

Article

A Pilot Study on AI-Powered Gamified Chatbot with OMO Strategy for Enhancing Parental Nutrition Knowledge [†]

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Abstract: This pilot study explores the efficacy of an AI-powered gamified chatbot integrated with an Online-Merge-Offline (OMO) strategy to enhance parental nutrition knowledge. Conducted in a Taiwanese public childcare setting, the intervention comprised eight weekly nutrition seminars delivered by registered dietitians, supplemented by a LINE-based chatbot providing interactive, gamified learning experiences. Pre-test and post-test evaluations were administered via the chatbot to assess knowledge acquisition. The results from 20 unique participants, including 9 with complete data, indicated a statistically significant improvement in nutritional knowledge ($p < 0.0001$, Cohen's $d = 2.50$), suggesting a substantial educational impact. The integration of gamification elements—such as level completion, community rankings, and personalized feedback—with OMO modalities allowed for sustained engagement, knowledge reinforcement, and seamless transition between digital learning and physical application. This study provides empirical evidence supporting the feasibility and pedagogical value of OMO-gamified chatbots in health promotion and lays the groundwork for future large-scale, longitudinal investigations.

Keywords: AI chatbot; gamification; Online-Merge-Offline (OMO); parental nutrition education; mHealth; health promotion; digital health interventions



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1. Introduction

Among all internet users, as many as 95% of the population have the habit of accessing the internet through their mobile phones; in contrast, the rate of using computers for internet access has decreased from 72.9% in 2022 to 68.2% [1]. In this era where everyone has a mobile device at hand, mobile phones have significantly transformed how people access information. These portable devices now enable users to obtain services and information anytime and anywhere [2]. In particular, chatbots used on social platforms to facilitate interaction are applied in various fields such as healthcare, education, entertainment, and e-commerce.

Mobile health (mHealth) applications have emerged as powerful tools for health promotion and education, with recent studies showing significant growth in their adoption and effectiveness [3]. The integration of interactive chatbots into health promotion programs can drive innovation and reform traditional initiatives. This approach enables the exploration and implementation of more modernized and diversified service models, achieving a beneficial integration within technology and societal welfare domains.

Gamification, defined as the application of game elements in non-game contexts, has shown considerable potential for enhancing user engagement and motivation in health interventions [4]. Recent systematic reviews indicate that gamified health applications can significantly improve health-related knowledge, motivation, and attitude outcomes, with 80% of studies demonstrating positive effects [5]. The integration of gamification elements such as points, badges, leaderboards, and challenges has been particularly effective in promoting sustained engagement with health education content [6].

A comprehensive analysis of Taiwan's National Nutrition Health Status Change Surveys reveals concerning trends. These surveys, conducted over three periods (1993–1996, 2013–2016, and 2017–2020), span nearly thirty years. The results show deviations from national dietary guidelines among Taiwanese citizens. Additionally, obesity rates have increased annually, contributing to metabolic syndrome symptoms, including hypertension, hyperlipidemia, and diabetes [7–9]. Scholars who conducted these large-scale cross-generational nutrition health surveys identified insufficient nutritional knowledge among Taiwanese citizens over the past two decades. This deficiency exists despite Taiwan's quality medical resources and robust social welfare systems. The nutritional issues affecting public health are difficult to fully discern, making their resolution equally challenging.

In reality, dietary habits and nutrition concepts are established during childhood and primarily influenced by parents providing healthy meals and proper dietary education, fostering good eating habits amongst children [10]. Research has demonstrated that parental nutrition knowledge and attitudes are significant predictors of children's dietary behaviors, with interventions targeting parents showing promising results in improving family nutritional outcomes [11]. In essence, correct parental understanding regarding diet forms the basis for children developing healthy eating habits.

The Online Merge Offline (OMO) strategy represents an innovative approach that transcends traditional boundaries between digital and physical experiences. Unlike the earlier Online-to-Offline (O2O) model, which primarily focused on driving online users to offline stores, OMO creates a seamless integration between virtual and physical environments [12]. In healthcare education, OMO strategies have demonstrated effectiveness by combining the accessibility and personalization of digital platforms with the interpersonal benefits of face-to-face interactions [13]. Recent studies have shown that OMO learning environments can enhance engagement, knowledge retention, and behavior change by leveraging the strengths of both modalities [14].

In summary, over the past twenty years, the people of Taiwan have become economically prosperous, with mobile communication devices becoming ubiquitous, seemingly enjoying abundance. However, a hidden issue of malnutrition coexists with this apparent affluence, presenting a paradoxical yet concurrent reality. This study endeavors to leverage familiar smartphones by integrating chatbot characteristics alongside the Online Merge Offline (OMO) model to revitalize nutritional knowledge, enabling seamless integration of this knowledge into daily lives, particularly emphasizing the childhood golden period for establishing healthy nutritional awareness.

Despite the growing body of research on mHealth applications and gamification in health education, several significant gaps remain in the literature. First, the application of gamified chatbots specifically in parental nutrition education remains understudied, with most existing research focusing on individual health behaviors rather than parental education that can influence children's health outcomes. Second, while the OMO model has shown promise in retail and general education contexts, its effectiveness in enhancing mHealth education outcomes has not been sufficiently validated through empirical research. Third, there is limited understanding of how gamification elements can be effectively

integrated with chatbot technologies to create engaging and effective health education experiences that bridge online and offline environments.

This pilot study aims to address existing gaps by evaluating the effectiveness of a gamified chatbot integrated with the Online Merge Offline (OMO) strategy to enhance parental nutrition knowledge. Specifically, the study examines patterns of user engagement that emerge when parents interact with a gamified chatbot for nutrition education and explores how demographic variables may influence the intervention's outcomes. Furthermore, the research investigates the potential of the chatbot–OMO model to facilitate the integration of online digital learning and offline health-related activities, thereby promoting active participation in health education among parents.

