutritious snacks are more frequently consumed in the morning (32%) compared to non-nutritious snacks (18%), whereas in the evening/night, non-nutritious snacks are more frequently consumed (36%) than nutritious ones (25%). Additionally, regardless of the nutritiousness of the snacks, users tended to consume them more at home than outside, and more often with others than alone. In Figure 4b, it is found that although both nutritious and non-nutritious snacks are connected with most motivation features, the intensity of the connection shows great difference. For instance, the co-occurrence frequency is approximative for the motivation of liking (FCM_Liking) with nutritious snacks and with non-nutritious snacks, whereas for habit (FCM_Habit), more associations are constructed with nutritious snacks. This is the same case as the motivation of health (FCM_Health), food freshness (FCM_FoodFreshness), etc. The discovery aligns with prior studies, in which individuals who prioritize health and natural content as food choice motives tend to have a preference for nutritious foods [96, 110].



(a) Snack Groups and Motivations (b) Nutritiousness and Motivations

Fig. 4. Chord diagrams between snack choices and the motivations for consumption. The lines (or chords) connecting each pairwise nodes indicate the co-occurrence between them, and the thickness of lines represents the strength or frequency of the co-occurrences. Only motivations with mean value > 1.5 across all snacking episodes are displayed for brevity.

4 Statistical Analysis: Identifying Key Factors for Snack Choices (RQ1)

4.1 Methodology

In this section, we gain insights into the multi-dimensional characteristics of Dutch Millennials' snacking behavior, and identify discrepancies of snack choices regarding different factors. Specifically, we used mixed-effects models [66] to examine feature differences across the dataset and identify factors that significantly contribute to distinguishing between two key product features: snack group and nutritiousness. Mixed-effects models account for both fixed effects (e.g., motivation features) and random effects (e.g., participant-level variation), and are particularly suitable for longitudinal repeated-measures data where observations are not independent, such as multiple snacking episodes reported by the same individual [42], as in our research. We regarded user-specific variations, i.e., the unique identifier of each user, as random effects, ensuring that feature differences are not confounded by individual user variability. These experiments were conducted using the `pymer4` library in Python, which is derived from the `lmerTest` package in R and integrates essential statistical functions into Python [64].

4.2 Results

The results are presented in Table 4, which displays two mixed-effects models, including the coefficients, t-statistics, and p-values for each feature. It is important to note that categorical features were converted into dummy variables based on their distinct classes, while motivation features were retained as numeric variables to represent the intensity of motivations, following common practice in behavioral modeling [44]. The statistics illustrate the extent to which these dummy variables differ from the reference category (i.e., the base category

Table 4. Report of mixed-effects models on the two tasks. T-statistics (p-value<10^{-3}: ***, p-value<10^{-2}: **, p-value<0.05: *) are displayed according to p-values after the Bonferroni correction. Top 20 features are shown in decreasing order.

	Feature	Coefficient	T-statistics		Feature	Coefficient	T-statistics
Snack Group (10 classes)	FCM_Habit	-1.269	-36.974***	Nutritiousness (2 classes)	FCM_Health	0.257	51.433***
	FCM_HungerThirst	-0.732	-21.212***		FCM_Habit	0.154	35.175***
	FCM_Pleasure	0.601	16.073***		FCM_FoodFreshness	0.097	20.924***
	FCM_Convenience	0.447	12.933***		FCM_Pleasure	-0.099	-20.632***
	FCM_VarietySeeking	-0.535	-12.564***		FCM_Convenience	-0.043	-9.622***
	FCM_ChoiceLimitation	0.607	11.776***		FCM_VisualAppeal	-0.044	-8.746***
	FCM_VisualAppeal	0.445	11.441***		Location: On the go	-0.078	-5.34***
	FCM_Sociability	-0.338	-7.956***		FCM_HungerThirst	0.023	5.294***
	FCM_FoodFreshness	-0.278	-7.680***		FCM_NaturalConcerns	-0.063	-5.104***
	SocialEnvironment: With partner and child(ren)	0.678	6.648***		FCM_ChoiceLimitation	-0.025	-3.833***
	ConsumptionOccasion: Replacement of breakfast	1.269	6.115***		FCM_WeightConcerns	-0.018	-2.813
	FCM_Appetite	-0.286	-5.491***		Location: Hospitality establishment	-0.060	-2.724
	ConsumptionOccasion: In-between meals	0.725	5.418***		SocialEnvironment: With colleagues	-0.091	-2.593
	Location: Hospitality establishment	-0.902	-5.195***		FCM_TraditionalEating	-0.019	-2.538
	FCM_Health	-0.201	-5.114***		relative_humidity_2m	0.001	2.512
	SocialEnvironment: With child(ren)	0.770	5.103***		SocialEnvironment: With co-inhabitants	-0.039	-2.512
	ConsumptionOccasion: Replacement of lunch	0.910	4.319***		TimeWindow: 18:00-20:00	0.041	2.204
	ConsumptionOccasion: Replacement of dinner	1.002	4.261***		Age	0.004	2.177
	FCM_SocialImage	-0.299	-3.826***		sunshine_duration	0.000	2.168
	Location: On visitation	-0.435	-3.708***		SocialEnvironment: With studymates	0.034	1.834

selected by the model) in discriminating the target variable. Bonferroni correction was applied to adjust for multiple comparisons and highlight significant features [120]. A higher t-statistic corresponds to a lower p-value.

Overall, motivation features (FCM) were particularly effective in distinguishing between the target variables, as indicated by their predominantly higher t-statistics compared to other features. For example, habits (FCM_Habit) demonstrated significant variation across records, making it the most effective feature for discriminating between different snack group classes. Other motivation features, such as hunger and thirstiness (FCM_HungerThirst) and pleasure (FCM_Pleasure), also exhibited significant internal variation. Beyond motivation features, certain dummy variables, such as being with partner and child(ren) (SocialEnvironment: With partner and child(ren)) where "With Partner and Child(ren)" is a category within the feature Social Environment, also showed high t-statistics, indicating significant differences from the reference variable (in this case, "Alone"). Notably, 21 out of 80 features remained significant after Bonferroni correction, including 13 motivation features, four dummy variables related to consumption occasion, and four dummy variables for contextual features (e.g., location and social environment). In contrast, demographic and weather features exhibited low t-statistics in the snack group model, suggesting they may be less relevant for classification tasks in this context.

For the nutritiousness model, fewer features were statistically significant (10 out of 80 after correction), though key motivation features such as health (FCM_Health), habit (FCM_Habit), food freshness (FCM_FoodFreshness), and pleasure (FCM_Pleasure) had high t-statistics. Notably, health (FCM_Health) showed a much higher t-statistic than habit (FCM_Habit) in the snack group model. Additionally, other features showed no statistical significance.

In summary, the statistical analysis revealed that some features were indicative of the target variables (snack group and nutritiousness). Motivation features, in particular, demonstrated substantial statistical significance in discriminating between the target variables, highlighting their role in distinguishing different snack groups and nutritiousness, and were expected to be valuable in the subsequent tasks.

