Route Recommendation for Healthcare by Reducing Approach Bias as a Food Desire

First Author[1][0000−0002−0399−1079], Second Author[2][0000−0001−8181−3465], Third Author[3][0000−0002−4695−6417], and Fourth Author[1][0000−0003−2627−6673]

[1] Kyoto Sangyo University, Kyoto, Japan
{i2486228,kawai}@cc.kyoto-su.ac.jp
[2] Yamaguchi University, Ube, Japan
y.wang@yamaguchi-u.ac.jp
[3] Kyoto Institute of Technolog University, Kyoto, Japan
spanote@kit.ac.jp

Abstract. In recent years, the increase in lifestyle-related diseases has become a significant global health issue, requiring effective methods to improve daily life. This study proposes a route recommendation method to reduce 'Food Approach Bias' (e.g. food desire) during daily activities such as jogging or walking for health care. Food approach bias refers to the cognitive and behavioral bias in which individuals either "choose" or "avoid" food. According to the route recommendation for health care, it is unrealistic to avoid ubiquitous food shops, cafes, or restaurants. To solve this problem, our proposed method recommends shops on the route, such as cafes or restaurants, based on the user's taste (specifically those with low calories), based on the users' obesity levels and their logs' histories of shop choices on the routes. The recommendation also aligns with three types of activities: normal walking, brisk walking, or jogging. This paper describes this recommendation approach, focusing on mitigating the Food Approach Bias relative to obesity levels, and evaluates the impact of user desire for food after the activity by recommending four types of shops on the routes, such as user tastes with high-calorie or low-calorie shops and opposite tastes with high-calorie or low-calorie shops.

Keywords: Route Recommendation · Food Approach Bias · Health Care.

1 Introduction

In recent years, there has been a global focus on promoting healthier and more economical lifestyles, including health promotion and the prevention of lifestyle-related diseases. In particular, there is a growing need to improve lifestyle habits that can lead to disease. According to the Ministry of Health, Labour and Welfare of Japan, the number of patients with lifestyle-related diseases is increasing, underscoring the fact that individual lifestyle choices have a significant impact on disease incidence. In line with this trend, there is a demand for more effective lifestyle improvement strategies and support systems based on scientific evidence. At the same time, companies such as Link and Communication Co., Ltd. and Toshiba Corporation[4] are advancing the development of applications that use AI technology to predict risks associated with lifestyle-related diseases and provide personalized advice on lifestyle changes. Although current research provides guidance based on the user's lifestyle and health status, including recommendations for appropriate exercise and dietary habits, it falls short of providing comprehensive support for lifestyle changes that align with the user's daily awareness and desires.

In this study, we propose a route recommendation method during exercise that aims to address the basic strategies for lifestyle-related diseases, specifically addressing insufficient physical activity and preventing overeating. The method focuses on increasing the metabolic rate of exercise while reducing food approach bias. This study personalizes recommendations based on the user's specific condition, such as obesity or diabetes, by calculating the distance and speed of movement required. It mitigates food approach bias, which is influenced by personal preferences and restaurant popularity, by recommending routes to shops based on physical activity levels. For example, for overweight users who enjoy sweets, the system can suggest a route to a coffee shop instead of a high-calorie cake shop, increasing the distance traveled and metabolic activity. These recommendations aim to mitigate the effects of food approach bias and increase metabolic rate, thus promoting health.

2 Related Work

In this section, we explore the integrated role of eHealth, machine learning, and food approach bias in improving lifestyle-related diseases.

2.1 EHealth to Improve Lifestyle-related Diseases

Research focused on improving lifestyle-related diseases began in the 1980s [8] and has recently seen a surge in popularity with the applied use of digital technology for data analysis and the development of innovative approaches. Aida et al. [1] investigated the impact of visual e-health interventions, such as educational videos and films, on improving public health literacy to help address lifestyle diseases. Similarly, Cardol et al. [2] detailed the creation of eHealth pathways tailored for patients with these diseases, using the BCW framework and collaborative design to create screening tools and self-management modules that address psychosocial and lifestyle challenges. Xu et al. [11] explored how a mobile app supports the creation and execution of physical activity plans by analyzing the impact of historical planning records on behavior, revealing insights and trends that inform improvements in planning support. Tamaki et al.

