Beyond Algorithms: Cultural Sensitivity and Cost Considerations in User Acceptance of AI-Driven Personalised Nutrition

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ABSTRACT

In the realm of digital health, the personalization of AI-driven nutritional guidance has emerged as a critical factor. This study aims to explore the user's perception regarding personalization and practicality in relation to AI-generated nutrition plans and diet plans created by dietitians. Furthermore, it highlights the significance of cultural sensitivity, emotional intelligence, and cost as essential determinants of user perceptions. It also emphasizes key factors like cultural sensitivity, emotional intelligence, and cost, which are crucial in determining user perceptions. Data were collected from 126 participants across various age groups ranging from adolescents to adults through a structured questionnaire assessing comfort with AI, personalization quality, cultural integration, and effectiveness relative to Dieticians. The economic aspect is also considered when assessing the feasibility of AI-generated plans. The findings suggest that while AI is perceived as advantageous and potentially more economical, reservations persist regarding its capacity to fully comprehend cultural nuances and offer emotionally attuned guidance. Consequently, the results indicate that enhancing personalization features within AI systems and fostering AI-human collaboration (hybrid models) would likely yield superior outcomes in the realm of nutritional care.

Keywords: Artificial intelligence (AI), Personalised nutrition, Cultural Preferences, Cost influence, AI-Human collaboration (Hybrid model)

INTRODUCTION

Artificial Intelligence (AI) has transformed modern healthcare by enabling complex data analysis, predictive modeling, and improved clinical decision-making. Recent advancements have broadened AI's applications, particularly in nutritional analysis, deficiency diagnosis, and personalized dietary advice. AI systems process large datasets, such as medical records, lifestyle data, and physiological parameters, to deliver efficient nutritional services. These innovations have increased access to dietary guidance, especially in communities with limited healthcare professionals (Wang et al., 2025; Agrawal et al., 2025). Despite these benefits, concerns persist regarding the reliability and contextual adaptability of AI-generated recommendations. This system evolves through user interaction and feedback, contributing to its dynamic and flexible nature (Aydın et al., 2025). However, research indicates that while AI offers a streamlined and consistent approach, it often lacks the personalisation provided by dietitians (Kaçar et al., 2025). Dietary choices are influenced by cultural traditions, social norms, and emotional factors. Food is closely linked to cultural identity, religious practices, and family habits, all of which shape eating behaviours.

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Emotional states such as stress, comfort, and mood fluctuations also affect dietary decisions, sometimes resulting in preferences that do not align with nutritional recommendations. Studies demonstrate that neglecting these factors can reduce adherence to dietary plans and negatively affect long-term health outcomes (Mundt et al., 2025). Cultural sensitivity is essential for the acceptability and sustainability of dietary recommendations. Dietitians often incorporate culturally relevant foods, preparation methods, and eating habits, which can enhance compliance with nutritional programs. In contrast, AI may not fully address cultural and emotional dimensions, potentially resulting in advice that is impractical or misaligned with users' lifestyles. Therefore, cultural competence is critical for improving the efficacy and trustworthiness of AI-based nutritional guidance (Erik et al., 2025). Economic considerations also influence the choice between AI-based applications and traditional dietitian services. Professional dietary services may be financially inaccessible for many individuals, whereas AI-based applications offer a cost-effective and convenient alternative. However, this approach may not be suitable for those requiring personalized attention and emotional support from a qualified expert. Research suggests that cost-effectiveness is a primary factor driving the adoption of digital health technologies, including AI-based nutrition platforms (Azzimani et al., 2026).

Research Gap

Although there is a growing body of research on AI's technological capabilities in healthcare and nutrition, studies that focus on user-centred perspectives, particularly regarding personalization and preferences, are still limited. Most current research emphasizes accuracy and efficiency, focuses on the accuracy and efficiency of the results, while the importance of cultural sensitivity, emotional intelligence, and economic considerations are often ignored. Moreover, there is a need to conduct comparative studies in which the perception of the users about the diet plans created by AI is compared to those created by professional dietitians, which is an area of concern that must be addressed in the near future to better understand the user and incorporate the concept of AI in the field of nutrition care.

OBJECTIVE OF THE STUDY

- To assess the importance of cultural and emotional factors in nutrition choices.
- To evaluate comfort with AI-based personalized diet advice.
- To examine AI's ability to incorporate cultural food preferences.
- To compare AI and dietitians in perceived personalization effectiveness.
- To analyse the influence of cost on user preference.

REVIEW OF LITERATURE

Artificial Intelligence (AI) is revolutionising personalised nutrition by moving beyond generic, one-size-fits-all advice to deliver recommendations tailored to individuals. Additionally, many AI-assisted nutrition platforms are now incorporated into mobile health apps, providing users with immediate dietary guidance. Nevertheless, factors such as a lack of transparency in AI algorithm functioning, ethical issues, and data privacy concerns have been shown to potentially influence users' trust and acceptance of AI-assisted personal nutrition tools (Wang et al., 2025; Agrawal et al., 2025). Machine learning (ML) has increased the capabilities of AI systems to support individualised diet planning, as it allows them to learn from the user and adapt their recommendations accordingly. The AI system can also use wearable device data, such as physical and metabolic activity, to improve accuracy and dynamic nature in diet recommendations. However, these models are largely dependent on the quality, quantity, and variety of data used to train them. If the data is biased or does not adequately represent a population, recommendations may not be accurate or relevant to culturally diverse groups (Aydın et al., 2025).

AI-powered nutrition recommendation systems integrate computational techniques with nutritional science to offer automated dietary advice. Natural language processing (NLP) enhances user interaction by enabling conversational interfaces, like chatbots, to assist users with meal planning and dietary inquiries. Despite being effective and catering to a large number of people, there can be issues with interpreting complex medical conditions and user preferences (Kaçar et al., 2025). It can be seen that an AI-based diet plan can be effective for providing energy and other requirements, but can be deficient in considering taste, the cultural importance of food, the availability of ingredients to prepare a dish, emotional connections with food, etc. This further indicates how nutritionists can be effective in complex cases.

