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Understanding the Adoption of Mobile Applications for a Healthy Diet Among Adults: The Role of Effort Expectancy, Social Influence, Price Value, Health Conditions, and Body Image

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Abstract

Non-communicable diseases (NCDs) account for 53% of premature deaths globally, posing substantial challenges to healthcare systems. In Indonesia, the rising prevalence of obesity and overweight among adults underscores the urgent need for effective health interventions. Mobile diet applications offer a promising solution for health monitoring and behavior modification; however, adoption rates remain low due to a limited understanding of user acceptance factors. This study examines the determinants of mobile diet application adoption among Indonesian adults using the UTAUT2 framework, extended with trust, perceived health threat, health consciousness, health conditions, and body image. Data were collected through an online survey of 218 respondents and analyzed using PLS-SEM. The findings reveal that effort expectancy, social influence, price value, health conditions, and body image significantly influence adoption. This study contributes to understanding health technology adoption and offers practical recommendations for optimizing mobile diet applications to address NCD challenges in Indonesia.

A. Introduction

Non-communicable diseases (NCDs) are one of the leading causes of premature death, defined as death under the age of 80, in various countries worldwide [1]. In 2019, NCDs caused 53% of premature death cases [2], which also constitute the highest burden in healthcare financing in Indonesia [3]. NCDs result from a combination of various factors, such as genetic predisposition, unhealthy lifestyle, metabolic risk factors, and environmental risk factors [4]. Nevertheless, the increasing prevalence of NCDs can be prevented and modified by adopting a healthy lifestyle, such as reducing alcohol, tobacco, and salt consumption, increasing physical activity, and lowering metabolic risk factors by addressing overweight and obesity [5], [6].

Data from Survei Kesehatan Indonesia 2023 (SKI) and the Riset Kesehatan Dasar 2018 (RISEKDAS) indicate that over the past five years, there has been an increase in obesity prevalence among adults in Indonesia [7], [8]. Adults, defined as individuals aged 19-44, are part of the productive age group [9], [10]. Considering the importance of adults for the country's economy and development, the Indonesian government is currently working to improve the health quality of this age group. This effort aims to leverage the demographic bonus projected to occur in 2035, where the productive age group, which includes adults, will dominate Indonesia's population [9].

The government recognizes the significant role of technology in addressing the increasing prevalence of NCDs, obesity, and overweight. Therefore, the government focuses on strengthening efforts to raise awareness and prevention through innovation and technology utilization [11]. One form of technology utilization that the Indonesian public has widely adopted is smartphones [12]. However, data show that only about 57% of smartphone users in Indonesia utilize health applications, including those that support a healthy lifestyle [13].

Mobile applications related to monitoring physical activity and healthy diets can effectively manage health interventions and promote behavioral changes toward a healthier lifestyle. This step is crucial given the high prevalence of obesity and overweight in Indonesia, which requires innovative and sustainable approaches for prevention and control. Studies have shown that such applications can enhance physical activity [14] and promote healthy eating patterns [15]. Moreover, mobile diet applications offer several advantages, such as lower costs, reduced administrative burden, increased adherence to health programs, the ability to reach a broad target population, and efficiency in disseminating information related to diet and food nutrition [14], [16], [17].

Nevertheless, most users find that the most significant challenge in achieving their desired health goals is maintaining motivation throughout the process [18], including while using mobile diet applications. Each user has different motivations for using mobile diet applications. Some may use these applications to maintain a healthy lifestyle, shape their body, keep it slim, or even lose weight [19]. Additionally, the use of mobile applications can contribute to establishing healthy lifestyle habits [20]. This challenge highlights that motivation is crucial in successfully using mobile diet applications.

This research aims to analyze the factors influencing the adoption of mobile diet applications among adults. Although mobile diet applications have been proven effective in various countries in promoting healthy behavior, the adoption rate of these applications remains relatively low in Indonesia. Several factors contribute to the limited adoption of these applications, particularly the low level of digital health literacy[21], the lack of public awareness regarding the importance of maintaining a healthy diet[22], and the disparity in cultural and dietary preferences within widely available diet apps in Indonesia, which limits the representation of local food diversity. This lack of localization hinders accurate dietary tracking, reducing user engagement and adoption. The urgency of this research is to support government programs in optimizing the prevention and control of NCDs by strengthening efforts to raise awareness and prevention through innovative and effective technology utilization.