2. Theoretical Background

2.1. Gamification in Education

Modern society has entered a digital immersion era, bringing about a new mode of knowledge learning through digital interaction. This approach has become the most important task in modern educational practice. The construction of most digital platforms focuses mainly on the functions within the platform, considering how interaction can have a substantial and direct impact on users [15]. This demonstrates elements of platform utility and self-purposiveness, which are the focus of this study. Gamification in health education has emerged as a powerful approach to enhance user engagement and promote behavior change. Recent systematic reviews and meta-analyses have demonstrated that gamified interventions significantly increase health-related behavior change in multiple studies, with particularly strong effects on motivation and knowledge acquisition [16]. The integration of game elements into health education contexts creates more engaging learning experiences that can sustain user interest over time [17].

Scholars propose that digital systems can best guide learning motivation through gamification mechanisms: (1). Gamification: Users' use of leaderboards, medals earned, and levels achieved. (2). Quantified-self: Visualizing relevant data obtained from participating in the platform. (3). Social networking: Obtaining social interactions through system platforms to establish a sense of community through feedback from social interactions.

The gamification design of social games on digital platforms can generate positive social interactions, and users will be more willing to use them because they will gain more active social interactions [15]. Research indicates that gamified health applications incorporating social elements show higher engagement rates and better outcomes compared to those without social components [18].

In addition, real-time online teacher customer service on digital learning platforms is necessary for maintaining platform usage rates [19]. However, providing individualized attention to each student and offering round-the-clock services with live teachers is very costly and challenging to achieve. Therefore, developing an artificial intelligence teaching assistant system is an ideal strategy. In recent years, artificial intelligence chatbot technology has made significant progress. The core technology in chatbots lies in understanding user intent in dialogue systems. It mainly includes three technologies: language understanding, dialogue management, and natural language generation. Through the development of dialogue systems, chatbots can quickly understand user needs during conversations and swiftly search for the information they require before ultimately providing it [20]. Modern AI-powered chatbots have demonstrated effectiveness in various healthcare applications, including nutrition education, mental health support, and chronic disease management [21].

When designing chatbots, scholars suggest focusing on their acceptability, security, and effectiveness [22]. To enhance user experience, the design of chatbots should consider factors such as system usability, usefulness, trustworthiness, compatibility, and production

quality [23]. In addition, the design process should follow principles based on theory combined with behavior change techniques, focusing on user experience, user-centered design (UCD), and user experience (UX) design fluency [24]. Recent studies have emphasized the importance of personalization in health chatbots, with evidence suggesting that tailored interactions lead to better engagement and outcomes [25].

2.2. *The Role of AI in Gamification*

Artificial Intelligence (AI) is increasingly central to the development of gamification and serious games in healthcare. Tolks, et al. [26] reviewed 16 studies and found that while both AI and game-based strategies are rising trends, only 19% of cases demonstrated direct integration. Most applications employed machine learning, particularly in rehabilitation for motor (63%) and cognitive impairments (19%), indicating technological potential and practical implementation.

Expanding on this, Damaševičius, et al. [27] identified a growing trend toward mobile-based platforms. Especially in mobile platforms, the use of gamification elements such as rewards, progression systems, and feedback loops has become a very effective model in digital health interventions. In this era of rapid advancement in artificial intelligence technology, integrating artificial intelligence with mobile platforms offers greater opportunities to enhance user engagement and therapeutic outcomes through smarter and more responsive game design.

Patel, et al. [28] further demonstrated the potential of large language models (LLMs) in health communication. Their evaluation highlighted the models' ability to generate responses that are both clinically accurate and user-friendly, supporting their use in gamified chatbots. These AI systems can analyze user behavior in real time, predict preferences, and dynamically adjust game content—an approach known as adaptive gamification—resulting in more personalized and effective user experiences.

Complementing these findings, Rahman and Uddin [29] emphasized that performance expectancy is the most influential factor in mHealth adoption among Generation Y. This reinforces the value of AI-enhanced gamification, which delivers not only engaging digital experiences but also tangible performance benefits through personalization and adaptivity.

Overall, AI enhances gamified health interventions by tailoring content and challenge levels to individual users, dynamically adjusting difficulty to maintain motivation, and offering timely, context-aware feedback that supports behavioral change. Furthermore, AI can anticipate potential disengagement and proactively sustain user participation, while natural language processing enables intuitive, conversational interactions that strengthen user engagement and trust.

2.3. *Online Merge Offline Model*

The diversification of interactive mobile devices is still dominated by the business sector, which leads the industry and creates more customers. Digital technology has advanced rapidly over the past twenty years. This progression has moved from basic official websites and graphic design to digital data uploading. Recent developments include management of social media platforms such as Facebook and Instagram, live streaming, and short videos. Most entrepreneurs have gradually realized the advantages of integrating virtual and reality with customer value at its core [30]. Integrating online and offline experiences allows consumers to interact according to their preferences and attitudes while creating the most favorable options for them [30].

This is known as the OMO (Online Merge Offline) model, a concept originating from retailers where online sales are not only an important strategy but also a primary battlefield for retail businesses. In Taiwan in 2021, physical retailers saw a significant 36.4% increase

in online sales revenue compared to previous years, indicating the growing influence of the OMO model on retail operations [31]. The transformation of operations for physical retailers shifting from brick-and-mortar stores to online platforms is not just about retail; this shift represents a significant change in people's lifestyles. The OMO model goes beyond traditional physical or virtual binary experiences by utilizing technology for real-world interactions that accurately capture audience profiles and provide personalized feedback. Particularly noteworthy is how physical audiences may come to appreciate the advantages of online interactions, leading them towards engaging more with online platforms instead. It can be seen that it has become increasingly challenging for O2O (Online-to-Offline) interactions to keep up with modern demands, thus fostering the formation of OMO models [32]. In the education and healthcare sectors, OMO approaches have demonstrated significant benefits. Recent studies show that OMO learning environments can enhance engagement and knowledge retention by combining the accessibility of digital platforms with the interpersonal benefits of face-to-face interactions [33]. The application of OMO strategies in health education has shown promising results, with evidence suggesting improved learning outcomes and behavior change compared to purely online or offline approaches [34].

