International Journal of Social Science and Human Research

ISSN (print): 2644-0679, ISSN (online): 2644-0695

Volume 08 Issue 10 October 2025

DOI: 10.47191/ijsshr/v8-i10-39, Impact factor- 8.007

Page No: 7865-7878

Study on The Intention to Use Personalized Mental Health Care Applications Among Vietnamese High School Students

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ABSTRACT: The mental health of high school students in Vietnam is facing numerous challenges due to academic pressure, important examinations, societal expectations, and the impact of the digital environment. In this context, the application of digital technology, especially personalized mental health apps, is considered a potential solution to help students manage stress, enhance concentration, and improve their quality of life. This study aims to analyze the factors (i) "Perceived Need for Mental Health Care", (ii) "Perceived Usefulness", (iii) "Perceived Ease of Use", and (iv) "Subjective Norm" influencing high school students' intention to use personalized mental health apps. The results indicate that Perceived Usefulness (PU) and Subjective Norm (SN) significantly influence BI, with PU being the strongest influencing factor. This implies that students are only willing to use the apps if they clearly perceive practical benefits and receive encouragement from family, friends, and school. The research findings contribute empirical evidence to the applicability of TPB and TAM in the context of school mental health in Vietnam.

KEYWORDS: Apps, mental health, personalized apps, high school students, TAM, TPB

1. INTRODUCTION

Mental health among adolescents is one of the significant public-health challenges both globally and in Vietnam. The World Health Organization defines a mental disorder as a significant disturbance in an individual's cognition, emotional regulation, or behavior. Among these disorders, depression and anxiety are the most common (WHO, 2022). Worldwide, depression affects 28% of the population, while anxiety affects 26%. The prevalence of mental health problems among adolescents (typically anxiety and depression) is approximately 10–20% (WHO, 2019). Notably, these conditions are often overlooked or not addressed in a timely manner, resulting in numerous negative consequences for students' academic, social, and physical development (NIMH, 2017).

In this context, mobile mental-health applications have attracted increasing attention because of their potential to support monitoring, prevention, and early intervention for psychological disorders. With more than 10,000 apps developed globally (Rubanovich et al., 2017), these digital tools allow individuals to access services anytime and anywhere, reduce costs, and lower stigma-related barriers to seeking help (Koh, Tng & Hartanto, 2022). Several systematic reviews suggest that such applications can enhance quality of life, improve resilience, and reduce levels of anxiety and depression (Kruse et al., 2022; Serrano-Ripoll et al., 2022). Alongside these benefits, concerns remain regarding safety, privacy, and sustained user engagement (Weisel et al., 2019; Koh et al., 2022).

For high-school students in Vietnam, the need for personalized mental-health care is increasingly urgent. A study by Ha N.T. & Minh N.H. (2025), based on data from 541 ninth-grade students in lower secondary schools in Hanoi, found that 58.4% of students exhibited depressive symptoms at various levels: minimal (26.1%), mild (13.9%), moderate (10.5%), and severe (7.9%). Factors statistically associated with depression prevalence included gender, academic pressure, physical bullying, cyberbullying, and problematic mobile-phone use ($p < 0.01$). This indicates a significant gap in access to mental-health services, and suggests that applications could play an essential role in closing that gap. Technologies such as mobile applications are expected to narrow disparities in access to care (Henson P. et al., 2019, p.1).

Although mHealth holds considerable potential, actual usage rates among patients with mental disorders range only from 12.51% to 34.07%. In contrast, interest in using these applications is very high, at 74.48%-83.46% (Guracho et al., 2023). This discrepancy reveals a "technology acceptance gap," reflecting users' willingness to adopt these tools that is not yet matched by sufficient trust, user-centered design, and cultural fit. Investigating the intention to use personalized mental-health applications will not only identify students' real needs but also guide the development of appropriate digital tools, contributing to narrowing the gap in access to adolescent mental-health services.

On this basis, the present study was conducted to analyze factors influencing the intention to use personalized mental health applications among high school students in Vietnam, drawing on the Theory of Planned Behavior (TPB - Ajzen, 1991) and the Technology Acceptance Model (TAM). The study aims to provide scientific evidence for the development of effective digital products and to contribute to the international discourse on the application of digital technologies in adolescent mental health care.

2. THEORETICAL FRAMEWORK AND LITERATURE REVIEW

2.1. Personalized Mental-Health Applications

Definition: In the context of individual mental health in general and adolescent mental health-specifically high-school students- in particular, becoming a global concern, the development of digital technologies has opened a new approach to overcoming barriers in mental-health care. Personalized mental-health applications are defined as digital platforms, primarily deployed on smartphones, that support users in the prevention, monitoring, and intervention of psychological problems based on each individual's needs, states, and characteristics (Rubanovich, Mohr, & Schueller, 2017).

Characteristics: Personalized mental-health applications have three core characteristics:

(i) Symptom self-management capabilities through tools such as emotion tracking, mood diaries, or brief assessments via rating scales. According to Council NAMH (2018), digital technologies, including mobile apps, can strengthen the mental-health care system by encouraging self-help behaviors and alleviating burdens on health services. Recent studies indicate that the use of mental health apps yields multiple benefits: improved quality of life, increased resilience, better sleep quality, and reductions in depression, anxiety, and anger (Kruse et al., 2022; Serrano-Ripoll et al., 2022; Levin et al., 2017).

(ii) Integration of digital interventions such as mindfulness meditation, online cognitive behavioral therapy (CBT), or breathing-relaxation exercises. Through personalized apps, mental health care can reduce stigma-related barriers to seeking direct support owing to anonymity and flexibility of use (Fuhr et al., 2024). However, one important challenge for mental-health apps is building a sense of engagement and trust (Bordin, 1979; Ardito & Rabellino, 2011). In the digital environment, the therapeutic alliance can be reconstructed by: (i) a user-friendly, easy-to-use interface; (ii) interactive, personalized feedback; and (iii) a sense of connection, whereby users feel the app "understands" and "accompanies" them (Mackie et al., 2017).

(iii) Personalization of content through analysis of user data to provide recommendations appropriate to the user's emotional state, circumstances, or culture (Schueller et al., 2019). A distinguishing feature compared with conventional mental-health apps is the degree of customization to individual characteristics, thereby increasing therapeutic effectiveness. Personalization is considered a central determinant of users' intention to adopt and their engagement level with mental-health apps (Rubanovich et al., 2017). Forms of personalization include: (i) content customization; (ii) real-time feedback based on behavioral-data analysis or emotion-diary inputs using artificial intelligence; and (iii) integration of cultural, linguistic, and religious-belief elements appropriate to the user.