B. Literature Review and Hypotheses Development

I. Mobile Health Application

Mobile Health Applications, forms of medical practice, and public health services are accessible through mobile phones or other wireless devices. The primary goal of mobile health applications is to provide healthcare services and promote disease prevention at an affordable cost [23], [24].

Although smartphone usage in Indonesia has grown rapidly, the adoption of applications supporting a healthy lifestyle remains relatively low. A PricewaterhouseCoopers (PwC) survey found that the most popular applications among consumers are those focused on exercise instruction and monitoring, which 49% of respondents use. 43% of consumers utilize the following applications, which focus on diet, weight management, and healthy eating. Additionally, sleep management applications are used by 37% of respondents [21].

Mobile health applications that support a healthy lifestyle, particularly diet applications, can intervene in user behavior change, especially when such changes require long-term adherence. These applications provide various features, such as self-monitoring of health-related behaviors (tracking food intake and exercise), health-related outcomes (tracking body weight), goal setting (diet goals, calorie intake, or target weight), activity reminders, feedback from experts tailored to the user's condition, and community support. These features are beneficial for implementing lifestyle changes, preventing diseases, managing conditions such as diabetes, and promoting behavioral adaptation [24], [25]. Notable examples of diet applications that integrate these features include FatSecret, Lifesum, Lose It!, and MyFitnessPal, which provide comprehensive tools for nutritional tracking, progress monitoring, and personalized recommendations to enhance user adherence and health outcomes.

II. Hypotheses Development

This study derived the factors proposed from several relevant previous studies that identify the factors influencing the adoption of mobile diet applications among adults. Several prior studies that serve as references and the foundation for this research were selected using a Systematic Literature Review (SLR) method. The SLR process identified eight journal articles [26], [25], [26], [14], [27], [28], [31] and one final project [32] that are relevant to the research topic. The primary theoretical framework for technology adoption used in this study is the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). Each core construct of the UTAUT2 theory, represented by light blue boxes in Figure 1, includes performance expectancy (PE), effort expectancy (EE), social influence (SI), hedonic motivation (HM), price value (PV), behavioral intention (BHI).

This study extended the basic theory by adding several external factors based on previous relevant studies. These external factors are trust [28], [29], perceived health threat [26], health consciousness [19], health conditions [32], and body image [32]. White boxes represent these external factors. Figure 1 illustrates the research model used in this study.

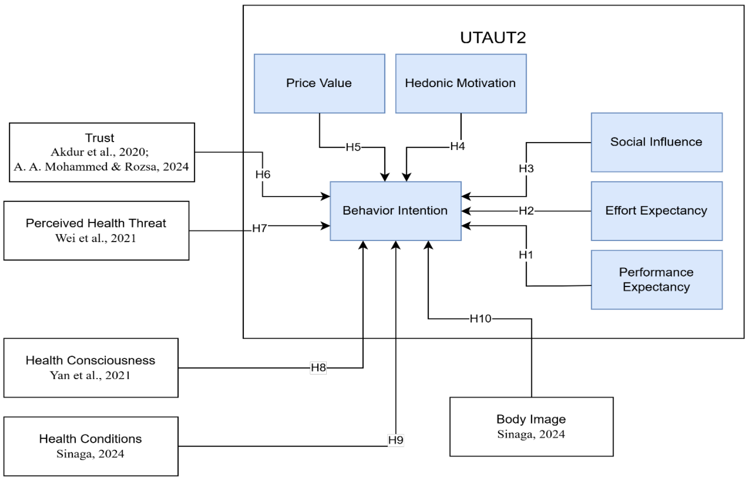

Figure 1. Research Model

1) **H1: Performance expectancy significantly influences users' intention to adopt mobile diet applications.**

Performance expectancy (PE) refers to an individual's belief that using a specific technology or system can support and enhance their performance in completing tasks [33]. This factor is also considered a core component in several theoretical models, albeit under different terminologies, such as perceived usefulness in the Technology Acceptance Model (TAM) and extrinsic motivation in the Motivational Model [30]. Previous studies that evaluate the factors influencing the adoption of mobile diet applications have shown that PE significantly affects users' intention to adopt and actual use of mobile diet applications [27].

