Study on Determinants of Trust, Data Sharing Attitudes, and User Preferences Toward AI-Based Dietary Recommendation Systems

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ABSTRACT

This research examines the integration of artificial intelligence (AI) in the healthcare industry, with specific reference to AI-based dietary recommendation systems. This research seeks to establish the key factors that affect user trust, attitudes toward information sharing, and user preferences. A questionnaire-based research method is adopted to collect data from the participants, who are asked about their engagement with mobile health applications, their willingness to share information, their level of trust in traditional dietitians, and their perceptions about AI-based dietary recommendation systems. The research results show that how familiar users are with diet application software differs. Trends suggest that familiarity may be linked to how often people use the application. However, this connection is mostly examined through correlation analysis and not backed by more thorough methods like regression. Also, while more frequent application usage seems to relate to greater user trust in AI-based dietary recommendation systems, this conclusion relies on correlation findings, not solid causal evidence. Although the participants showed comfort with information sharing, they showed reluctance in sharing information about their dietary history. The results show that the level of trust in traditional dietitians is relatively high, indicating the significant role played by traditional dietitians in dietary recommendation. The results show that the cost-effectiveness of AI-based dietary recommendation systems is an important motivational factor, with the majority showing unwillingness to adopt AI-based dietary recommendation systems without professional counselling, even if the costs are reduced. Moreover, the results show that the participants show a preference for flexible dietary plans over rigid dietary plans.

Keywords: Artificial Intelligence, Dietary Recommendation Systems, User Trust, Health Data Sharing, Mobile Health Applications

INTRODUCTION

The application of Artificial Intelligence in the health sector has been rising dramatically over the past few years, specifically in areas such as nutrition and diet planning, which need to be individualized for each and every individual. For instance, the application of Artificial Intelligence in the development of diet recommendation systems utilizes individual parameters such as age and lifestyle to develop individualized diet plans for users of such systems. Such systems are now being contemplated as viable options to consult and seek recommendations for diet planning and other related issues due to their ease of availability and the potential to reduce costs. The rising prevalence of non-communicable health conditions such as Obesity and Type 2 Diabetes also necessitates effective and individualized interventions for diet and nutrition (Ordovas et al., 2018).

Digital health technologies such as mobile-based applications have also been identified as having the potential to influence and encourage users to make healthier lifestyle choices through continuous interaction and engagement mechanisms. Rather than relying on periodic consultations to seek recommendations and guidance for health and related issues, such applications have been identified as having the potential to encourage continuous interaction and engagement to promote and encourage users to make healthier lifestyle choices and adhere to recommendations and guidance provided for diet and other related issues. Research indicates that such applications have the potential to encourage and assist users to manage their health in a more active manner; however, the effectiveness of such applications is also subject to individual perceptions of such applications (Wang et al., 2022). On the other hand, individualized interventions for nutrition and diet planning through the application of Artificial Intelligence have also been identified as having a positive impact when compared to general recommendations and guidance (Ordovas et al., 2018).

However, despite these potential benefits of AI-based dietary systems, it has also been recognized that their adoption is not dependent on the capabilities of these systems alone. One of the most important factors affecting the acceptance of AI-based dietary systems is trust. Since AI-based dietary systems are dependent on computerized processes for decision-making, it has also been recognized that users may have difficulty trusting such systems compared to human dietitians who make recommendations based on their expertise and knowledge. Trust has also been related to the transparency, accuracy, and consistency of these dietary systems. Users who perceive these systems as untrustworthy or vague may be less inclined to use these systems for a longer period of time (Beldad & Hegner, 2018).

Another important aspect of AI-based dietary systems is related to the sharing of personal information. Since AI-based dietary systems require access to personal information to function optimally, it has also been recognized that users may have difficulty sharing such information. Even though users may be willing to share some information with AI-based dietary systems, they may be hesitant when it comes to more personal information such as their health condition and dietary habits. Such attitudes have also been recognized as potential factors affecting user acceptance of AI-based dietary systems (Beldad & Hegner, 2018).

In addition to these factors, user preferences and economics also play a significant role in affecting user attitudes toward AI-based dietary systems. Since AI-based dietary systems are considered to be more affordable than human consultations for dietary recommendations, it has also been recognized that such factors may play a significant role in user acceptance of these systems. Users may also have a preference for more flexible dietary plans that are capable of being adapted to their daily routines rather than more rigid plans that require strict adherence to a set of dietary principles.