5 Association Patterns: Mapping Motivations and Snack Choices (RQ2)

5.1 Methodology

Based on the findings of Section 4.2 (RQ1), where motivation features were significantly informative of snack choices (i.e., snack groups and nutritiousness), this section aims to identify the frequent and interpretable association patterns between consumers' motivations and snack choices. To this end, we leveraged association rule mining with Apriori algorithm [2] to extract relevant associations between pairs of itemsets (the sets that are composed of different combinations of items) from our dataset. While association rule mining is traditionally used in market analysis, recent studies have demonstrated its applicability in health informatics, for example, to uncover patterns linking physical activity, dietary behavior, and disease risk [75].

We extracted the most significant motivations (i.e., with the FCM value of 3), the class of snack group, and the class of nutritiousness in each snacking episode to conduct association rule mining. The experiments were carried out separately between motivations and snack groups (Figure 5a), and between motivations and nutritiousness (Figure 5b). We assumed that $I = \{I_1, I_2, \dots, I_m\}$, where I represents the whole set of m items (encompassing all motivations and snack groups/nutritiousness). A snacking episode S is considered as a subset of these items, such that $S \subseteq I$. An association rule takes the form of $M \Rightarrow N$, where M, N are subsets of I, known as itemsets, with $M \cap N = \emptyset$. In this context, M is regarded as the antecedent itemset and N as the consequent itemset, and the rule signifies that M implies N. The mining process was conducted in two steps: finding the frequent itemsets (the ones with more occurrences) throughout the dataset using the Apriori algorithm, and generating association rules from those frequent itemsets. For instance, for a snacking episode that includes health (FCM_Health), habit (FCM_Habit), and fruit, three 2-itemsets {*FCM_Health*, *FCM_Habit*}, {*FCM_Health*, *Fruit*}, {*FCM_Habit*, *Fruit*} along with three corresponding 1-itemsets would be extracted, while the mutually exclusive itemsets would then form six possible association rules. To focus our analysis specifically on the association between single motivation and snack group/nutritiousness, we filtered the generated association rules by selecting rules where the antecedent M contains only 1-itemsets representing motivations, and the consequent N contains only 1-itemsets representing snack groups/nutritiousness. This approach allowed us to directly investigate the associations among these three features.

We mainly referenced three metrics to evaluate the significance of each association rule: support, confidence, and lift. Support is a metric concerning the frequency of the itemsets throughout all the possible itemsets and is defined as the fraction of the number of snacking episodes containing the itemset $M \cup N$ (or M/N for antecedents/consequents support) to the total number of snacking episodes S in the dataset D [2], as indicated in the equation shown below. We predetermined frequent itemsets with support ≥ 0.01 as the threshold to screen itemsets with more occurrences and computed the support, confidence, and lift of each association rule.

$$\text{Support}(M \Rightarrow N) = \frac{|\{T \in D \mid M \cup N \subseteq T\}|}{|D|} \tag{1}$$

In comparison to support, confidence is the measure of a rule's strength [2], defined as the fraction of the number of snacking episodes containing the itemset $M \cup N$ to the total number of snacking episodes that contain antecedent M. This can be explained as the frequency of antecedents among the snacking episodes that have both the antecedents and consequences, followed by another equation:

$$\text{Confidence}(M \Rightarrow N) = \frac{\text{Support}(M \cup N)}{\text{Support}(M)} \tag{2}$$

Lift is defined as the fraction of the number of transactions containing the itemset $M \cup N$ to the product of the total number of snacking episodes that respectively contain antecedent M and N. It can represent the intensity of the rule and evaluates whether the co-occurrence probability of antecedents and consequents is significantly higher than that of independent occurrence, and can be explained in this equation:

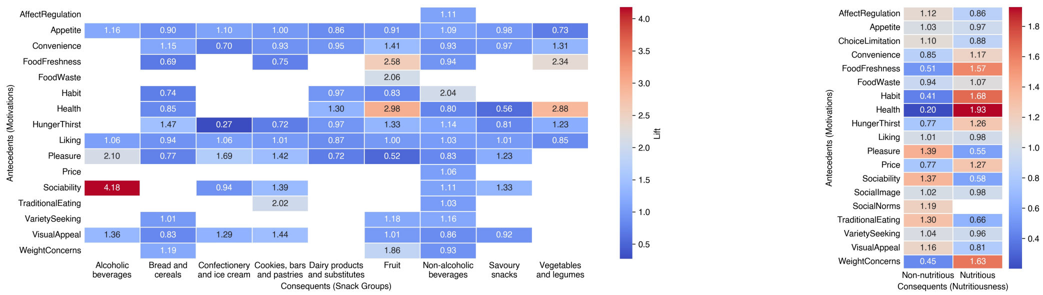
$$\mathrm{Lift}(M \Rightarrow N) = \frac{\mathrm{Support}(M \cup N)}{\mathrm{Support}(M) \times \mathrm{Support}(N)} \tag{3}$$

5.2 Results

5.2.1 Association between Snack Groups and Motivations. Figure 5 illustrates the lift values for each association rule, while Table 5 highlights the top 10 association rules, focusing on three key metrics. Notably, the rule *FCM_Sociability ⇒ Alcoholic beverages* exhibited the highest lift value, despite low support and confidence due to the infrequent co-occurrence of these items in the dataset. Specifically, within the dataset of 14,312 records, 2.8% contain both sociability (FCM_Sociability) and alcoholic beverages, and 17.2% of records with sociability (FCM_Sociability) also involve alcoholic beverages. The frequency of the co-occurrence of the two items is 4.180 times that of their independent occurrences, indicating a positive association. This association is also consistent with [79, 94], highlighting that social interactions play a role in alcohol drinking behaviors. Similar trends of associations are observed in the rules *FCM_Health ⇒ Fruit* and *FCM_Health ⇒ Vegetables and legumes*, where the probability of consuming fruits or vegetables increased when users were motivated by health (FCM_Health). Additionally, 9 out of the top 10 rules exhibited lift values exceeding 2.0, implying a significant positive association in these pairwise itemsets. However, non-alcoholic beverages appear in only one of the top 10 rules (*FCM_Habit ⇒ Non-alcoholic beverages*), despite having the highest frequency (i.e., consequents support) in the dataset, suggesting that a single motivation seldom elevated the probability of consuming non-alcoholic beverages.

5.2.2 Association between Nutritiousness and Motivations. In contrast, the lift values for association rules between motivations and snack nutritiousness are generally lower than those between motivations and snack groups, with all values below 2.0, as illustrated in Figure 5. Table 5 complements this by presenting metrics for the top 10 rules with the highest lift values, revealing that rules involving nutritious snacks tended to have higher lift values compared to those involving non-nutritious snacks. The most notable rule is *FCM_Health ⇒ Nutritious*, which shows that 22.8% of snacking episodes include both health (FCM_Health) and nutritious, with 89.2% of episodes involving health (FCM_Health) also involving nutritious. The frequency of these items co-occurring is 1.926 times greater than expected by chance, further supporting a positive association between nutritious snacks and health-driven motivations. Additionally, motivations such as habit (FCM_Habit), weight concern (FCM_WeightConcern), and food freshness (FCM_FoodFreshness) also showed relatively higher lift values, reinforcing their positive association with the consumption of nutritious snacks. Conversely, while the lift values for non-nutritious snacks are lower, motivations such as pleasure and sociability are still frequently linked to the consumption of non-nutritious snacks to a certain degree.