2) **H2: Effort expectancy significantly influences users' intention to adopt mobile diet applications.**

This study defines effort expectancy (EE) as an individual's perception of how easy it is to use a particular technology or system [33]. Users may encounter challenges or obstacles due to unfamiliarity during the initial stages of using a technology or system. However, as users become more familiar with the system over time, the perceived ease of use becomes increasingly relevant. The importance of ease of use, especially during the initial stages of adoption, can significantly influence users' intention to adopt mobile applications [27].

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3) H3: Social influence significantly influences users' intention to adopt mobile diet applications.

Social influence (SI) refers to how an individual perceives that people in their social environment, such as family, friends, reference groups, or colleagues, provide support and encouragement in utilizing a technology or system[33]. This factor highlights the role of social support in influencing an individual's intention to adopt a technology. Moreover, sharing knowledge with people in one's social circle can raise awareness and encourage the adoption of a technology or system [27].

4) H4: Hedonic motivation significantly influences users' intention to adopt mobile diet applications.

Hedonic motivation (HM) refers to an individual's enjoyment of using a specific technology or system [33]. This concept was previously known as perceived enjoyment in the Technology Acceptance Model (TAM). Satisfaction gained from using a technology or system can significantly influence an individual's acceptance of the technology [30].

5) H5: Price value significantly influences users' intention to adopt mobile diet applications.

Price value (PV) represents the balance between the cost users allocate to use a technology and the perceived benefits obtained from its use. This concept emphasizes that the cost incurred for utilizing a technology is critical in influencing its adoption [33].

6) H6: Trust significantly influences users' intention to adopt mobile diet applications.

Trust (TR) can be defined as the belief in and reliance on a partner in a transactional relationship based on the partner's reliability and integrity [28], [34]. Trust plays a significant role in attracting new and retaining existing users. Users who already trust the services provided by the application are more likely to adopt the technology [29].

7) H7: Perceived health threat significantly influences users' intention to adopt mobile diet applications.

Perceived health threat (PHT) refers to an individual's perception of potential threats or risks that may affect their health. The perception of danger or risk motivates individuals to take preventive actions. The higher the perceived threat, the more likely individuals are to engage in health-related activities [35].

8) H8: Health consciousness significantly influences users' intention to adopt mobile diet applications.

Health consciousness (HC) represents the extent to which an individual is aware of their health status and the motivation and readiness to improve their health condition [36]. HC is a key predictor in understanding individuals' behaviors in seeking, comprehending, and applying health information [37]. Individuals with a high level of health consciousness tend to have better health knowledge and more explicit health goals.

9) H9: Health conditions significantly influence users' intention to adopt mobile diet applications.

Health conditions (HS) refer to an individual's physical health status, which includes being in good health, physically fit, having an ideal body mass index (BMI), and being free from diseases. Physical health is an important factor in predicting the use of diet applications [32], [38].

10) H10: Body image significantly influences users' intention to adopt mobile diet applications.

Body image (BI) is how an individual perceives, feels, and evaluates their body, physically and emotionally [32]. BI is multidimensional, encompassing attitudes, cognitive perceptions, and behaviors. This study classifies BI into three main aspects: appearance, fitness, and health [39].

III. Partial Least Squares SEM (PLS-SEM)

The Partial Least Squares Structural Equation Modeling (PLS-SEM) approach is a method that assumes composite variables can represent constructs. This approach forms constructs by combining indicators linearly. Fundamentally, PLS-SEM utilizes formative measurement models but can also accommodate reflective measurement models. This study applies PLS-SEM to assess the proposed model's validity and test all previously formulated hypotheses.