The aforementioned benefits of personalized mental-health applications are supported by empirical evidence. Apps such as ACHESS and Ginger.io have been reported to yield positive outcomes in symptom monitoring, increased user satisfaction, and improved communication with health professionals (Forchuk et al., 2016; Bauer et al., 2018). Clinical trials also indicate that mobile apps supporting depression treatment deliver superior effectiveness compared with conventional interventions without digital tools (Bae et al., 2023). Nevertheless, some studies report limitations: users sometimes lack a sense of safety and express concerns about support availability when apps experience technical faults or unstable performance (Mackie et al., 2017). This highlights the pivotal role of safety, security, and reliability features in app design.

Core features: Based on surveys and usability testing, the features deemed essential in personalized mental-health apps include: (i) provision of educational information about depressive and anxiety disorders; (ii) self-care strategies such as mindfulness, mood journaling, and breathing techniques; (iii) self-assessment tools (e.g., PHQ-9, GAD-7); and (iv) medical reminders for medication or appointment schedules. These features help increase perceived behavioral control (PBC) according to the Theory of Planned Behavior (TPB), while also reinforcing users' confidence and proactivity.

Given these core features, personalized mental health applications are playing an increasingly important role amid shortages of healthcare services, rising school-related psychological pressure, and demand for flexible, private solutions. They offer advantages in access, cost, and stigma reduction, while facing challenges related to engagement, security, and clinical effectiveness. Particularly for high school students, personalization is not only a technological trend but also a key factor that can make an app genuinely useful and sustainable.

2.2. High-School Students and the Need to Use Personalized Mental-Health Application

Definition of high-school students

According to the Law on Education of Vietnam (2019), upper secondary education is delivered over three academic years, from grade 10 through grade 12. Entrance to grade 10 requires a lower-secondary (lower secondary school) graduation certificate, typically at age 15, and students complete upper secondary education at approximately 17–18 years of age. This level is the final stage of general education, serving to consolidate knowledge, skills, and character, while also orienting students toward career paths before they enter higher education such as university, college, or vocational schools (Article 28 - Law on Education, 2019). Thus, "high-school students" are understood here as adolescents aged 15 to 18 who are enrolled in grades 10, 11, and 12, with the admission requirement of a lower-secondary graduation certificate.

Prominent psychophysiological characteristics of high-school students

At this stage, students enter late adolescence and early adulthood, a critically important period in human development. They must absorb a large volume of academic content while also confronting substantial psychophysiological, personality, and social changes. The salient characteristics can be analyzed across three dimensions:

(i) Physical and physiological characteristics: During the high-school years, students' bodies generally reach a relatively mature level of development compared with early adolescence. Increases in height, weight, musculature, and neural maturation enable greater capacity for learning, work, and participation in more complex social activities. However, uneven development may leave many students with difficulties in emotion regulation or maintaining physiological stability. This period also ties physical and mental health closely together: fatigue, sleep deprivation, or prolonged academic stress can directly affect emotional states and cognitive functioning.

(ii) Cognitive and reasoning characteristics: A notable feature of high-school students is the transition from concrete to more abstract and logical thinking. They become better able to analyze, compare, synthesize, and generalize, and begin to develop critical thinking and self-evaluation skills. This stage is also marked by a growing need for self-affirmation through academic performance, extracurricular achievements, or social status within peer groups. Nevertheless, adolescents' reasoning remains vulnerable to emotional influences and personal experience; many tend to absolutize their own views or idealize social issues, which may lead to conflicts with parents and teachers. This reflects a need for respect and autonomy in both learning and personal decision-making.

(iii) Emotional characteristics: High-school students are susceptible to intense and rapidly fluctuating emotional states. They may feel exhilarated, optimistic, and confident at one moment, and anxious, pessimistic, or disappointed the next when faced with setbacks. The development of moral sentiments, humanitarian concern, peer attachments, and adolescent romantic feelings becomes more pronounced. These emotional changes present both opportunities and challenges: strong emotions can motivate students' efforts but may also destabilize them in the absence of adequate coping skills. Upper secondary is the period when students make critical decisions about their future-particularly their choice of field and pathway after high school-thus many experience stress and confusion if family, teacher, and school support are lacking.

The necessity of mental health care

The psychophysiological profile of high-school students indicates that they constitute a distinct group characterized by substantial developmental changes that pose both risks and opportunities for holistic development. Correctly identifying these characteristics helps teachers and parents adopt appropriate educational strategies and serves as a basis for designing mental health support solutions, including personalized mental health applications. International reports show that the prevalence of any mental illness (AMI) is highest among young adults aged 18–25, reaching 36.2%, compared with 29.4% among those aged 26–49 and 13.9% among those aged 50 and over (NIMH, 2024). This demonstrates that adolescents and young people, including high-school students, are among the groups at greatest risk for mental-health problems. Despite this, only about 43.1% of adults with mental health issues in the United States received treatment in the most recent year (NIMH, 2017). The figure for developing countries like Vietnam may be substantially lower due to shortages of school psychologists, limited service availability, and low mental-health literacy among students, while social barriers and stigma deter many from seeking direct help. Deploying personalized mental-health applications enables students to access support anytime and anywhere, reduces costs relative to traditional therapy, and creates a discreet, safe environment. Moreover, apps designed to fit Vietnamese culture and language, for example, by integrating mindfulness practices informed by Buddhist traditions or school-based inspirational narratives, increase user acceptance and uptake.

2.3. Factors Influencing High-School Students' Intentions to Use Personalized Mental-Health Applications

In research on technology adoption in general and mental-health applications in particular, behavioral and technology-acceptance theoretical models have been widely applied to explain and predict user behavior. For high-school students, use of personalized mental-health apps is influenced by multiple context-specific factors, including age-related psychological characteristics, the learning environment, social pressures, and access to technology. Within the scope of this study, the authors focus on two principal theoretical frameworks—the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB)—and supplement these with the personalization factor to clarify determinants of intention to use.

The TAM, proposed by Davis (1989), asserts that behavioral intention to use a technology is primarily affected by Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). In the context of mental-health applications, PU reflects the degree to which students believe that using the app can improve their mental state, reduce stress, or enhance concentration. PEOU refers to the ease of operation and the user-friendliness of the app interface.

