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Challenges of diet planning for children using artificial intelligence

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ABSTRACT

BACKGROUND/OBJECTIVES: Diet planning in childcare centers is difficult because of the required knowledge of nutrition and development as well as the high design complexity associated with large numbers of food items. Artificial intelligence (AI) is expected to provide diet-planning solutions via automatic and effective application of professional knowledge, addressing the complexity of optimal diet design. This study presents the results of the evaluation of the utility of AI-generated diets for children and provides related implications.

MATERIALS/METHODS: We developed 2 AI solutions for children aged 3–5 yrs using a generative adversarial network (GAN) model and a reinforcement learning (RL) framework. After training these solutions to produce daily diet plans, experts evaluated the human- and AI-generated diets in 2 steps.

RESULTS: In the evaluation of adequacy of nutrition, where experts were provided only with nutrient information and no food names, the proportion of strong positive responses to RL-generated diets was higher than that of the human- and GAN-generated diets ($P < 0.001$). In contrast, in terms of diet composition, the experts' responses to human-designed diets were more positive when experts were provided with food name information (i.e., composition information).

CONCLUSIONS: To the best of our knowledge, this is the first study to demonstrate the development and evaluation of AI to support dietary planning for children. This study demonstrates the possibility of developing AI-assisted diet planning methods for children and highlights the importance of composition compliance in diet planning. Further integrative cooperation in the fields of nutrition, engineering, and medicine is needed to improve the suitability of our proposed AI solutions and benefit children's well-being by providing high-quality diet planning in terms of both compositional and nutritional criteria.

Keywords: Children; dieticians; artificial intelligence; diet planning

INTRODUCTION

Preschoolers spend a large portion of their time in out-of-home childcare, which consumes approximately half to 3-quarters of their daily energy intake outside the home [1,2]. In the

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Organization of Economic Co-operation and Development (OECD) countries, over 80% of children aged 3–5 yrs participated in early childhood education and care [3]. Because the social participation of mothers has increased in developed countries, daycare service attendance rates have also shown a significant increase. Early childhood is a critical period for the prevention of diet-related diseases [4,5] and the development of food preferences and dietary patterns [6,7]. Therefore, not only families, but also childcare centers have a responsibility to provide healthy and safe meals, and these roles should be managed by nutrition and dietetics practitioners in childcare services [8,9].

Previous studies have suggested that health efforts and expert-led interventions are warranted to support healthy eating programs and practices in early childcare settings [10,11]. In South Korea, nutrition and meal planning guidelines are regulated and provided to childcare centers in consideration of the optimal nutrition standards for the growth and development of young children, including healthy dietary habits and food safety. However, the implementation of these dietary guidelines in childcare menus is challenging [12,13]. Among the requirements to the implementation of dietary guidelines, including knowledge, skills, social influence, and environmental context [14], the lack of human resources remains significant. In South Korea, most childcare centers do not have dedicated on-site registered dieticians capable of supporting menu planning, which is consistent with the guidelines, regulations (e.g., food allergies), and customization options in daycare centers. To overcome these issues, registered dieticians under the regional Centers for Children's Food Service Management of the Ministry of Food and Drug Safety supervise their jurisdiction. A Cochrane systematic review reported that face-to-face training of cooks and monthly visits by dietitians led to a reduction in the saturated fat contents in children's meals [15]. These studies have indicated that diet planning is a highly complex and resource-intensive task [16].

Among the various roles of dieticians in childcare centers, diet planning for children is critical to ensure adequate intake of nutrients to enable healthy growth and development in children [17]. Thus, dietitians are required to have knowledge of children's development [18] and the ability to address the high design complexity associated with the large number of food items available for children. Meanwhile, monthly diet plans must consider the cost-effectiveness, safety (e.g., food allergy), and hygiene of cooking facilities, as well as the availability of various types of labor, including skilled cooks. Recently, the effectiveness of a web-based menu planning intervention for childcare services has been investigated to improve compliance with dietary guidelines [3,19]. An Australian randomized controlled trial of this intervention found that it was associated with a significant improvement in the consumption of fruit and dairy foods [3]. Additionally, a study on the usefulness of web-based programs reflected the economic value of menu planning with reduced costs [20]. Given the above concerns, advanced systems need to be developed to help dietitians efficiently plan diets and implement appropriate dietary guidelines.