[4] https://www.global.toshiba/jp/news/corporate/2023/01/news-20230131-01.html

[9] proposed a system designed for non-diabetic individuals that predicts blood glucose levels based on images of meals before consumption and recommends against meals that would cause significant increases in glucose levels.

2.2 Machine Learning for Improving Lifestyle-related Diseases

In recent years, with the rapid advancement of computer processing speed, the field of health information analysis using machine learning techniques has experienced significant development. Active research is being conducted on the use of machine learning to improve dialogue and visualization methods for improving lifestyle-related diseases. Iguchi et al. [4] developed a Bayesian network model that integrates lifestyle questionnaires with health examination results to promote better lifestyle habits. In addition, Fukuzawa et al. [3] have been instrumental in promoting outdoor exercise activities by developing an application that visualizes unhealthy levels and supports indoor exercise routines. A notable aspect of this research is the use of machine learning technologies to create systems that uniquely respond to the health status of users. Moreover, Tsunekawa et al. [10] proposed an innovative method for predicting the onset of non-cancerous lifestyle-related diseases by analyzing data from regular health check-ups. The precision and recall of the proposed method were 0.32 and 0.89, respectively. Compared with a baseline that sets thresholds for each examination item and considers their logical sum, it was found that much higher precision could be obtained while maintaining recall. Sivaraman et al. [7] describes a novel decision support interface for sepsis management, demonstrating the potential of AI to improve patient outcomes in critical care. [6] presents a machine learning model that classifies obesity levels based on lifestyle factors, excluding traditional metrics such as BMI, to explore how lifestyle choices affect weight categorization, achieving an accuracy of 75% in its predictions.

2.3 Food Approach Bias

Recent studies have focused extensively on the concept of food approach bias, a cognitive and behavioral pattern characterized by the tendency to choose or avoid certain foods. In their detailed investigation, Kahveci et al. [5] identified several key factors that influence this bias: food deprivation, the caloric content of foods, and individual taste preferences. Notably, their findings revealed that neither food deprivation nor the caloric value of foods significantly affected this bias. In contrast, personal taste preferences were found to play a critical role, predominantly facilitating the choice aspect of the bias, while not significantly affecting the avoidance aspect. This research leads to the conclusion that, within the realm of food approach bias, individual preferences are likely to be the primary drivers of choice behavior, overshadowing the effects of opportunity deprivation.

Building on these findings from the research of Sercan et al., our current study explores innovative methods to simultaneously increase metabolic rate during physical activity and reduce cognitive biases related to food choices. Specifically, we are focusing on tailoring interventions to individual preferences and desires, and strategically recommending appropriate food shops to facilitate more effective lifestyle changes and improvements in the management of lifestyle-related diseases.

3 Implementation of Route Recommendation

The system takes into account metabolic rate and food intake bias based on the severity of lifestyle-related diseases. The system begins with the user entering personal information and selecting the specific lifestyle-related disease they wish to improve. Initially, the steps of distance calculation and Point-of-Interest (POI) extraction are depicted in Figure 1. The detailed steps are as follows:

(1): The shortest route is generated using the Google Maps API, followed by the calculation of an appropriate exercise distance based on the user's BMI index.

(2): All shop information within the rectangular area of the departure and destination points is extracted, and the average calorie count for each shop is computed.

(3): Low-calorie shops are selected as POIs based on the user's BMI. This allows the user to prioritize the presentation of low-calorie establishments.

(4): The process consists of classifying POIs according to food preferences (e.g., sweet, salty, Japanese taste, Western taste, etc.).

(5): The POIs extracted according to food preference are sorted according to the calorie level, and the top 2 POIs that satisfy the exercise distance are recommended to the user.