Meanwhile, Ajzen's (1991) TPB posits that behavioral intention is determined by three factors: Attitude toward the behavior (ATT), Subjective Norm (SN), and Perceived Behavioral Control (PBC). TPB is considered an appropriate theoretical lens for explaining the use of personalized mental-health apps among high-school students because it encompasses both individual and social influence factors.

The factors considered in this article as affecting high-school students' intention to use personalized mental health applications include:

- **Perceived need for mental health care**. According to Ajzen (1991), attitude toward a behavior results from personal beliefs about the costs and benefits of performing that behavior. In this context, if high school students clearly perceive a need for mental health care, they will form more positive attitudes toward using an app. When students recognize that stress, anxiety, or exam pressure can impact their learning and overall well-being, they will view a mental health app as a necessary and valuable resource. Higher perceived need leads to more positive attitudes because students regard the app as a practical solution to their personal needs (Rubanovich et al., 2017).
- **Subjective norm (SN)**. This factor reflects the influence of peers, family, teachers, and society. In the Vietnamese cultural context, encouragement or guidance from family and teachers further increases students' intention to use mental-health apps.
- **Perceived usefulness (PU)**. According to TAM, this factor is especially important. Students will be willing to use an app if they believe it can deliver practical benefits such as improved study concentration, stress management before exams, or better sleep quality. Systematic reviews (Kruse et al., 2022; Serrano-Ripoll et al., 2022) have demonstrated that mobile mental-health apps can indeed improve quality of life and reduce psychological symptoms.
- **Perceived ease of use (PEOU)**. Among determinants of technology adoption, PEOU is a fundamental factor. For high school students, simplicity, ease of operation, and intuitive interface design are crucial. If an app is complex, requires many registration steps, or demands advanced technical skills, students are likely to abandon it despite its helpful features.
- **Behavioral intention (BI)**. Behavioral intention is understood as the degree of students' willingness to adopt a personalized mental-health app in their daily lives or in the near future. Ajzen (1991) affirms that intention is the strongest predictor of behavior. Torous et al. (2018) also show that intention to use mental health apps is an important indicator of long-term adoption. In general, high school students' intentions to use personalized mental health applications arise from a combination of personal perceptions and social influence (SN). When students believe an app is easy to use, useful, and socially supported by peers and family, they will form positive attitudes and exhibit greater intention to use.

2.4. Research Model and Proposed Measurement Scales

On the basis of clarifying theories of consumer behavioral intention, the Theory of Planned Behavior (TPB), and the Technology Acceptance Model (TAM), the research team proposes the following research model:

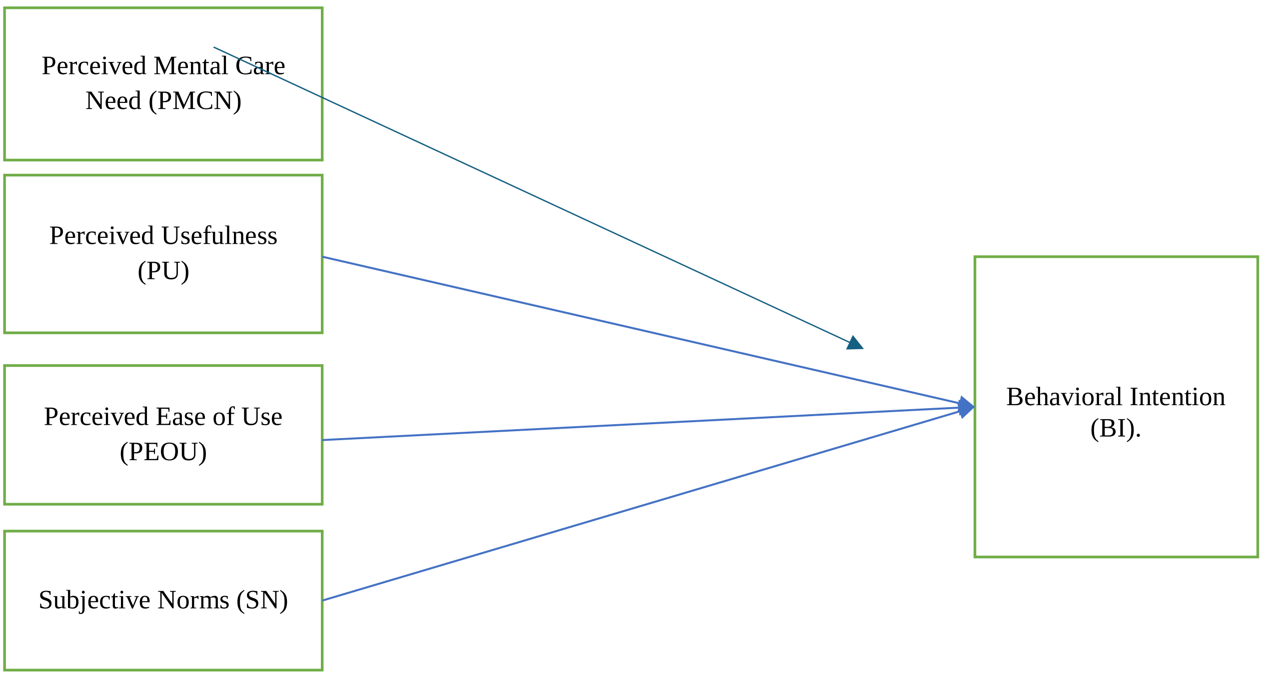


Figure 1: Proposed research model
Source: Proposed by the author group

Research Hypotheses: Independent variables

H1: Perceived mental care need (PNMC) has a positive effect on the intention to use personalized mental-health applications.
H2: Perceived usefulness (PU) has a positive effect on the intention to use personalized mental-health applications.
H3: Perceived ease of use (PEOU) has a positive effect on the intention to use personalized mental-health applications.
H4: Subjective norm (SN) has a positive effect on the intention to use personalized mental-health applications.