Artificial intelligence (AI) is expected to provide diet-planning solutions by applying professional knowledge automatically and by addressing the complexity of optimal diet planning efficiently. Machine learning enables applications with performance levels that are close to those of skilled experts. However, to the best of our knowledge, no machine-learning models have been developed to assist dieticians in designing diet plans for children. In this study, we developed 2 AI solutions for children and evaluated their effectiveness.

MATERIALS AND METHODS

Food and diet plan datasets

Because we intended to provide complete-diet-level plans rather than menu-level food lists, we defined our diet recommendation system under the "diet planning" problem, including the constraints of diet-related problems and considering psychological parameters such as color, texture, shape, and flavor [21]. To train machines for diet planning, we used a dataset of 1,726 foods including information on nutrition, ingredients, and food group categories. The nutrition section provided data on 14 nutrients, including energy, carbohydrates, protein, fat, trans fats, saturated fats, total dietary fiber, calcium, iron, sodium, phosphorus, vitamin A, vitamin C, and vitamin D, that come in a standard serving of each food. A section of 298 ingredients indicated whether each food item contained a specific ingredient or not. For example, kimchi contains cabbage but not pumpkin; therefore, the cabbage column is assigned a value of 1 and the pumpkin column is assigned a value of 0. The group section indicates the types of food, such as soups, main dishes, and side dishes. In this dataset, foods were grouped according to a list of dishes in the Korean cuisine.

The 220 diet plans for AI training was obtained from publicly available standard diets from one of the Centers for Children's Food Service Management in Gyeonggi-do, which was established by the Ministry of Food and Drug Safety to support hygiene and nutrition management in daycare centers. The diet provided in this dataset was designed by professional dietitians. Because the training diet plan dataset was from a daycare center, the menu composition included a morning snack, lunch, afternoon snack, and dinner, but not breakfast.

Development of the 2 AI solutions

The first AI mimicked existing diets designed by human dieticians using a generative adversarial network (GAN) model (**Fig. 1**) [22]. The GAN-based AI was designed with a focus on the ability to learn "composition patterns" underlying the records of human-made diets (e.g., identifying the co-occurrence of different foods) and was able to reproduce a diet created by human nutritionists. In GAN, the generator model (G) and discriminator model (D) are initially trained with real data. The purpose of G is to estimate the real data distribution, and the purpose of D is to distinguish between the real and generated data. G generates data that mimic real data based on the estimated data distribution, and D returns the probability that the generated data come from real data. Based on the probability of return from D, G is trained to confuse D by generating realistic data. It is proven that the output of D converges to 0.5 when G and D are ideal (i.e., when G and D are well trained). Entering diet data directly into the GAN is not effective because the diet dataset does not involve all types of foods in the food dataset. In this case, the GAN generates a diet based on limited foods. To avoid this problem, we categorized foods using a clustering algorithm and transformed the 'food-level' diet data into 'category-level' diet data. For example, in real data, when 'food A' is entered into the GAN, it is expressed as 'a food in category X' (i.e., it does not specify what food it is). Consequently, the GAN outputs category-level data, which should be restored to food-level data by the random sampling of a candidate food in the category.

