A Conceptual Model for Mobile Health-enabled Slow Eating Strategies

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ABSTRACT

Ingestive behaviors (IBs) (eg, bites, chews, oral processing, swallows, pauses) have meaningful roles in enhancing satiety, promoting fullness, and decreasing food consumption, and thus may be an underused strategy for obesity prevention and treatment. Limited IB monitoring research has been conducted because of a lack of accurate automated measurement capabilities outside laboratory settings. Self-report methods are used, but they have questionable validity and reliability. This paper aimed to present a conceptual model in which IB, specifically slow eating, supported by technological advancements, contributes to controlling hedonic and homeostatic processes, providing an opportunity to reduce energy intake, and improve health outcomes.

Keywords: ingestive behaviors, eating behaviors, slow eating, energy intake, mHealth (*J Nutr Educ Behav.* 2023;55:145−150.)

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INTRODUCTION

Self-monitoring of eating behaviors (EB) may be among the most valuable approaches for individuals to pursue healthy changes in eating habits.[1] Changes in EB may help reduce obesity, a chronic and progressive disease associated with an increased risk for comorbidities that carry significant psychosocial and economic consequences.[2] An EB that has had limited research attention is health monitoring of momentary timescales ingestive behavior (IB) processes, such as the number of chews per bite (chew-bite ratio), the pause duration between chews or bites, and bite sizes, referred to as the microstructure of eating. The lack of accurate automated measurement capabilities in free-living settings has made this monitoring difficult to attain until recently. Eating at a slower pace can have a meaningful impact on enhancing satiety, promoting fullness, and decreasing food consumption.[3] Incorporating technology to support health monitoring and interventions will likely lead to key advances. We offer a conceptual model in which IBs (bites, chews, oral processing, swallows, pauses) can contribute to reduced energy intake. The influential role of technology in the tracking of IB is explained. In light of the model, we emphasize 3 important themes: (1) the current need for further technological advancement for tracking and monitoring EB, (2) the potential value that passive and accurate assessment may have on promoting individuals' awareness of EB, and (3) the salience of assessment and awareness for behavior change and improvement of health outcomes.

DISCUSSION

Based on data collected in the National Health and Nutrition Examination Survey from 2013−2016, 49.1% of US adults tried to lose weight in a given year, and overall, 66.7% of adults with obesity tried to lose weight.[4] The methods of weight loss are various, but the majority report dieting and physical activity, 2 major modifiable contributors to obesity for individuals.[5] Interventions to reduce obesity have strategies aimed at weight loss treatment[5] and may be composed of 1 or more of 3 main items: lifestyle interventions promoting healthy dietary and physical activity behaviors, pharmacologic therapy as an adjunct to lifestyle modifications, and bariatric and metabolic surgery.[6] For example, lifestyle modifications, even when modest (ie, 3% to 5% weight loss), produce clinically significant health benefits, such as reduction in triglycerides, blood glucose, hemoglobin A1c, diabetes development, and blood pressure.[2] Although the benefits of these approaches are well-documented in the literature, few clinicians can offer appropriate care,[7] and only a minority of people with obesity receive an intervention.[8] For

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example, only 0.4% of patients who qualify for bariatric surgery, based on the National Institute of Health, undergo surgery,[9] and lack of insurance coverage for pharmacotherapy leaves individuals with an inviable out-of-pocket cost.[10] On the contrary, 2.5 billion people worldwide owned a smartphone by 2019,[11] and by 2017, > 50% of them downloaded mobile health (mHealth) applications,[12] which are defined by the National Institute of Health as the use of mobile or wireless devices, such as cell phones and tablets, to improve health outcomes, health services, and research. The number of mHealth applications related to health and fitness exceeded 325,000 in 2017,[13] and in the US, > 60% of patients manage their health using mHealth applications,[14] illustrating that there is enough interest in using devices to assist with behavior change. Health monitoring, such as frequent monitoring of body weight and physical activity time, is a valuable strategy for changing weight-related behaviors.[2,15] Mobile health (mHealth) devices that offer passive physical activity monitoring (ie, do not require manual input using pen and paper or data entry into an application) from the user are widely available, offer easy monitoring, and can be a tool for exercise behavior change. However, passive monitoring devices for diet and IB are lacking. Crucial research and clinical needs justify the potential benefit that IB monitoring can aggregate to approaches central to reducing obesity and associated comorbidities.