5.2.3 Temporal Patterns in Association between Nutritiousness and Motivations. To investigate discrepancies in the intensity of association rules across different periods, we conducted a temporal analysis by computing the lift values for the top rules across three day parts: morning, afternoon, and evening/night (see Table 6). Notably, the association intensity between most motivations and the consumption of nutritious snacks peaked during the evening/night, with the exception of price (FCM_Price), which reached its highest lift in the afternoon (1.302). Specifically, health (FCM_Health, lift = 2.424), weight concerns (FCM_WeightConcerns, lift = 2.017), and habit (FCM_Habit, lift = 1.958) showed their strongest associations with nutritious choices during the late-day period. This suggests that when users chose nutritious snacks in the evening or at night, they were more likely to have these specific motivations than during the morning or afternoon. Conversely, associations involving non-nutritious snacks generally exhibited greater intensity earlier in the day. Motivations such as pleasure (FCM_Pleasure, lift = 1.460), traditional eating (FCM_TraditionalEating, lift = 1.416), and social norms (FCM_SocialNorms, lift = 1.369) demonstrated their peak lift values in the morning. These findings reveal a



(a) Snack Groups

(b) Nutritiousness

Fig. 5. Heatmap of the lift values generated by association rules between each motivation feature and snack group/nutritiousness. Only the rules containing 1-itemsets with support ≥ 0.01 are displayed. (a) excludes the group "meat, poultry, fish, eggs, and substitutes" due to insufficient support, as this snack group has low frequency in the dataset.

Table 5. Top 10 association rules between motivations and snack groups, and between motivations and nutritiousness in decreasing order by lift separately. Only the rules containing 1-itemsets with support ≥ 0.01 are considered.

	Antecedents	Consequents	Support	Confidence	Lift		Antecedents	Consequents	Support	Confidence	Lift
Snack Group	FCM_Sociability	Alcoholic beverages	0.028	0.172	4.180	**Nutritiousness**	FCM_Health	Nutritious	0.228	0.892	1.926
	FCM_Health	Fruit	0.106	0.414	2.981		FCM_Habit	Nutritious	0.147	0.778	1.679
	FCM_Health	Vegetables and legumes	0.024	0.094	2.877		FCM_WeightConcerns	Nutritious	0.061	0.757	1.634
	FCM_FoodFreshness	Fruit	0.075	0.358	2.579		FCM_FoodFreshness	Nutritious	0.153	0.728	1.572
	FCM_FoodFreshness	Vegetables and legumes	0.016	0.076	2.336		FCM_Pleasure	Non-nutritious	0.243	0.745	1.387
	FCM_Pleasure	Alcoholic beverages	0.028	0.086	2.098		FCM_Sociability	Non-nutritious	0.121	0.733	1.365
	FCM_FoodWaste	Fruit	0.012	0.286	2.059		FCM_TraditionalEating	Non-nutritious	0.029	0.695	1.295
	FCM_Habit	Non-alcoholic beverages	0.113	0.601	2.045		FCM_Price	Nutritious	0.028	0.587	1.267
	FCM_TraditionalEating	Cookies, bars and pastries	0.010	0.239	2.022		FCM_HungerThirst	Nutritious	0.240	0.586	1.265
	FCM_WeightConcerns	Fruit	0.021	0.258	1.858		FCM_SocialNorms	Non-nutritious	0.015	0.640	1.193

temporal shift in snacking behavior. While the psychological drivers for pleasure and social demands are most salient during the morning hours, the commitment to health and weight concerns becomes a more distinct indicator of food choice as the day progresses.

6 Predictive Inference: Validating Performance and Feature Importance (RQ3)

6.1 Methodology

In this section, we evaluated the feasibility of leveraging machine learning to infer snack groups and nutritiousness based on motivations and a combination of contextual and non-contextual features. Building on the significance of motivations in the statistical model in Section 4.2, and the associations between snack choices and motivations identified in Section 5.2, our objective is to determine the ability of these factors in classifying snack choices. By validating the extent to which motivations and other (non-)contextual variables contribute to snack choice inference, this analysis can provide insights for enhancing mobile food diaries, especially on the development of personalized interventions within ubiquitous computing systems, which may enable real-time interventions that promote healthier snacking behaviors tailored to individual users. We used the same features employed in the statistical analysis (Section 4.2) and treated snack group and nutritiousness as the target variables for two classification tasks: a multi-class classification task for snack groups, and a binary classification task for nutritiousness. For this phase, we utilize the `scikit-learn` library in Python [93] and experiment with four

Table 6. Temporal patterns of top 10 association rules between motivations and nutritiousness. Values represent the Lift metric across three day parts (morning, afternoon, evening/night). The strongest association per rule is in bold.

Association Rules	Lift by Day Part		
	Morning	**Afternoon**	**Evening/Night**
FCM_Health ⇒ Nutritious	1.467	1.984	**2.424**
FCM_Habit ⇒ Nutritious	1.391	1.661	**1.958**
FCM_WeightConcerns ⇒ Nutritious	1.346	1.612	**2.017**
FCM_FoodFreshness ⇒ Nutritious	1.291	1.605	**1.776**
FCM_Price ⇒ Nutritious	1.082	**1.302**	1.271
FCM_HungerThirst ⇒ Nutritious	1.142	1.229	**1.435**
FCM_Pleasure ⇒ Non-nutritious	**1.460**	1.407	1.269
FCM_Sociability ⇒ Non-nutritious	1.367	**1.370**	1.243
FCM_TraditionalEating ⇒ Non-nutritious	**1.416**	1.368	1.155
FCM_SocialNorms ⇒ Non-nutritious	**1.369**	1.092	1.239

different classifiers commonly used in ubiquitous computing studies: Support Vector Machine (SVM) [48], Random Forest [18], LightGBM [59], and XGBoost [22]. These classifiers were selected due to their widespread adoption in ubiquitous computing and their suitability for relatively small datasets like ours.

Although the dataset is imbalanced in terms of snack group distribution, we did not apply resampling techniques. This was driven by the need to maintain the integrity of the natural snacking episodes observed in daily life. Furthermore, given that most features in our dataset are categorical, resampling techniques typically offer limited performance benefits and may introduce noise [21]. Additionally, all categorical features were preprocessed using one hot encoding to transform each unique class within a feature into a dedicated binary dummy variable. This approach ensures that every specific class is represented independently, and thus facilitates a more comprehensive interpretation during the subsequent SHAP analysis, in which the contribution of each individual category could be quantified. While this encoding method generates N variables for N classes, tree-based models such as LightGBM and XGBoost are inherently robust to the redundancy in comparison to linear models [22, 47, 59]. By maintaining all classes independently, the models can effectively identify the most informative splits for each context. Finally, after splitting the dataset into training and testing sets, we standardized all independent features to ensure consistent feature scaling across classifiers.