The second AI solution was designed to simulate multiple menu combinations to learn the optimal data design process policies using a reinforcement learning (RL) framework (**Fig. 2**) [23]. The proposed RL-based AI focuses on learning an "optimal strategy" for diet design processes by simulating a massive number of cases of food combinations and evaluating the cases using multiple criteria (e.g., calorie, carbohydrate-protein-fat ratio). The evaluation
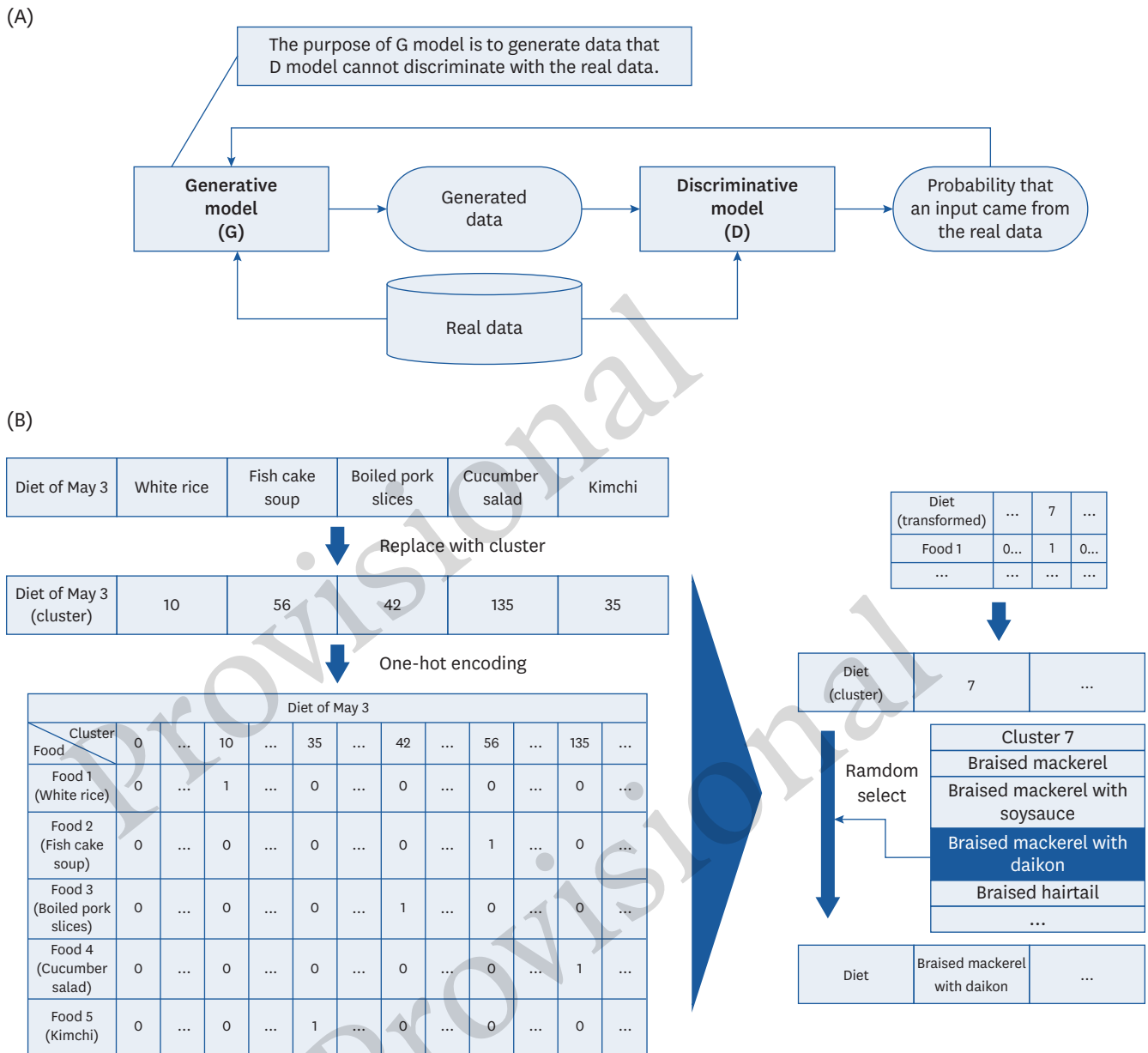
(A)

(B)

Fig. 1. Data transformation (A) and restoration process (B) for diet planning with the generative adversarial network.
G, generator model; D, discriminator model.