Empirical studies have shown that individuals can achieve a more satisfactory regulation of hunger (homeostatic state), desire to eat (hedonic state), and satiety (homeostatic and hedonic states) by slowing down their eating rate.[3] Because of these states' important roles as potential moderators of energy intake, we have selected them as the drive states in our conceptual model of EB.

Our conceptual model of EB (Figure) integrates multiple aspects of the eating experience, such as the macrostructure and food type, in which technology holds potential for passive monitoring, but it centers on how IB modulates the key drive states of hunger, desire to eat, and satiety (see right). The eating behavior process is initiated by these states, and awareness of their occurrence can lead to a more or less automatized eating behavior. This model illustrates a system in which drive states are likely to be controllable through improved IB.

Because energy intake and energy expenditure to obesity are interrelated, and the contribution of energy intake on active weight loss may have a greater influence than exercise,[16] many strategies for weight management include efforts to promote and maintain the individual's energy balance (avoiding chronically positive energy balance) by tracking dietary intake and improving nutritional quality.[17] In addition, positive physiological changes have been associated with reduced energy intake in mammals, such as the reduced risk of cardiovascular disease and diabetes, and in humans, overeating may promote type 2 diabetes and cardiovascular disease.[18]

Much of the literature about EB is devoted to the macrostructure aspects (ie, portion sizes, the timing of meals, other eating experiences, and food types) and, to a lesser extent, to IB (microstructure). For example, public health authorities suggest reductions in sugar, fat, and salt intake[19] but rarely consider the functional role of IB on homeostatic and hedonic regulation and impacts on food intake and choices. This important point is explored in the following paragraphs. Moreover, dietary self-monitoring is associated with weight loss success and has been one of the principal elements of behavioral weight loss programs,[17,20] and more frequent self-monitoring is associated with improved outcomes.[1,21] Traditional methods for tracking include tools such as 24-hour dietary recall, food frequency questionnaires, and food records. Tracking provides information regarding energy intake and nutrient distribution, aiming to channel participants' self-regulation of EB, and is vastly used by nutrition professionals, researchers, and at the individual level.[17,22] Self-regulation can increase awareness of dietary behaviors and may predict healthy dietary behaviors.[22]

Historically, the standard approach to assessing dietary intake and behavior relies on self-reporting tools, which are prone to biases and errors.[23] Keeping records of food consumption for days to months to indicate dietary intake by the individual can be daunting. The usual intake is what most professionals are interested in, but people grow tired of the burden of tracking food intake for long periods.[20] Furthermore, most consumers have difficulty estimating portion sizes,[24] many lack skills and knowledge regarding the vast array of food types and contents when others prepare, and underreporting may occur because of social desirability or lack of clear memory of actual consumption.[25] Studies have shown that people with obesity, in particular, underreport dietary energy intake.[26] Such research suggests that dietary studies should include independent measures of validity,[27] reinforcing the need for new approaches to passive, accurate, and objective measures to assess dietary and EB. In addition, the time and cost associated with estimating the composition of food records and recalls make the process challenging.[20,28,29] The question is why we still rely on self-reported methods that have validity dependent on the accuracy of the report, which is well known to be misreported in adults and children.[26,27,30]

Automated dietary monitoring (ADM) devices promise easier tracking and monitoring and real-time feedback on behaviors.[31] We can already track bites and chews through various techniques, such as the bite counter, a device worn on the wrist that uses bite count to estimate kcal intake without the need for journaling food intake, and the gold standard universal eating monitor,[32] albeit with limitations to accuracy and practicality, especially in free-living situations. More research is needed to ensure that the devices come to be accepted more widely in practice. Challenges with ADM include accurate detection of eating activities (ie, without falsely detecting noneating activities as eating activities),[33] passive participation (ie, without the individual having to