In the first stage, we applied a user-hybrid approach using Stratified-K-Fold cross-validation [47] to both tasks (Table 7). This approach allowed us to assess the performance of the four machine learning models and identify the best-performing classifier for user-agnostic approaches. The percentage distribution of each class in the target variables was preserved in the test sets, ensuring a balanced class representation after splitting the dataset into training and test sets. The number of users per fold was set to four to maintain consistency in user distribution across the folds. We evaluated model performance using Accuracy, F1-score, and AUROC (Area Under the Receiver Operating Characteristic Curve) for both classification tasks. Additionally, for the multi-class classification task, we reported Top-3 Accuracy to provide a more comprehensive assessment of model performance. For multi-class classification, AUROC was computed using the One-vs-One (OvO) strategy with macro-averaging, which calculates pairwise AUROC scores and averages them across all class pairs. F1-score was also computed using macro-averaging, which computes the metric for each class and reports their unweighted mean, thereby amplifying the influence of lower-frequency classes. To benchmark our results, we implemented two baseline models for comparison: Random Guess, which randomly shuffles the target variables while maintaining their frequency distribution; and Majority Class, which assigns all records in the dataset to the most frequent class in the target variable. For example, in the nutritiousness inference task, the Majority Class model labeled all records as “Non-nutritious” before computing performance metrics.

To enhance model robustness beyond the user-hybrid approach and to identify the most influential features affecting model performance, we further applied three user-agnostic approaches: Leave-One-Out (LOO), Group-K-Fold (GKF), and Stratified-Group-K-Fold (SGKF), each with different feature group combinations (Table 8). The primary objective was to partition the dataset by user, ensuring that data from the same individual did not appear in both the training and test sets. A textual explanation of these implementations is provided in Table 1. To maintain consistency with the user-hybrid approach, we set the number of users per fold to four for both GKF and SGKF. When dividing feature combinations, we retained all independent features but structured them into several group combinations. Demographic and weather features were not treated as separate feature groups due to their low statistical significance, as indicated in Table 4. Additionally, since demographic features remain static for each user, and the user-agnostic approaches explicitly separate users into training and test sets, these features were not expected to contribute significantly to the inference tasks.

In addition to the feature importance values generated by the models, we utilized SHAP (SHapley Additive exPlanations) analysis [73] to examine the specific influence of key features on model outcomes. SHAP is a game-theoretic approach for explaining model inferences, offering an intuitive interpretation, particularly for binary classification tasks. Since the nutritiousness inference task is a binary classification problem, we employed SHAP analysis to elaborate on how different features impact nutritiousness predictions.

6.2 Results

6.2.1 User-Hybrid Results. Table 7 summarizes the inference results for both tasks using the user-hybrid approach. Overall, the models trained with this approach performed relatively well. For the snack group inference task, all classifiers achieved accuracy scores above 50%, with AUROC and top-3 accuracy scores exceeding 80%. The discrepancy between accuracy and AUROC scores is likely due to the models performing significantly better at inferring higher-frequency classes. Given that this is a 10-class classification task, the performance was noteworthy, particularly in terms of AUROC and top-3 accuracy, demonstrating the models’ ability to effectively infer the top three most probable classes. The results for the nutritiousness inference task were also notable, with even higher accuracy, F1, and AUROC scores, outperforming the snack group inference task. Among the four classifiers, LightGBM and XGBoost classifiers achieved the best performance, with LightGBM slightly outperforming the others, achieving marginally higher scores across all metrics in the binary classification task (by approximately 0.4%). This is contrary to some previous research involving food diaries in ubiquitous computing, which find Random Forest classifier perform the best [14, 80, 82]. Consequently, we focused on the results obtained using LightGBM for brevity.

6.2.2 Inference on Snack Groups. Table 8 compares the results of the user-agnostic approach (LOO, GKF, and SGKF) with those of the user-hybrid approach for both inference tasks. Overall, the user-agnostic approach yielded similar but slightly lower performance compared to the user-hybrid approach. This difference may be attributed to the cross-validation methods, which account for the consistency of data recorded by individual users and prevent splitting a single user’s data between training and test sets, thereby improving model robustness. This assumption is further supported by the user-hybrid approach results, where the CONT+MOTI+DEMO feature group outperformed all others, likely because demographic features help distinguish individual users, making them valuable identifiers for inference. Under the user-agnostic approach, however, the CONT+MOTI feature group consistently outperformed other combinations across nearly all metrics, reinforcing the importance of combining motivation and contextual features for accurate snack group inference. For example, under SGKF, the AUROC of CONT+MOTI exceeded that of CONT+DEMO+WEA by approximately 16%, underscoring the greater significance of motivation features compared to demographic and weather features. Interestingly, the MOTI-only feature group

Table 7. Inference results for snack group and nutritiousness under user-hybrid approach with different machine learning models. Mean and standard deviation (in brackets) of inference Accuracy, F1, AUROC and Top-3 Accuracy (all in %) are displayed for comparison. For each metric, the highest mean value is in bold while the second highest value is underlined.

	Metrics	Baseline Models		Classifiers			
		Random Guess	Majority Class	Support Vector Machine	Random Forest	LightGBM	XGBoost
Snack Group (10 classes)	Accuracy	15.3	29.4	52.7 (2.8)	54.0 (2.6)	<u>55.0</u> (3.0)	**55.6** (2.7)
	F1	15.3	13.3	37.5 (3.2)	39.9 (3.5)	<u>42.0</u> (4.2)	**43.2** (3.6)
	AUROC	NA	NA	84.6 (2.0)	84.0 (2.2)	<u>85.2</u> (2.3)	**85.3** (2.1)
	Top-3 Acc.	55.5	55.5	83.0 (2.2)	82.5 (2.7)	**83.8** (2.4)	<u>83.5</u> (2.3)
Nutritiousness (2 classes)	Accuracy	50.0	53.7	84.0 (2.2)	84.4 (2.1)	**85.1** (2.1)	<u>84.7</u> (2.1)
	F1	50.0	37.5	83.8 (2.2)	84.3 (2.1)	**85.0** (2.2)	<u>84.6</u> (2.1)
	AUROC	NA	NA	83.8 (2.2)	84.4 (2.1)	**85.0** (2.2)	<u>84.6</u> (2.2)

also demonstrated good performance, with AUROC and top-3 accuracy scores approaching 80%, significantly outperforming CONT-only and nearly matching the full feature set's performance. This finding highlights that while the combination of motivation and contextual features produced the best overall performance, motivation features alone were the most critical in these inference tasks, improving F1, AUROC, and top-3 accuracy scores by over 15%. While contextual features provided additional complementary information, they alone did not significantly influence snack group classification outcomes. This finding provides additional insights to [14] in which contextual features are significant in differentiating snacking vs. meal eating, and reveals that motivation features are also informative to discern snack choices. Table 9 presents class-specific precision, recall, and F1-score to evaluate the impact of class imbalance on model performance. Majority classes, such as non-alcoholic beverages, fruit, and cookies, bars and pastries, exhibited the strongest inference performance. In contrast, minority classes showed lower scores due to their sparse representation in the dataset, illustrating how the distribution of snacking behaviors shapes the classification outcomes.