Food choices are influenced by a blend of cultural, social, environmental, and psychological factors. Research indicates that recommendations that do not align with an individual's cultural background often result in low adherence and dissatisfaction (Mundt et al., 2025). Therefore, considering cultural and social factors is essential for developing nutrition strategies that are both effective and sustainable over the long term. Cultural food practices are closely associated with social norms, religious beliefs, and regional traditions. Evidence suggests that incorporating familiar, culturally relevant foods into diet plans enhances their acceptability and the likelihood of long-term adherence. Unless AI systems are specifically trained on diverse cultural-dietary data, they may struggle to achieve the same level of cultural sensitivity (Erik et al., 2025).

Dietitians are well-equipped to address these aspects through counselling and behavioural strategies. In contrast, current AI tools have a limited ability to interpret emotional signals or respond with genuine empathy. This gap underscores the need to incorporate psychological insights into the design of AI-based nutrition interventions (Mundt et al., 2025). Cultural competence plays a key role in effective and equitable nutritional care services. In diverse societies, adapting recommendations to distinct cultural contexts is critical. While AI systems can develop some cultural knowledge, achieving true cultural competence depends largely on human understanding and contextual awareness.

Dietitians play a pivotal role in harmonising the principles of nutritional science with individuals' quotidian dietary practices. They skilfully translate research-backed recommendations into nutrition plans that are both scientifically accurate and considerate of cultural practices and dietary needs. This may involve adjusting traditional recipes, recommending appropriate ingredient substitutions, and considering socio-economic factors. In addition, dietitians provide emotional and motivational support and guidance, which are the key components of the required long-term dietary changes. Their conversational skills allow for adjustments in the process that are difficult to capture in their entirety by purely algorithmic models (Erik et al., 2025).

Despite these advances, online diet aids are not very effective in offering a real form of cultural customisation. This is mainly due to the fact that most online diet aids rely on limited or uniform data sets that do not show the wide variety of worldwide eating habits. In addition, the most important aspects, such as family obligations, social obligations, and emotions related to food, are not considered by AI-based nutrition apps. This reduces the contentment and trust levels among the users. The problem can be solved by using diverse data inputs in the development of AI-based diet solutions (Kaçar et al., 2025). Economic considerations shape the adoption of digital health tools. With AI nutrition applications generally being more affordable or free compared to consultations with registered dietitians, access increases among underserved populations. Cost-efficient digital alternatives are increasingly favoured in resource-limited settings, while professional nutritionist services may be financially or logistically out of reach (Azzimani et al., 2026).

Affordability alone, however, does not assure efficacy, particularly amid multifaceted health challenges. Certain users derive greater value from interpersonal professional interactions. Thus, synergistic models fusing AI automation with clinician supervision capitalise on technological prowess alongside irreplaceable human discernment (Agrawal et al., 2025). The strength of users' faith in the efficacy of health guidance from AI plays a significant role in determining their reliance on it. While complete reliance is not seen in many cases, especially when dealing with persistent illnesses and complex circumstances where AI cannot comprehend complex stories, subtle nuances, or personal preferences reflecting those of an expert, empirical knowledge indicates recognition of AI's speed and efficiency while preferring expert intervention in critical instances (Wang et al., 2025). The enhancement of perceived effectiveness requires great accuracy, personalisation, and integration into large-scale healthcare systems that involve professional verification, thus eliminating any possibility of mistrust and strengthening endorsement (Agrawal et al., 2025).

Uptake of AI nutrition instruments hinges on usability, customisation extent, fiscal viability, confidentiality concerns, technological proficiency, societal pressures, and risk evaluations. Empirical support also emphasises hybrid models, consisting of the interweaving of AI augmentation and practitioner involvement, as facilitators of enhanced assurance and permeation (Aydın et al., 2025; Azzimani et al., 2026). Such models combine the general accessibility and responsiveness of AI with human expertise. Humans are particularly efficient at contextualisation, emotional engagement, and making sound decisions.

METHODOLOGY

Research Design

An exploratory method was adopted in this research to investigate the perception of individuals towards nutrition plans created by artificial intelligence and nutrition plans created by professional dietitians. This is because the field is relatively new, combining two fast-growing areas, namely nutrition and technology, which at the moment have little empirical support in the literature.

The method allows the researcher to study the phenomenon without imposing any assumptions on participants beforehand. In other words, an exploratory method enables the researcher to gain insight into the thoughts, feelings, and experiences of participants regarding nutrition plans designed by artificial intelligence and those created by professional dietitians. Also, this type of research design helps reveal patterns and connections that would otherwise remain unknown.

The main purpose of this study was to investigate the perception of individuals towards nutrition plans created by artificial intelligence compared with those created by professional dietitians. Some important variables were considered in the study, including trust and preference. The primary aim of this study was to assess individuals' preferences regarding nutritional advice generated by artificial intelligence in comparison to that provided by professional dietitians.

Study Population and Sampling Technique

In terms of the participants that were used in the current research, their background was highly diverse, thus allowing the collection of multiple perspectives regarding the issue under discussion. Specifically, there were students, working professionals, homemakers, and retirees who were willing to contribute to the completion of the study. As individuals at different stages of their life cycle were involved in the study, unique perspectives of people who have been exposed to various amounts of information related to health matters. In addition, there was a variation in terms of where the participants lived and what kind of lifestyle they led, which made it possible to discuss the impact of the environment, lifestyle, and access to digital technologies on participants' perception of professional advice and AI-based nutrition plans.

In order to make sure that the results of the research would be objective and not influenced by bias, the random sampling technique was chosen for the recruitment of participants. It is evident that, by employing this approach, it became possible to make sure that all members of the target population had an equal opportunity to take part in the research.

Sample Size and Participant Characteristics

A total of 126 people were approached for the purpose of taking part in the research study. Out of these, 26 participants were chosen for conducting a pilot study. It was undertaken in order to test the validity, reliability,

and clarity of the research tool being used in the study.

It was important for determining any ambiguities in the process, analyzing the relevancy of the question posed in the tool, and assessing how well the instrument captures the required data. Based on feedback from this stage, the questionnaire was modified as per the need.

The next step taken was to conduct the actual study with a sample of 100 participants. Information on age, occupation, and residential location was collected from all participants so as to allow a thorough analysis of various demographic characteristics of the participants. By doing so, it became possible to conduct an analysis of perceptions of participants in relation to nutrition plans devised using artificial intelligence compared to those prepared by professional dietitians.

Development of the Research Instrument

For this current study, data collection was done using a structured questionnaire prepared based on thorough literature review and already validated tools.