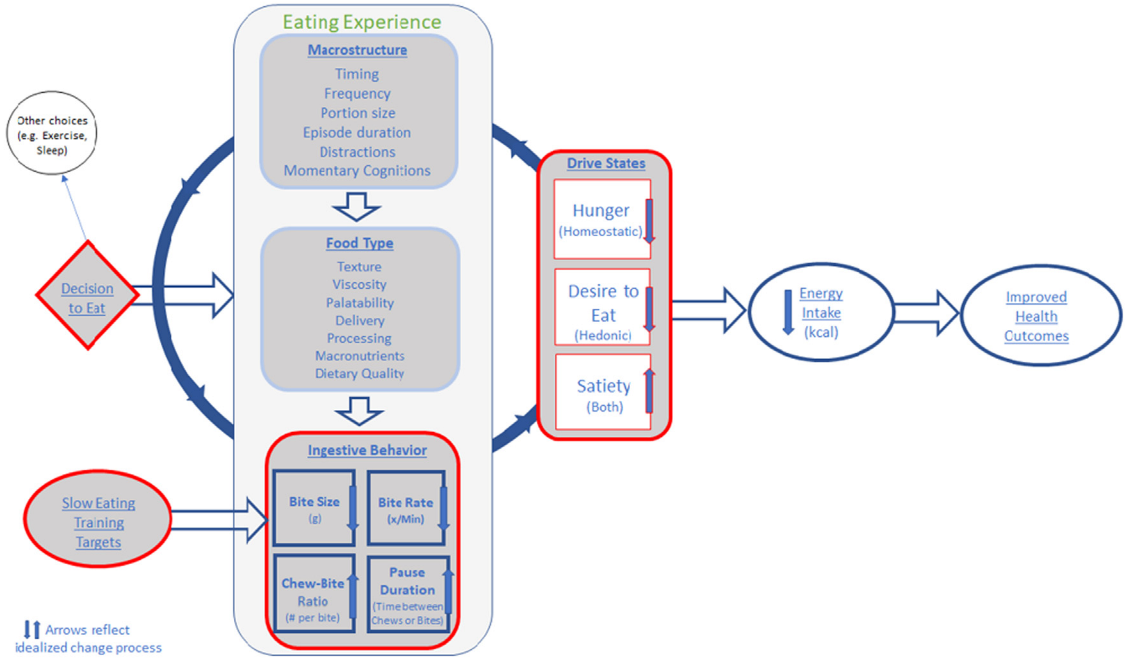

Figure. A conceptual model of eating behavior stressing the role of ingestive behaviors.

turn a device on and off), battery life, and practicality. Some ADM approaches have shown encouraging performance but require impractical and burdensome sensors such as large neck collars for swallowing detection and microphones inside the ear canal for chewing detection. Popular smartphone applications aimed at food journaling that are widely available also present their challenges. For example, users of a popular mobile application (MyFitnessPal; Under Armour, 2011) omitted a mean of 18% of food items, including those with energy-dense and low-nutritional value, causing a mean underestimation of energy intake of 1863 kilojoules, partly because of confusing portion sizes and time-consuming data entry, and only 20% of users said they would continue using the application because of issues in matching foods, estimating portion size, and time consumption.[34] This aligns with other studies that have indicated that regardless of the method used by the participant to monitor dietary intake, the number of d/wk participants tracked was low,[20,31] reinforcing the need for advancements of mHealth for devices that require passive participation to decrease attrition that occurs when participants use technology.[35]

Consistent with broader approaches in the mHealth field, our framework includes potential technologies to go beyond providing increased measurement accuracy and decreased attrition by detecting IB in free-living settings. Such technologies could alert the person about a certain modifiable behavior, such as eating rate, in real-time so that the behavior can be modified at the time of action. Tracking dietary intake allows the person to learn about their caloric intake and nutrient breakdown, but it does not necessarily help the person with strategies to promote and become attuned with homeostatic and hedonic processes, improving meal satisfaction and consequently helping regulate energy intake.

Traditional methods of measuring food intake may be helpful to understanding nutrient intakes and their associations with health outcomes, but they do not focus on other important aspects of eating, IB, possibly because of insufficient measurement technology available in the real world.[36] Modifying integral processes of the microstructure of IB in such a way as to slow overall eating pace is likely to enhance satiety, enjoyment, and memory of eating and reduce hunger and energy intake.[3,37–39] This holds promise for effective weight management strategies if brought to the attention of the individual regularly.[3,39] So, how does becoming aware of the microstructure of eating and meal composition assessment help with obesity prevention and treatment, and why should researchers invest in advancing the technology from laboratory experiments to the real world?