6.2.3 Inference on Nutritiousness. The binary classification task (nutritious vs. non-nutritious) generally outperformed the multi-class classification task in terms of F1-score and AUROC. Similar to the snack group inference, the CONT+MOTI feature group achieved near-optimal performance among all feature combinations under the user-agnostic approach. Notably, the MOTI-only feature group also demonstrated good performance, with F1 and AUROC scores exceeding 82% in both GKF and SGKF, significantly outperforming the CONT+DEMO+WEA group by approximately 15%. These findings further confirm that contextual, demographic, and weather features were less significant than motivation features in predicting snack choices. The results suggest that snack choices, particularly nutritious vs. non-nutritious snacks, can be effectively discriminated based on consumer motivations. Additionally, within the user-agnostic approach, GKF and SGKF outperformed LOO in nutritiousness inference, though the difference was less pronounced in the snack group inference task.

6.2.4 Inference Performance on Snack Groups: Solid vs. Liquid Snacks. Given the skewness of the frequency distribution of snack group, especially on non-alcoholic beverages, we conducted an additional analysis comparing the inference results on snack groups between solid (i.e., food) and liquid (i.e., beverage) snacks. The two physical states of snacks are defined on a per-product basis (i.e., NEVO code), and thus are not dependent on the snack group. The snack group dairy products and substitutes, for example, can be regarded as either solid or liquid. Therefore, we distinguished the liquid snacks (3 classes, incl. alcoholic beverages, non-alcoholic beverages, and part of dairy products and substitutes) from solid snacks (8 classes, incl. the other seven product groups and part of dairy products and substitutes), to perform inference tasks separately under the combination of LightGBM

Table 8. Complete inference results for snack group and nutritiousness. Mean and standard deviation (in brackets) of inference F1, AUROC and Top-3 Accuracy (all in %) are displayed. The number in the brackets in the column of feature groups denotes the number of independent features used in the feature group combination before conducting one-hot encoding. For each metric, the highest mean value is in bold while the second highest value is underlined.

	Feature Group (# of Features)	**User-Hybrid Approach**			**Leave-One-Out**			**Group-K-Fold**			**Stratified-Group-K-Fold**		
		F1	**AUROC**	**Top-3 Acc.**	**F1**	**AUROC**	**Top-3 Acc.**	**F1**	**AUROC**	**Top-3 Acc.**	**F1**	**AUROC**	**Top-3 Acc.**
Snack Group (10 classes)	Baseline (Random Guess)	15.3	NA	55.5	15.3	NA	55.5	15.3	NA	55.5	15.3	NA	55.5
	Baseline (Majority Class)	13.3	NA	55.5	13.3	NA	55.5	13.3	NA	55.5	13.3	NA	55.5
	CONT (7)	16.1 (3.0)	67.0 (2.4)	63.6 (2.9)	13.8 (6.6)	63.8 (8.3)	61.2 (11.9)	14.3 (3.1)	64.7 (4.0)	61.9 (5.8)	14.7 (3.0)	64.8 (3.9)	61.5 (5.1)
	MOTI (20)	33.2 (3.7)	79.6 (2.5)	78.2 (3.0)	28.4 (9.5)	78.0 (7.3)	75.7 (9.6)	29.0 (3.9)	76.9 (3.9)	75.4 (4.7)	29.8 (4.2)	76.7 (3.5)	75.4 (4.3)
	CONT+MOTI (27)	38.5 (3.5)	83.1 (2.7)	81.4 (2.3)	**32.0** (9.7)	**80.9** (7.1)	**78.6** (9.2)	**33.4** (4.7)	80.4 (3.6)	**78.5** (4.8)	**33.9** (3.7)	**80.4** (3.3)	**78.6** (3.7)
	CONT+DEMO+WEA (19)	23.3 (4.0)	72.7 (2.7)	68.6 (2.8)	13.2 (6.0)	63.9 (7.6)	60.4 (12.1)	13.9 (3.5)	65.2 (4.0)	61.5 (6.0)	14.4 (2.9)	64.6 (3.5)	61.4 (4.9)
	MOTI+DEMO+WEA (32)	39.1 (3.5)	83.6 (2.4)	81.6 (2.6)	29.2 (10.3)	78.7 (7.1)	75.6 (10.2)	28.7 (4.3)	77.7 (3.7)	75.4 (4.7)	28.9 (4.5)	77.6 (3.4)	75.2 (4.2)
	CONT+MOTI+DEMO (34)	**44.3** (3.9)	**86.0** (2.5)	**84.4** (2.2)	31.6 (9.8)	80.8 (6.7)	78.1 (10.0)	32.1 (5.0)	80.1 (3.5)	78.0 (4.7)	32.5 (4.3)	80.0 (3.6)	78.1 (4.3)
	CONT+MOTI+WEA (32)	38.4 (3.8)	82.6 (2.6)	80.9 (2.5)	31.9 (9.7)	80.6 (6.9)	78.0 (9.8)	32.6 (4.9)	**80.4 (3.5)**	78.2 (4.6)	33.1 (4.4)	80.1 (3.3)	78.2 (3.9)
	All features (39)	42.0 (4.2)	85.2 (2.3)	83.8 (2.4)	31.6 (10.5)	80.8 (6.9)	78.1 (9.7)	31.7 (4.8)	79.9 (3.4)	78.3 (4.8)	32.0 (4.1)	79.9 (3.3)	78.1 (4.4)
Nutritiousness (2 classes)	Baseline (Random Guess)	50.0	NA	NA	50.0	NA	NA	50.0	NA	NA	50.0	NA	NA
	Baseline (Majority Class)	37.5	NA	NA	37.5	NA	NA	37.5	NA	NA	37.5	NA	NA
	CONT (7)	60.2 (3.3)	60.3 (3.3)	NA	57.1 (11.6)	59.7 (11.6)	NA	58.9 (5.4)	59.8 (5.2)	NA	59.2 (5.5)	59.6 (5.2)	NA
	MOTI (20)	83.5 (2.2)	83.5 (2.3)	NA	80.7 (10.9)	82.1 (10.2)	NA	82.5 (4.4)	83.0 (4.3)	NA	82.6 (5.6)	82.7 (5.6)	NA
	CONT+MOTI (27)	83.9 (2.2)	83.9 (2.2)	NA	**81.0** (10.9)	82.4 (10.3)	NA	**82.9** (4.3)	**83.3** (4.2)	NA	**82.9** (5.6)	**83.0** (5.5)	NA
	CONT+DEMO+WEA (19)	64.3 (3.1)	64.3 (3.1)	NA	54.1 (10.9)	58.1 (9.8)	NA	57.7 (5.5)	58.8 (5.1)	NA	57.8 (5.8)	58.6 (5.3)	NA
	MOTI+DEMO+WEA (32)	84.8 (2.0)	84.9 (2.0)	NA	79.7 (11.5)	81.2 (10.7)	NA	81.8 (4.4)	82.2 (4.3)	NA	81.9 (6.1)	82.0 (6.0)	NA
	CONT+MOTI+DEMO (34)	**85.3** (2.1)	**85.3** (2.1)	NA	80.7 (10.8)	82.2 (10.0)	NA	82.1 (4.5)	82.6 (4.4)	NA	82.3 (6.2)	82.4 (6.0)	NA
	CONT+MOTI+WEA (32)	83.9 (2.1)	84.0 (2.1)	NA	81.0 (10.8)	**82.5** (10.1)	NA	82.7 (4.3)	83.1 (4.2)	NA	82.8 (0.7)	82.8 (0.8)	NA
	All features (39)	85.0 (2.2)	85.0 (2.2)	NA	80.5 (11.2)	81.9 (10.6)	NA	82.1 (4.4)	82.6 (4.2)	NA	82.2 (5.8)	82.4 (5.6)	NA

Table 9. Class-specific performance metrics derived from the LightGBM models in snack group inference under SGKF and all feature sets. Precision, Recall, and F1 (All in %) are displayed.

