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# Implementation and Evaluation of a Nutrition Information Chatbot Using UTAUT and TAM

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***Abstract*— This study aims to evaluate the use of a Telegram-based question-answering chatbot for accessing nutrition information using the UTAUT and TAM approaches to measure user intention and behavior. The system utilizes LangChain and Large Language Models (LLMs) to deliver rapid and precise nutrition-related replies. Validity and reliability assessments were performed to confirm that the measurement equipment exhibited optimal consistency, with Cronbach's Alpha values surpassing 0.7. The multiple linear regression results demonstrate that Effort Expectancy (EE) and Social Relationship (SI) significantly affect Behavioral Intention (BI), whereas Performance Expectancy (PE), Perceived Usefulness (PU), and Perceived Ease of Use (PEOU) reveal no substantial relationship. The findings indicate that usability and social impact are more pivotal in enhancing users' propensity to use the chatbot than system utility and efficiency.**

***Index Terms*— *Question Answering; LangChain; UTAUT; Behavioral Intention*.**

## I. INTRODUCTION

The rapid growth of artificial intelligence (AI), particularly in Natural Language Processing (NLP) and Large Language Models (LLMs), has significantly transformed how information is accessible and communicated in a variety of fields, including healthcare, education, and public services. The question-answering chatbot is one of the most popular AI applications, allowing users to receive instant, automated, and interactive responses through natural language interaction. Chatbots have demonstrated significant potential in healthcare for information distribution, decision assistance, and public awareness, particularly in areas that require frequent and accessible consultation, such as nutrition information.

In the healthcare sector, researchers investigated the use of Retrieval-Augmented Generation (RAG) and Mistral 7B to deliver more accurate, data-driven replies regarding Indonesian medicinal plants [1]. The results showed that this strategy successfully increased the quality of responses delivered by the chatbot. A Telegram-based question-and-answer system to disseminate information about Health Law No. 17 of 2023, which uses LangChain and LLMs, plays a role in accelerating this process [2]. The system was assessed using the BERTScore, which showed satisfactory performance in delivering relevant and correct responses.

Similar technological apps have been developed for Islamic studies to help people grasp tafsir and fiqh. A Telegram-based chatbot system that can be used to answer questions on Ibn Kathir's Tafsir [3]. Their findings show that the use of LangChain and LLMs can help provide extremely accurate replies; however, further enhancements are required to attain optimal outcomes. As a similar work, using GPT-3.5, can create a Qur'anic question-and-answer system [4]. Their findings suggest that this approach may provide speedy responses with an accuracy rate of 78.85%, despite issues with answer relevancy and the possibility of disinformation (hallucination).

A question-and-answer system for purification (fiqh of ṭahārah) with LangChain and LLMs suggests that AI technology can improve public knowledge of Islamic legal rulings in more efficient and accessible ways [5]. Another related study created a Telegram-based chatbot to deliver knowledge about Prophet Muhammad's (peace be upon him) hadiths using LangChain and GPT-4 [6]. The study discovered that the method was effective at providing extremely correct replies based on pertinent hadiths.

Furthermore, a study on chatbot applications for public service organizations investigated the use of RAG and vector databases to increase the correctness of responses to regulatory documents [8]. Their research found that LLM-based systems can deliver more relevant replies based on official laws. In another study, the application of LangChain and GPT-4 was examined in Qur'anic exegesis, notably the Tafsir of Ibn Kathir [9]. Their results indicate that, while the Telegram-based chatbot may generate generally appropriate responses, further work is needed to increase contextual comprehension and accuracy. Whereas a web-based health sector chatbot utilizing a LangChain Retriever was also generated [10].

Despite the increasing usage of chatbot technologies in healthcare-related context, there is still a significant study gap in terms of user acceptance and behavioral intention toward AI-based nutrition information systems. Most present research focuses on the technical performance, response accuracy, or architectural design of LLM-based chatbots, with little attention paid to experimentally studying the aspects that influence users' adoption, intention to use, and sustained use of such systems. This disparity emphasizes the necessity for a systematic evaluation approach that not only examines system functionality but also explains user behavior and technology adoption.