(6): Allowing the user to select one POI and generate a route. During first-time use, the user's selection is recorded in the system and used as feedback, but no preference-based recommendation is made at this stage. Instead, the system only suggests low-calorie shops to help the user make health-conscious route choices.

In subsequent uses, the system uses the recorded selections to recommend shops in categories that match the user's preferences among the low-calorie options. This allows the user to select shops that closely match his or her preferences, resulting in more personalized route recommendations the next time the application is used.

Fig. 1. A route recommendation application interface with six steps: (1) Generating the shortest route and calculating the distance based on the movement method instead of BMI. (2) Extracting all POIs within a rectangle. (3) Extracting low-calorie POIs based on BMI. (4) Classifying POIs according to food preferences (sweetness, saltiness, Japanese taste, Western taste). (5) Generating routes via POIs with the lowest calories in each category and recommending the top 2 closest routes to the route calculated in step (2). (6) User selects one POI from the two recommended routes (the route is selected) → Updating history.

3.1 Food Shop Extraction Using Food Approach Bias

This research highlights the importance of promoting healthy eating habits as a critical aspect of combating lifestyle-related diseases. The study focuses on "food approach bias," a tendency to automatically favor certain types of foods. By understanding and managing this bias, we can encourage healthier food selections. We propose a system designed to analyze individual food selection records, focusing specifically on the food approach bias, and to suggest personalized healthy food options based on these records.

The system operates by collecting and analyzing the user's past food selections. It then makes recommendations aimed at shifting the user from a bias toward high-calorie foods to healthier alternatives. For example, for users who prefer sweet, high-calorie desserts, the system would suggest lower-calorie substitutes.

When calculating food shop ratings, the system takes into account several key factors: the individual's BMI, food preferences, and past food selections. The methodology is designed not only to promote a healthier lifestyle but also to encourage healthier food choices that match the user's preferences. The first step is to analyze the individual's BMI index and food preferences. This analysis helps to understand the user's physical health and dietary preferences, and forms the basis for personalized healthier eating recommendations. Importantly, the system strives to provide options that not only address health considerations but also fit the user's preferences and lifestyle. The next step is to analyze the user's past food selections. Based on this analysis, the system makes recommendations that guide the user toward healthier food options while taking into account their existing preferences. The methodology is designed not only to promote a healthier lifestyle, but also to encourage healthier food choices that match the user's preferences. By integrating these factors, the system calculates a food shop rating that suggests healthy food selections that are appropriate for each user and meet their individual preferences. This approach effectively guides users toward healthier eating habits, taking into account their unique needs and preferences.

For example, if a user prefers cosmetics, the system would recommend a drugstore instead of a ramen shop. For users who prefer sweets, the system would suggest cafes with lower-calorie options, providing healthier choices. This approach proposes a new way of recommending food shops that effectively balances individual preferences with a healthy lifestyle, making it easier for users to make informed decisions that align with their health goals.

4 Consideration and Evaluation of POI Extraction According to Food Approach Bias

In this study, we explore the influence of individual taste preferences on food choices to anticipate the extraction of POIs in the context of reducing food approach bias. Personal preferences, particularly in the area of dietary choices, have a significant impact on daily decisions that are closely related to health