This study explores the application of intervening with parents' nutrition knowledge to prevent childhood obesity through a mechanism that integrates online and offline, leading the audience to integrate core values with the organization, driving audience identification with the organization, and creating models of stickiness and loyalty. In the context of this study, 'stickiness' refers to the ability of the intervention to keep the audience engaged and committed, while 'loyalty' denotes the audience's continued support and participation. In constructing a chatbot system for this project, strategies from the retail industry's OMO virtual-physical integration are introduced to intervene in children's parents' nutrition knowledge. The aim is to create physical nutrition seminars that lead to online interactions and then guide actual actions through online interactions. For children's parents, value fusion lies not in products but in nutritional knowledge. Through the chatbot's OMO operation mode, physical seminars are transformed into online interactive interventions aimed at enhancing children's parents' nutrition knowledge. Based on personalized feedback and experiences online, a transformation in attitudes towards nutrition among children's parents is created before integrating these interactions back into practical nutritional actions offline.

3. Materials and Methods

This study employed an AI-powered gamified chatbot as the primary framework for health promotion, implementing research across three key dimensions: (1) Health Lectures: An eight-week series of health lectures, designed by professional nutritionists, was conducted for parents at childcare centers. (2) Chatbot OMO Integration: The "Eat Well" chatbot was introduced at the commencement of the program. This chatbot, integrated with the LINE messaging platform, provided community engagement functionality. Participants received personalized learning experiences when responding to messages, with the system delivering individualized feedback based on each person's responses. Additionally, participants could review their questions and answers at any time. (3) Effectiveness Evaluation: The efficacy of the chatbot-enhanced OMO health lectures in promoting nutritional health knowledge among parents was assessed through analysis of interaction feedback messages between the chatbot and participants.

This research was approved by the Ethics Review Committee of National Cheng Kung University (approval number: 110-306). Each participant thoroughly reviewed and signed an informed consent form prior to participation.

3.1. Design of Gamified Chatbots

This study utilizes the framework and elements of gamified chatbots, along with the OMO (Online-Merge-Offline) concept, to construct the design of gamified chatbots. The design framework is shown in Figure 1 below.

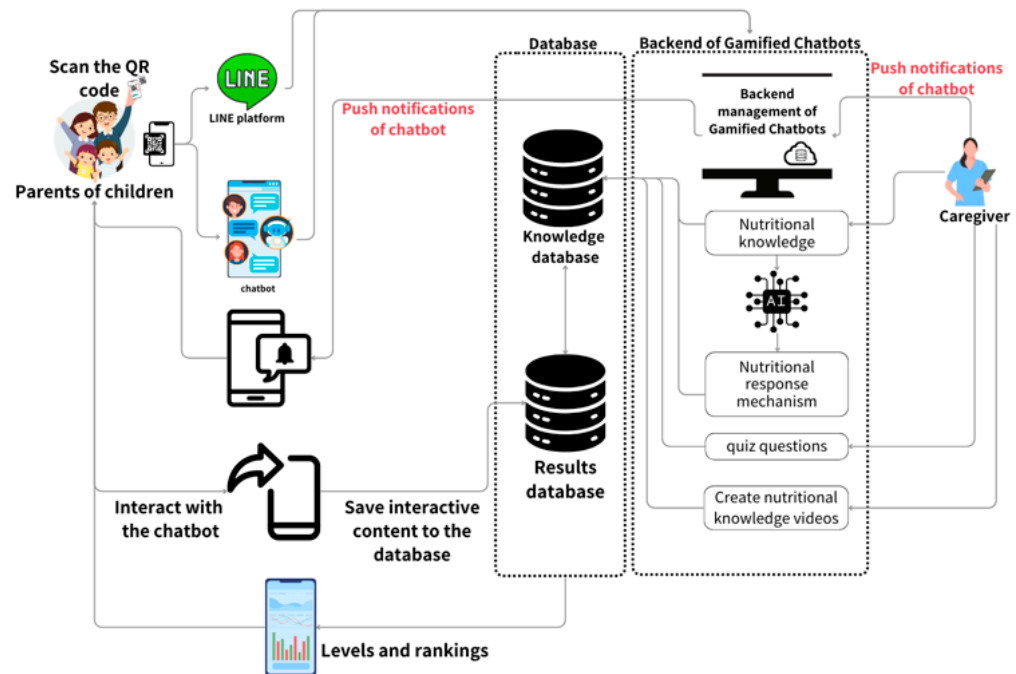


Figure 1. Design of Gamified Chatbots.

- (1) **User Interface:** The system leverages the LINE messaging platform as the primary interface. Parents can access the chatbot by scanning a QR code, facilitating easy onboarding. The chatbot provides an interactive conversational interface for user engagement.
- (2) **Backend Infrastructure:** The backend is composed of two primary databases and a management system: (a) **Knowledge Database:** stores nutritional information and content. (b) **Results Database:** captures user interactions and progress data. (c) **Backend Management of Gamified Chatbots:** oversees the chatbot's functionality and gamification elements.
- (3) **Artificial Intelligence Integration:** An AI component is central to the system. The knowledge imparted by professional dietitians in each lecture was incorporated into the learning process, becoming a source of knowledge that can provide user feedback. It is responsible for: (a) Processing nutritional knowledge. (b) Implementing the nutritional response mechanism. (c) Generating quiz questions. (d) Creating educational nutrition videos.
- (4) **Gamification Elements:** The system incorporates levels and rankings, displayed on a mobile interface, to enhance user engagement and motivation.
- (5) **Stakeholder Interactions:** (a) Parents interact directly with the chatbot through LINE. (b) Caregivers receive push notifications, allowing for timely interventions or support.
- (6) **Data Flow:** (a) User interactions are saved to the Results Database. (b) The system can push notifications to both parents and caregivers.

This architecture demonstrates a sophisticated approach to digital health education, combining mobile technology, AI, gamification, and nutritional expertise. The design aims to create an engaging, personalized learning experience while facilitating data collection for ongoing research and improvement of nutritional interventions for children.