outcome was then fed back to the AI to enable it to reinforce itself. First, we define the state as a diet that has a vector of length 14, in which each element is filled with a token assigned to each food. Second, the agent selects one element (i.e., the agent selects an action) from the 14 elements of the diet vector and removes the token in the element. The environment then returns a new token to fill in the blank element. The vector with the added token becomes the next state, and the number of nutrient requirements fulfilled in the new state is given to the agent as the reward. We based the nutrient requirements for the diet design on the recommended dietary reference intakes (DRI) for Korean children aged 3–5 yrs (published by the Ministry of Health and Welfare, Sejong, South Korea). Third, the aforementioned process is iterated until the agent learns to select an action that always increases the reward. In
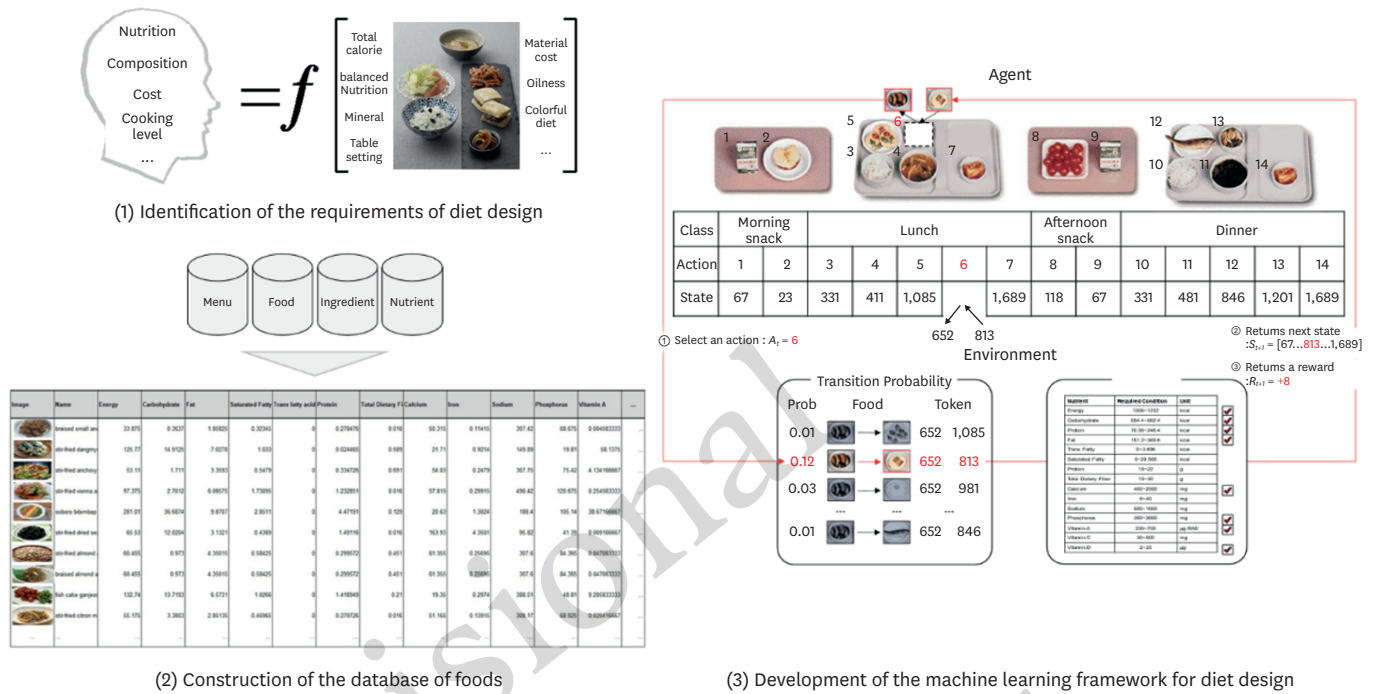
Fig. 2. Development process of the reinforcement learning-based artificial intelligence solution.