Table 1: Proposed Measurement Scale

Variable	Code	Measurement Scale
Perceived Mental Care Need	PNMC1	I believe that high school students need to receive mental-health care.
	PNMC2	I feel that I need a tool to support my personal mental well-being.
	PNMC3	Academic stress and pressure make me feel the need for mental-health care products.
	PNMC4	Stress and pressure in daily life make me feel the need for mental-health care products.
Perceived Usefulness	PU1	I think that a personalized mental-health care product would be useful for me.
	PU2	I believe that a personalized mental-health care product can help me manage stress more effectively.
	PU3	I feel interested in the idea of using a personalized mental-health care application.
Perceived Ease of Use	PEOU1	I think that using a mental-health care application would be very easy.
	PEOU2	I feel that I can quickly learn how to use a mental-health care application.
	PEOU3	I think that accessing the functions of the application is simple and easy to understand.
Subjective Norm	SN1	My friends support the use of personalized mental-health care applications.
	SN2	My family encourages personalized mental-health care through the use of such applications.
	SN3	My school is concerned about providing personalized mental-health care for students.
	SN4	Society in general supports the use of personalized mental-health care applications for students.
Behavioral Intention	BI1	I intend to use a personalized mental-health care application in the near future.
	BI2	If there is a suitable application available, I am willing to register and use it.
	BI3	I am willing to recommend a personalized mental-health care application to my friends.

Source: Proposed by the author group

3. RESEARCH METHODOLOGY

3.1. Data Collection Method

Based on theoretical foundations and a review of studies on factors influencing the intention to use personalized mental health care products, the variables included in the research model consist of: (i) *Perceived Need for Mental Health Care* (PN), (ii) *Perceived Usefulness* (PU), (iii) *Perceived Ease of Use* (PEOU), (iv) *Subjective Norm* (SN), which influence (v) *Behavioral Intention to use personalized mental health care products* (BI).

A quantitative research method was employed to collect opinions from high school students. After developing the questionnaire, a pilot survey was conducted with 5 randomly selected students. The preliminary results indicated agreement on the inclusion of the proposed factors in the model. The questionnaire content was based on Table 1, using a Likert 5-point scale as follows:

1. Strongly disagree
2. Disagree
3. Neutral
4. Agree
5. Strongly agree

Due to limitations in time and resources, a convenience sampling method was applied. The minimum required sample size was calculated using the formula *n = 50 + 8*m* (m: number of independent variables) (Tabachnick & Fidell, 1996). With five variables in this study, the minimum required sample size was *50 + 8*5 = 90 respondents*. To ensure greater reliability and stability of the effects, more data were collected through an online Google Form distributed via the following link: https://forms.gle/jYkoXao6pv2eeQik9. A total of 222 valid responses were collected for analysis.

3.2. Data Analysis Method

The **quantitative research method** was employed to process data collected from the high school student survey. The general structural regression equation is expressed as:

$$\mathbf{BI = a * PNMC + b * PU + c * PEOU + d * SN}$$

The SMARTPLS software was used to test the hypotheses and assess the effects of the influencing factors.

Step 1: Evaluating Measurement Model

Evaluating measurement model based on examining values of reliability, quality of observed variable, convergence, and discriminant

- Testing the quality of observed variables (Outer Loadings)

Outer Loadings of observed variables are indicators showing the degree of association between observed variables and latent variables (proxy variables). Basically, outer loadings in SMARTPLS are the square root of the absolute value of R2 linear regression from the latent variables to the sub-observed variables.

Hair et al. (2016) suggest that the outer loadings should be greater than or equal to 0.708 observed variables that are quality. To make it easier to remember, the researchers rounded off the threshold to 0.7 instead of the number 0.708.

- Evaluating Reliability

Evaluating the reliability through SMARTPLS by two main indicators, Cronbach's Alpha and Composite Reliability (CR). Composite Reliability (CR) is preferred by many researchers over Cronbach's Alpha because Cronbach's Alpha underestimates the reliability compared with CR. Chin (1998) claims that in exploratory research CR must be over 0.6. For confirmed studies, the 0.7 threshold is the appropriate level of CR (Henseler & Sarstedt, 2013). Other researchers agree that 0.7 is the appropriate threshold for the vast majority of cases such as Hair et al. (2010), and Bagozzi & Yi (1988).

Thus, the reliability through SMARTPLS is shown by Cronbach's Alpha ≥ 0.7 (DeVellis, 2012); Composite Reliability CR ≥ 0.7 (Bagozzi& Yi, 1988).

- Testing Convergence

Evaluating Convergence on SMARTPLS is based on Ave (Average Variance Extracted). Hock & Ringle (2010) claim that a scale reaches a convergence value if AVE reaches 0.5 or higher. This level of 0.5 (50%) means that the average latent variable will explain at least 50% of the variation of each sub-observed variable. Thus, convergence is evaluated by Average Variance Extracted AVE $\geq$ 0.5 (Hock & Ringle, 2010).

- Testing Discriminant Validity

Discriminant value is used to consider whether a research variable is really different from other research variables in the model. To evaluate the discriminant validity, Sarstedt & et al (2014) said that considering two criteria including cross-loadings and the measurement of Fornell and Larcker (1981).

Cross-loading coefficients are often the first approach to evaluating the discriminant validity of indicators (observed variables) (Hair, Hult, et al., 2017). The load factor of the observed variable (indicator) linked in the factor (latent variable) should be greater than any of its cross-load factors (its correlation) in the other factors.

Fornell and Larcker (1981) recommend that discriminant is ensured when the square root of AVE for each latent variable is higher than all correlations between latent variables. In addition, Henseler & et al (2015) used simulation studies to demonstrate that discriminant validity is better evaluated by the HTMT index that they developed.

With the HTMT index, Garson (2016) said that the discriminant validity between two latent variables is guaranteed when the HTMT index is less than 1. Henseler & et al (2015) propose that if this value is below 0.9, the discriminant validity will be guaranteed. Meanwhile, Clark, L. A., & Watson, D. (1995) used a stricter standard threshold of 0.85. SMARTPLS preferred a threshold of 0.85 in the evaluation.

- Testing Multicollinearity

In this study, the author uses a scale related to multicollinearity as a variance magnification factor (VIF). Very high levels of multicollinearity are indicated by VIF values >= 5; the model does not have multicollinearity when VIF indicators < 5 (Hair et al., 2016).

Step 2: Evaluating Structural Model

After evaluating the satisfactory measurement model, evaluate the structural model through the impact relationship, path coefficient, R squared, and f squared.

- Evaluating impactful relationships

To evaluate impact relationships, use the results of Bootstrap analysis. Based mainly on two columns (1) Original Sample (normalized impact factor) and (2) P Values (sig value compared to 0.05 significance level).

- Original Sample: Standardized impact factor of the original data. SMARTPLS have no unstandardized impact factor.
- Sample Mean: The average standardized impact factor of all samples from Bootstrap.
- Standard Deviation: Standard deviation of the standardized impact factor (according to the original sample).
- T Statistics: Test value t (test student the meaning of the impact).
- P Values: The significance level of the T Statistics. This significance level is considered with comparative thresholds such as 0.05, 0.1, or 0.01 (usually used as 0.05).