Snack Groups (% across the Dataset)	**Precision**	**Recall**	**F1**
Alcoholic beverages (4.1)	48.8	45.4	47.1
Bread and cereals (12.2)	33.6	24.6	28.4
Confectionery and ice cream (9.7)	40.5	44.8	42.5
Cookies, bars and pastries (11.8)	39.1	42.6	40.8
Dairy products and substitutes (5.6)	27.3	11.7	16.4
Fruit (13.9)	55.7	70.3	62.2
Meat, poultry, fish, eggs and substitutes (0.9)	0.0	0.0	0.0
Non-alcoholic beverages (29.4)	58.4	74.9	65.6
Savoury snacks (9.2)	26.1	15.4	19.4
Vegetables and legumes (3.3)	17.9	3.2	5.5
Macro Average	**34.7**	**33.3**	**32.8**
Weighted Average	**44.0**	**48.2**	**45.1**

model and SGKF cross-validation. The result is shown in Table 10, in which the same metrics are reported for both tasks, with the exception of top-3 accuracy that is only included in the 8-class classification task. In general, the inference on snack groups within only liquid snacks exhibited a better performance with MOTI+CONT feature group, achieving the AUROC of 88.2%. Nonetheless, it is notable that the performance was not pronounced compared to the baseline models, or even inferior with a lower F1 score. This result reinforces the assumption that non-alcoholic beverages, as the predominant class in the target variable, influence the model performance to a distinct degree. For the inference task within solid snacks, however, the CONT+MOTI+WEA feature group

Table 10. Inference results for snack group under SGKF by distinguishing solid vs. liquid snacks. Mean and standard deviation (in brackets) of inference Accuracy, F1, AUROC, and Top-3 Accuracy (all in %) are displayed. The number in brackets in the column of feature groups denotes the number of independent features used in the feature group combination before conducting one-hot encoding. For each metric, the highest mean value is in bold while the second highest value is underlined.

Feature Group (# of Features)	Solid Snacks (8 classes)				Liquid Snacks (3 classes)		
	Accuracy	AUROC	Top-3 Acc.	F1	Accuracy	AUROC	F1
Baseline (Random Guess)	16.7	NA	59.3	16.7	68.0	NA	68.0
Baseline (Majority Class)	21.7	NA	59.3	7.8	81.4	NA	73.1
CONT (7)	28.5 (1.8)	61.1 (2.1)	65.2 (2.5)	18.7 (1.4)	81.8 (3.0)	75.1 (2.9)	43.1 (1.7)
MOTI (20)	44.0 (2.5)	73.5 (1.8)	80.4 (2.3)	29.2 (1.7)	85.6 (2.7)	84.6 (2.2)	60.7 (4.6)
CONT+MOTI (27)	47.7 (1.7)	76.7 (1.3)	82.1 (1.4)	**33.5** (1.3)	87.2 (2.2)	**88.2** (3.2)	**63.2** (4.4)
CONT+DEMO+WEA (19)	27.7 (1.7)	60.0 (2.0)	63.5 (2.3)	18.4 (1.4)	81.7 (3.6)	74.2 (2.5)	42.9 (2.0)
MOTI+DEMO+WEA (32)	44.8 (3.2)	74.5 (1.1)	80.9 (1.7)	30.4 (2.7)	85.3 (3.1)	84.8 (2.8)	57.0 (3.7)
CONT+MOTI+DEMO (34)	47.3 (2.4)	76.7 (1.5)	82.5 (1.9)	33.0 (1.5)	**87.4** (2.5)	87.4 (3.4)	61.6 (4.0)
CONT+MOTI+WEA (32)	**47.9** (2.8)	**76.8** (1.3)	**82.7** (1.3)	33.0 (1.7)	86.9 (2.3)	88.0 (3.0)	61.8 (3.5)
All features (39)	46.8 (2.6)	76.5 (1.6)	82.0 (1.7)	32.2 (1.7)	86.9 (2.8)	88.1 (2.9)	60.2 (3.9)

outperformed other combinations across nearly all metrics, with approximate scores to those when all 10 snack groups are included as in Table 8, and significantly outperforming CONT-only feature group. This finding also suggests that motivation features were the most informative in discerning snack groups of only solid snacks.

6.2.5 Feature Importance and Interpretability Analysis. We assessed feature importance using LightGBM models, focusing on the gain metric in SGKF, as shown in Figure 6. The results confirm that health (FCM_Health) was the most influential feature across both tasks, with substantially higher importance values than other features. Other motivation features, such as habit (FCM_Habit) and pleasure (FCM_Pleasure), also exhibited significant importance. In the nutritiousness inference task, the dominance of health (FCM_Health) was more pronounced, with a larger gap between it and other features. Additionally, features such as BMI, humidity (relative_humidity_2m), temperature (temperature_2m), wind speed (wind_speed_10m), and age (Agein2022) ranked higher than other demographic and weather features. However, contextual features did not exhibit high importance in either task, supporting the notion that they were weaker indicators of snack choices.

Figure 7 presents the SHAP values of the top 20 most important features in the trained LightGBM model with the highest AUROC score under SGKF. For example, health (FCM_Health), which is divided into three classes (1, 2, 3), shows a red area representing class 3, indicating strong health motivation. This red area corresponds to positive SHAP values, meaning that when a snacking episode was motivated by health, the probability of the snack being inferred as nutritious was higher, shifting the output from 0 (Non-nutritious) to 1 (Nutritious). Similar patterns were observed for habit (FCM_Habit) and food freshness (FCM_FoodFreshness), whereas pleasure (FCM_Pleasure) exhibited the opposite trend, suggesting that pleasure-driven motivations were associated with non-nutritious snacks. This SHAP-based interpretability analysis further reinforces the associations identified in the mixed-effects models in Section 4.2. Specifically, the influence of key motivation features remains highly consistent across both results. As illustrated in Figure 7a, health (FCM_Health) exhibits significantly positive SHAP values. This aligns with the statistical analysis in Table 4, where health (FCM_Health) was identified as the strongest predictor for nutritiousness ($t = 51.433$). Conversely, pleasure (FCM_Pleasure) shows negative SHAP values, which is consistent with the significant negative coefficient ($t = -20.632$) observed in the statistical model, confirming that hedonic motivations were primarily associated with non-nutritious snack choices. Furthermore, both results align on the hierarchical importance of features, identifying health (FCM_Health), habit (FCM_Habit), and pleasure (FCM_Pleasure) as the principal factors to infer snack choice, while contextual and weather features exhibit relatively limited influence. This consistency underscores the predominant role of dietary motivations in discerning snacking behavior, demonstrating the robustness of these findings. Furthermore, we extracted absolute SHAP values for data segmented by demographic features, such as BMI, and categorized users into two weight groups, as shown in Figure 7b. The results suggest that for healthy or underweight users, the influence of health (FCM_Health) on the model output was greater than for overweight or obese users, and this trend was reversed for habit (FCM_Habit). This suggests that healthy or underweight individuals were more likely to be motivated by health when choosing nutritious snacks, whereas overweight or obese users were more influenced by habit in their snack choices.