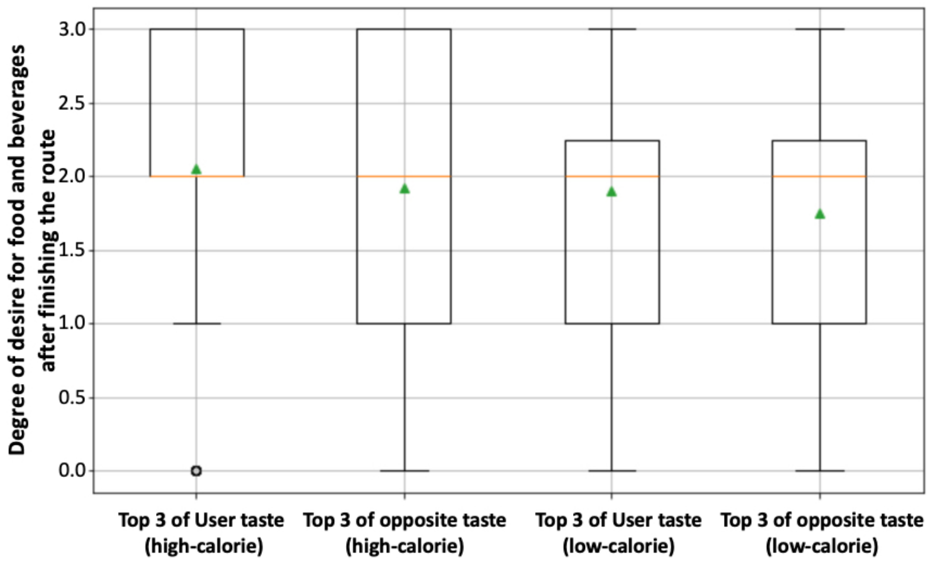

Fig. 2. Impact of personal preferences on food desires: a box-and-whisker plot analysis.

and lifestyle. Our research examines how preferences for sweet, salty, Japanese, and Western cuisines affect food choices in specific scenarios. We focus on the choices offered by restaurants along specific routes in Kyoto City. These routes are categorized based on their alignment with the user's preferences and their assigned rating values: the highest and lowest rated routes that match the user's preferences and the highest and lowest rated routes that do not match the user's preferences. The rating value is determined by calculating the optimal caloric intake for a meal, taking into account the user's personal information such as age, gender, height, weight, and daily activity level. The study involved 20 university students in their 20s, including 12 males and 8 females, all of whom had previous experience using the route recommendation application. They answered questions about their preferences for sweet, salty, Japanese, and Western foods. They then made food choices and rated the results of those choices at the end of routes determined by their preferences.

The evaluation targets were the choices presented to the participants upon reaching food establishments along specific routes in Kyoto. First, the participants selected their preferences. Preferences were selected from "sweet" or "salty" and "Japanese" or "Western." Finally, after reviewing each route and shop information, participants selected "what food they would like to have when they arrive at their destination." For example, if the preference was sweet, participants would rate on a four-point scale (very much want, want, not much want, not at all want) whether they would like to have food with a sweet taste (according to their preference).

Figure 2 shows a box-and-whisker plot that captures the impact of personal preferences on the desire for foods. The results indicate a significant increase in food desires when participants navigated routes that included their three most preferred options. In contrast, strategically suggesting the three least preferred options, contrary to the user's preferences, resulted in a significant decrease in food desires. These findings underscore the significant influence of personal preferences on everyday food choices and illustrate how these preferences can guide decision-making in specific situations and potentially have a profound impact on consumers' health and lifestyles.

This study deepens our understanding of consumer behavior by highlighting the critical role that personal preferences play in determining food choices. Furthermore, the study suggests that strategically suggesting less preferred food options can effectively mitigate users' inherent food desires.

5 Conclusion

In this study, we proposed a method for extracting shops that aims to reduce food approach bias while increasing metabolic rate during physical activity. Based on walking time, the system calculates the exercise distances for different activities, such as brisk walking and jogging, to increase metabolic rate. In addition, by identifying shops near the shortest route and calculating their calories, it effectively recommends shops based on user preferences and creates appropriate routes.

Future research will focus on evaluating user response and satisfaction with these routes. The collection and statistical analysis of actual user data from the proposed system will facilitate more tailored health promotion advice. Additionally, we plan to explore other ways to extract points of interest (POIs). To improve the prediction of POI extraction, especially in the context of reducing the food approach bias, we will explore different shapes for extracting shop information. The current method extracts all shop information within a rectangular area from origin to destination, which can be limiting. Future research will consider using different shapes, such as extending beyond the destination point, to allow the system to build "better" routes. Furthermore, we plan to investigate how preferences influence choices, to improve POI extraction predictions, especially in the context of reducing food approach bias.