Furthermore, individual characteristics and experience with technology also play a significant role in influencing the attitude of the users toward AI-based dietary systems. Individual characteristics include age and experience with mobile health applications and frequency of usage of such applications. It has been found that users who are more experienced with mobile health applications are likely to show higher attitude toward AI-based dietary systems. On the contrary, users who are not experienced with mobile health applications are likely to show a negative attitude toward AI-based dietary systems. Furthermore, users who are more frequent users of mobile health applications are likely to show higher attitude toward AI-based dietary systems.

Apart from individual characteristics and experience with technology, user preference and influence of others also play a significant role in influencing the attitude of the users toward AI-based dietary systems. It has been found that users are likely to show a positive attitude toward AI-based dietary systems based on their perceived usefulness and convenience of use. Furthermore, users who are likely to recommend AI-based diet applications to others are likely to show a higher attitude toward AI-based dietary systems.

Although previous studies have focused on the adoption of digital health technologies, it has also been recognized that there is a lack of research on the attitudes of users toward AI-based dietary recommendation systems in terms of trust, attitudes toward sharing personal information, and user preferences. Thus, the present study seeks to identify the determinants of trust, attitudes toward data sharing, and user preferences pertaining to AI-based dietary recommendation systems. The results of the present study are expected to offer valuable insights for the improvement of AI-based dietary recommendation technologies.

REVIEW OF LITERATURE

Artificial intelligence (AI) has recently become a major player in healthcare, especially in areas like nutrition that require personalized approaches. AI-driven nutritional recommendation systems aim to provide customized dietary advice, considering a person's lifestyle, health, and eating habits, among other factors. These AI-based technologies have been shown to improve healthcare services by increasing their accuracy and effectiveness (Jiang et al., 2017; Mehta et al., 2019).

The emergence of precision nutrition has amplified the significance of artificial intelligence within this domain. This methodology centers on tailoring dietary guidance to the unique biological and lifestyle characteristics of each individual. Studies indicate that AI-driven systems possess the capacity to dynamically refine and modify recommendations by leveraging real-time data, thereby facilitating more effective adherence to dietary plans and promoting improved health results (Agrawal, 2025; Wang, 2025).

One of the major factors in the use of AI in healthcare is trust. People are likely to be interested in AI systems when they believe the recommendations provided are both reliable and helpful for their health. Kauttonen (2025) claims that building trust largely depends on a person's ability to understand how the system works and to feel confident in its accuracy.

Another important factor is transparency. This is because, when users are aware of how and why a recommendation is being done, they will be able to trust the system. This is supported by Zhang and Chen (2020), who state that, through the help of explainable AI, users are able to understand the process of recommendation. This is also supported by Kaplan and Haenlein (2019), who state that systems need to be clear and understandable for them to be accepted.

Another factor is the familiarity of people with technology. For instance, people who are used to using mobile applications are likely to be comfortable around AI systems. This is supported by Kim and Park (2012), who state that ease of use and user intention are factors that influence the adoption of health technologies.

Mobile health apps have helped users to easily access AI-based dietary recommendations. The apps enable users to monitor their dietary habits and health. Lupton (2014) argues that such technologies have helped users to change their interactions with healthcare services by making them more easily accessible.

However, data privacy is a significant concern for users. This is because AI technologies require users to provide personal and health-related data. Ema (2023) argues that data handling is crucial in addressing users' concerns to help them gain confidence in AI-based technologies.

The willingness of users to share the information also depends upon the nature of the information that is to be shared. Users are often not willing to share their health and diet information. This aspect has been identified in the research related to digital health technologies (Bickmore & Giorgino, 2006).

Understanding user behavior is also essential in the study of AI adoption. Consumer behavior theories have identified that the decision-making process is influenced by both psychological and technological factors. Fogg (2003) has mentioned that technology helps in the direction of user behavior and promotes healthier behavior.

Another factor to be considered is cost, which is associated with AI-based systems. It is cheaper than consulting a dietitian. This is because, as highlighted by Miller and Brown (2018), AI is cost-effective and still effective in its application.

Despite the rise of AI, traditional dietitians are still viewed as very reliable. This is because people prefer to interact with them, as they are empathetic. This, as highlighted by Rho et al. (2015), is an indication that AI is meant to be used alongside other health professionals.

Culture and society are other factors that can influence the response of users to the recommendations provided by AI systems. The eating culture of people varies from region to region, and this is something that AI systems need to consider for effective functioning. According to Wang (2025), this can lead to increased satisfaction for the users of the AI systems.