Evaluating the level of interpretation of the independent variable for the dependent variable by R2 coefficient (R square). To evaluate the R2 coefficient, we will use the results of the PLS Algorithm analysis. The R2 value evaluates the predictive accuracy of the

model and shows the level of interpretation of the independent variable for the dependent variable. R square is between 0 and 1, the closer to 1 indicates the more independent variables that account for the dependent variable (Hair, Hult, et al, 2017).
Additionally, during factor evaluation, data collected were aggregated, computed, and visualized through charts, tables, and figures using Microsoft Excel**.**
For constructs measured using the 5-point Likert scale, the mean score of each factor was calculated to determine the level of agreement and the strength of influence based on mean value ranges.

Interval value= (Maximum - Minimum) / n = (5-1)/5 = 0.8

Evaluation thresholds based on mean scores:

+ 1.00 -1.80: Strongly disagree
+ 1.81 - 2.60: Disagree
+ 2.61 - 3.40: Neutral
+ 3.41 - 4.20: Agree
+ 4.21 - 5.00: Strongly agree

4. RESEARCH RESULTS

4.1. Characteristics of Respondents

A total of 222 valid responses were collected from the distributed survey. Details regarding the gender and age distribution of respondents are presented below.

Table 2. Descriptive Statistics of Survey Participants

Occpation			**Age**		
Grade Level	**Number of participants**	**Percentage (%)**	**Gender**	**Number of participants**	**Percentage (%)**
Grade 10	71	31,8%	Male	97	43,7%
Grade 11	101	45,5%	Female	123	55,4%
Grade 12	50	22,7%	Do not want to be specific	2	0,9%
Total	222	100%	Total	222	100%

Source: Survey results

The majority of survey respondents were female, accounting for **123 individuals (55.4%)**, while **97 respondents (43.7%)** were male, and 2 respondents (**0.9%)** preferred not to specify their gender.

Since the respondents were high school students, their ages ranged from **15 to 18 years**, corresponding to the following grade levels: 71 students in Grade 10 (31.8%)**,** 101 students in Grade 11 (45.5%)**,** and 50 students in Grade 12 (22.7%)**.** The participants were mainly from private schools (50%), followed by public schools (27.3%)**,** as illustrated in Figure 2.

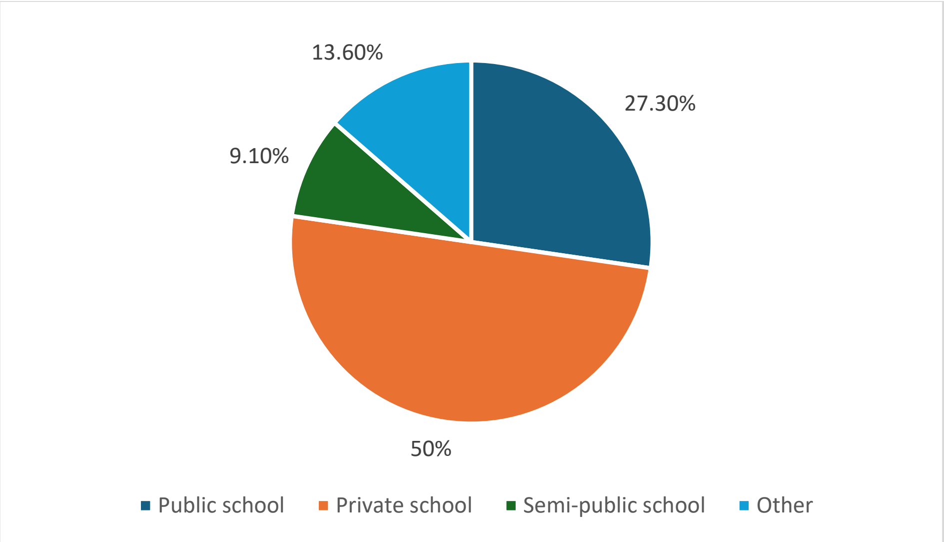


Figure 2. Classification of School Types Attended by Surveyed Students
Source: Survey results

4.2. Survey Results

4.2.1. Assessment of Observed Variable Quality

The quality of observed variables was evaluated through the outer loadings coefficients.

The quality of the observed variables influencing the intention to use personalized mental-health care products is presented in Table 3.

Table 3. Outer Loadings of Factors Affecting the Intention to Use Personalized Mental-Health Care Products

	BI	PEOU	PNMC	PU	SN
BI1	0,877				
BI2	0,868				
BI3	0,885				
PEOU1		0,883			
PEOU2		0,908			
PEOU3		0,925			
PNMC2			0,773		
PNMC3			0,754		
PNMC4			0,854		
PU1				0,861	
PU2				0,879	
PU3				0,813	
SN1					0,827
SN2					0,842
SN3					0,894
SN4					0,850
PNMC1			0,790		

Source: Data analysis conducted by the research team

The results from Table 3 indicate that the *outer loadings* of all correlation coefficients between the observed variables and the total variables affecting the intention to use personalized mental health care applications are all greater than 0.7 (Hair et al., 2016), demonstrating that the observed variables are statistically significant.

Reliability testing of measurement scales

The reliability of the measurement scales for factors influencing the intention to use personalized mental health care applications was assessed in PLS-SEM through two main indicators: *Cronbach's Alpha* and *Composite Reliability (CR).*

Table 4. Cronbach's Alpha and Composite Reliability of factors affecting the intention to use personalized mental health care applications

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
BI	0,850	0,853	0,909	0,768
PEOU	0,890	0,892	0,932	0,820
PNMC	0,806	0,817	0,872	0,630
PU	0,809	0,811	0,887	0,725
SN	0,876	0,877	0,915	0,729

Source: Data analysis conducted by the research team

According to Table 4, the results of the reliability analysis using Cronbach's Alpha indicate that: *"Perceived Need for Mental Care" (PNMC)* achieved 0.806, *"Perceived Usefulness" (PU)* achieved 0.809, *"Perceived Ease of Use" (PEOU)* achieved 0.890, *"Subjective Norm" (SN)* achieved 0.876, and *"Behavioral Intention to Use Personalized Mental Health Care Applications" (BI)* achieved 0.850. Therefore, all measurement scales satisfy the condition of being greater than 0.7 (DeVellis, 2012) and do not violate any rule requiring variable removal. Hence, no variable was eliminated, and all are considered reliable.