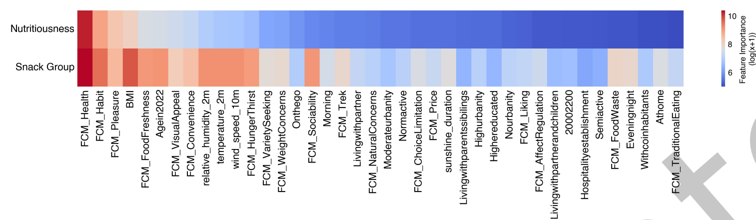
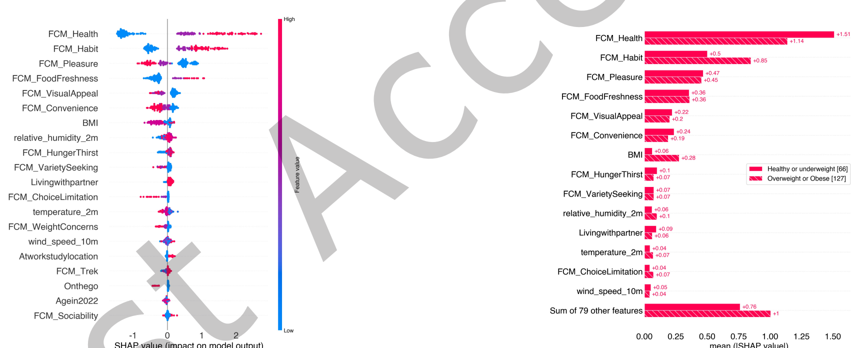


Fig. 6. Average feature importance values computed from all iterations in SGKF in LightGBM models. Only 40 out of 93 features (after one-hot encoding) which had higher feature importance are displayed for visibility.



(a) Summary of features

(b) Comparison of different weight groups

Fig. 7. SHAP values of the features run from the test set in the trained LightGBM model which had the highest AUROC score under SGKF. A positive SHAP value indicates that the feature contributes to increasing the model's output value, while a negative SHAP value indicates that the feature contributes to decreasing the model's output value. In (b), BMI > 25 is regarded as overweight or obese, while BMI ≤ 25 is considered healthy or underweight, and the legend represents the number of snacking episodes belonging to each weight group in the test set.

7 Discussion

In this section, we first summarize the key findings. We then discuss some of the implications for theoretical work on nutrition and behavior and for practical applications. We finally discuss the work's limitations and possible future directions.

7.1 Summary of Key Findings

This study reveals that specific dietary motivations were predominant factors to influence snack choices compared to the other factors (i.e., contextual, demographic, and weather features). Statistical analysis through mixed-effects models (RQ1) identifies motivations such as habit, pleasure, and health as the most significant factors in distinguishing snack groups and nutritiousness. These relationships are further detailed via association rule mining (RQ2), which uncovers high-intensity patterns linking the motivation of sociability to alcoholic beverages (lift = 4.180) and the motivation of health to nutritious intake (lift = 1.926), and suggests a temporal shift in these patterns from the morning to the evening/night. Machine learning (RQ3) confirms the robustness of these findings, with LightGBM classifiers achieving AUROC scores exceeding 80% for both classification tasks under the user-agnostic approach. Feature importance and interpretability analyses further validate that motivations, particularly health-related ones, possess higher predictive power than the other factors.

7.2 Implications for Theories on Nutrition and Behavior

This study presents a computational perspective on the understudied phenomenon of snackification by systematically integrating statistical modeling, association rule mining, and machine learning-based inference. The outcomes of three main analyses were built upon each other and consistent, revealing strong associations between specific motivations and snack choices. We extended the application of association rule mining beyond traditional transaction analysis to health informatics and ubiquitous computing, demonstrating its adaptability and providing valuable insights into possible inference performance. Moreover, we utilized both user-hybrid and user-agnostic approaches, incorporating various feature combinations to enhance model robustness in inferring new users' behavior while facilitating cross-feature comparisons, and then explained the influence of different features on model outputs through SHAP-based interpretability analysis. These methodological insights could be useful to guide future studies to explore variable associations or explain machine learning outcomes.

Theoretically, our findings highlight the central role of motivations in dietary behavior, particularly in distinguishing between nutritious and non-nutritious snack consumption. This aligns with prior studies in behavioral nutrition [46, 89, 96, 110] from a computational perspective and can be interpreted through the lens of the Theory of Planned Behavior [3], which implies that consumers' behavior can be directly affected by their motivations. In contrast to earlier work that associated frequent snacking with negative health outcomes [87], our findings suggest that snacking may contribute positively to nutrient intake when driven by health-conscious motivations.

Although motivation features were proved to be key indicators of snack choices, contextual features, particularly seasonality, were less effective in distinguishing snack groups and nutritiousness. This contrasts with studies suggesting seasonality influences dietary patterns [111, 113], but aligns with other research which found no significant seasonal effects on food consumption behavior [13]. Additionally, while weather features were less informative in our inference tasks, factors such as temperature, wind speed, and relative humidity demonstrated moderate importance, warranting further investigation. The limited influence of weather and seasonality on snacking behavior in this study may be due to the relatively mild seasonal variations in the Netherlands and the predominance of indoor living, which reduces sensitivity to outdoor weather changes [78]. However, the temporal analysis of association rules indicates that day parts could moderate the association intensity between specific motivations and snack choices, with contrasting patterns observed for nutritious vs. non-nutritious choices. This finding aligns with previous research highlighting the context-dependent nature of food choice motives [118], and warrants further investigation into time-aware analysis on subjective motivations, physical contexts, and snacking behavior.

Lastly, we implemented different cross-validation techniques in our inference tasks, with Leave-One-Out cross-validation performing the best on inferring snack groups, while Stratified-Group-K-Fold was optimal for inferring nutritiousness. However, both were marginally outperformed by the user-hybrid approach. This finding suggests that individual habits [91] and characteristics [57] also play a crucial role in snack choice inference. Future studies could build on this insight by developing personalized models that predict users' snack choices based on their unique demographics, characteristics, and longitudinal consumption patterns.

7.3 Practical Implications

7.3.1 Public Initiatives for Nutritional Transparency. Our results provide potentially actionable insights for public health initiatives. We identified distinct associations between health-related motivations (e.g., health, food freshness) and nutritious snacks, as opposed to hedonic motivations (e.g., pleasure, visual appeal, convenience) linked to non-nutritious snacks. Recognizing that consumers are not always aware of the nutritional quality of their snacks, public health agencies and manufacturers could enhance nutritional transparency by standardizing and highlighting snack taxonomy based on nutritional levels on packaging. This would make nutritional information more accessible to consumers. Additionally, labeling snack functions on packages to align with specific consumer motivations, such as using prominent "fresh" labels for snacks appealing to health-conscious consumers, could provide personalized guidance and support informed decision-making. Specifically, manufacturers could implement "fresh" labels based on production timelines for snack groups such as fruit, non-alcoholic beverages, and bread and cereals. To maximize impact, retailers could strategically aggregate these labeled snacks in high-visibility zones where customers could easily spot them, especially during the evening/night when the motivation of food freshness is the most pronounced. Enhancing the availability and visibility of fresh snacks during these hours could provide a timely intervention that aligns healthy consumer motivations with retail environments.