This study descents within the research areas of artificial intelligence, health informatics, and technology acceptability research. The novelty of this research lies in integrating a Large Language Model-based nutrition information chatbot with a complete acceptance evaluation framework that includes the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM). Their complementary strengths motivated the use of UTAUT and TAM in this study. UTAUT presents a strong paradigm for explaining user acceptance, drawing on social and organizational characteristics such as Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. In contrast, TAM focuses on users' cognitive perceptions, notably Perceived Usefulness and Perceived Ease of Use, which are critical in understanding how users access system advantages and usability. By combining these two models, this study provides a more complete and nuanced explanation of the social-contextual and individual-perceptual aspects that influence users' behavioral intention to utilize an AI-based nutrition chatbot. This integrated approach improves explanatory power and adds theoretical depth to the body of research on technology acceptability in AI-driven health information systems.

The scope of this study is defined as follows:

- Although most existing studies primarily emphasize system architecture, response accuracy, or technical performance, there is limited empirical evidence explaining the factors that influence users' acceptance and behavioral intention toward nutrition information chatbots, particularly those deployed on widely used messaging platforms such as Telegram.
- Previous research rarely considers both social-contextual factors and individual cognitive perceptions when assessing user adoption of AI-based nutrition systems, indicating the lack of a comprehensive acceptance model that explains why users are willing or unwilling to adopt nutrition chatbots powered by large language models.
- The primary research problem addressed in this study is how important determinants from the UTAUT and TAM frameworks affect users' behavioral intention to use a Telegram-based nutrition information chatbot.

## II. Methodology

The study approach begins with a literature review on the usage of Telegram-based chatbots using LangChain and LLMs for question-answering systems. The nutritional information was then gathered to use as the chatbot's knowledge base. Next, a data requirements analysis and the selection of an acceptable language model were performed. The system architecture includes the creation of a Telegram-based chatbot using LangChain and LLM technologies, which RAG assists in improving answer accuracy, as demonstrated in the study by [11]. The system was then implemented in accordance with the planned design, utilizing the same process as [12] when constructing a legal chatbot with Mistral 7B and RAG. Finally, the UTAUT and TAM models were used to evaluate the system's performance in providing accurate and relevant nutrition information and to assess user acceptance. The overall research workflow is presented in Fig. 1.

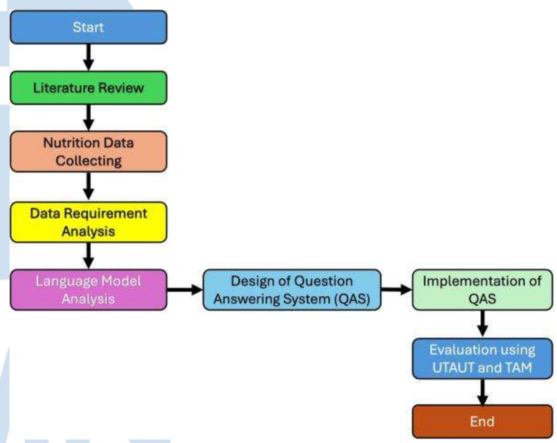


Fig. 1. Research stage

### A. Literature Review

The data gathering process began with a literature review, which involved examining relevant studies [13] that developed an LLM-based chatbot for student admissions information using FAISS and Sentence Transformers to improve response relevance. Another related study employed LangChain in a question-answering system for the Fiqh of the Four Madhabs, leveraging LLMs to generate responses from PDF-based textual sources [14].

Nutrition-related data was acquired to create the chatbot's knowledge base, which was then analyzed using language models to ensure response relevancy. LangChain was used to create a quick and context-aware question-and-answer system, and its efficacy was assessed using the UTAUT and TAM models [15], [16].

*B. Nutrition Data Collecting*

The nutrition data utilized in this study were sourced from a publicly available dataset maintained on Kaggle, the Indonesian Food and Drink Nutrition Dataset. This dataset, which offers complete nutritional information for Indonesian food and nutrition items, is available on the Kaggle repository.

The dataset contains detailed features for each food item, such as its name, category, calorie content, protein, fat, and carbohydrate levels, as well as descriptive information, health advantages, and flavor characteristics. A total of 1,346 food entries is provided, reflecting a diverse range of popular Indonesian dishes and beverages [3]. This dataset was chosen because it is relevant to the research environment, has complete nutritional features, and is suitable for constructing a nutrition-focused question-and-answer system. The data were preprocessed and saved in a MySQL database before being transformed to textual format for use as the knowledge base for the LangChain-based Retrieval-Augmented Generation (RAG) technique. This approach allows the chatbot to efficiently obtain contextually relevant nutrition information and provide accurate responses to user requests.