The rationale for choosing this method is as follows: (1) this study is exploratory, aiming to explore the factors influencing the adoption of mobile diet applications among the adult age group in Indonesia; (2) the total sample size in this study is relatively small; and (3) the research model includes a large number of constructs and indicators. Additionally, this approach has been employed in several prior studies focusing on analyzing the factors influencing the adoption of applications in Indonesia, such as [40]–[42].

SmartPLS 4.0 was employed to streamline the data processing. Below are the key stages of the data analysis process using the PLS-SEM method:

1. Defining the Structural Model
   The first step is defining the structural model by identifying the relevant constructs within the research framework. This study analyzed these constructs as latent variables throughout the study. This step is crucial for setting up the hypothesized relationships between the constructs in the proposed model [43].
2. Defining the Measurement Model
   After defining the structural model, the next step is to specify the measurement model. This activity involves selecting the appropriate instruments to measure each construct. The goal is to ensure that the instruments used are valid and reliable to capture the intended data accurately [44].
3. Data Collection
   This study collected data for this study through an online questionnaire divided into two main parts: demographic questions to gather information about the respondents' background and main questions aimed at identifying the factors that influence the adoption of mobile diet applications. After

collecting the data, this study conducted a preliminary analysis before proceeding to the primary analysis using the PLS-SEM method [44].

4. Assessing the Measurement Model
   This study assessed the measurement model to evaluate the instruments' quality at this stage. Check if the indicators accurately represent the constructs. Additionally, this step includes evaluating the validity and reliability of the overall measurement model [44].
5. Assessing the Structural Model
   Once this study validates the measurement model, proceed to the next stage of analysis, which is to assess the structural model. This activity involves evaluating the relationships between the constructs in the model. The purpose is to measure how well the model predicts outcomes and to determine the significance of the relationships among the constructs. The results from this stage provide insights into how well the proposed model explains the studied phenomena [44].

C. Research Methodology

This study adopts a quantitative research design to analyze the factors influencing the adoption of mobile diet applications among adults in Indonesia. Use the UTAUT2 framework extended with additional external factors to collect data through a structured survey targeting respondents who used diet applications within the past six months. Based on validated items from previous studies, the questionnaire employed a five-point Likert scale to capture user perceptions. PLS-SEM was utilized for data analysis, offering robust insights into the relationships among the variables and the applicability of the extended UTAUT2 framework in the health technology context.

I. Data Collection

This study employed a quantitative research design and utilized a purposive sampling method to gather data through a structured survey conducted via Google Forms, enabling targeted respondent selection based on specific criteria relevant to the research objectives. The questionnaire was disseminated online through social media platforms, including X (formerly known as Twitter), WhatsApp, Instagram, and Telegram, to reach a broad yet specific audience. The criteria for selecting respondents were as follows:

1. Indonesian citizens aged 19 to 44 represent the adult and productive age group.
2. Individuals have used mobile diet, nutrition management, or calorie tracking applications within the past six months.

The mobile diet applications considered in this study included Cronometer, FastEasy, Fastic, FatSecret, KFasting, Lifesum, Lose It!, and MyFitnessPal. By focusing on respondents with experience using these applications, the study ensured that the collected data was relevant, reliable, and aligned with the research objectives.

However, as a non-probability sampling method, purposive sampling carries the risk of selection bias, potentially leading to an overrepresentation of individuals actively engaged with social media and digital health applications. The survey was strategically disseminated across multiple online platforms and digital communities to mitigate this limitation and enhance the generalizability of the findings, ensuring a more representative sample.

II. Survey Design and Measurement Items

The instrument utilized in this study was a questionnaire employing a 5-point Likert scale, where one represents "strongly disagree" and five represents "strongly agree." The questionnaire items were developed based on a thorough review of relevant prior studies. Design this questionnaire as a reference for analyzing the factors influencing the adoption of mobile diet applications among adults. Conduct a readability test to ensure the questions are clear, comprehensible, and free from ambiguity. Six participants were involved in the readability test to validate that the questionnaire was easy to understand and suitable for use in the study.