Satiety regulation is complex, with multiple interconnected systems working in conjunction. On initiation of an eating episode (meal, snack, nibbling), food is brought to the mouth, and a bite is taken. Bites can vary greatly in size,[40,41] which can introduce significant variability in energy intake, but this has not been studied in free-living settings because of a lack of accurate technology to measure it. Chewing, or mastication is integral to oral processing following a bite.[39] Mastication is associated with the promotion of satiety and with decreased food intake.[42,43] Chewing allows the mechanical process of breaking down food into nutrients, which conduces gut signaling, controls transit time, and the digestive and absorptive processes.[44] This pathway involves hormones, enzymes, and neurochemicals that naturally occur in the body without one's interoceptive awareness. The stimulation provided by the muscular and oro-sensory processes of chewing and the release of foods' nutrients are stimuli for the release of satiety hormones, such as cholecystokinin,[45] glucagon-like peptide-1, peptide-YY, and insulin.[46,47] The complexity of mastication and associated physiological responses are explained in detail elsewhere.[43,44] Increasing mastication (chewing) is 1 component of IB that can slow down the eating rate and contribute to a cascade of physiological mechanisms contributing to satiety.[48,49] Other components include taking smaller bites, pausing between bites and chews, and decreasing bite sizes.[3] Previous studies have shown that eating rates can impact the overall energy intake of an individual, and a 20% change in eating rate can alter the energy intake by between 10% and 13%,[50] and profiling eating rate may be a useful way to assess the effects that eating rate has on energy intake.[51] People who consume foods at a slower rate tend to have reduced energy intake,[3,52] and people who eat at faster rates have higher energy consumption[37,53] and may be at risk of overconsumption. Furthermore, faster eating rates have been associated with higher body mass[54,55] and risk factors for chronic diseases.[56,57]

It is important to note that solely prolonging meal duration is different than practicing modified IB, which includes all aspects of IB by modifying bite sizes, the number of chews, oral processing time, and pauses between bites and swallows as these techniques work in conjunction to successfully decrease eating rate, reduce food intake and promote satiation.[52] For example, if only 1 IB is modified, meal duration is increased, but bite rate and size are not modified, and the chew-bite ratio is not increased, energy intake may not be decreased. The point relevant to this perspective paper is that IB is largely understudied, particularly outside of laboratory settings, mainly because of a lack of technology. As the possibility for advanced automated technology emerges, it will enable leveraging of this potentially valuable tool for helping people modify hedonic and homeostatic processes of food intake regulation and raise awareness of everyday EB that may increase the risk for excess energy intake or poor dietary quality.[41,52,55] We also note that several concerns concerning privacy, anonymity, participant consent, and data security arise with these approaches; these have been chronicled in the literature as safe, user-sensitive techniques continue to evolve.[58,59]

The association between eating rate and energy intake is evident, and over the years, researchers have explored various methods for detecting IB, such as using sensors embedded in smartwatches to detect intake gestures, leveraging earphones to detect eating sounds, and developing new sensors for detecting intraoral activities.[60,61] However, broader accessibility to ways of measuring and establishing norms and standards of such EB in free-living people has not yet been attained. Although this may seem daunting for professionals, the first step would be to increase awareness of times and situations that put individuals at risk for rapid IB and overconsumption. That starting point will offer practitioners and their patients/clients a baseline from which to make appropriate changes. Including such technological advances of IB monitoring in weight management strategies may help them achieve their full potential.

IMPLICATIONS FOR RESEARCH AND PRACTICE

Assessing IB components of EB with the advancement of accurate technology for long-term free-living studies can help researchers improve their knowledge about how people eat, an underused and understudied area to date. Our conceptual model presents IB as a tool to control key drive states (hedonic and homeostatic) that are consequent to slow eating, potentially promote a reduced overall energy intake and ultimately improve health outcomes. Technological advancements are pivotal to allow for passive and accurate monitoring of EB, especially IB, and to make it possible to personalize interventions, making these tools widely accepted in practice, thus, promoting opportunities for behavior change. Detailed tracking of IB components in real-time holds promise for the field to advance toward new treatment modalities.

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