Table 1. Examples of the reinforcement-leaning-produced diet plan in the first survey

Category	Diet plan			
Morning snack	Yogurt	Plain bread		
Lunch	Mushroom rice with nutritious ingredients	Seaweed soup	Grilled mackerel	Seasoned cucumber	(Empty)
Afternoon snack	Grilled fish cake with ketchup	Orange juice		
Dinner	Sanxian jajang rice	Potato and kelp soup	Potato salad	Seasoned parsley and radish	(Empty)

other words, the agent repeats the diet design processes to learn a policy that maximizes the total return, which is similar to the practice and learning processes of human nutritionists. Specifically, deep Q-learning [23] was used as the training method.

Using the datasets of 1,726 food items and 220 daily diet plans, we trained AI solutions to produce daily diet plans for daycare centers in South Korea. An example of a diet plan created using the proposed RL is presented in **Table 1**. This study was approved by the Institutional Review Board (IRB) of the Kosin University Gospel Hospital (IRB file No. KUGH 2019-10-003). As the data used in the present study included only de-identified data, informed consent was not required.

Evaluation of the diet AI generating system

We conducted 2 surveys to evaluate the diet plans generated by AI in comparison with those generated by professional human nutritionists. The survey subjects consisted of dietitians who were dedicated to hospitals or children's food service management centers, teachers in daycare centers, and pediatricians. In the first survey, we randomly presented 15 diet plans created by GAN, RL, and by human dietitians and provided a list of food names that were in the diets without the relevant nutrient information (e.g., the human-made diet was randomly selected from our standard diet databases). The questionnaire was categorized into 3 items: adequacy of nutrients, food composition, and overall evaluation (**Table 2**). The

Table 2. Question list of the first and second survey

Category	Question	Answer type	First survey	Second survey
Adequacy of nutrients	Does the configured diet meet nutritional standards?	One of strongly agree, weakly agree, weakly disagree, or strongly disagree	●	●
	Is the carbohydrate, protein and fat ratio appropriate?		●	●
	Is the use of frozen and processed foods appropriate?		●	
Foods composition style	Are various recipes used within the one-day menu?	One of strongly agree, weakly agree, weakly disagree, or strongly disagree	●	
	Does the plan avoid the duplicate use of same ingredients?		●	
	Is the composition of snacks appropriate?		●	
	Are various food groups used for the nutritional intake balance?		●	
Comprehensive evaluation	Overall, do you think this diet is appropriate for children aged 3 to 5?	Yes or No	●	●

Table 3. Example of the diet form provided in the second survey

Category	Morning snack	Lunch	Afternoon snack	Dinner	Sum
Energy (kcal)	136.20	682.97	223.18	345.35	1,387.70
Carbohydrate (g)	12.47	87.55	35.79	52.68	188.49
Protein (g)	12.36	12.97	3.60	5.43	34.36
Fat (g)	6.67	20.32	3.65	8.30	38.94
Trans fatty acids (g)	4.35	4.53	0.14	1.70	10.72
Saturated fatty acids (g)	0	0	0	0	0
Total dietary fiber (g)	0.62	6.93	1.97	2.50	12.02
Calcium (mg)	230.80	117.54	17.97	120.85	487.16
Iron (mg)	0.16	3.71	0.67	1.81	6.35
Sodium (mg)	76.60	1,204.85	185.59	834.74	2,301.78
Phosphorus (mg)	176.40	416.16	92.31	209.11	893.98
Vitamin A (µg RE)	201.93	180.77	55.19	75.59	513.48
Vitamin C (mg)	2.18	11.88	3.02	10.59	27.66
Vitamin D (µg)	0	8.66	0	0.04	8.70

questionnaire concerning the adequacy of nutrients included the following questions: "Does the configured diet meet nutritional standards?" and "Is the carbohydrate, protein, and fat ratio appropriate?" The questionnaires on food composition style included the following items: "Are various food groups used evenly?" "Is the composition of the snack appropriate?" "Are various cooking methods used within each one-day menu?" "Does the diet plan avoid use of the duplicate ingredients?" and "Is the proportion of frozen and processed products appropriate?"