D. Result and Discussion

I. Result

Collected data over eleven days, from December 6 to December 15, 2024. During this period, 310 respondents completed the questionnaire. After data collection, we analyzed the responses to identify duplicates, irregular patterns, and responses from individuals who did not use mobile diet applications. This analysis resulted in 218 valid responses for the study.

The demographic data collected in this study include age, gender, educational background, occupational background, monthly income, health history, type of mobile diet application used, and type of membership utilized by users. Table 1 provides detailed information regarding the demographic characteristics of the respondents.

Table 1. Demographic Characteristics of The Respondents

Demographic	Items	Frequency	Percentage
Gender	Woman	159	73%
	Man	59	27%
Aged	19-24 year	110	50%
	25-29 year	65	30%
	30-34 year	33	15%
	35-39 year	7	3%
	40-44 year	3	1%
Education	Junior High School	3	1.4%
	Senior High School	92	42.2%
	Diploma (D1/D2/D3)	12	5.5%
	Bachelor's Degree	101	46.3%
	Master's Degree	10	4.6%
Occupation	Student	60	27.5%
	Private Sector Employee	88	40.4%
	Government Employee	5	2.3%

Demographic	Items	Frequency	Percentage
	Entrepreneur	25	11.5%
	Housewife	18	8.3%
	Others	22	10.1%
Income	< Rp 3,000,000.00	108	50%
	Rp 3,000,000.00 – Rp 5,000,000.00	59	27%
	Rp 5,000,000.00 – Rp 10,000,000.00	37	17%
	> Rp 10,000,000.00	14	6%
Specific Health Condition	Yes	70	32%
	No	148	68%

After collecting valid data from the questionnaire, the next step is to process and analyze it using appropriate statistical methods. This study used the Partial Least Squares (PLS) approach, facilitated by SmartPLS software, due to its reliability in handling complex models with latent variables. The primary objective is to evaluate and measure the relationships between the variables in the model, providing a comprehensive understanding of the factors influencing the adoption of mobile diet applications among adults.

Evaluating the measurement model involves three key stages: convergent validity, discriminant validity, and reliability testing. Each stage ensures the research instrument meets the required validity and reliability standards, confirming the constructs' accuracy and consistency before proceeding to structural model analysis.

The reliability of the measurement model's internal consistency was assessed using Cronbach's alpha, Composite Reliability (rho_a), and Composite Reliability (rho_b) based on the collected data. Categorize a variable as having acceptable reliability for exploratory research if the results of Cronbach's alpha meet the required threshold. Composite Reliability (rho_a) and Composite Reliability (rho_b) fall within the range of 0.60 to 0.70. Meanwhile, values between 0.70 and 0.90 indicate adequate reliability [45].

Table 2 presents the results of reliability evaluation and convergent validity testing using Cronbach's Alpha, Composite Reliability (rho_a), Composite Reliability (rho_c), and Average Variance Extracted (AVE) for the constructs in the model. The Cronbach's Alpha values for all constructs exceed 0.70, indicating that each construct possesses a satisfactory level of internal consistency. Additionally, the Composite Reliability (rho_a) and Composite Reliability (rho_c) values for all constructs are above 0.70, demonstrating that the constructs exhibit adequate reliability as required for the analysis.

Assess convergent validity by calculating the Average Variance Extracted (AVE) to determine how well the indicators represent the measured constructs. Consider the AVE value acceptable for convergent validity if each construct has a value greater than 0.50 [45]. Furthermore, the AVE values for all constructs exceed 0.50, indicating that each construct meets the acceptable standard for convergent validity, confirming that the indicators used adequately represent the underlying constructs.