7.3.2 Context- and Motivation-Aware Just-in-Time Adaptive Interventions. Mobile food diary-based interventions could be designed in light of our findings. While the use of mobile ecological momentary assessments (mEMA) has proven advantageous over traditional paper-based methods by capturing real-time consumption and context [9], future systems can evolve from passive data collection tools into proactive intervention interfaces. In Section 5.2.1 and 5.2.2, we identified a strong association between sociability and non-nutritious choices, particularly alcoholic beverages. This highlights social occasions as critical moments for intervention. As smartphone sensors can track daily routines, GPS data, and physical activity patterns, such information could underlie personalized recommendations of healthier snack options for users through just-in-time adaptive interventions (JITAIs) [88, 112]. For instance, future systems embedded with privacy-preserving techniques could detect possible social gatherings by using: GPS to identify the location of the user (e.g., a popular neighborhood with bars), and Bluetooth to estimate the density of devices in the surroundings. This would enable the system to infer the probability of the user situated in a social environment and whether the user is likely to snack [99]. Upon detecting a high probability of a social gathering, the system could trigger notifications before the user starts logging a snacking episode. For instance, the application could recommend substitutes for alcoholic beverages or suggest more nutritious snacks suitable for sharing, thereby converting the socializing context into actionable dietary support. Furthermore, building on the temporal patterns revealed in Section 5.2.3, these interventions could be adaptive to the time of day. Our analysis indicates that social and hedonic motivations are more intensely associated with non-nutritious choices in the morning. Therefore, notifications during morning hours could be direct and prioritize substitution strategies (e.g., suggesting yogurt or fruit). In contrast, evening interventions could focus on reinforcing health goals to facilitate users' concerns about personal health and fitness, as health-related motivations were found to be more prominent during later hours. Finally, personalization can be adaptive to user demographics. In line with Figure 7b, interventions targeting users with higher BMI could prioritize stricter nutritional filtering for substitutes compared to those for users with lower BMI.

7.3.3 ML-Supported Motivation-First Food Diaries. Currently, most mEMA-based food diaries do not require users to record psychological states and often rely on manual process to search, select, and log snacks, and users may still miss entries due to fatigue or time constraints. To address potential omissions, ML-supported systems can enhance data completeness and model accuracy by inferring motivations and identifying probable snack choices. Beyond using physiological signals (e.g., heart rate) or app usage patterns to estimate user states [6, 25, 80], applications can directly integrate motivation logging via a confirmation mechanism. By analyzing current contexts and user behavioral patterns, the system could infer the most likely motivations and present them as a large-button option for one-tap confirmation. This design reduces the barrier to entry and enables the delivery of immediate motivation-driven snack recommendations, when combined with other contexts captured by the sensors. Given the high top-3 accuracy scores (≈0.8) shown in Table 8, the system could highlight the top-3 most likely snack choices on the interface, which will significantly optimize the user experience by reducing the cognitive load of searching. Ideally, these inferences should be personalized based on user demographics and consumption history. For example, if a user confirms a hedonic motivation, the system might initially hide their frequent hedonic choices (e.g., cookies), but immediately offer healthier alternatives (e.g., dark chocolate) alongside them. This approach seamlessly integrates motivation awareness into the user's routine while improving data coverage. Moreover, to maintain long-term awareness, systems could visualize these snack consumption patterns via a dashboard available to the user at will, highlighting the strongest associations between specific motivations and snack choices to encourage user reflection.

7.4 Limitations and Future Work

The studied dataset spans one year, which was collected comprehensively through a dedicated study-oriented smartphone application. Nevertheless, the taxonomy of snack groups could be refined. For instance, non-alcoholic beverages constituted an overly broad category, dominating the snack classifications and thereby reducing multi-class classification performance, particularly for less frequent snack categories. Moreover, each snacking episode in this study was recorded as a single snack, meaning simultaneous consumption of multiple snacks was not accounted for, even when the motivations were identical. Lastly, the majority of participants were women, introducing a potential gender bias in the findings. Future studies should aim to work with data produced by a more balanced participant demographic to improve generalizability.

In this study, we applied one-hot encoding to process most categorical features, which resulted in an excessive number of features, as some categorical variables, such as social environment, had more than 10 classes. To address this, feature engineering techniques, such as Principal Component Analysis (PCA) [1], could be applied before inference tasks to reduce feature dimensionality and improve machine learning efficiency and predictive performance. Furthermore, we primarily employed user-agnostic approaches to compare model performance and identify the most indicative features, without exploring the potential of fully personalized models for mobile application design. Future research should consider developing personalized models that train and test on user-specific data, enabling customized notifications and interventions tailored to individual users.

It is important to note that we focused specifically on snacking behavior among Dutch Millennials. However, behavior can vary significantly based on age [63], gender [46], culture [124], and individual perception [101]. Therefore, our findings are primarily applicable to Dutch Millennials. Future research is necessary, conducting comparative analysis on the relationship between motivations and snack choices among participants from diverse social, geographical, and cultural backgrounds, considering the impact of diversity on machine learning models [58, 61]. Although contextual and weather features showed limited significance in this study, they still hold research value for gaining a deeper understanding of snacking behavior in varying environments.

Moreover, the underlying physiological and psychological mechanisms influencing snack consumers' motivations remain to be fully understood. Questions such as: (1) which objective factors influence current motivations, (2) why hedonic motivations frequently lead to non-nutritious snack consumption, and (3) why certain healthful foods are recognized as snacks, warrant further investigation. Linking subjective motivations to objective and observable factors could contribute to advancing behavioral nutrition research and digital health interventions.

Finally, we believe that the replication of similar longitudinal data collection and analysis initiatives is an important future research direction.

8 Conclusion

In this study, we examined the associations between Dutch Millennials' snack choices (i.e., snack groups and nutritiousness) and their motivations for consumption in various contexts, using mobile food diaries as the sole data collection method. This research is situated within the contemporary "snackification" trend, emphasizing the role of mobile-based dietary tracking in understanding motivation-aware snacking behaviors. We applied association rule mining, and binary and multi-class classification, leveraging both user-hybrid and user-agnostic approaches to identify the most significant features influencing snack choices. Our findings show that motivation features were effective in inferring both 10-class snack groups and binary nutritiousness, with slightly improved performance when combined with contextual features. Feature importance analysis further revealed connections between health-conscious motivations and nutritious snacks, as well as between hedonic motivations and non-nutritious snacks. In contrast, contextual, demographic, and weather features were found to be less informative in predicting snack choices. These insights have practical implications for public health initiatives and digital dietary interventions. Furthermore, our findings underscore the potential of mobile devices as behavioral intervention tools, capable of delivering real-time notifications when specific snacking motivations are expressed, thereby encouraging healthier dietary choices. Finally, our study provides a foundation for future research integrating mobile food diaries with wearable devices to enrich data dimensions and improve inference performance.

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