This methodology helped ensure that the research instrument adequately covered major dimensions related to the topic of the study such as trust, preference, and people's perceptions about nutrition plans produced by AI and professional dietitians.

In the study, most of the questions asked in the survey were closed-ended, which provided responses based on a Likert scale, thereby giving researchers an easy way of knowing how strongly participants agreed or disagreed with certain statements. This method made it easier to collect data for analysis since a rating scale was used.

For the data collected from participants to be credible and dependable, validity and reliability were tested. Validity refers to whether the instrument can measure what it intends to, and this was achieved by using content validation. Here, the questionnaire was evaluated by experts to see whether it contained appropriate information. Reliability involved testing for the consistency of results yielded by the items used in the questionnaire.

Data Collection Procedure

Data for the study was gathered by means of conducting a survey using an online questionnaire via Google Forms, making data gathering accessible and convenient. The participants were briefed about the research study and its objective prior to answering questions in order to ensure full understanding of what the study entailed.

Ethical issues were taken into serious consideration during the data gathering stage. It was made sure that the responses given by the participants will stay confidential and will only be used for academic purposes. All participants were asked for their consent prior to taking the survey.

After conducting a pilot test and improving the research instrument accordingly, the final survey was distributed to a total number of 100 respondents.

Statistical Tools Used for Analysis

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Analysis of data involved the application of both descriptive and inferential statistical procedures to ensure thorough investigation of the data collected. Descriptive statistics was used for the purposes of analyzing data and giving it a structured form.

Further, there was a use of inferential statistics to help in determining the significance of the relations and the differences among variables in the study. With the help of this approach, the study was able to come up with generalizations that could be made outside the particular set of data collected.

Descriptive Statistical Analysis

The use of statistics was essential to organize and synthesize information collected from various sources. The use of descriptive statistics such as frequencies and percentages was crucial in presenting the pattern of respondents' answers.

The measures of central tendency were established by calculating the mean to find out the average answer, thus determining the common view of all respondents. Furthermore, measures of dispersion were used to determine the extent of differences among the answers collected.

All the above techniques enabled identifying the pattern of views held by the participants concerning their perception of nutritional plans created by artificial intelligence compared to that created by professional dieticians.

Spearman Rank Correlation Analysis

The relationships among the ordinal variables were studied using the Spearman's rank correlation test. It should be noted that this type of statistical analysis is very effective and useful in the case of ranked data, thus there is no need to assume that the data are normally distributed.

Spearman's rank correlation in this research paper has been used in order to measure the relationship between demographic characteristics such as age and occupation and the level of trust and preferences toward certain nutrition plans that are offered to the respondents. With the help of this technique, it was possible to determine the nature of these relationships as well as to find out how the demographic characteristics affect people's attitude towards artificial nutrition plans compared to professional dietitian-based nutrition plans.

One-Way ANOVA

One-Way Analysis of Variance (ANOVA) test was used to evaluate the differences between the means of different demographics, including age, occupation, and place of residence. This methodological approach can be applied in research aimed at analyzing the differences between mean values of multiple independent samples.

The main reason behind conducting the One-Way ANOVA test was the necessity to determine whether the differences between the responses of participants were statistically significant or accidental. In this way, One-Way ANOVA allowed identifying differences in people's views concerning nutrition plans created by artificial intelligence and nutrition plans suggested by experts.

The information received during the One-Way ANOVA test helped analyze the impact of different demographic variables on people's attitudes towards nutrition plans generated by artificial intelligence in contrast to plans designed by dietitians.

RESULTS

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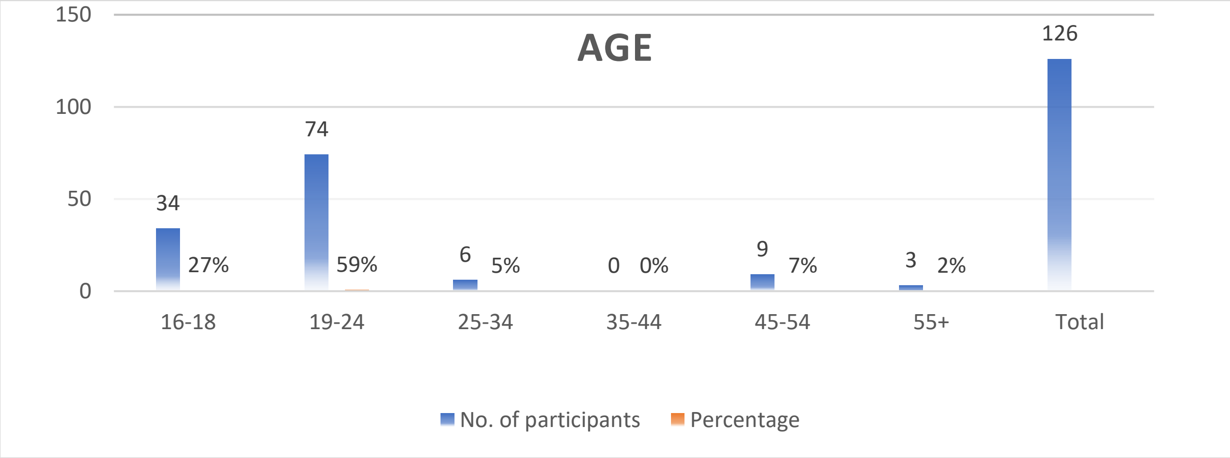
Demographic Profile of Respondents