The second survey was conducted with voluntary consent from those who participated in the first survey. One week after the first survey, we administered the second survey to obtain the nutrient information from the same diet plan as that in the first survey, without the food name information (**Table 3**). We provided information on the DRI for Korean children aged 3–5 yrs in the second survey to help the subjects compare the nutrients in the presented diets and menus. This survey included questions that were identical to those in the first survey, except those questions related to food composition were not present (**Table 2**). We used pairwise χ^2 tests to compare the responses to the human-, RL-, and GAN-designed diets using Scipy 1.5.2 in Python 3.7.1.

RESULTS

Of the 41 participants, 38 reported their careers: 24 were dieticians, 9 were daycare teachers, and 5 were pediatricians. (**Table 4**). The average job experience duration was 9.18 yrs. The second survey comprised 27 participants from the first survey: 21 were dieticians, 3 were daycare teachers, and 3 were pediatricians.

Table 4. Characteristics of the survey subjects

Characteristics	First survey (n = 38)[1]	Second survey (n = 27)
Female	33 (86.8)	22 (81.5)
Occupation		
Dietitian	24 (63.1)	21 (77.8)
Teacher at a daycare center	9 (23.7)	3 (11.1)
Pediatrician	5 (13.2)	3 (11.1)
Career (yrs)		
Dietitian	9.2 ± 5.7	9.2 ± 5.8
Teacher at a daycare center	10.9 ± 11.5	7.3 ± 5.7
Pediatrician	7.4 ± 1.8	6.0 ± 1.7

Values are presented as number (%) or mean ± SD.
[1]Of the 41 subjects in the first survey, 3 subjects did not report their occupation. The participants were not required to respond to the second survey.

In the first survey, the proportions of positive overall diet evaluations were 82.4%, 43.7%, and 35.1% for the human-, RL-, and GAN-generated diet plans, respectively (all $P < 0.001$) (**Fig. 3A**, left). The proportions of strong positive responses to adequacy of nutrition were 45.7%, 31.5%, and 26.2% for the human-, RL-, and GAN-generated diets, respectively (all $P < 0.005$) (**Fig. 3B**, left). Interestingly, although the same diets were evaluated in both surveys, the results of the second differed from those of the first. The second survey provided only nutrient information without food names, and based on the proportion of positive responses, we determined that the overall RL-generated diets (86.7%) were superior to those of the human- (43.7%) and GAN-generated diets (28.5%) (all $P < 0.001$) (**Fig. 3A**, right). In addition, the RL-designed diets provided better nutritional adequacy (29.6%) than the human- (10.7%) and GAN-designed diets (5.6%) (all $P < 0.001$) (**Fig. 3B**, right). When evaluating the food composition style in the first survey, participants' responses regarding the use of various food groups and appropriate snack compositions were more strongly positive for the human-designed diets (48.6% and 46.8%, respectively) than for the RL- (27.0% and 28.0%, respectively) and GAN-designed diets (24.4% and 18.7%) (all $P < 0.001$) (**Fig. 3C**). In addition, there was a higher strong positive response for the items related to duplication of ingredients, appropriate frozen or processed food, and various cooking methods in human-made diets than in the RL- and GAN-made diets (all $P < 0.001$).

DISCUSSION

To the best of our knowledge, this is the first study to demonstrate the development and evaluation of AI to support diet planning for children. The results of the 2 surveys indicate that most experts could not precisely evaluate the nutritional quality of diets (**Fig. 3B**) and that most experts considered composition style to be an important factor in dietary evaluation (**Fig. 3C**). In this study, we found that both composition style and satisfaction with nutrient requirements should be considered when planning children's diets using AI.