*C. Data Requirement Analysis*

The data requirements analysis stage seeks to identify data that is relevant and supportive of the investigation. The data collected, and the selection procedure focused on nutrition information, featuring various aspects, including product, category, nutritional content, and additional supplemental information. This data was then converted to a text (.txt) file format, which contained the critical information required to build the knowledge base for the chatbot-based question-answering system. Like approaches used in the blockchain domain to develop chatbots that integrate external data through Retrieval-Augmented Generation (RAG) to enhance answer relevance and accuracy, this study optimizes the use of external data to enrich the chatbot's knowledge and improve the accuracy and timeliness of nutrition-related information provided [17].

*D. Language Model Analysis*

Language model analysis was used to establish the best LLM for the question-answering system. To handle nutrition-related data, the researchers used OpenAI's GPT-3.5 Turbo with the LangChain framework, which allowed for automatic answer generation and storage of the results in a vector store as a knowledge base. This technique is consistent with the work of [18], who utilized GPT-3.5 and LangChain to provide feedback on student business ideas, and employed LangChain and LLMs to develop a question-answering system on contemporary Islamic law [19], AI in Education [20] and cinema industry [21]. In this work, LangChain handles data processing and query handling to produce accurate and contextually relevant responses, where embeddings and vector stores accelerate information retrieval.

*E. Design of Question-Answering System (QAS)*

The design of the question-answering system includes processing nutrition-related data to generate responses using a Telegram-based chatbot. This procedure uses GPT-3.5 Turbo in conjunction with LangChain to ensure answer accuracy, and the processed data is saved in a vector store as a knowledge base to provide rapid and contextually relevant responses. Fig. 2 illustrates the architecture of the question-answering system, covering the entire workflow from the acquisition of nutrition information data to the delivery of responses to users through the Telegram chatbot.

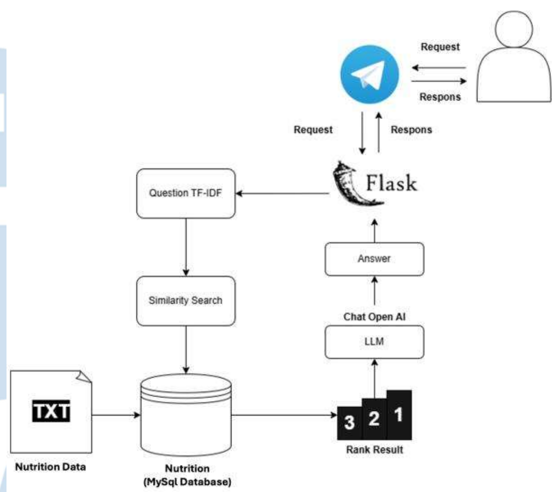


Fig. 2. Telegram chatbot architecture

*F. Implementation of Question-Answering System (QAS)*

The database in this system was implemented using the Python programming language, which includes various libraries that help question-answering system development, such as LangChain. LangChain is a framework that allows Large Language Models (LLMs) to respond appropriately to contextual input. The nutrition information is saved in the Knowledge Base. In the next stage, the researchers used Flask to create an API service that serves as the backend for the question-answering system [3]. This system features a Telegram-based chatbot interface that serves as a question-answering platform, serving as a link between users and the system. One major advantage of the Telegram chatbot is that it is simple to create and can be accessed immediately from the Telegram client.

*G. Evaluation of Question-Answering System (QAS) using UTAUT and TAM*

This study evaluates the question-answering system using the UTAUT and TAM models through investigating seven main elements that influence users' intentions and behaviors when using a LangChain- and LLM-based Telegram chatbot. The suggested chatbot system was evaluated using a survey of 100 undergraduate students participating in the Nutrition Study Program at a private university in Indonesia. The respondents were chosen because they are potential users with a basic understanding of nutrition and experience with digital information systems.

The respondents' target age range was 18 to 25, which is common for undergraduate university students. This age group was chosen because it represents active users of mobile messaging platforms like Telegram and is thought to be appropriate for evaluating chatbot-based information systems.

The questionnaire was made available online through Google Forms, allowing respondents to participate voluntarily and conveniently. The poll link was distributed by several academic communication channels, including class group chat systems. Prior to complete distribution, a pilot test with ten respondents was conducted to ensure the questionnaire items' clarity, validity, and reliability. Responses were gathered anonymously to ensure confidentiality and prevent response bias.