The other reason for the increased user engagement through AI systems is that they can provide users with interactive features. This can motivate the users of the systems, who can thereby adhere to their diets. According to Verma, K., Gupta, P**.,** et al (2025), this can lead to increased commitment from the users.

In conclusion, the implementation of dietary recommendations using AI technology will depend on various critical factors such as trust, privacy, cost, personalization, and technology familiarity. These factors will help in ensuring the effective implementation of AI technology in healthcare and nutrition (Amadeh et al., 2025).

METHODOLOGY

Research Design

This study used a quantitative, cross-sectional survey design to examine factors that influence user trust, data-sharing attitudes, and preferences for AI-based dietary recommendation systems.

Sampling Strategy and Participants

The study used a convenience sampling method to gather responses online. Participants were chosen based on their availability and willingness to take part.

A total of 126 respondents took part in the study.

This study included participants aged from 18 to 40 years, covering late adolescence and adulthood. This age group was chosen because they are more likely to be familiar with digital technologies and mobile health apps, making them suitable for assessing views on AI-based dietary recommendation systems.

Demographic Profile

The study included participants with various demographic traits. The main factors considered were age, gender, education, and occupation.

Age: Participants ranged from 18 to 40 years, covering late adolescence, early adulthood, and adulthood.

Gender: Both male and female participants were included, with more female respondents.

Education/Occupation: The sample mainly included students and working professionals, representing individuals involved in education and work.

Instrument Development

Data were collected using a structured questionnaire, developed based on an extensive review of literature related to:

- Artificial Intelligence in healthcare
- Technology Acceptance Model (TAM)
- Trust in digital health systems

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- Data privacy concerns

The questionnaire consisted of close-ended questions, ensuring consistency and ease of statistical analysis.

Measurement Scale

Most of the questionnaire items were measured using **a** 5-point Likert scale, such as:

- Strongly Agree to Strongly Disagree
- Very Comfortable to Very Uncomfortable

This scaling method allowed for quantification of attitudes and perceptions.

Data Collection Procedure

Data were collected using Google Forms, and the survey link was distributed through messaging applications

Participation was:

- Voluntary
- Anonymous
- Confidential

Respondents were informed about the purpose of the study, and no personal identifying information was collected.

Data Analysis

The collected data were exported and analyzed using statistical methods. The analysis included Descriptive statistics (frequency and percentage) to summarize responses and Inferential statistics which includes One-Way ANOVA to test differences across age groups, Correlation analysis to examine relationships between key variables

A significance level of $p < 0.05$ was used for all statistical tests.

FINDINGS AND DISCUSSION

This chapter presents the findings from a survey of 126 participants. The survey assessed their views on AI-based dietary recommendations and professional dietitian guidance. We analyzed the data using descriptive statistics, bar charts, and One-Way ANOVA. This helped us understand participants' preferences, trust levels, and their willingness to use AI-based dietary platforms.

Descriptive Analysis

Table 1: Usage of mobile health or diet-related applications

Particulars	No Of Participants	Percentage
Never	38	30.4%
Occasionally	57	45.6%
Often	21	16.8%
Always	9	7.2%

Usage Of Mobile Health Or Diet-Related Applications

Most participants use mobile health or diet-related applications occasionally. About 45.6% reported occasional usage, while 30.4% said they never use such applications. A smaller group, 16.8%, reported frequent usage, and only 7.2% stated they always use these applications. These findings suggest that while mobile health applications are available, regular use among respondents is low, indicating moderate adoption of these digital health tools.

Table 2: Comfort in sharing personal data with AI-based diet platforms

Particulars	No Of Participants	Percentage
Very comfortable	18	14.4%
Somewhat comfortable	35	28%
Neutral	44	35.2%
Uncomfortable	22	17.6%
Very uncomfortable	6	4.8%

Comfort In Sharing Personal Data With AI-Based Diet Platforms

The results show different levels of comfort among participants when it comes to sharing personal data with AI-based diet platforms. A majority, 35.2%, reported a neutral stance, followed by 28% who felt somewhat comfortable sharing their data. Additionally, 14.4% indicated they were very comfortable. However, 17.6% were uncomfortable sharing, and 4.8% were very uncomfortable. These findings highlight that while some respondents are willing to share personal data, concerns about privacy and data security still exist.