3.2. Research Subject

This study was conducted in a public childcare center in Taiwan. Information about the seminar was announced through the childcare center, allowing the children's parents to sign up freely. The parents attended the activities with their children. Thus, the number of participants in each event was controlled to be no more than 15 parents to ensure quality interaction and personalized attention. After signing up in advance, parents attended a weekly health seminar for eight weeks (two months). These seminars included nutritional lectures by dietitians, each lasting 1 h. The sessions consisted of nutritional lecture units, interactive seminar activities, and pre-test and post-test assessments. The number of participating parents is shown in Table 1.

Table 1. Nutritional Seminar Planning.

	Nutritional Lecture Units	Pre-Test and Post-Test Question Count	Children's Parent Participants
1.	Nutritional Supplements & My Healthy Meal Plate	6 Questions	11
2.	Sweet and Sour Yogurt	6 Questions	9
3.	Whole Grains and Cereals	6 Questions	7
4.	Vegetable READY GO	6 Questions	13
5.	Fruit Party	6 Questions	11
6.	Bean, Fish, Egg, Meat Salad	6 Questions	9
7.	Little Chefs	6 Questions	7
8.	My Healthy Meal Plate	6 Questions	10

Given the nature of this study, which was implemented within a public childcare center and involved health-related educational activities, the number of participants was relatively small. This limitation was primarily due to spatial constraints and the characteristics of the participant group. As such, the study is positioned as a pilot investigation. To enhance the precision and focus of the research outcomes, several participant-related limitations are acknowledged as follows:

- (1) Mobile phone use: It was specified in the recruitment announcement that participants of the health seminar should be capable of using a mobile phone, allowing parents to register themselves.
- (2) Pre-test and post-test surveys: Participants completed a pre-test questionnaire before each health seminar to gauge their initial overall knowledge of nutrition. A pre-test was administered before each health seminar and a post-test afterward. At the final health seminar, a comprehensive post-test was conducted, ensuring a thorough assessment of the overall improvement in nutritional knowledge among the children's parents.

3.3. Data Collection and Analysis

Data were collected through multiple methods to evaluate the effectiveness of the gamified chatbot and OMO strategy:

- (1) Pre-test and Post-test Assessments: Participants completed knowledge assessments before and after each seminar to measure changes in nutritional knowledge. These assessments were administered through the chatbot interface.
- (2) Engagement Metrics: The system automatically tracked various engagement metrics, including frequency of chatbot interactions, completion rates for quizzes and activities, and time spent on different features.

- (3) **Demographic Information:** Basic demographic data were collected from participants, including gender, age range, and educational level, to explore potential relationships between these factors and intervention outcomes.

Statistical analysis was performed using SPSS 25 Paired samples *t*-tests were conducted to compare pre-test and post-test scores, with a significance level set at $p < 0.05$. Effect sizes (Cohen's *d*) were calculated to assess the magnitude of the intervention's impact. While the primary analysis focused on knowledge improvement, we also examined correlations between engagement metrics and knowledge gains to explore the relationship between participation levels and outcomes. We acknowledge that the statistical approach could be enhanced in future studies by incorporating more sophisticated analyses, such as ANOVA or regression analysis, to evaluate whether factors like age, education level, or previous nutrition knowledge influenced the results. Additionally, qualitative data collection through interviews or focus groups would provide valuable insights into user experiences and perceptions of the intervention.

4. Results

This study was designed and constructed with a gamified chatbot aimed at enhancing the nutritional knowledge of children's parents through interactions with the chatbot.

4.1. Gamified Chatbot System

This study constructed a gamified chatbot on a social chat platform, enabling users to select and use it quickly. Familiarity with the system eliminates the issue of users abandoning it due to a lack of understanding of its operations. Users can start interacting with the chatbot simply by scanning a QR code, and the system's backend will push notifications to facilitate the interaction. The system function and interface are shown in Figure 2.

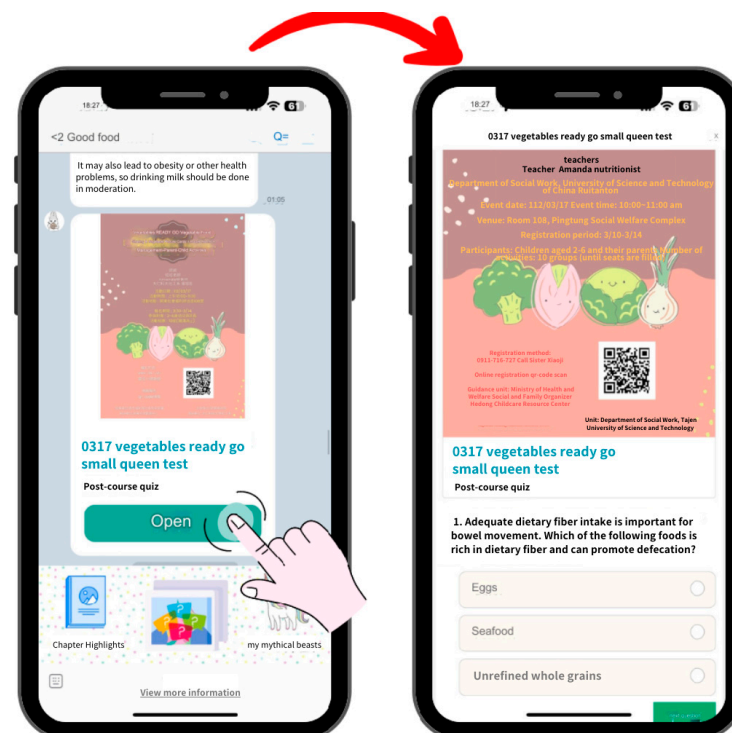


Figure 2. Push notifications of chatbot information.

4.2. The OMO Strategy of the Gamified Chatbot

This study employs the OMO (Online-Merge-Offline) strategy to drive user engagement with the gamified chatbot mechanism. The development outcomes of this gamified chatbot are explained through the OMO strategy operation model. The OMO strategy of the gamified chatbot developed in this study is shown in Figure 3.