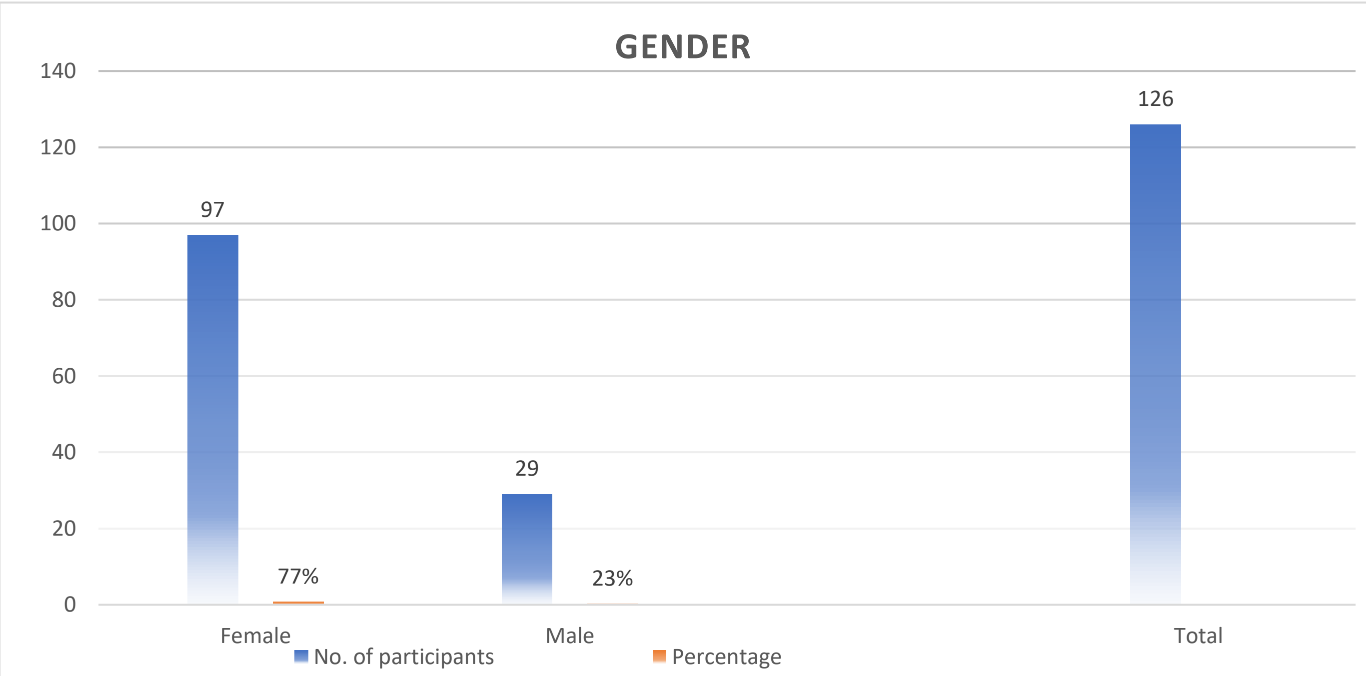
Age Distribution



Interpretation

- Most of the people who answered the questions were between 19 and 24 years old. This means the study is really about what young adults think. The young adults are very used to technology and artificial intelligence because they have been using these things in their day-to-day life.
- Because they know much about technology and artificial intelligence, they are not afraid to try new things like new ways to eat healthy.Other studies have found the thing that young people who know a lot about computers and technology are more likely to trust artificial intelligence when it comes to their health. They like it because it is easy to use and they can get advice easily.

Gender Distribution



Interpretations

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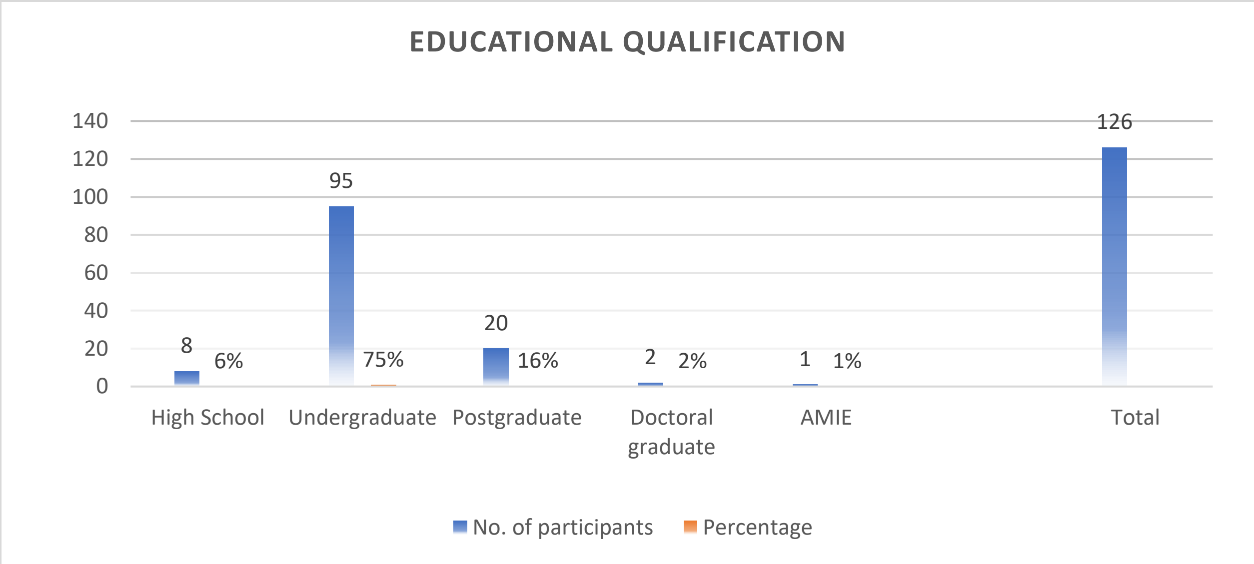
- The women in the sample were the majority of 77%. This is probably because women usually care more about food and health. That is why what women think is very important when we compare trust in nutrition plans made by computers and plans made by dietitians.
- Women and their opinions are very important, in this case because women are the ones who usually make food decisions for their families and they care about nutrition and health.

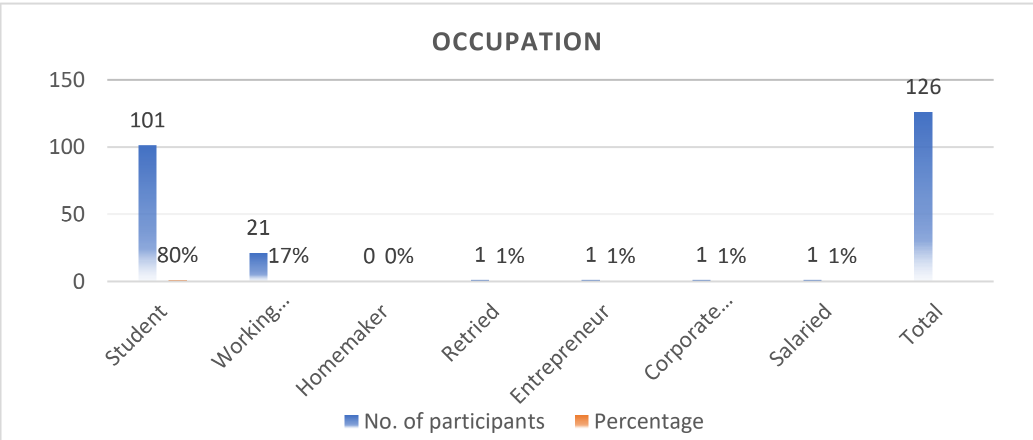
Educational Qualification



Interpretations

- Most respondents were undergraduates of 75%, meaning they are currently studying or have recently completed a bachelor’s degree.
- This suggests they are fairly educated and familiar with digital tools and AI in health and nutrition.
- A smaller group were postgraduates, who may have more advanced knowledge in the field.