Diet planning by registered dietitians has long been an important tool for implementing recommended dietary guidelines to improve diet quality and health [24]. In addition to adequate nutrient intake in diet planning, literature and textbooks on dietetics have emphasized the importance of composition style in diet planning [25]. Several factors that take into consideration the recipient's eating habits, preferences, and menu styles, as well as nutritional quality in diet planning, have been reported. If food cultures or eating habits are not reflected in the composition of menus, regardless of how balanced and nutritionally
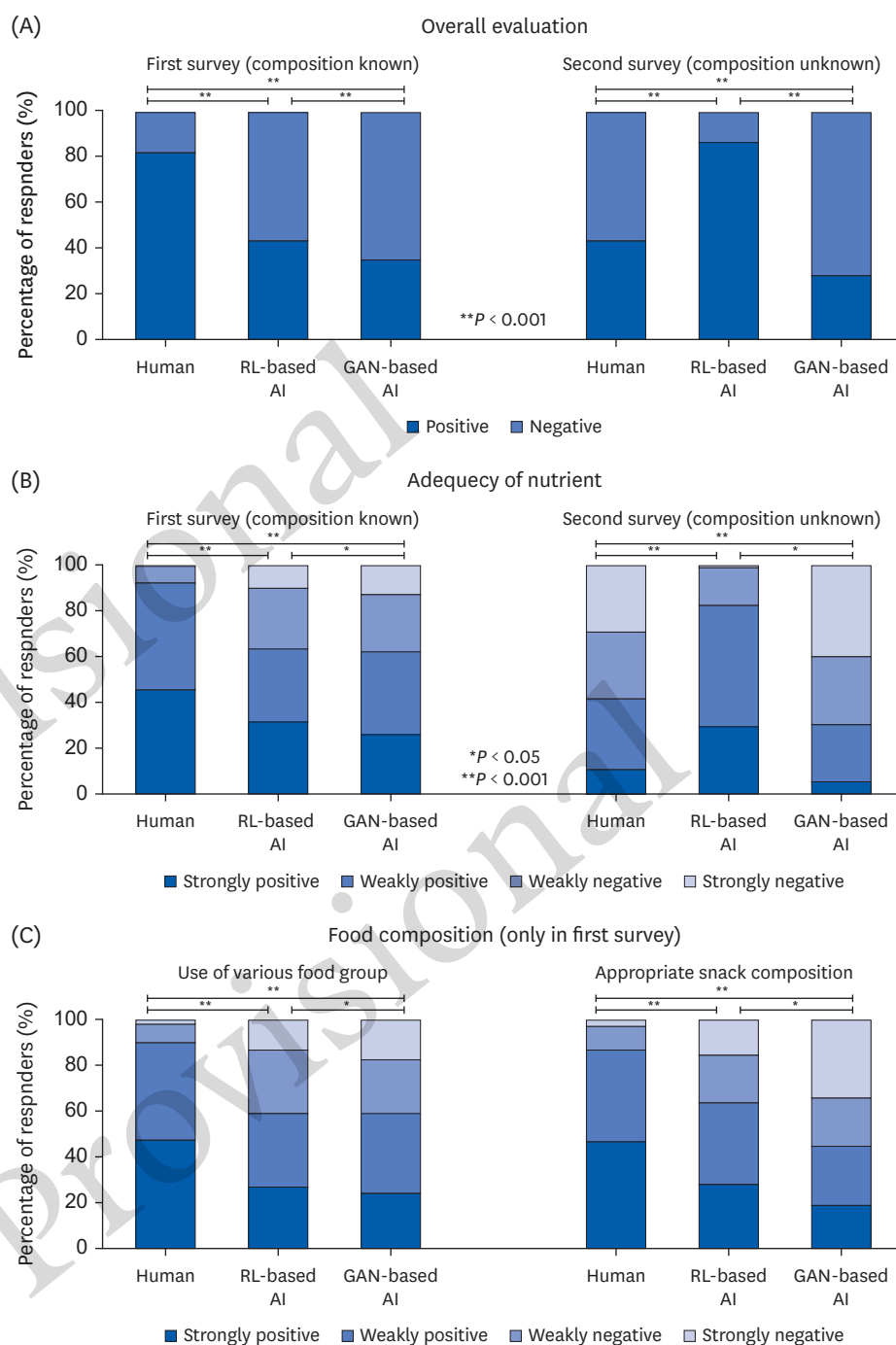
(A)