Acknowledgments. This work was partially supported by JSPS KAKENHI Grant Numbers JP23K24955, JP20H00584, and the Institute of Advanced Science and Technology, Kyoto Sangyo University (M2001).

References

1. Aida, A., Svensson, T., Svensson, A.K., ll Chung, U., Yamauchi, T.: ehealth delivery of educational content using selected visual methods to improve health literacy on lifestyle-related diseases: Literature review. JMIR Mhealth Uhealth **8**, 12 e18316 (2020)

2. Cardol, C.K., Tommel, J., van Middendorp, H., Ciere, Y., Sont, J.K., Evers, A.W.M., van Dijk, S.: Detecting and treating psychosocial and lifestyle-related difficulties in chronic disease: Development and treatment protocol of the e-goal ehealth care pathway. International journal of environmental research and public health **18**, 6 3292 (2021)
3. Fukuzawa, T., Sugimura, H., Isshoku, M.: Proposal for a support system for prevention of lifestyle-related diseases using wearable devices. In: The 84th National Convention of IPSJ, 5ZA-03 (2022)
4. Iguchi, T., Yoshino, T., Takagi, T., Koike, H.: Proposal of a bayesian network model combining a medical questionnaire and medical checkup results for improving lifestyle diseases. In: Information Processing Society of Japan Kansei Branch, G39 (2022)
5. Kahveci, S., Meule, A., Lender, A., Blechert, J.: Food approach bias is moderated by the desire to eat specific foods. Appetite **154**, 104758 (2020). https://doi.org/https://doi.org/10.1016/j.appet.2020.104758, https://www.sciencedirect.com/science/article/pii/S0195666320302749
6. Khater, T., Tawfik, H., Singh, B.: Machine learning for the classification of obesity levels based on lifestyle factors. In: Proceedings of the 2023 7th International Conference on Cloud and Big Data Computing. p. 28–33. ICCBDC '23, Association for Computing Machinery, New York, NY, USA (2023). https://doi.org/10.1145/3616131.3616135, https://doi.org/10.1145/3616131.3616135
7. Sivaraman, V., Bukowski, L.A., Levin, J., Kahn, J.M., Perer, A.: Ignore, trust, or negotiate: Understanding clinician acceptance of ai-based treatment recommendations in health care. In: Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems. CHI '23, Association for Computing Machinery, New York, NY, USA (2023). https://doi.org/10.1145/3544548.3581075, https://doi.org/10.1145/3544548.3581075
8. Sugimoto, K.: Prevalence of anemia and improvement of eating habits in yamato kohgenrural districts or nara prefecture [jn japanese]. Journal of Nara Medical Association pp. 361–376 (1989)
9. Tamaki, R., Fujimoto, M., Suwa, H., Yasumoto, K.: Data analysis for developing blood glucose level control system. In: Adjunct Proceedings of the 2021 International Conference on Distributed Computing and Networking. p. 104–109. ICDCN '21, Association for Computing Machinery, New York, NY, USA (2021). https://doi.org/10.1145/3427477.3428191, https://doi.org/10.1145/3427477.3428191
10. Tsunekawa, M., Oka, N., Araki, M., Shintani, M., Yoshikawa, M., Tanigawa, T.: Prediction of the onset of lifestyle-related diseases using regular health checkup data. In: The 33rd Annual Conference of the Japanese Society for Artificial Intelligence, 2019, 4D3-E-2-05 (2019)
11. Xu, K., Yan, X., Newman, M.W.: Understanding people's experience for physical activity planning and exploring the impact of historical records on plan creation and execution. In: Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems. CHI '22, Association for Computing Machinery, New York, NY, USA (2022). https://doi.org/10.1145/3491102.3501997, https://doi.org/10.1145/3491102.3501997