Occupation and Area of Residence



Interpretations

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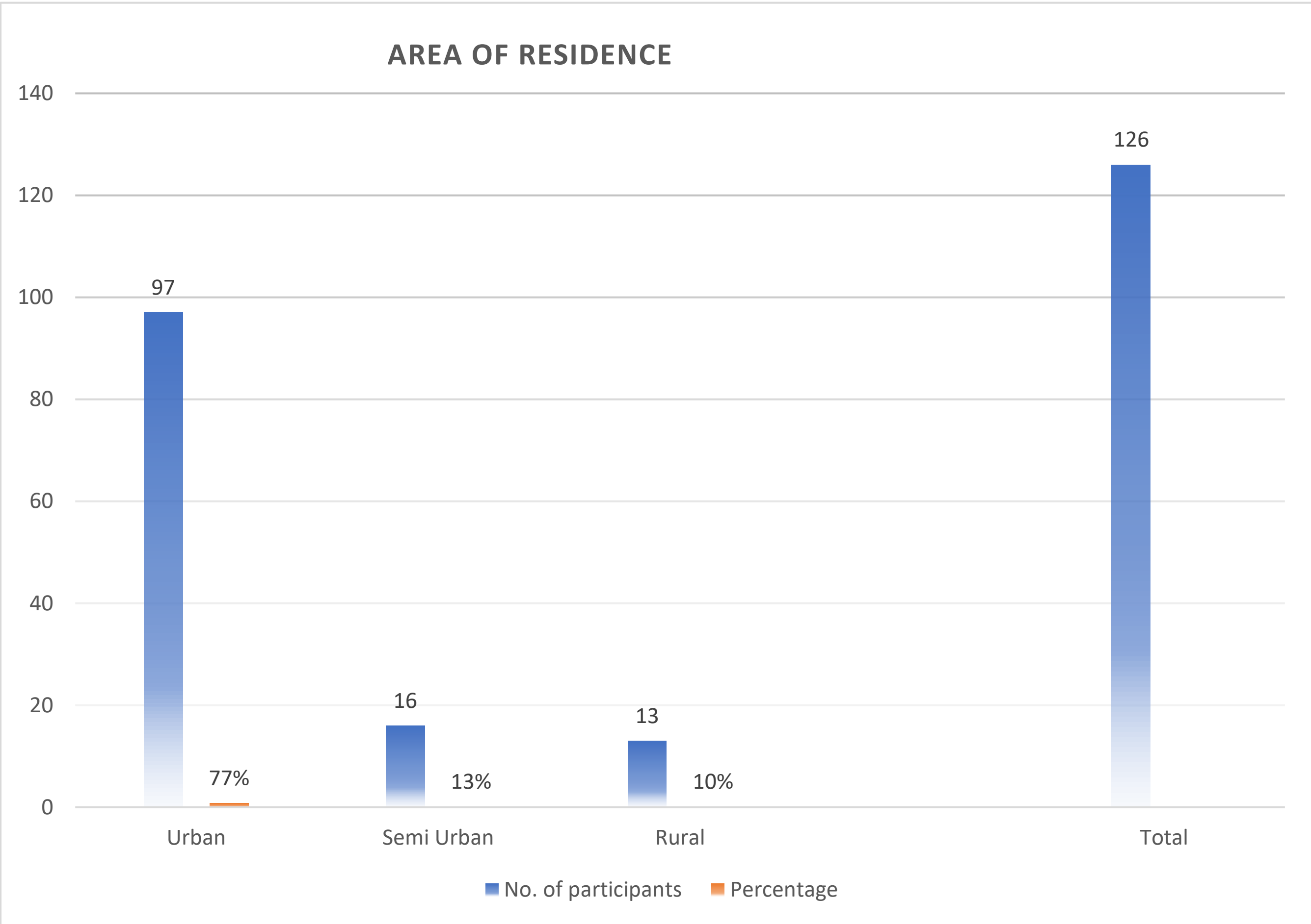
- The data tells us that 80% of people who took part were students. This means the study mostly shows what younger people think and they are more used to technology and AI tools.
- 17% were people who work and they might have different ideas about food and health because of their lifestyle and experience.
- Other groups, like retired people, business owners and people who get a salary made up a small part of the group. So, they don't affect the results much.

AREA OF RESIDENCE



Interpretations

- The data shows that most people who answered the questions (77%) live in cities. This means the study is mostly about what city people think. City people usually have access to doctors, the internet and new technologies like artificial intelligence.
- Some people (13%) who answered the questions live in areas that're not totally urban, but not totally rural either. This adds a bit of variety but not enough.
- Only a small number of people (10%) who answered the questions live in areas. This means that people from areas do not have a big say in the study. In areas it can be hard to get access to technology and artificial intelligence.