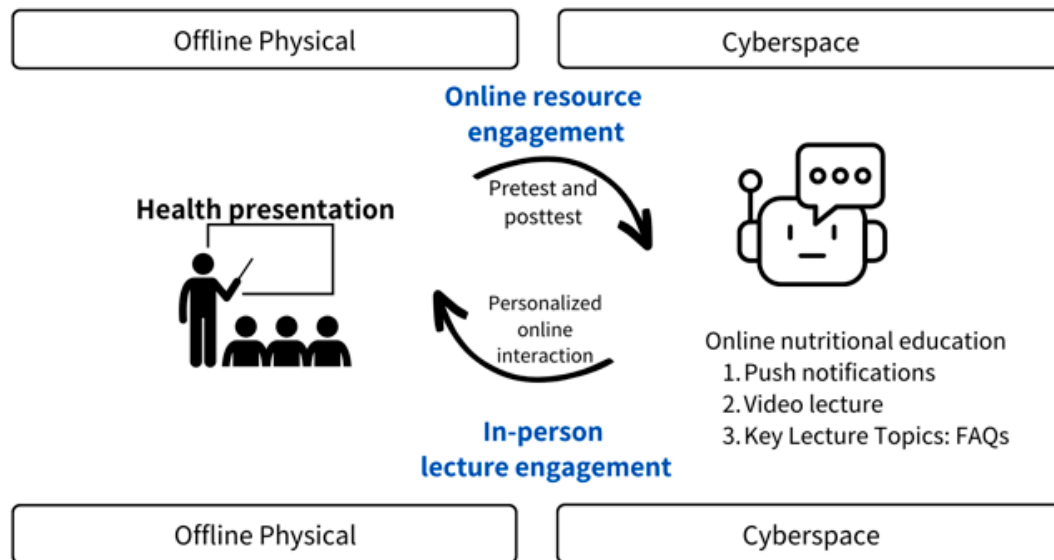


Figure 3. The OMO strategy of the gamified chatbot.

1. Offline Physical
 - (1) Conducting eight health presentations: These lectures focused primarily on parents of children and introduced eight sessions related to nutrition from the perspective of essential nutritional health.
 - (2) Implementing pre-tests and post-tests: To evaluate the effectiveness of the nutritional knowledge intervention, each health lecture involved guiding parents to scan a QR code to access the chatbot and complete a pre-test. After the health lecture, post-test information was pushed to participants via the chatbot to conduct the post-test.
2. Online resource engagement and in-person lecture engagement
 - (1) Conduct "pre-tests" before starting physical seminars: The content of each pre-test is based on nutritional knowledge literature summaries related to the particular seminar. This approach allows parents not only to take a pre-test but also to better understand the key points of each health seminar. The pre-test is built on a chatbot platform, which plays a crucial role in the pre-testing process, providing parents with an interactive and engaging online space.
 - (2) Pre-testing and post-testing: The pre-tests and post-tests for each health seminar are channels integrating OMO (Online Merges Offline), guiding parents into chatbots, and enabling them to access personalized interactive channels.
3. Cyberspace
 - (1) Pre-test content serves as personal online resources: Individuals can continuously view their answers from each health seminar's pre-test responses. By reviewing these answers, they become more familiar with the nutritional knowledge conveyed by nutritionists in each session. The system interface is shown in Figure 4.

- (2) Individualized online interaction after health seminars: Users can watch videos on nutrition topics they are interested in. When encountering relevant issues or questions, they can inquire within the chatbot, which has been trained by AI technology to respond with answers related to questions raised during the health seminars. The system interface is shown in Figures 5 and 6.

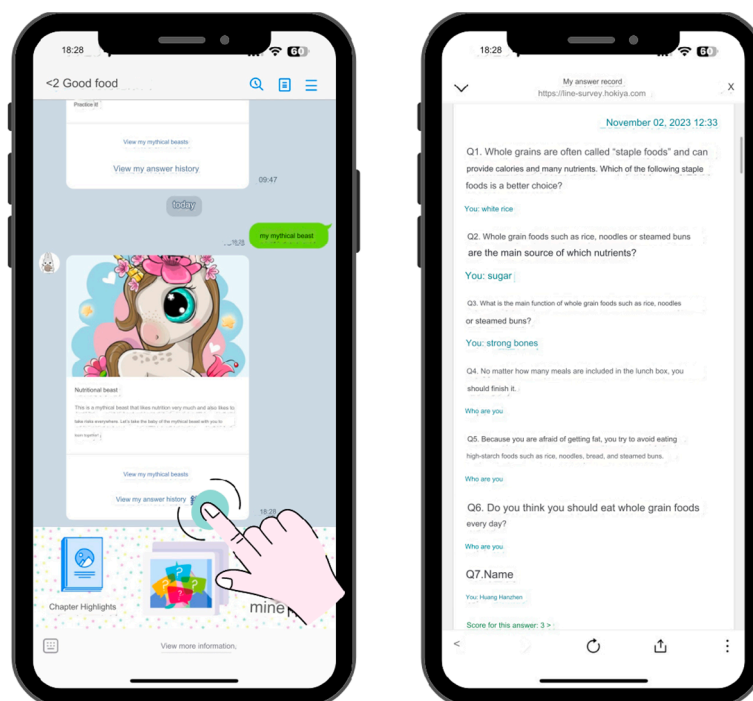


Figure 4. Review the responses to the quiz questions.