Table 2. Validity and Reliability Test

Construct	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE
BHI	0.922	0.922	0.945	0.810
BI	0.901	0.902	0.931	0.771
EE	0.850	0.858	0.898	0.688
HC	0.866	0.874	0.918	0.789
HM	0.853	0.853	0.911	0.773
HS	0.803	0.850	0.909	0.832
PE	0.889	0.902	0.931	0.818
PHT	0.798	0.869	0.875	0.700
PV	0.789	0.793	0.876	0.702
SI	0.832	0.849	0.898	0.746
TR	0.913	0.917	0.945	0.852

Discriminant validity testing describes the extent to which a construct is unique compared to other constructs. This study applied the Heterotrait-Monotrait Ratio (HTMT) to ensure that different constructs measure distinct concepts. Set a threshold value of < 0.90 when testing conceptually similar constructs [45]. Table 3 presents the results of the HTMT testing for each construct in the model. Based on the table, the HTMT values for the relationships between constructs are less than 0.90. This condition indicates that each construct meets the acceptable standard for discriminant validity.

The evaluation of the structural model involves four key stages: *collinearity*, explanatory power (R^2), predictive relevance (Q^2), and evaluation of path coefficients. This activity involves evaluating the relationships between the constructs in the model. The purpose is to measure how well the model predicts outcomes and to determine the significance of the relationships among the constructs [45]. Conduct the Variance Inflation Factor (VIF) test to evaluate the degree of correlation between constructs. A VIF value exceeding 5 indicates significant multicollinearity, suggesting the constructs are highly correlated.

Table 3. Heterotrait Monotrait Rasio

	BHI	BI	EE	HC	HM	HS	PE	PHT	PV	SI	TR
BHI											
BI	0.858										
EE	0.724	0.612									
HC	0.510	0.480	0.624								
HM	0.750	0.746	0.820	0.458							
HS	0.772	0.822	0.685	0.590	0.716						
PE	0.619	0.564	0.799	0.461	0.714	0.653					
PHT	0.399	0.413	0.424	0.726	0.463	0.479	0.334				
PV	0.698	0.587	0.671	0.357	0.751	0.609	0.530	0.270			

	BHI	BI	EE	HC	HM	HS	PE	PHT	PV	SI	TR
SI	0.670	0.623	0.472	0.163	0.719	0.557	0.472	0.148	0.753		
TR	0.677	0.603	0.754	0.414	0.789	0.616	0.588	0.376	0.789	0.533	

Conversely, a VIF value between 3 and 5 indicates a mild multicollinearity issue, but the correlation is still considered acceptable for analysis [45]. Based on Table 4, the VIF values for the correlation between constructs are less than 5, indicating that the correlation between constructs is within an acceptable range.

Table 4. VIF

Correlation Between Constructs	VIF
BI -> BHI	2.556
EE -> BHI	3.252
HC -> BHI	2.165
HM -> BHI	3.462
HS -> BHI	2.507
PE -> BHI	2.229
PHT -> BHI	1.780
PV -> BHI	2.401
SI -> BHI	2.151
TR -> BHI	2.658

The test to evaluate the model's explanatory power is the coefficient of determination or R^2 value. This test measures the extent to which endogenous constructs in the model can explain the proportion of variance in the data. R^2 values of 0.75, 0.50, and 0.25 generally indicate substantial, moderate, and weak explanatory power, respectively [45]. The result of the R^2 test in this study is 0.727, or 72.7%, indicating that the endogenous variable exhibits a level of explanatory power classified as moderate to substantial.

Table 5. Hypotheses Test

Hipotesis	Path Coefficient	STDEV	T statistics	P values	F^2	Result
H1	0.023	0.054	0.426	0.335	0.001	Rejected
H2	0.175	0.079	2.211	0.014	0.034	Accepted
H3	0.158	0.064	2.485	0.007	0.042	Accepted
H4	-0.048	0.082	0.584	0.28	0.002	Rejected
H5	0.092	0.063	1.465	0.071	0.013	Accepted
H6	0.074	0.068	1.091	0.138	0.008	Rejected
H7	0.017	0.054	0.309	0.379	0.001	Rejected
H8	0.05	0.06	0.825	0.205	0.004	Rejected
H9	0.083	0.059	1.401	0.081	0.01	Accepted
H10	0.449	0.068	6.613	0.000	0.289	Accepted

Conduct predictive relevance testing to analyze how effectively the model predicts the endogenous variables based on the available data. Predictive relevance is categorized as small (> 0), medium (> 0.25), or large (> 0.50) [41].