Overall evaluation

Fig. 3. Proportion of responses to diets designed by humans, RL, and by a GAN. Though the provided diets were the same, the results were different between the first and second surveys. Study experts evaluated the overall evaluations (A), adequacy of nutrients (B), and composition styles of the foods (C).
RL, reinforcement learning; GAN, generative adversarial network; AI, artificial intelligence.

perfect a diet may be, the recipients will not consume it. The Academy of Nutrition and Dietetics in the US defines the role of dietitians as leading diet recipients to accept and consume nutritionally balanced menus [8]. In addition, different regions have their own culture-oriented criteria for evaluating the composition quality of diets [26,27]. For example,

important composition criteria in Korean diet planning include harmony of colors in foods, use of seasonal ingredients, and avoiding duplication of cooking methods [28]. The planning of traditional Japanese food involves the high consumption of seafood and soybean products, as well as relatively small portions of main and side dishes, and considers the combination of taste, smell, and tactile sensations of the ingredients as important [29]. In Southeast Asian cultures, most food is cooked by fast blanching or stir-frying using woks, which require only a relatively low amount of heat [30]. Each unique food culture and composition style is very difficult to specify in a mathematical model, yet it can be accommodated by machine learning.

Meanwhile, our research has limitations in that the development and evaluation of machine learning models involve a limited scope of datasets and experts. Although we prepared the dataset for the AI solution based on the diets used in the public Centers for Children's Food Service Management, the dataset may not represent the comprehensive diet sets for Korean children, as it was used in a single institution and did not meet all the recommended daily intakes. Furthermore, the number of experts participating in the second survey was relatively small. Therefore, careful interpretation of our results is required. Nevertheless, this is a first investigation of the possibility and challenges of AI diet recommendations for children. Based on this work, we found that not only nutrients of menus but also their composition are very important in AI-based diet planning. It is challenging to define the composition of a diet, unlike the explicit knowledge of nutrients, such as the DRI of nutrients. This finding would be reflected in our next diet planning study with machine learning, which may extract the composition patterns from real diet planning and apply these patterns when generating diets. In addition, to overcome the limitations of the data, we are currently extending the food and diet datasets for machine learning, because there has been no benchmark large and qualified diet and food datasets accessible to the public. These datasets can be publicly available for future research on diet planning in children. After the development of a new AI diet planning method with a new dataset, incorporating feedback from more experts is needed for the validation of AI-equipped diet planning approaches. In addition, we identified that dietitians need to precisely evaluate the nutritional quality of diet planning for children. Further investigations to improve the performance of AI solutions based on the results of this study could be beneficial in diet planning tasks for dietitians in the future.

In future work, our next aim will be to develop and clinically test AI-based personalized diet management services [31] that can be used not only in daycare centers but also in hospital settings (e.g., children with multiple food allergies, inflammatory bowel diseases, diabetes mellitus, and obesity). Recently, there has been an increasing trend of children with food allergies [32] and who are vegetarians [33], and registered dietitians in daycare centers or school meal programs are required to prepare separate meals for them. For children with food allergies, dietitians not only consider food allergen elimination in meals but also prepare alternative foods tailored to provide appropriate nutrients [34]. In addition, care should be taken to avoid cross-contamination during the cooking process [35]. In the case of vegetarian children and adolescents, some vegetarian diets may be low in specific nutrients such as calcium and vitamin B12, and attention is needed to support their healthy growth and development [36]. Given the time- and resource-consuming processes of diet planning and clinical nutrition tasks, information and communication technologies and AI are expected to serve a complementary role in these fields [37-39]. As with our related ongoing work [40,41]. we hope that the present work will serve as a foundation for future studies on the development of AI diet planning solutions for different types of patients in different countries and cultures.

In summary, this study shows the possibility of developing AI to plan diets for children. We found that the developed AI was superior to human nutritionists in designing nutritionally appropriate diet plans, but inferior in terms of compositional quality. Further integrative expert cooperation among dieticians, engineers, and pediatricians is needed to improve the capability of the proposed AI solution in order to satisfy expectations relating to meal composition and to benefit the well-being of children.

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