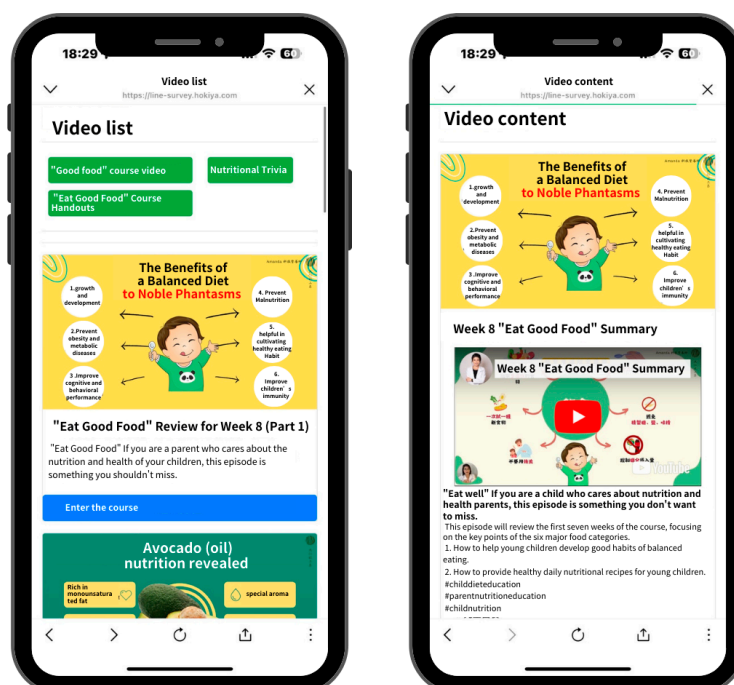


Figure 5. Watch videos based on nutritional topics.

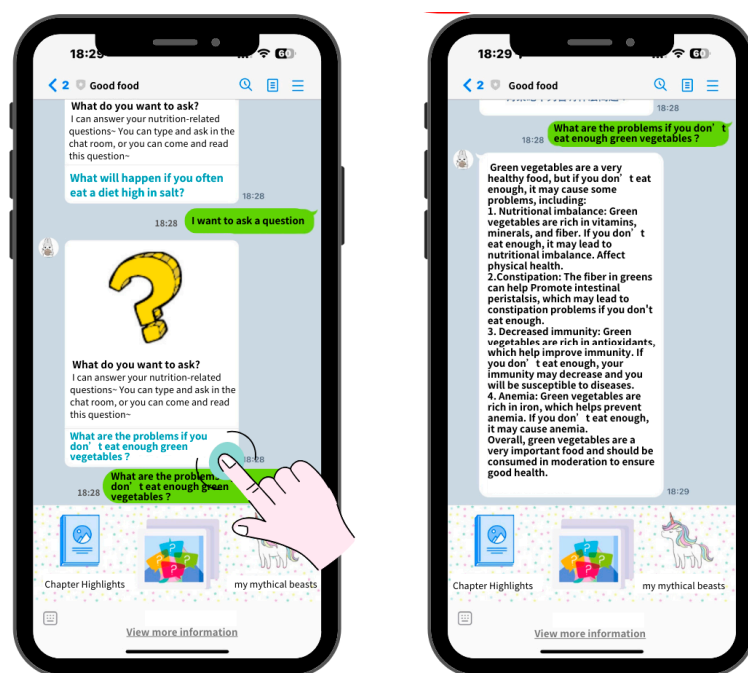


Figure 6. Respond to the questions and answers.

4. Gamification

- (1) **Level Completion Mechanism:** Both the pre-test and post-test consist of nutritional knowledge questions with correct answers. Each completion of the pre-test or post-test will have a score. Reaching a certain threshold allows the participant to pass the level. This gamified chatbot system is equipped with a level completion mechanism.
- (2) **Community Ranking:** As the chatbot is built on a social platform, the level completion scores of participants on this platform are ranked. The community ranking creates a sense of fun and competition among users, enhancing the enjoyment of using this chatbot and promoting the improvement of nutritional knowledge. It is shown in Figure 7.

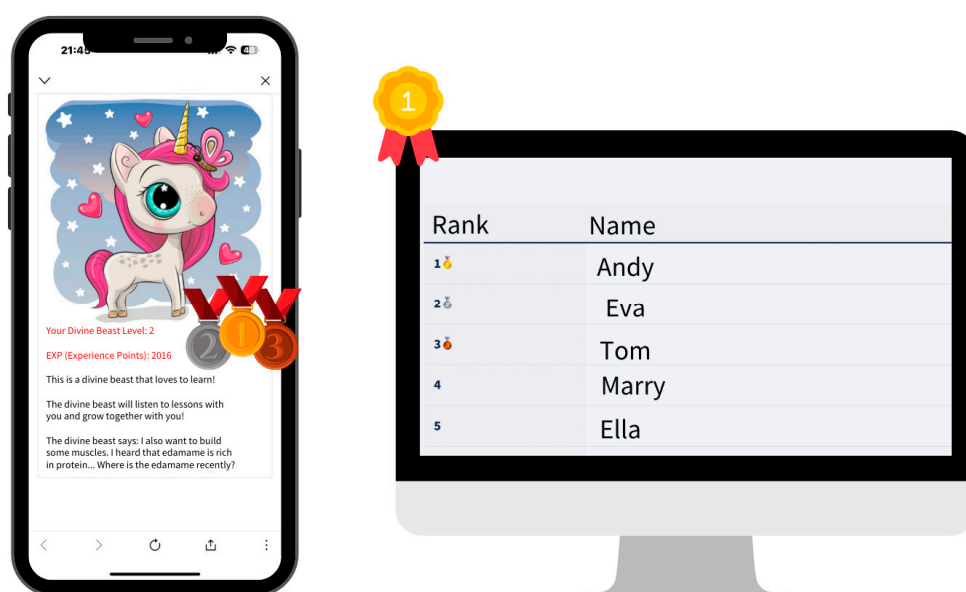


Figure 7. Level Completion and Community Ranking.

4.3. Basic Information Description

Eight health lectures were held during this in-person activity, with a cumulative attendance of 77 person-times by parents of children. Since parents registered voluntarily, some could only participate in some sessions due to work, relocation, or family events, while others joined midway. The total number of unique participants was 20, predominantly female, mostly aged between 31–50, with the educational level mainly being university/college. The happiness level of participation and the anticipation for the event both exceeded 90%. The descriptive statistics of the basic information of the children's parents are shown as Table 2:

Table 2. Descriptive statistics.