The Composite Reliability (CR) of all observed variables is also greater than 0.7 (Bagozzi & Yi, 1988) (Table 4). Consequently, the measurement scales are reliable, analytically valid, and suitable for subsequent factor analysis.

Convergent Validity

According to the data analysis results presented in Table 4, the *Average Variance Extracted (AVE)* values for each construct are as follows: *"Perceived Need for Mental Care" (PNMC)* = 0.630, *"Perceived Usefulness" (PU)* = 0.725, *"Perceived Ease of Use" (PEOU)* = 0.820, *"Subjective Norm" (SN)* = 0.729, and *"Behavioral Intention to Use Personalized Mental Health Care Applications" (BI)* = 0.768. Therefore, since all AVE values exceed the 0.5 threshold (Hock & Ringle, 2010), the model satisfies the conditions for convergent validity.

Discriminant Validity

The results in Table 5, based on the Fornell–Larcker criterion, indicate that all constructs in the research model influencing *Behavioral Intention to Use Personalized Mental Health Care Applications (BI)*—including (i) *Perceived Need for Mental Care*, (ii) *Perceived Usefulness*, (iii) *Perceived Ease of Use*, and (iv) *Subjective Norm*—meet the discriminant validity requirements. This is evidenced by the fact that all square roots of AVE values along the diagonal are higher than their corresponding off-diagonal correlations. Therefore, according to both the cross-loading criterion and the Fornell–Larcker criterion, the model satisfies the requirements for discriminant validity (Fornell & Larcker, 1981).

Table 5. Fornell–Larcker Criterion of the Research Model on Factors Influencing the Intention to Use Personalized Mental Health Care Applications

	BI	**PEOU**	**PNMC**	**PU**	**SN**
BI	0,876				
PEOU	0,676	0,905			
PNMC	0,630	0,614	0,794		
PU	0,748	0,673	0,648	0,851	
SN	0,706	0,766	0,728	0,706	0,854

Source: Data analysis conducted by the research team

The value of the function f^2

The **f^2** value represents the degree of influence of a construct (factor) when it is removed from the model. According to Cohen (1988), **f^2** values of 0.02, 0.15, and 0.35 correspond to *small*, *medium*, and *large* effect sizes of exogenous variables, respectively. If the effect size < 0.02, it is considered to have no impact.

Table 6. Summary of f^2 Values

	BI	**PEOU**	**PNMC**	**PU**	**SN**
BI					
PEOU	0,033				
PNMC	**0,014**				
PU	**0,214**				
SN	0,030				

Source: Data analysis conducted by the research team

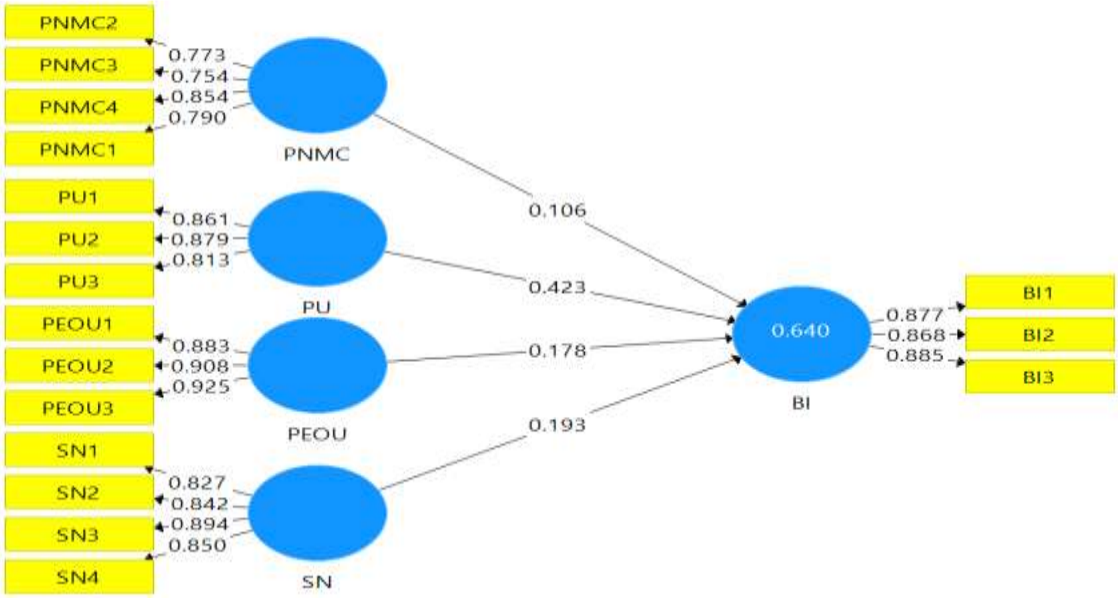
In this model, as shown in Table 6, the factor *"Perceived Need for Mental Care" (PNMC)* has $f^2 < 0.02$, indicating no significant influence. Meanwhile, *"Perceived Ease of Use" (PEOU)* and *"Subjective Norm" (SN)* have $0.02 < f^2 < 0.15$, representing medium effect sizes, whereas *"Perceived Usefulness" (PU)* has $0.15 < f^2 < 0.35$, indicating a significant effect on *"Behavioral Intention to Use Personalized Mental Health Care Applications" (BI).*

Evaluation of the Influence Level Using the Structural Model

Assessment of the Relationships and Their Effects

The relationships and effect magnitudes of factors influencing the intention to use personalized mental health care applications in the SMARTPLS model are illustrated in Figure 3.

Figure 3. Factors Influencing the Intention to Use Personalized Mental Health Care Applications



Source: Results of the research team's analysis using SMARTPLS

The results of the Bootstrap analysis evaluating the relationships among variables are presented in Table 7**.** Accordingly, the variables "Perceived Usefulness (PU)" and "Subjective Norm (SN)" were found to have a significant influence on "Behavioral Intention (BI)" to use personalized mental health care products. These factors have P Values < 0.05 **(**hypotheses H2 and H4 are accepted at the 5% significance level**).** The variables "Perceived Need for Mental Care (PNMC)" and "Perceived Ease of Use (PEOU)" do not have a significant impact on "Behavioral Intention (BI)"**,** as their P Values > 0.05 **(**Hypotheses H1 and H3 are not supported at the 5% significance level**).**

Table 7. Path Coefficients of the Structural Model

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
PEOU -> BI	0,178	0,183	0,115	1,545	**0,123**
PNMC -> BI	0,106	0,111	0,067	1,583	**0,114**
PU -> BI	0,423	0,418	0,070	6,000	**0,000**
SN -> BI	0,193	0,191	0,095	2,030	**0,043**

Source: Results of the research team's analysis using SMARTPLS

The results presented in **Table 7** indicate that, at a 95% confidence level, "Perceived Usefulness (PU)" and "Subjective Norm (SN)" have a significant influence on "Behavioral Intention (BI)" to use personalized mental health care products. Accordingly, the regression equation is expressed as follows:

BI=0.423*PU + 0.193*SN

Both coefficients - 0.423 (PU → BI) and 0.193 (SN → BI) - are positive, which supports hypotheses H2 and H4, confirming the existence of a positive relationship.