Table 3: Willingness to share full dietary history with AI tool

Particulars	No Of Participants	Percentage
Definitely not	34	27.2%
Probably not	56	44.8%
Definitely yes	17	13.6%
Probably yes	18	14.4%

Willingness To Share Full Dietary History With AI Tool

Most participants were hesitant to share their full dietary history with AI tools. A significant portion, 44.8%, said they would probably not share their dietary history, while 27.2% stated they would definitely not share this information. In contrast, only 14.4% reported they would probably share, and 13.6% indicated they would definitely share. This suggests that participants are careful about providing detailed dietary information to AI platforms, likely due to trust and privacy concerns.

Table 4: Trust in dietitian for accurate diet advice

Particulars	No Of Participants	Percentage
Completely trust	49	39.2%
Mostly trust	44	35.2%
Neutral	25	20%
Slightly trust	7	5.6%
Not trust	0	0%

Trust In Dietitian for Accurate Diet Advice

The results show a high level of trust in dietitians among respondents. A majority, 39.2%, reported that they completely trust dietitians, while 35.2% mostly trust them for dietary advice. Additionally, 20% remained neutral, and only 5.6% slightly trust dietitians. None of the participants reported not trusting dietitians. These findings indicate that dietitians are a highly trusted source of dietary guidance among respondents.

Table 5: Willingness to pay for AI-generated dietary recommendations

Particulars	No Of Participants	Percentage
Definitely not	52	41.6%
Probably not	48	38.4%
Definitely yes	10	8%
Probably yes	15	12%

Willingness To Pay For AI-Generated Dietary Recommendations

Most participants were unwilling to pay for AI-generated dietary recommendations. About 41.6% said they would definitely not pay, while 38.4% indicated they would probably not pay. In contrast, only 12% reported they would probably pay, and 8% stated they would definitely pay for AI-generated dietary advice. These findings suggest limited willingness to invest in AI-based dietary services.

Table 6: Use of AI-based plans if cheaper without counselling

Particulars	No Of Participants	Percentage
Yes	19	15.2%
No	74	59.2%
Maybe	32	25.6%

Use of AI-Based Plans If Cheaper Without Counselling

A majority of respondents, 59.2%, stated they would not use AI-based diet plans even if they were 50% cheaper and lacked counselling support. Meanwhile, 25.6% said they might consider using such plans, and only 15.2% indicated they would use AI-based plans without counselling. These findings emphasize the importance of human interaction and professional counselling in dietary guidance.

Table 7: Preference For Strict Vs. Flexible Diet Plan

Particulars	No Of Participants	Percentage
Strict	20	16%
Flexible	89	71%
Not sure	16	12.8%

Preference For Strict Vs. Flexible Diet Plan

Most respondents prefer flexible diet plans. A majority, 71.2%, reported a preference for flexible plans, while 16% preferred strict plans. Additionally, 12.8% were unsure about their preference. These findings indicate that flexibility and adaptability in dietary planning are highly valued.

Table 8: Recommendation of AI-based diet APPS

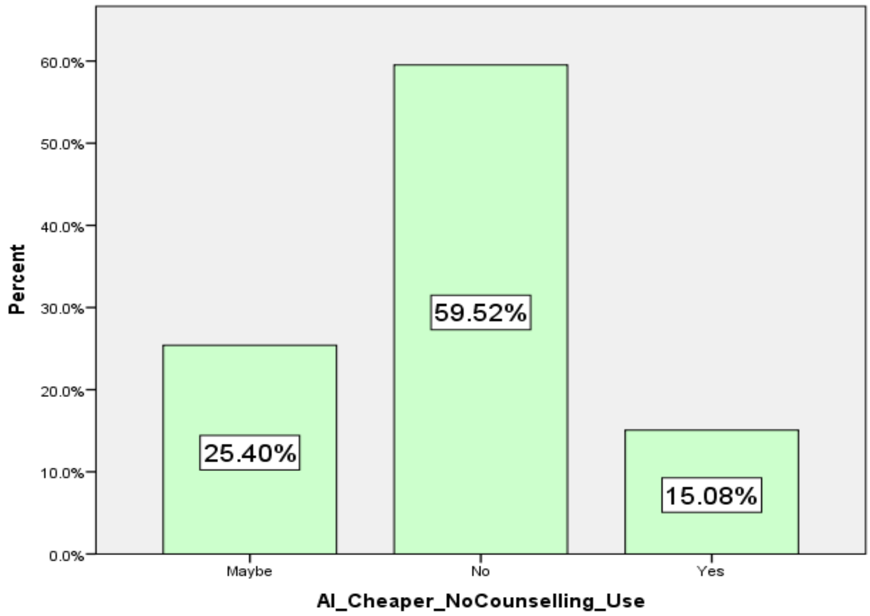
Particulars	No Of Participants	Percentage
Definitely yes	8	6.4%
Probably yes	33	26.4%
Not sure	54	43.2%
Definitely no	26	20.8%
Probably no	4	3.2%