This study found the Q^2 value for the endogenous variable in the model to be 0.686. This result indicates that the model demonstrates high predictive capability, showing significant predictive relevance.

Subsequently, the significance of the structural model relationships was tested by analyzing the t-values and p-values. In this study, a one-tailed test was applied, with the critical values for significance set at 1.28 (error level = 10%), 1.65 (error level = 5%), and 2.33 (error level = 1%). The bootstrap sample size used in this study was 5,000 [45]. Based on the test results presented in Table 5, researchers identified five constructs that significantly influence behavioral intention, as their t-values and p-values met the required significance thresholds. These constructs are effort expectancy ($t = 2.211$; $p < 0.05$), social influence ($t = 2.485$; $p < 0.05$), price value ($t = 1.456$; $p < 0.1$), health conditions ($t = 1.401$; $p < 0.05$), and body image ($t = 6.613$; $p < 0.001$). Therefore, hypotheses H2, H3, H5, H9, and H10 are accepted, as they meet the criteria for statistical significance.

Conversely, five other constructs did not significantly influence behavioral intention, as indicated by their t-values and p-values, which exceeded the significance threshold. These constructs are performance expectancy ($t = 0.426$; $p > 0.1$), hedonic motivation ($t = 0.584$; $p > 0.1$), trust ($t = 1.091$; $p > 0.1$), perceived health threat ($t = 0.309$; $p > 0.1$), and health consciousness ($t = 0.825$; $p > 0.1$). Consequently, researchers rejected hypotheses H1, H4, H6, H7, and H8, as the constructs do not satisfy the statistical significance criteria.

II. Discussion

This study aims to analyze the factors influencing the adoption of mobile diet applications among adults. This study model builds on the UTAUT2 theoretical framework, extended by adding five external factors. These factors come from a review of relevant prior studies aligned with the research topic. The complete set of factors used to construct the research model includes performance expectancy (PE), effort expectancy (EE), social influence (SI), hedonic motivation (HM), price value (PV), behavioral intention (BHI), trust (TR), perceived health threat (PHT), health consciousness (HC), health conditions (HS), and body image (BI).

PE does not significantly influence the decision of the adult age group to adopt mobile diet applications, as indicated by the hypothesis testing results using PLS-SEM. This outcome may occur due to a gap between users' expectations regarding the application's performance and their experience [26]. The findings suggest that users do not solely evaluate the application based on its functional performance but rather consider other aspects, such as ease of use. This result contradicts previous studies [27][30], which indicate that Performance Expectancy (PE) plays a crucial role in the adoption of health applications. Furthermore, it challenges the assumption within the UTAUT2 framework, which identifies PE as a dominant factor in technology adoption.

Identify EE as a significant factor influencing the adult age group's decision to adopt mobile diet applications. This influence arises when potential users perceive the application as easy to use, increasing their motivation to try and adopt it [30]. The results strengthen the argument that ease of use is critical in adopting technology-based applications, especially in the health sector. This finding is consistent with previous research conducted by [27], [30], [26], [32] and supports the UTAUT2 theory, which emphasizes the importance of effort expectancy as one of the key determinants of technology adoption.

Identify SI as a significant factor influencing the adult age group's decision to adopt mobile diet applications. This finding demonstrates that support from individuals in one's social environment can influence a person's decision to try and use an application [27]. The results also indicate that recommendations and user communities can strengthen social influence in adopting technology in the health sector. This finding is consistent with previous research conducted by [27], [32] and supports the UTAUT2 theory, which emphasizes the importance of social influence as one of the key determinants of technology adoption.

HM does not significantly influence the decision of the adult age group to adopt mobile diet applications. This finding contradicts previous studies that served as the foundation for developing the theoretical framework and hypotheses[14], [30], [32]. This condition may occur because users of mobile diet applications are more goal-oriented, focusing on achieving specific health outcomes rather than using the application solely for entertainment purposes [27]. In mobile diet applications, functional needs appear more dominant than emotional motivations. This study also offers a new perspective, suggesting that hedonic motivation may influence health-focused applications less than factors such as effort expectancy.