The evaluation includes the following factors:

- Performance Expectancy (PE) has a strong positive effect on Behavioural Intention (BI), showing that users believe the chatbot will improve their efficiency when accessing nutrition information.
- Effort Expectancy (EE) significantly and favorably influences Behavioural Intention (BI), reflecting users' perceptions of the chatbot's ease of use.
- Social Influence (SI) has a favorable effect on Behavioural Intention (BI), implying that support from others, such as nutrition experts or peers, can improve users' willingness to utilise the chatbot.
- Facilitating Conditions (FC) have a large and favorable influence on Behavioural Intention (BI), whereas supporting conditions such as internet availability and suitable chatbot functionality encourage system utilization.
- Perceived Usefulness (PU) has a strong positive impact on Behavioural Intention (BI), indicating that users believe the chatbot will improve access to nutrition information.
- Perceived Ease of Use (PEOU) has a positive relationship with Perceived Utility (PU), implying that ease of use influences users' evaluations of the chatbot's utility.

The findings indicate that simplicity of use, perceived utility, and social impact are all important factors in molding users' intentions and behaviors while getting nutrition information through the chatbot.

## III. Result

*A. Data Collection and Analysis Results*

The researchers gathered nutritional data from a Kaggle source https://www.kaggle.com/datasets/anasfikrihanif/indonesian-food-and-drink-nutrition-dataset, which includes numerous Indonesian items and their nutritional content. The data imported into the MySQL database was then analyzed to identify and choose key nutritional features. This analysis yielded important attributes such as food name, protein, fat, carbs, and calories, which were then used in the study. Table 1 presents an example of the data contained in the MySQL database used to power the nutrition chatbot. The data contains information about numerous types of food, such as nutritional value, brief descriptions, linked health benefits, and flavor qualities.

The data in Table 1 serves as the foundation for the chatbot to generate nutrition-related responses to user inquiries. With an organized data structure, the chatbot may make food recommendations based on user preferences or specific nutritional requirements. Furthermore, the table enables developers to update or expand the dataset as needed, keeping the system relevant and helpful. Understanding the structure and content of this table will allow the nutrition chatbot to provide more accurate and useful responses, as well as improve the overall user experience when accessing health and dietary information.

*B. System Design Results*

At this stage, the question-answering system was developed using OpenAI's GPT-3.5-Turbo language model integrated with the LangChain framework. The workflow began by retrieving nutrition data in text format, which was subsequently stored in a MySQL database. The data was preprocessed to detect similarities with user searches using the TF-IDF approach, and the processed query was sent to Flask for additional processing. Flask then sent the question to the OpenAI LLM, which generated a meaningful response. The resulting answers were sorted according to their relevance and then provided to users through the Telegram network, as depicted in Fig. 2. The next step was to link them with the Telegram chatbot.

TABLE I. NUTRITION DATA

| id | A combination of the food item and its nutritional attributes (protein, fat, carbohydrates, and calories) | Description | Benefit | Taste |
|---|---|---|---|---|
| [1] | shredded meat contains 280 kcal, 9.2 g of protein, 28.4 g of fat, and 0 g of carbohydrates | shredded meat is a food product with nutritional contents of…... | This food contains protein that helps support vital physiological functions…... | The taste of shredded meat is generally savory, salty, and slightly spicy… |
| [..] | …………. | …………... | ………… | ……….. |
| [1346] | Yogurt contains 52 calories, 3.3 grams of protein, 2.5 grams of fat, and 4 grams of carbohydrates… | Yogurt is a food product with a caloric content of 52.0 kcal… | This food contains protein that supports essential bodily functions… | The taste of this food varies depending on its base ingredients … |

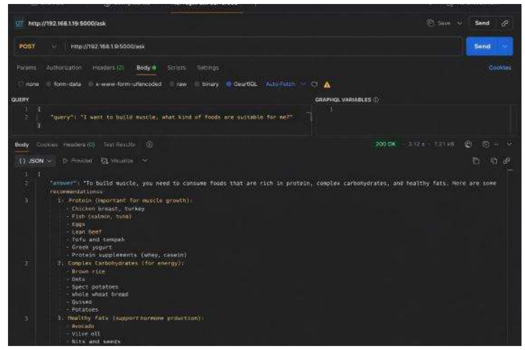


Fig. 3. API service output display

## C. Implementation Results

The architecture of the question-answering system that had been designed was then implemented in two aspects: database implementation and user interface implementation.