Recommendation of AI-Based Diet Apps

The results show mixed opinions on recommending AI-based diet applications. A majority, 43.2%, were unsure about recommending such applications. Meanwhile, 26.4% said they would probably recommend them, and 6.4% reported they would definitely recommend AI-based diet apps. Conversely, 20.8% stated they would definitely not recommend these applications, and 3.2% indicated they would probably not recommend them. These findings suggest that respondents are cautious about recommending AI-based dietary tools to others.

Descriptive Analysis

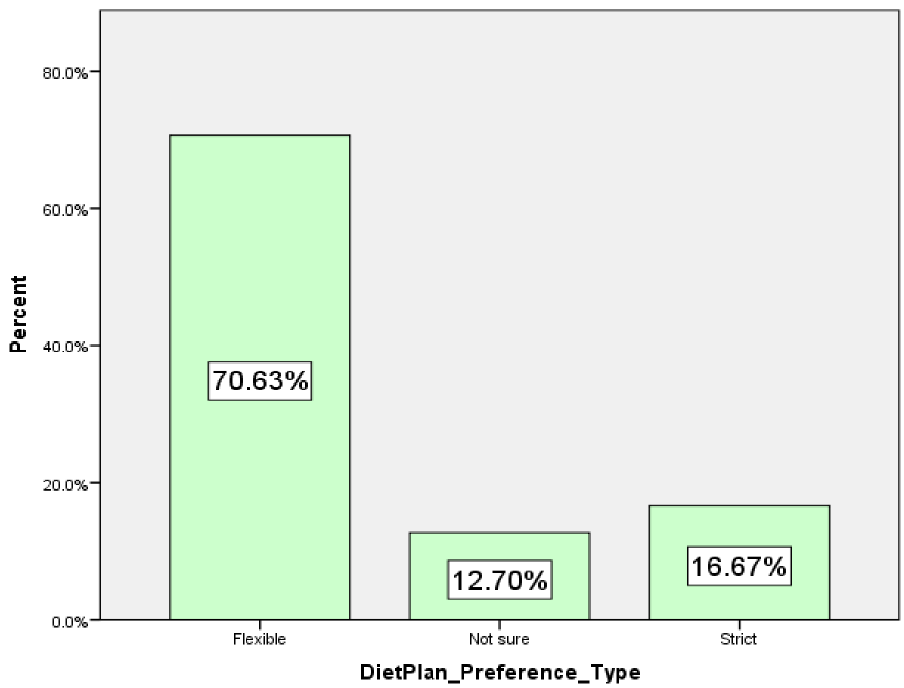
Use AI Plan If Cheaper But Without Counselling



Interpretation:

The bar chart shows how willing respondents are to use AI-based diet platforms if they are cheaper and do not involve counselling. The results reveal that most respondents, 59.52%, said they would not use these AI platforms without counselling. This suggests that many people still value professional guidance when getting dietary advice. Meanwhile, 25.40% selected “Maybe,” indicating some uncertainty depending on factors like reliability, cost, or effectiveness. Only 15.08% reported being willing to use AI-based diet services without counselling. Overall, these findings suggest that while cost-effective AI solutions may interest some, most respondents prefer to have professional counselling instead of relying only on AI-generated dietary advice. The findings also indicate that dietitians are still the most trusted sources of dietary guidance among respondents.