Identify PV as a significant factor influencing the adult age group's decision to adopt mobile diet applications. This finding aligns with previous research, which provided the foundation for developing the theoretical framework and hypotheses. User satisfaction is closely related to the balance between the features provided by the application and the price paid. Users tend to feel satisfied when the features offered meet their needs at a reasonable price [29]. This condition indicates that price value has varying relevance across different user groups.

TR does not significantly influence the adult age group's decision to adopt mobile diet applications. Generally, trust plays a crucial role in encouraging users to adopt applications and retaining existing users [29]. In the context of mobile diet applications, this result indicates that other factors, such as effort expectancy and functional needs, play a more significant role than trust. Additionally, the low level of perceived risk associated with using this application may explain why trust is not a primary consideration, unlike in other applications with higher perceived risks.

This study found that PHT does not significantly influence the adult age group's decision to adopt mobile diet applications. While perceived health threats may raise individuals' awareness of the importance of maintaining their health, such awareness does not necessarily translate into adopting health-related applications. Individuals with a high level of health risk awareness often prefer traditional methods, such as physical exercise or consulting healthcare professionals, as their primary approach to managing health. Consequently, individuals tend to utilize health applications as complementary tools rather than primary solutions in their health management efforts [26].

HC does not significantly influence the adult age group's decision to adopt mobile diet applications. Individuals with high levels of health consciousness may perceive health applications as less beneficial, as they have already developed well-established routines for independently managing their health. Such routines often involve consistent engagement in health-related activities, including regular physical exercise and other preventive health measures, which may reduce the perceived added value of adopting health applications [46].

Meanwhile, this study identified HS as a significant factor influencing the adult age group's decision to adopt mobile diet applications. Users' health status is critical in motivating their decision to utilize such applications. This finding is consistent with the previous research [32].

This study found that BI significantly impacted the adoption of mobile diet applications. For some users, the primary motivation is to manage their weight and achieve a desired body perception, which drives their decision to use such applications. The significant influence of this factor indicates that aesthetic motivations, such as the desire to control weight and attain an ideal appearance, serve as key drivers for the adoption of mobile diet applications among most users. This finding aligns with previous research, which provided the foundation for developing the theoretical framework and hypotheses[32].

E. Conclusion

This study analyzed the factors influencing the adoption of mobile diet applications among adults in Indonesia using the UTAUT2 framework, extended with five external factors: trust, perceived health threat, health consciousness, health conditions, and body image. The findings reveal that effort expectancy, social influence, price value, health conditions, and body image significantly impact the adoption of mobile diet applications. These results highlight several practical implications for developers.

First, the significance of effort expectancy underscores the need for a simplified and intuitive user interface to ensure ease of use, especially for new users. Social influence also plays a critical role, emphasizing the importance of incorporating community-driven features, such as discussion groups and peer encouragement, to foster engagement.

Additionally, price value suggests that developers should offer flexible subscription plans, including a free tier with essential features, to attract a broader user base. Health conditions were identified as a significant factor, indicating the importance of personalized features based on user’s health data, such as tailored nutritional recommendations.

Finally, the strong influence of body image suggests that features supporting aesthetic goals, such as weight trackers, body progress visualizations, and motivational reminders, can enhance user engagement and adoption rates. By implementing these strategies, mobile diet applications can better support healthier lifestyles and contribute to the government’s efforts to reduce NCDs.

This study has certain limitations that should be acknowledged. First, most respondents were female (73%), which may limit the generalizability of the findings across genders. Future research should aim for a more balanced demographic profile to improve the representativeness of the data. Second, the study did not evaluate the long-term impact of mobile diet applications on reducing obesity or sustaining lifestyle changes, which could provide deeper insights into their effectiveness.

Third, the study focused exclusively on users in Indonesia, which might restrict the applicability of the findings to other cultural contexts. Comparative studies across different cultural settings would provide a broader understanding of the factors influencing adoption. Lastly, the rapid advancement of technology poses a challenge, as new features and trends may quickly alter adoption patterns. Regularly update mobile diet application adoption research to capture dynamic changes and maintain relevance.

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