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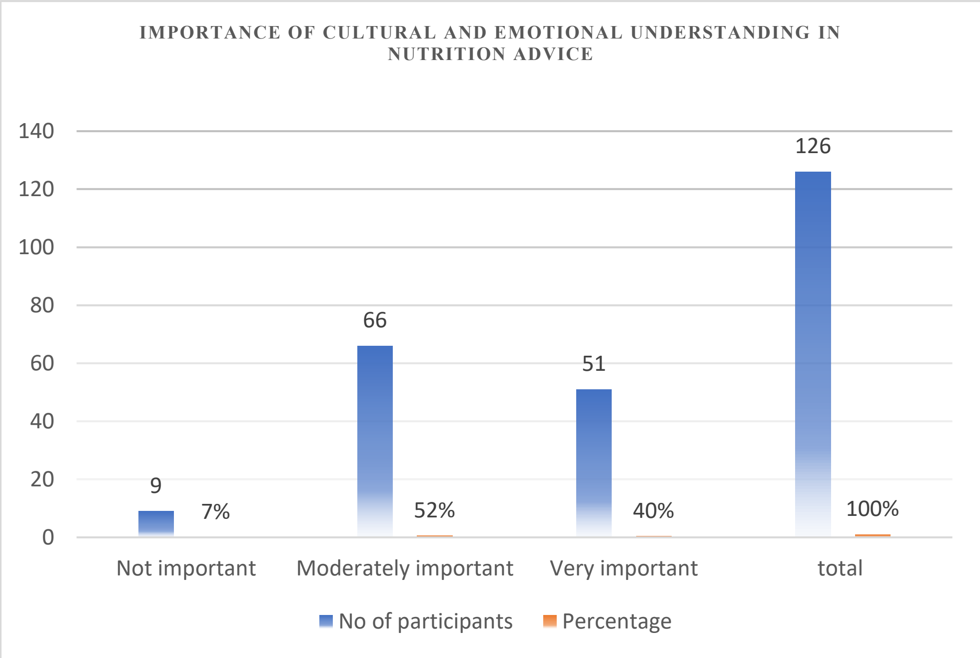
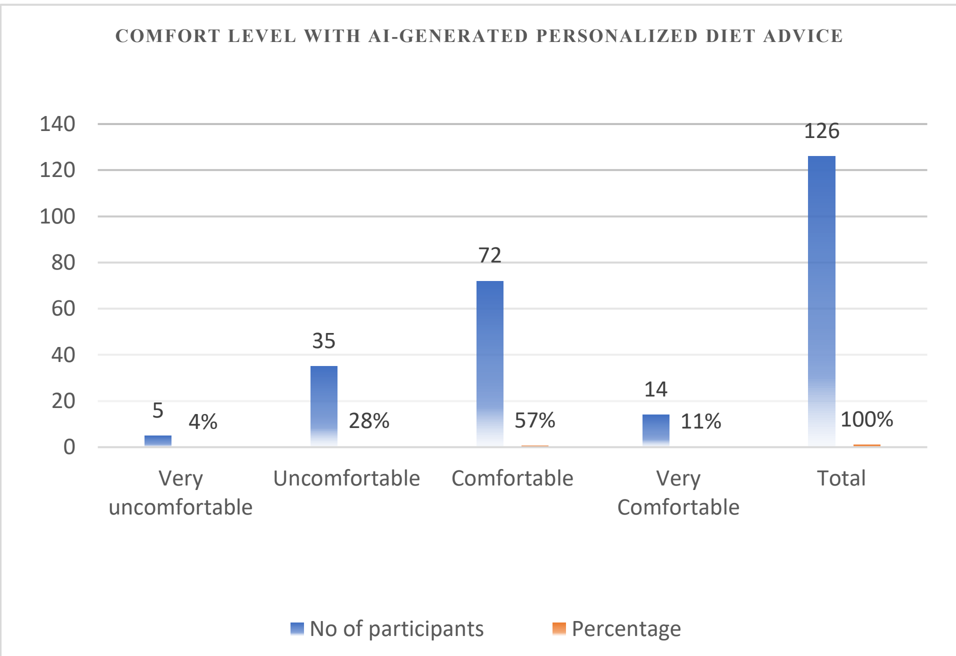
Importance of Cultural and Emotional Understanding in Nutrition Advice



Interpretation

- The chart shows that cultural and emotional factors are really important when it comes to the food we choose with 52% of people saying they think about these things when they pick what to eat. This means people consider things like what their family used to make how food makes them feel what is available and if it is good for them along with ideas like food plans made by computers.
- A lot of people 40% think these factors are very important which shows that what we eat is closely tied to where we come from and what we believe in and people like to get advice that fits with their traditions.

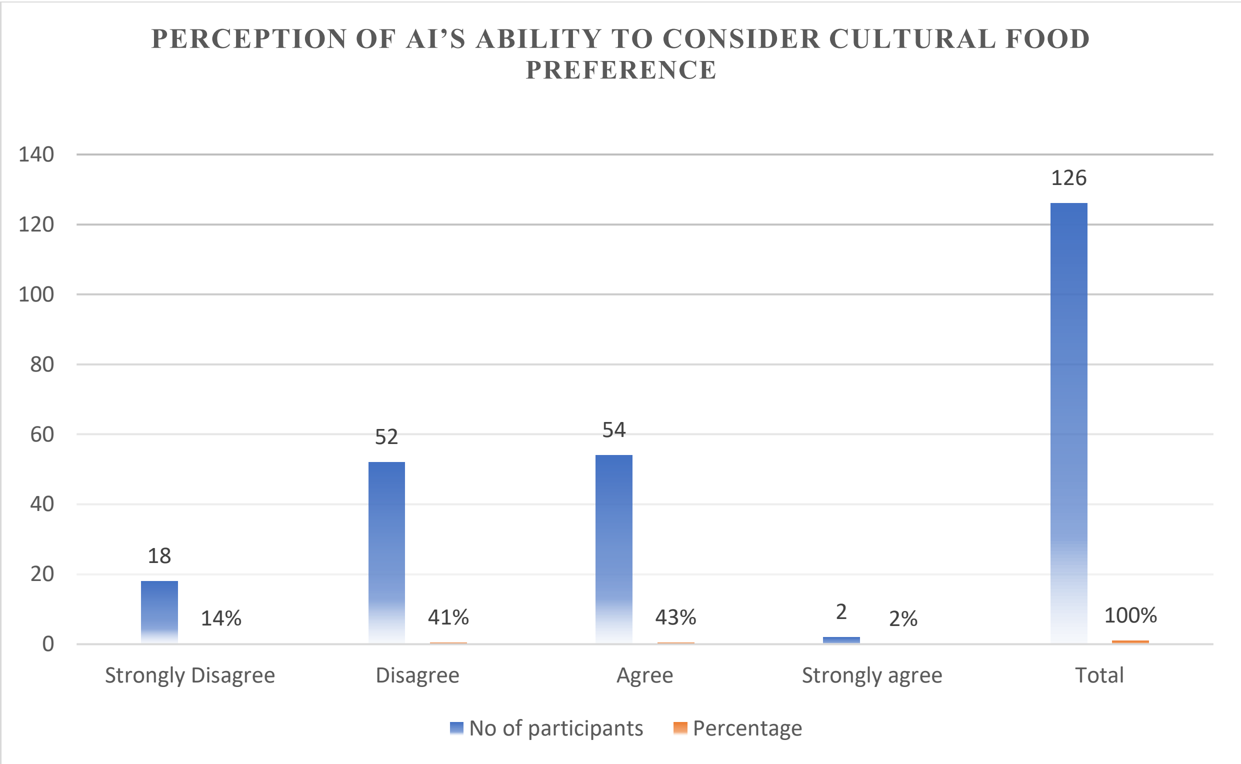
Comfort Level with AI-Generated Personalized Diet Advice