Evaluation of the Coefficient of Determination R^2 (R Square)

The results of the PLS analysis provide the R^2 value, which reflects the level of explanation of the dependent variable by the independent variables. The R^2 index measures the overall coefficient of determination (R-square value), which is an indicator used to assess the goodness of fit of the model to the data (the explanatory power of the model). According to Hair et al. (2010), the suggested R-square values are at the levels of 0.75, 0.50, or 0.25**.**

Table 7. Coefficient of Determination of Independent Variables for the Dependent Variable (R Square)

	R Square	R Square Adjusted
BI	0,640	0,633

Source: Results of the research team's analysis

The results from Table 7 show that the R^2 value of the factor *"Behavioral Intention" (BI)* is 0.640, and the adjusted **R^2** value is **0.633**, which is appropriate for this study. Thus, the independent variables explain 64% of the variance in the *"Behavioral Intention to Use Personalized Mental Health Care Applications" (BI)*.

5. DISCUSSION AND RECOMMENDATIONS

5.1. Discussion of Results

The *behavioral intention to use personalized mental health care applications* serves as the central dependent variable of the model, reflecting the readiness of high school students to adopt digital technology for mental health care. The survey results indicate that all measurement items of BI achieved relatively high mean scores, ranging from 3.865 to 4.036, demonstrating a positive tendency among students toward the use of personalized mental health care products.

Table 8. Mean Value of the Variable "Behavioral Intention to Use" (BI)

Code	Measurement scale	Mean score	Level of perception
BI1	I intend to use a personalized mental health care application in the near future.	4,036	Agree
BI2	If there is a suitable application, I am willing to register and use it.	3,865	Agree
BI3	I am willing to recommend the personalized mental health care application to my friends.	3,973	Agree

Source: Survey results

Among the three measurement items, BI1 "I intend to use the application" recorded the highest mean score (4.036), indicating that students show a positive tendency toward intending to use the application in the near future. BI3 "I am willing to recommend it to my friends" also achieved a relatively high mean score (3.973), reflecting the potential for social diffusion if the application is successfully implemented. Meanwhile, BI2 "I am willing to register and use it if there is a suitable application," had a slightly lower score (3.865). This result can be explained by the significant influence of the "Perceived Usefulness" factor in this study. According to Ajzen (1991), in the Theory of Planned Behavior (TPB), behavioral intention is the most direct and powerful predictor of actual behavior. However, in practice, students still need to be convinced of the application's suitability and reliability before committing to use it. This serves as an important basis for developers and educational administrators to promote the implementation of the application, with particular emphasis on enhancing its relevance, credibility, and social encouragement in order to transform intention into actual behavior.

The SEM/PLS analysis results, with a 95% confidence level, show that among the four factors included in the model, only *Perceived Usefulness (PU)* and *Subjective Norm (SN)* have a significant influence on *Behavioral Intention (BI)* to use personalized mental health care applications among high school students. The regression equation is defined as follows:

BI=0.423*PU + 0.193*SN

This result aligns with the study by Torous et al. (2018) in the field of digital mental health, which found that adolescents' intention to use tends to be high when the application meets their personal needs and receives social endorsement.

(1)The Influence of Perceived Usefulness (PU)

With a coefficient of 0.423, PU is the strongest factor affecting BI, implying that students are only willing to use the application if they believe it provides specific and practical benefits. This finding is consistent with previous research based on the Technology Acceptance Model (TAM), in which PU has often been identified as the most influential factor on technology usage intention (Davis, 1989).

Table 9. Perceived Usefulness (PU)

Code	Measurement scale	Mean score	Level of perception
PU1	I think that a personalized mental-health care product would be useful for me.	3,869	Agree
PU2	I believe that a personalized mental-health care product can help me manage stress more effectively.	3,779	Agree
PU3	I feel interested in the idea of using a personalized mental-health care application.	3,887	Agree

Source: Survey results

The mean scores of all three measurement items for the factor *Perceived Usefulness (PU)* reached the "agree" level, indicating that high school students generally rated the usefulness of the personalized mental health care application quite positively. Among them, the measurement item **PU3** achieved the highest mean score, suggesting that students hold an open and interested attitude toward the idea of such an application. The item PU2 had a slightly lower mean score, reflecting a certain degree of caution among students regarding whether the application can truly help them manage stress effectively.

In the field of mental health, Kruse et al. (2022) and Serrano-Ripoll et al. (2022) demonstrated that mental health care applications can improve sleep quality, reduce stress, and enhance resilience-thereby increasing users' motivation to engage with such tools. For Vietnamese high school students, the practical benefits may include reducing exam-related anxiety, improving concentration in study, or managing emotions in relationships with peers and family. Thus, *Perceived Usefulness (PU)* plays a decisive role in shaping usage intention, as students' perception that the application provides specific and tangible benefits-such as reducing anxiety, controlling stress, and improving focus-directly determines their willingness to adopt it. This also has important implications for developers: applications should emphasize features that directly address school-related psychological needs in order to enhance students' perceived value of usefulness.

(2) The Influence of Subjective Norm (SN)

The factor *Subjective Norm (SN)* has a significant impact on the intention to use personalized mental health care applications, with a coefficient of 0.193, indicating that students' behavior is influenced not only by their personal perceptions but also by social encouragement and pressure. In the context of Vietnamese culture, family, friends, and schools play a crucial role in shaping behavioral norms; therefore, this result is entirely consistent with the theoretical foundation of the Theory of Planned Behavior (Ajzen, 1991). It also demonstrates that social factors can either increase or decrease students' motivation to adopt mental health technologies.