- Database Implementation: Fig. 3 shows the database implementation results, which are delivered as an API service. This service was designed to handle and efficiently access data within the chatbot system.
- User Interface Implementation: Fig. 4 depicts the user interface for interacting with the Telegram chatbot. Users can submit nutrition-related inquiries by entering the /askgizi command, followed by their query. The designed interface enables users to access information efficiently and intuitively. Users are only required to enter their inquiry following the /askgizi command, after which the chatbot will provide a relevant response.

## D. Question-Answering System Evaluation

### 1) Assessment Instruments and Questionnaires.

The evaluation was conducted to determine the level of acceptance and usefulness of the Telegram-based chatbot question-answering system that provides nutritional information to users. This assessment employs an approach that combines the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM). A questionnaire was distributed to 100 respondents, consisting of students from the Nutrition Study Program at a private university. The questionnaire consists of 21 items, organized into seven categories, with each category comprising three elements. Using a 5-point rating scale, respondents selected one of five answer options: strongly agree (SA), agree (A), neutral (N), disagree (D), or strongly disagree (SD). Table 2 lists the questionnaire items.

Table 2 delineates the questionnaire items employed to assess the Telegram-based chatbot system according to the seven fundamental constructs of UTAUT and TAM. Each construct quantifies a distinct dimension, including Performance Expectancy (PE), which pertains to perceived advantages and productivity; Effort Expectancy (EE), which gauges usability; and Social Influence (SI), which appraises social pressure or motivation. Furthermore, Facilitating Conditions (FC) evaluate the accessibility of resources and knowledge, Perceived Usefulness (PU) gauges the system's utility, Perceived Ease of Use (PEOU) assesses the simplicity of interaction, and Behavioral Intention (BI) quantifies users' intent to persist in utilizing and endorsing the chatbot.

### 2) Descriptive Statistics

Descriptive statistics were used to summarize the respondents' responses to questionnaire items related to the research variables. The data were further analyzed using SPSS software. The results of the analysis were presented in a table for each construct and questionnaire item. The mean values were used to assess respondents' level of agreement with each item, whilst the standard deviation reflected the variability or dispersion of replies for each item. Table 3 summarizes the descriptive data for the questionnaire items.

TABLE II. QUESTIONNAIRE ITEMS BASED ON UTAUT AND TAM CONSTRUCTS

| Construct | Questions |
|---|---|
| Performance Expectancy (PE) | This chatbot helps me complete tasks more quickly |
| | I feel that this chatbot increases my productivity |
| | This chatbot is useful in supporting my needs |
| Effort Expectancy (EE) | This chatbot is easy to use without requiring additional guidance |
| | I feel comfortable using this chatbot for daily tasks |
| | Learning to use this chatbot is easy for me |
| Social Influence (SI) | People around me support the use of this chatbot |
| | The use of this chatbot is recommended by my colleagues or friends |
| | My social environment influences my decision to use this chatbot |
| Facilitating Conditions (FC) | I have adequate resources (such as devices or internet access) to use this chatbot. |
| | I have sufficient knowledge to use this chatbot. |
| | Technical support is available if I encounter issues with this chatbot. |
| Perceived Usefulness (PU) | I feel that this chatbot is helpful in completing my work |
| | This chatbot improves the quality of my work |
| | This chatbot provides significant benefits to me |
| Perceived Ease of Use (PEOU) | This chatbot is easy to learn and understand |
| | I find interactions with this chatbot very simple |
| | I do not need to put much effort into using this chatbot. |
| Behavioral Intention (BI) | I plan to use this chatbot regularly in the future |
| | I am interested in recommending this chatbot to others |
| | I would like to use this chatbot for other purposes |

Table 3 displays the distribution of scores from 100 respondents, with mean values ranging from 2.47 to 3.67, demonstrating a preference for neutral to positive replies. The standard deviations vary from 0.652 to 1.443, indicating significant heterogeneity in answers. Variables with smaller standard deviations suggest greater consistency, whereas those with larger values show greater variety in respondents' assessments. Overall, while the means are close to three, there are significant disparities in respondents' experiences and perceptions.