Interpretations

- The data shows how people feel about getting personalized diet advice from Artificial Intelligence. Overall, it shows that people are careful and prefer to get advice from a dietitian.
- Most people, 57%said they are fine with getting diet advice from Artificial intelligence. This means they are willing to try these tools because they are easy to use and can be accessed from anywhere. This does not mean they completely trust artificial intelligence. They are just open to trying it as another option or for some help.
- Only a small number of people 11% feel very comfortable with Artificial intelligence. This shows that not many people have a lot of confidence in intelligence. On the hand 32% of people do not feel comfortable with artificial intelligence. Hence, people believe that artificial intelligence should be seen as a tool that can help not as a replacement for a person who knows a lot, about nutrition and can give people personalized advice.

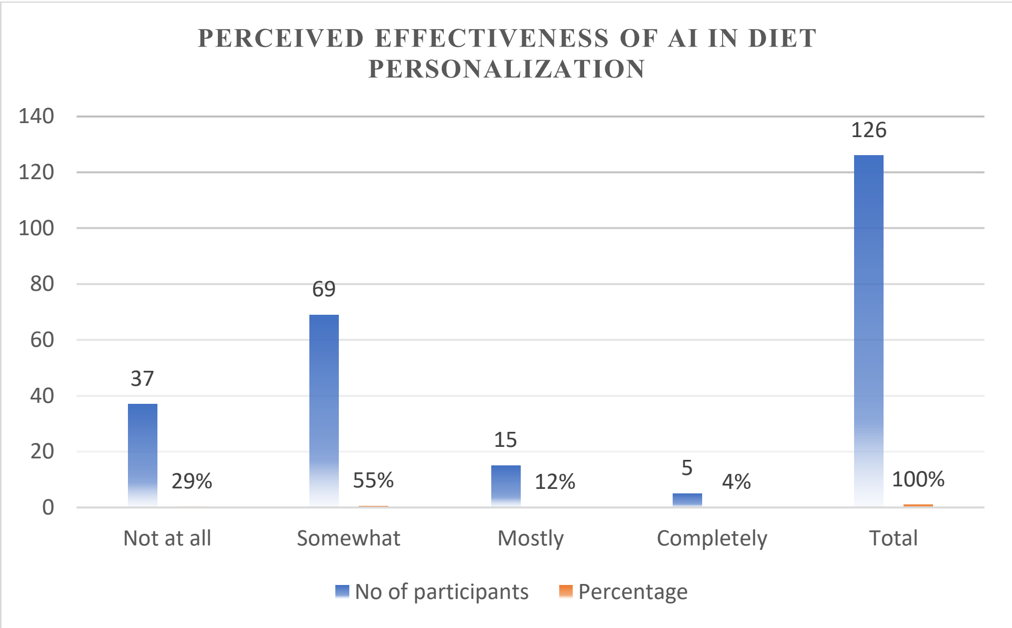
Perception of AI's Ability to Consider Cultural Food Preference



Interpretations

- The chart shows what people think about AI making diet plans that consider the food people like to eat and the food that is part of their culture. About 42.86 %of people think that AI can include food in the plans. This means that some people think AI is pretty good at making plans that're personal.
- 41.27 % of people do not think so and 14.29 % really do not think so. This shows that a lot of people are not sure if AI can really make diet plans that work for people with food habits. 1.59 % of people really think AI can do this. This means that not many people have faith in AI.
- The results show that people have ideas about AI making diet plans that are right for their culture. This means that AI still has to work on making plans that're good for people from different backgrounds. Most of the people who answered the questions are students who're 19 to 24 years old. These students are used to using computers and phones so they might be more okay with using AI.

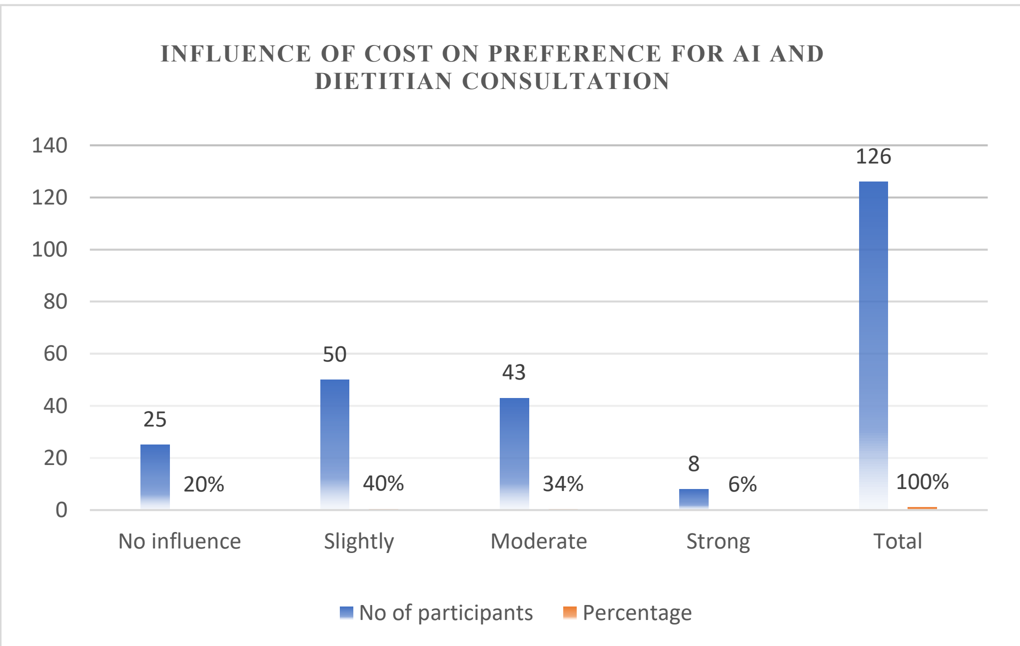
Perceived Effectiveness of AI in Diet Personalization



Interpretations

- This chart shows what people think about AI-generated nutrition plans. Most people, (55%) said they have somewhat trust in AI. This means that a lot of people are willing to use AI. They still have some doubts.
- 29% of people said they do not trust AI all which shows that a lot of people do not think AI can give good nutrition advice. This shows that people are still worried about whether AI can give them the information if it is personalized for them and if it is reliable.
- 12% of people said they mostly trust AI and a very small number of people 4% of people completely trust AI. This indicates that not many people have a lot of trust in AI.