Basic Attributes	Category	Frequency	Proportion
Gender	female	18	90%
	male	2	10%
Age range	31–40	6	30%
	41–50	5	25%
	21–30	4	20%
	61–70	4	20%
Education	University/Junior College	16	80%
	High School/Higher Vocational	4	20%
Occupation	Stay-at-home mom	12	60%
	public servant	5	25%
	retire	3	15%
How happy you are to participate in the event		18	90%
		2	10%
Are you looking forward to the next event?		19	95%
		1	5%

Note: To simplify the answering process and increase the fun, 'The happiness level of participation' is rated on a scale up to 5 stars, and 'Anticipation for the next event' is rated on a scale up to 3 smiley faces, allowing the respondents to fill in their answers accordingly.

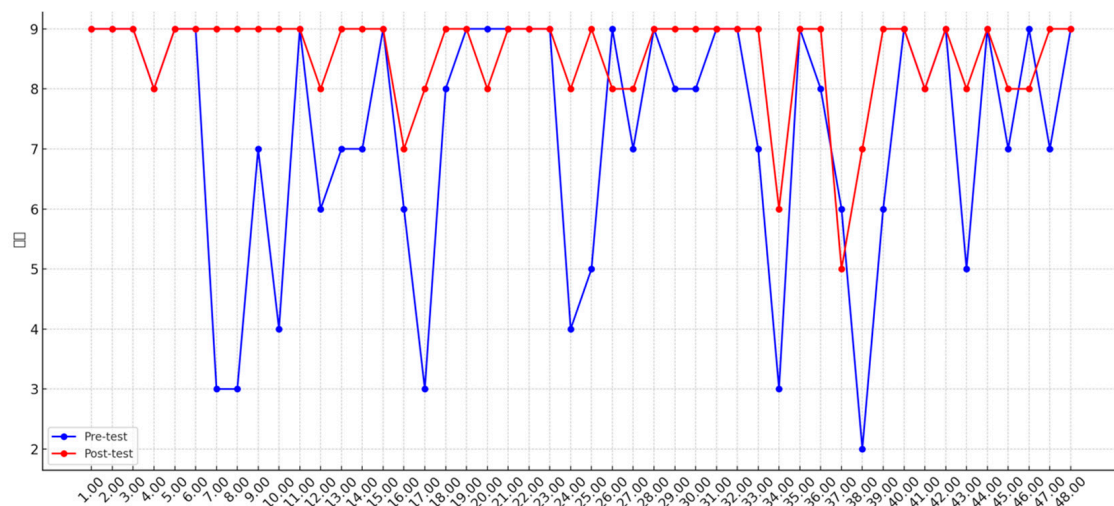
4.4. Pre-Test and Post-Test Data Analysis

According to the results of the data survey, although the number of participants was 20, a total of 9 parents actually participated in each time and filled in the pre-test and post-test each time, and their nutrition knowledge pre-test and post-test results were the basis for evaluating the effectiveness of the OMO chatbot introduction, and the results are as Table 3 and Figure 8:

According to the data and graphs, it can be clearly seen that the pre-test score (blue) of nutrition knowledge has obvious ups and downs, and it can be seen that the parents' nutrition knowledge obviously has a high error rate, and after eight lectures and the introduction of the OMO chatbot, the post-test score (red) is obviously almost maintained in a full score.

Table 3. Pre-test and post-test results.

No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Pre-test score	9	9	9	8	9	9	3	3	7	4	9	6	7	7	9	6	3	8	9	9
Post-test score	9	9	9	8	9	9	9	9	9	9	9	8	9	9	9	7	8	9	9	8
No.	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	21
Pre-test score	9	9	9	8	9	8	8	9	9	9	9	9	9	6	9	9	5	7	9	9
Post-test score	9	9	9	4	5	9	7	9	8	8	9	9	7	3	9	8	6	2	6	9
No.	40	41	42	43	44	45	46	47	48											
Pre-test score	9	8	9	8	9	8	8	9	9											
Post-test score	9	8	9	5	9	7	9	7	9											

**Figure 8.** The trend of pre-test and post-test scores.

4.5. Pre-Test and Post-Test Evaluation of Effectiveness

Due to the small sample size in this study, careful determination of data normality was essential. Therefore, both Kolmogorov–Smirnov and Shapiro–Wilk tests were employed to assess normality distribution, with results presented in Table 4.

Table 4. Results of the Kolmogorov–Smirnov and Shapiro–Wilk tests.

Test	Variable	Statistic Value	Degrees of Freedom	p-Value
Kolmogorov–Smirnov	pre-test total scores	0.222	9	0.2
	post-test total scores	0.25	9	0.11
Shapiro–Wilk	pre-test total scores	0.903	9	0.268
	post-test total scores	0.795	9	0.018

For the pre-test total scores, the Kolmogorov–Smirnov test yielded a significance value of 0.200 ($p > 0.05$), indicating that we failed to reject the null hypothesis of a normal distribution. Similarly, the Shapiro–Wilk test for pre-test total scores showed a significance value of 0.268 ($p > 0.05$), thus not rejecting the assumption of normality. However, for the post-test total scores, the Kolmogorov–Smirnov test produced a significance value of 0.110 ($p > 0.05$), again leading to the non-rejection of the normality assumption.

In contrast, the Shapiro–Wilk test for post-test total scores resulted in a significance value of 0.018 ($p < 0.05$), leading to the rejection of the null hypothesis of normally distributed data. Based on these test results, the data generally appear to approximate a normal distribution. However, the Shapiro–Wilk test specifically suggested that the post-test data did not follow a normal distribution. When normality tests yield inconsistent results, increased caution is warranted, especially considering the greater statistical power often attributed to the Shapiro–Wilk test in smaller samples. Consequently, this study employed both the parametric paired-samples *t*-test, assuming normality, and the non-parametric Wilcoxon signed-rank test.

The paired-samples *t*-test statistics and results indicated a *p*-value of less than 0.05 ($p < 0.05$), substantially below the conventional significance level (e.g., $\alpha = 0.05$), thus leading to the rejection of the null hypothesis and supporting a significant difference between the pre-test and post-test scores. Furthermore, the negative *t*-statistic suggests that the post-test mean score was higher than the pre-test mean score. The findings from the paired samples *t*-test demonstrate a statistically significant increase in post-test total scores compared to pre-test total scores, with the relevant statistics presented in Table 5.