Fig. 4. Question-Answering Interface Display

TABLE III. DESCRIPTIVE STATISTICS FOR UTAUT AND TAM CONSTRUCTS

| | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| PE1 | 100 | 1 | 5 | 2.95 | 1.132 |
| PE2 | 100 | 1 | 5 | 2.90 | .893 |
| PE3 | 100 | 1 | 5 | 2.77 | 1.213 |
| EE1 | 100 | 2 | 5 | 3.07 | 1.008 |
| EE2 | 100 | 1 | 5 | 2.87 | .960 |
| EE3 | 100 | 1 | 5 | 2.72 | 1.443 |
| SI1 | 100 | 1 | 5 | 2.96 | .942 |
| SI2 | 100 | 2 | 5 | 3.21 | 1.047 |
| SI3 | 100 | 1 | 5 | 2.83 | 1.256 |
| FC1 | 100 | 1 | 5 | 3.30 | .893 |
| FC2 | 100 | 2 | 5 | 3.10 | .969 |
| FC3 | 100 | 2 | 5 | 3.44 | 1.057 |
| PU1 | 100 | 2 | 5 | 2.87 | 1.012 |
| PU2 | 100 | 1 | 5 | 2.74 | 1.330 |
| PU3 | 100 | 1 | 5 | 2.47 | 1.167 |
| PEOU1 | 100 | 1 | 5 | 3.17 | 1.288 |
| PEOU2 | 100 | 2 | 5 | 3.36 | 1.087 |
| PEOU3 | 100 | 1 | 5 | 3.09 | .830 |
| BI1 | 100 | 1 | 5 | 3.67 | .652 |
| BI2 | 100 | 1 | 5 | 3.60 | .778 |
| BI3 | 100 | 1 | 5 | 3.48 | 1.123 |

*3) Validity.*

The validity test found substantial correlations among items within each variable and between each item and the total variable score (p-values < 0.01). All variables show good consistency in measuring their intended constructs. Table 4 shows the results of the validity test.

TABLE IV. CORRELATIONS AMONG ITEMS AND BETWEEN ITEMS AND TOTAL VARIABLE SCORES

| Variables | Item | Correlation Among Items and Between | Correlation Between Item and Total Score |
|---|---|---|---|
| PE | PE1 | PE1 - PE2: 0.784<br>PE1 - PE3: 0.727 | 0.910 |
| | PE2 | PE2 - PE1: 0.784<br>PE2 - PE3: 0.817 | 0.929 |
| | PE3 | PE3 - PE1: 0.727<br>PE3 - PE2: 0.817 | 0.927 |
| EE | EE1 | EE1 - EE2: 0.824<br>EE1 - EE3: 0.924 | 0.960 |
| | EE2 | EE2 - EE1: 0.824<br>EE2 - EE3: 0.848 | 0.924 |
| | EE3 | EE3 - EE1: 0.924<br>EE3 - EE2: 0.848 | 0.977 |
| SI | SI1 | SI1 - SI2: 0.869<br>SI1 - SI3: 0.865 | 0.949 |
| | SI2 | SI2 - SI1: 0.869<br>SI2 - SI3: 0.865 | 0.953 |
| | SI3 | SI3 - SI1: 0.865<br>SI3 - SI2: 0.865 | 0.961 |
| FC | FC1 | FC1 - FC2: 0.852<br>FC1 - FC3: 0.843 | 0.950 |
| | FC2 | FC2 - FC1: 0.852<br>FC2 - FC3: 0.795 | 0.935 |
| | FC3 | FC3 - FC1: 0.843<br>FC3 - FC2: 0.795 | 0.939 |
| PU | PU1 | PU1 - PU2: 0.905<br>PU1 - PU3: 0.805 | 0.955 |
| | PU2 | PU2 - PU1: 0.905<br>PU2 - PU3: 0.782 | 0.956 |
| | PU3 | PU3 - PU1: 0.805<br>PU3 - PU2: 0.782 | 0.914 |
| PEOU | PEOU1 | PEOU1-PEOU2: 0.887<br>PEOU1 - PEOU3: 0.884 | 0.974 |
| | PEOU2 | PEOU2 - PEOU1: 0.887<br>PEOU2 - PEOU3: 0.826 | 0.951 |
| | PEOU3 | PEOU3 - PEOU1: 0.884<br>PEOU3 - PEOU2: 0.826 | 0.935 |
| BI | BI1 | BI1 - BI2: 0.613<br>BI1 - BI3: 0.687 | 0.863 |
| | BI2 | BI2 - BI1: 0.613<br>BI2 - BI3: 0.534 | 0.807 |
| | BI3 | BI3 - BI1: 0.687<br>BI3 - BI2: 0.534 | 0.902 |

Overall, Table 4 demonstrates that most items within each variable have very high correlations, both among themselves and with the total scores, indicating that the items are good at assessing their intended dimensions. However, the BI variable has lower inter-item correlations than the other factors.