Preference For Strict Vs Flexible Diet Plan



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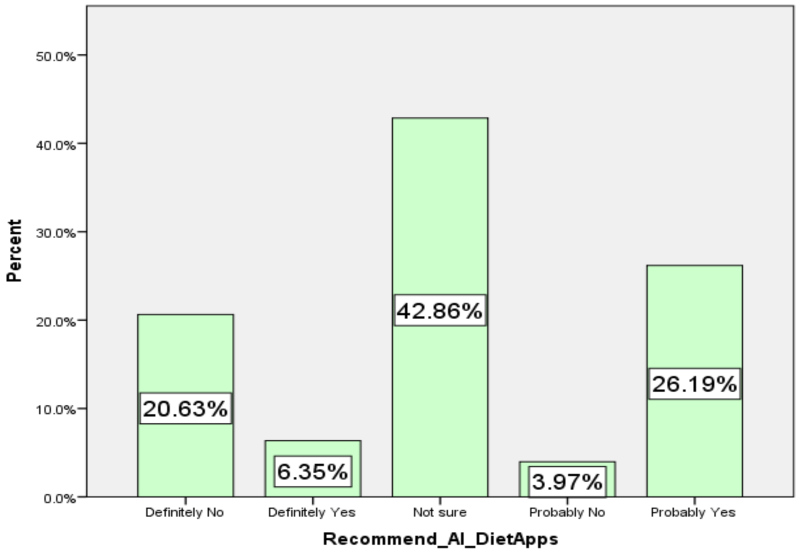
Interpretation:

The bar chart presents respondents' preferences for diet plans. The results show that a significant majority, 70.63%, prefer flexible diet plans. This indicates that most people favor dietary approaches that allow for personal choice and adaptability over strict guidelines. In comparison, 16.67% prefer strict diet plans, meaning a smaller group is comfortable with highly regulated dietary regimes. Additionally, 12.70% reported being unsure about their preference, highlighting some uncertainty about the diet plan that best fits their needs. Overall, the findings show that flexibility in dietary planning is highly valued, emphasizing the need for adaptable and personalized diet recommendations.

Willingness To Recommend Ai Diet Apps



Interpretation:

The bar chart illustrates how likely respondents are to recommend AI-based diet applications to others. The findings show that the largest group, 42.86%, indicated they are not sure whether they would recommend AI diet apps. This reflects considerable uncertainty about the reliability, effectiveness, or trustworthiness of these technologies. Meanwhile, 26.19% reported that they would probably recommend AI diet apps, indicating a moderate level of acceptance toward these tools. In contrast, 20.63% stated they would definitely not recommend them, while 3.97% said they would probably not recommend AI diet apps. Only a small group, 6.35%, indicated they would definitely recommend AI-based diet applications. Overall, the results suggest that while some respondents are open to recommending AI diet apps, a large portion remains uncertain. This highlights the need for greater trust and confidence in AI-driven dietary solutions.

Inferential Analysis

One-Way ANOVA

Differences in Frequency of using health/diet apps across different age groups

Hypotheses

ANOVA

HealthApp_Usage_Frequency

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	3.830	3	1.277	1.726	.165
Within Groups	88.040	119	.740		
Total	91.870	122			

H_0: There is no significant difference in the frequency of using mobile health or diet-related apps among respondents of different age groups.

H_1: There is a significant difference in the frequency of using mobile health or diet-related apps among respondents of different age groups.

Interpretation

A one-way A NOVA was conducted to see if there was a significant difference in how often respondents from different age groups used mobile health or diet-related applications. The analysis showed that the p-value (0.165) was higher than the significance level of 0.05. As a result, the null hypothesis was not rejected. This means there is no significant difference in the use of mobile health or diet-related applications among respondents of different age groups. The findings suggest that age does not greatly affect the usage of mobile health or diet-related applications among the participants in this study

Correlation Analysis

A correlation analysis examined the relationship between familiarity with diet-related applications, how often they are used, and trust in AI-based dietary recommendation systems. The results show a positive link between familiarity and usage frequency. This means that participants who are more familiar with diet-related applications tend to use them more often. Additionally, there is a positive connection between usage frequency and trust in AI-based dietary systems. This suggests that more frequent use is related to higher trust levels in AI-based dietary recommendation systems.

CONCLUSION

This study evaluated how participants view dietary recommendations based on Artificial Intelligence and the services of professional dietitians. The findings showed that while AI-based diet apps are attracting interest, most respondents still prefer advice from professional dietitians. Many participants raised concerns about privacy, accuracy, and the lack of human interaction in AI-based platforms. The results also indicated that respondents favor flexible diet plans over strict ones, emphasizing the need for personalized and adaptable dietary guidance. Additionally, the One-Way ANOVA analysis revealed no significant differences in mobile health app usage among different age groups. Overall, the study concludes that even though Artificial Intelligence can help with dietary planning, professional dietitians remain the most trusted source for nutrition advice. AI should be seen as a supportive tool, not a replacement for professional dietitians.

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