Table 5. Paired sample *t*-test ($n = 9$).

Measure	Mean	Standard Deviation	Standard Error	95% CI Lower Bound	Upper Bound	t-Statistic	Degrees of Freedom	p-Value
Pre-test Score	38.67	3.08	1.03	36.03	41.30	—	—	—
Post-test Score	44.67	1.58	0.53	43.35	45.98	—	—	—
Difference (Post-Pre)	6.00	2.40	0.80	4.17	7.83	7.50	8	<0.0001

Given the Shapiro–Wilk test results indicating that the post-test total score distribution did not conform to normality, this study employed the non-parametric Wilcoxon signed-rank test as a complementary analysis to comprehensively evaluate the pre-test and post-test results. According to the Wilcoxon test results, the *p*-value was less than 0.05, leading to the rejection of the null hypothesis and confirming a significant difference between pre-test and post-test scores. The Wilcoxon statistical results are presented below, in Table 6:

Table 6. Wilcoxon signed-rank test.

	post-test total scores—pre-test total scores
Z	−2.670 ^b
Asymptotic Significance (2-tailed)	0.008

^b Based on negative ranks.

To quantify the practical significance of this improvement, we calculated Cohen's *d* effect size using the pooled standard deviation method. The formula for Cohen's *d* is:

$$\begin{aligned}
 \text{Cohen's } d &= (\text{Mean}_{\text{Post-test Score}} - \text{Mean}_{\text{Pre-test Score}}) / \text{SD} \\
 &= (44.67 - 38.67) / 2.40 \\
 &= 6.00 / 2.40 \\
 &= 2.50
 \end{aligned}$$

The effect size (Cohen's *d* = 2.50) indicates an extremely large practical significance of the intervention, demonstrating the substantial impact of our gamified chatbot intervention combined with the OMO strategy on participants' health knowledge.

5. Discussion

The findings of this pilot study provide preliminary evidence of the potential effectiveness of a gamified chatbot using the OMO strategy to enhance parental nutrition knowledge. The observed improvement in post-intervention nutrition knowledge scores ($p < 0.05$, Cohen's *d* = 2.50) suggests that the integration of gamification elements within an OMO framework may contribute to the growing body of knowledge on gamified chatbot applications in health promotion by implementing an innovative OMO strategy. Our findings align with recent research by Rahman and Uddin [29], who emphasized the importance of performance expectancy in mobile health adoption.

The integration of AI in our gamified chatbot system represents a significant advancement in health promotion technology. As demonstrated by Patel, Jasani, AlAshqar, Doshi, Amin, Panakam, Patil and Sheth [28], AI models can effectively provide health information while maintaining user engagement. Our approach extends this concept by incorporating AI-driven gamification elements that adapt to user preferences and behaviors, creating a more personalized and effective health promotion tool. The chatbot's ability to analyze user interactions and adjust game elements accordingly exemplifies the adaptive gamification concept discussed in current literature.

The contribution of research lies in the novel combination of the OMO strategy with an AI-powered gamified chatbot for nutrition education. While previous studies have explored either gamification in health contexts or online-merge-offline approaches separately, our research demonstrates the synergistic potential of combining these strategies with an AI-powered gamified chatbot. The results from our intervention provide evidence that this integrated approach can effectively influence dietary knowledge and behaviors among the target population.

The implications for theory development are significant. Our findings suggest that traditional technology acceptance models should be expanded to include gamification elements and AI capabilities when applied to health promotion contexts. The positive user response to our AI-enhanced gamified chatbot indicates that such technologies can help overcome adoption barriers commonly experienced by individuals who lack the time or opportunity to participate in conventional health education programs. This is particularly relevant to the target population of this project—parents of young children who often have limited access to reliable health information and are uncertain about where to obtain the knowledge needed to support their children's well-being.

6. Conclusions and Future Work

While the results of this pilot study are promising, several limitations should be acknowledged. First, the small sample size (20 unique participants) limits the generalizability of the findings. As this was designed as a preliminary investigation, future research should

include larger, more diverse samples to validate these results. Second, the lack of a control group makes it difficult to attribute the observed improvements solely to the gamified chatbot intervention. Future studies should employ randomized controlled designs to more rigorously evaluate the effectiveness of this approach compared to traditional methods or no intervention.

Third, the relatively short duration of the study (eight weeks) is a significant limitation that prevents us from assessing long-term knowledge retention or behavioral change. We recognize that nutrition education interventions ideally should demonstrate sustained effects over time. Therefore, follow-up assessments at 3–6 months post-intervention would provide valuable insights into the durability of the knowledge gains observed in this study and should be incorporated into future research designs. Fourth, while knowledge improvement is an important outcome, future research should also assess whether this translates into actual behavioral changes in nutritional practices. Fifth, a notable limitation of this study is the absence of qualitative data regarding user experiences with the gamified chatbot. Qualitative insights could provide deeper understanding of how parents perceived the intervention, what aspects they found most valuable, and what challenges they encountered. Future research should incorporate qualitative methods such as in-depth interviews or focus group discussions to complement quantitative findings and provide a more comprehensive understanding of the intervention's impact. Such mixed-method approaches would be particularly valuable for understanding the nuanced ways in which parents engage with and apply the nutritional knowledge gained through the intervention.

Furthermore, this pilot study provides preliminary evidence that gamified chatbots with OMO strategies can effectively improve parental nutrition knowledge. The integration of gamification elements with the seamless blending of online and offline experiences creates a comprehensive learning ecosystem that promotes engagement and knowledge acquisition. Future research should build on these findings by addressing the limitations noted above, particularly by employing larger sample sizes, including control groups, conducting longitudinal follow-ups to assess long-term effects, and incorporating qualitative research methods to gain deeper insights into user experiences. Additionally, exploring the applicability of this approach across diverse populations and health education contexts remains an important direction for future work. As digital technologies continue to evolve, the potential for innovative approaches like gamified chatbots with OMO strategies to enhance health education and promote positive health behaviors remains an exciting area for continued exploration and development.

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