*4) Reliability*

The reliability test findings present that the instrument is reliable, since Cronbach's Alpha values for most of the variables evaluated surpass 0.7. Table 5 summarizes the Cronbach's Alpha values for all variables.

TABLE V. CRONBACH'S ALPHA FOR EACH VARIABLE

| Variables | *Cronbach's Alpha* |
|---|---|
| Performance Expectancy (PE) | 0.902 |
| Effort Expectancy (EE) | 0.934 |
| Social Influence (SI) | 0.943 |
| Facilitating Conditions (FC) | 0.933 |
| Perceived Usefulness (PU) | 0.929 |
| Perceived Ease of Use (PEOU) | 0.936 |
| Behavioural Intention (BI) | 0.792 |

Cronbach's Alpha is used to determine the internal consistency of measurement equipment. Cronbach's Alpha values greater than 0.7 suggest that the measurement device has good to acceptable reliability. Although the Behavioral Intention (BI) variable has a somewhat lower value of 0.792, it remains within an acceptable range for accurate measurement. Overall, the reliability test shows that the instrument has strong internal consistency, with Cronbach's Alpha values more than 0.7 for all variables examined, validating its suitability for this study.

*5) Multiple Linear Regression Test.*

This section examines the influence of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Facilitating Conditions (FC) affect Behavioral Intention (BI) when utilizing a chatbot system. The multiple linear regression findings reveal the extent to which these characteristics influence users' intent to employ the chatbot. The regression analysis results are summarized in a Table VI. Table VI presents the standardized coefficients, significance values, and the impact of relationships among the UTAUT and TAM variables.

As shown in Table VI, Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) have a significant positive effect on Behavioral Intention (BI). In contrast, Performance Expectancy (PE) and Perceived Usefulness (PU) do not significantly influence BI. Furthermore, Perceived Ease of Use (PEOU) does not significantly affect Perceived Usefulness (PU).

## IV. CONCLUSION

The findings of the multiple regression analysis determine that users' intention to develop the nutrition information chatbot is primarily affected by effort expectancy, social influence, and facilitating factors. Conversely, performance anticipation and perceived usefulness exhibit no significant impact on behavioral intention. Despite the system being regarded as user-friendly, the perceived ease of use has a compelled impact on perceived utility, indicating that usability alone is insufficient to influence users' assessments of system advantages.

TABLE VI. SUMMARY OF REGRESSION ANALYSIS RESULTS FOR UTAUT AND TAM VARIABLES

| No | Relationship | β (Standardized) | t-value | p-value | R² | Decision |
|---|---|---|---|---|---|---|
| 1 | Performance Expectancy (PE) → Behavioral Intention (BI) | 0.176 | 1.769 | 0.080 | 0.031 | Not Supported |
| 2 | Effort Expectancy (EE) → Behavioral Intention (BI) | 0.551 | 6.541 | 0.000 | 0.304 | Supported |
| 3 | Social Influence (SI) → Behavioral Intention (BI) | 0.348 | 3.672 | 0.000 | 0.121 | Supported |
| 4 | Facilitating Conditions (FC) → Behavioral Intention (BI) | 0.505 | 5.799 | 0.000 | 0.255 | Supported |
| 5 | Perceived Usefulness (PU) → Behavioral Intention (BI) | -0.125 | -1.245 | 0.216 | 0.016 | Not Supported |
| 6 | Perceived Ease of Use (PEOU) → Perceived Usefulness (PU) | -0.032 | -0.316 | 0.753 | 0.001 | Not Supported |

The results reveal that social encouragement, ease of interaction, and the presence of supportive technological conditions are more essential than functional performance in influencing user intention within the UTAUT and TAM frameworks.

Future research could broaden this study by including more diverse user groups besides university students, comparing different large language model architectures or chatbot platforms, and incorporating additional variables like trust, privacy, or information quality to better understand user adoption of AI-based nutrition information systems.

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