The measurement items for SN clearly reflect the various dimensions of social influence, as shown in the following table:

Table 10. Results of the Subjective Norm (SN) Measurement Scale

Code	Measurement scale	Mean score	Level of perception
SN1	My friends support the use of personalized mental-health care applications.	3,797	Agree
SN2	My family encourages personalized mental-health care through the use of such applications.	4,045	Agree
SN3	My school is concerned about providing personalized mental-health care for students.	3,842	Agree
SN4	Society in general supports the use of personalized mental-health care applications for students.	3,707	Agree

Source: Survey results

The results of the *Subjective Norm (SN)* measurement items presented in Table 10 show that family influence (SN2) is the most dominant social factor, with the highest mean score of 4.045, reflecting the cultural characteristic of Vietnam where the family plays a central role in shaping students' behavior. Other influential social agents include schools (SN3, mean = 3.842) and friends (SN1, mean = 3.797)**,** providing evidence that students tend to seek opinions and behavioral cues from those around them when deciding whether to use an application. The general social environment (SN4, mean = 3.707) received a lower score, suggesting that the broader social context exerts less influence compared to the immediate and close social groups of students. These findings are consistent with the study by Ha, N.T. & Minh, N.H. (2025)**,** in which *subjective norm* was identified as a key predictor of technology acceptance in the fields of education and healthcare in Vietnam. The result also reinforces the conclusion of Torous et al. (2018)**,** who argued that support from friends and family is a crucial factor encouraging adolescents to sustain their engagement with mental health applications.

The above findings provide practical implications: in order to enhance high school students' intention to use personalized mental health care applications, it is essential to leverage the influence of key reference groups. Specifically, efforts should focus on encouraging family involvement, strengthening schools' communication and educational initiatives, and developing community-based programs to foster a supportive social environment for digital mental health care adoption.

5.2. Recommendations

To promote both intention and actual behavior of using personalized mental health care applications, coordinated efforts are required among multiple stakeholders -including app developers, families, schools, and students themselves. Specific recommendations are outlined as follows:

(1) Enhancing Perceived Usefulness (PU)

Developers should focus on designing features that address the specific psychological needs of high school students, such **as** reducing exam anxiety, improving concentration, and managing emotions in peer and family relationships. Ensuring data reliability and privacy protection is crucial for building user trust, as students tend to be cautious about privacy risks before committing to long-term use. Moreover, integrating AI-driven personalization, instant feedback, and tailored user experiences can enhance engagement and strengthen perceived usefulness *(PU)* -the strongest predictor of behavioral intention. Key considerations in developing personalized mental health applications include:

- Interface and Language: The application should feature a user-friendly interface and use simple, clear Vietnamese language suitable for the high school age group. This not only reduces technological barriers but also improves user experience and accessibility.

-Cultural Integration: Developers should incorporate Vietnamese cultural elements such as mindfulness meditation**,** traditional breathing techniques**,** or inspirational folktales into relaxation exercises. Such cultural relevance enhances users' sense of familiarity and connection, thereby increasing their intention to use the app.

-Community Features and Subjective Norm (SN): Integrating online support groups and discussion forums can strengthen the influence of *subjective norms (SN)* as proposed in the Theory of Planned Behavior (TPB). These features can help students feel socially supported by peers, teachers, and society. Within the school context, collaboration with Youth Unions and psychological counseling programs can reinforce collective motivation and normalize mental health app usage among students.

-AI-Based Personalization**:** Artificial Intelligence can analyze users' emotional states, behaviors, and habits to provide personalized recommendations that optimize the app's effectiveness. This aligns with global *mHealth* trends (Kruse et al., 2022; Guracho et al., 2025). However, developers must also implement strict data protection and privacy measures to safeguard users' personal information while leveraging AI technologies.

(2) Promoting the Impact of Subjective Norm (SN)

-For families: Families play a central role in Vietnamese culture; therefore, parental encouragement directly increases students' intention to use the application. Parents should demonstrate companionship and view digital mental health care as a positive behavior rather than associating it with stigma. Communication programs for parents can help improve awareness and skills to support their children. In addition, the application could include features that connect parents and students, while maintaining a balance between guidance and respect for students' privacy.

-For schools: Schools are among the most influential institutions shaping students' behavior. Thus, the application should be integrated into extracurricular activities, homeroom sessions, and life skills education programs. Teachers and school counselors should receive training to understand the app's functions and to guide and encourage students to use it. When schools create a supportive environment that normalizes and values mental health app use, students will experience less psychological resistance and show stronger behavioral intention.

-For students: Students are the direct beneficiaries of the application, so they should actively engage with it and provide feedback to improve its suitability. The high mean score of BI3 (willingness to recommend to friends) indicates strong potential for social diffusion; therefore, students could be encouraged to act as "user ambassadors." Moreover, group-based activities within the app, such as meditation or stress management challenges, can sustain user engagement and strengthen the influence of subjective norms (SN1-peer influence).

-For policymakers and the community: Educational and health authorities should implement supportive policies, including pilot programs in schools and financial subsidies to enhance accessibility. Public communication campaigns should also be launched to reduce stigma and emphasize that using mental health apps is a modern and positive choice. Additionally, longitudinal studies should be encouraged to assess long-term impacts, while extending the TAM/TPB framework by incorporating new variables such as perceived data security and degree of personalization, to improve the prediction of actual usage behavior.

6. CONCLUSION

This study explored the factors influencing high school students' intention to use personalized mental health care applications in Vietnam, based on the theoretical frameworks of TAM and TPB. The survey results and SEM/PLS analysis revealed that Perceived Usefulness (PU) and Subjective Norm (SN) significantly affect Behavioral Intention (BI), with PU exerting the strongest influence ($\beta = 0.423$). This finding indicates that students are more likely to use the application when they believe it provides tangible benefits and when they receive encouragement from family, peers, and schools. Despite these positive findings, the study focuses only on behavioral intention rather than actual usage behavior. The survey sample is limited to several high schools in urban areas, which may not fully capture regional differences, particularly among students in rural or economically disadvantaged settings. Moreover, the study does not comprehensively address other potential factors such as data security trust, level of personalization, or technological readiness.

Future research should expand the sample to include students from diverse regions to compare differences based on geography, socioeconomic status, and digital literacy. Additional variables such as "trust in data security," "degree of personalization," and "cultural norms" could be integrated into the theoretical model to enhance predictive power. Finally, a multi-stakeholder approach involving students, parents, teachers, psychologists, and technology developers should be adopted in the design and testing process to establish a robust "digital therapeutic alliance," thereby optimizing both user experience and application effectiveness.

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