Influence of Cost on Preference for AI and Dietitian Consultation



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Interpretation

- This chart shows that the cost has an impact on most people decision to choose between AI-based nutrition plans and consulting a dietitian though the cost is not the only thing that people think about when making this decision.
- 40 percent of people said that the cost has an influence, which means that people think about how much it costs but it is not the most important thing.
- 34 percent of people said that the cost has an influence, which shows that the cost is very important to many people.
- Overall while the cost matters to people (94 percent) people think that getting good nutrition guidance that is tailored to them is important enough to pay more for so they try to find a balance, between what they can afford and what is good quality.

Statistical Analysis

Relationship Between Cost Influence and Comfort with AI-Generated Diet Advice

Spearman Rank Correlation:

Hypotheses

H_0 (NULL HYPOTHESIS): There is no significant relationship between cost influence and comfort with AI diet advice.

H_1 (ALTERNATIVE HYPOTHESIS): There is a significant relationship between cost influence and comfort with AI diet advice

Correlations

			Cost_Influence_Preference	Comfort_from_AI_Personalized_Diet
Spearman's rho	Cost_Influence_Preference	Correlation Coefficient	1.000	.438
		Sig. (2-tailed)	.	.000
		N	126	126
	Comfort_from_AI_Personalized_Diet	Correlation Coefficient	.438	1.000
		Sig. (2-tailed)	.000	.
		N	126	126

Interpretation

- The study investigated the association between cost sensitivity and the preference for artificial intelligence nutrition programs based on Spearman's rank correlation.
- There was a positive correlation, showing that cost-sensitive people tended to favor AI nutrition plans.
- This preference could be because such nutrition programs were more affordable and easily available.

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- The majority of the respondents were college students who probably lacked experience with professionally prescribed nutrition plans.
- Being a factor in the sample population, it could explain the preference of most people for AI nutrition plans.
- Overall, AI nutrition programs were preferred by cost-sensitive and convenience-oriented people.

Differences in Belief in AI Personalization Across Educational Levels

One-Way ANOVA

Hypotheses

H_0 (NULL HYPOTHESIS): There is no significant difference in belief that AI can personalize diets effectively across educational levels.

H_1 (ALTERNATIVE HYPOTHESIS): There is a significant difference in belief that AI can personalize diets effectively across educational levels.

ANOVA

AI_Personalization_Effectiveness

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.706	4	.176	.304	.875
Within Groups	70.151	121	.580		
Total	70.857	125			

Interpretation

- A study was done to see if people with levels of education think AI personalization is effective in planning what they eat. The study looked at the numbers. Found that the difference is not big enough to matter.
- This means that it does not matter what level of education someone has they are likely to think AI personalization is just as effective. The study found that people with educational backgrounds do not have very different opinions about how well AI can make a diet plan that is right for them.
- Educational background does not seem to change what people think about AI personalization in nutrition planning. AI personalization in nutrition planning is seen as effective by people, with different educational qualifications.

Implications

Implications for Dietitians and Nutrition Professionals

- Dietitians are very important in giving people nutrition advice. They help people by making diets that fit their needs, likes and backgrounds. Artificial Intelligence can help dietitians do their job

better. It can make their work easier. Help them make good decisions using data. When dietitians use AI they can help patients more. Still give them personal care.
- Dietitians and nutrition professionals should use AI as a tool. This tool can help them give advice. The advice should be right for each person. It should also be sensitive to their culture.

Implications for AI Health Technology Developers

- People who make AI health tools need to make sure they are easy to use. These tools should work well for people from cultures. The tools should help doctors and dietitians not replace them. AI tools should also learn from people over time. This way they can get better and better.
- The tools should be made to help healthcare professionals. They should not replace them. AI systems should also be able to get feedback. This way they can improve over time.
- Developers should make sure AI tools are inclusive. They should be accurate and transparent. This way people will trust them more.

Implications for Public Health and Digital Health Policy

- Public health policies should make sure AI in nutrition is used in fairly. We need to make sure everyone can use these tools. This way we do not make health problems worse, for some people.
- Policies should help people learn about AI tools. This way they can use them well. Doctors and dietitians should also get training. This way they can use AI tools to help patients.
- Good policies can help us use AI tools in a way. This way we can make public health better. AI can help us make nutrition care. This way we can improve health outcomes.

Limitations of Study

- The study only included adolescents and adults, so it does not reflect the opinions of children or older age groups.
- Only a limited number of occupations students, working professionals, homemakers, and retired individuals were studied.
- Participants came from urban, semi-urban, and rural areas, but some regions or communities may not be fully represented.
- The research focused on perceptions and preferences rather than actual dietary behaviour or health outcomes.

Future Research Directions

- Launch prospective studies comparing sustained clinical efficacy, patient adherence, and health metrics of AI-formulated diets against conventional dietitian-led protocols.

- Develop and rigorously test integrated AI-human counselling frameworks, evaluating enhancements in personalization, satisfaction, and measurable health improvements.

- Refine AI algorithms for culturally sensitive, region-specific, and psychosocially attuned dietary guidance that resonates with diverse lived experiences and culinary traditions.

- Probe psychological drivers including motivation, trust-building, engagement patterns, and compliance factors influencing uptake of AI-assisted nutrition interventions.

- Scrutinize data governance, privacy safeguards, informed consent processes, and transparency's role in fostering user confidence, alongside scalability for underserved populations.

- Establish robust standardization protocols for AI nutrition tools' accuracy and safety, while exploring their potential in preventive strategies against diet-related chronic conditions.

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