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Role of Technology Self-Efficacy and Digital Alliance in Digital Mental Health Tool Acceptance Among University Students in Singapore

Toh Hsiang Benny Tan[1, 2] ✉, Sufang Lim[2], and Chan Hua Nicholas Vun[1]

ABSTRACT

Mental health challenges, accentuated by stress, are escalating in high-income countries, especially among adolescents and university students. Traditional mental health approaches face issues such as scalability and accessibility, making the emergence of digital tools crucial. However, adherence remains a challenge. This study examines the role of technology self-efficacy and digital alliance in influencing the acceptance of digital mental health tools among Singaporean university students. The results provide strong support for the role of digital alliance as a key factor impacting a student's intention to use mental health tools, as well as technology self-efficacy and digital alliance as serial mediators of task-technology fit and intention to use, highlighting our ever-evolving relationship with technology.

KEYWORDS

task-technology fit; technology acceptance; technology self-efficacy; digital alliance; digital mental health; intention to use

Mental health is a growing issue around the world, affecting multiple aspects of a person, and imposing a significant burden on the host country. With 75% of mental disorders beginning during a person's stressful adolescence and university students experiencing higher-than-average levels of stress, interventions during this period are crucial in preventing long-term psychological problems. In contrast to conventional mental health approaches, which often face obstacles like scalability and accessibility, digital mental health solutions offer a promising alternative. These digital innovations—spanning apps, platforms, and web-based interventions—are poised to redefine mental health support by bridging many of the extant gaps. However, digital solutions are not without their problems. Often intended for unguided use in self-service environments, adherence, or rather the lack of it remains a pressing issue, significantly impacting the potential of such technologies to make an impact. In order to address this issue, an understanding of the factors which affect a user's intention to acceptance and adopt these tools is indispensable. Only when these factors are understood can the issue be addressed, and digital mental health tools succeed.

1 Theoretical Background and Hypothesis

1.1 Technology acceptance model

First proposed by Davis[1], the technology acceptance model (TAM) explains the factors affecting a user's decision to accept and use a new piece of technology. Since then, the TAM has been one of the most researched and cited models in the field of information systems. The TAM is builds upon the theory of reasoned action (TRA), a social psychological model explaining how people make decisions. The TRA posits that people's intentions to perform a behavior are determined not only by how they feel about the behavior but also their perception of how others feel about the behavior.

The TAM extends TRA by adding two new constructs: perceived usefulness and perceived ease of use[2]. Perceived usefulness is defined as how much a person believes that using the piece of technology will improve their performance. According to Davis[2], if people believe that a piece of technology will increase their productivity or performance, they are likely to use it. Perceived ease of use on the other hand is defined as how much effort a person believe using a piece of technology will take. This factor is critical as even useful technology will be avoided by people if they perceive it as being too complicated or difficult to use. As shown in Fig. 1, the original TAM proposes that perceived usefulness and perceived ease of use influence "attitude toward using", which in turn affects "behavioral intention to use", and finally actual system use. In other words, the more a person believes that a technology is useful and easy to use, the more positive his attitude (ATT) towards the technology, the more likely he or she is to intend to use it, and the more likely he or she is to use it.

While TAM has been extensively studied, some criticisms

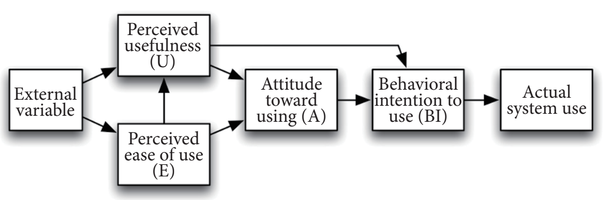

Fig. 1 Technology acceptance model.

1 School of Computer Science and Engineering, Nanyang Technological University, Singapore 639798, Singapore
2 Joint NTU-WeBank Research Centre on Fintech, Singapore 637335, Singapore
Address correspondence to Toh Hsiang Benny Tan, bennytanth@ntu.edu.sg

remain. One criticism is that the TAM is relatively simplistic and does not take into account all of the factors that can influence technology acceptance[3]. Another common criticism questions its predictive validity, with some studies finding that TAM does not accurately predict technology acceptance in all contexts[4]. Despite these limitations, TAM remains one of the most widely used models in the area of technology acceptance and use research. The model, being simple and easy to understand, has been used as a base or extended upon to study the acceptance of a wide variety of healthcare technologies including but not limited to telemedicine[5,6], mobile health systems[7,8], and mobile health applications[9,10].

1.2 Task-technology fit

Task-technology fit (TTF) is a theory that originated in the field of information systems and proposes that the likelihood of an individual performing well using a technology, depends on the degree to which the technology fits the task that it is intended to support. The theory was first proposed by Goodhue and Thompson[11] based on the technology-to-performance chain shown in Fig. 2. In their paper, Goodhue and Thompson[11] proposed that TTF can be conceptualized as a two-dimensional construct, with the first dimension representing the task requirements and the second dimension representing the technology characteristics. The task requirements dimension of TTF refers to the cognitive, behavioral, and social demands of a task. These demands can vary depending on the type of task, how complex the task is, and the environment surrounding the task. For example, taskings requiring a high level of cognitive processing would have different task requirements compared to tasks requiring a high level of social interaction.

The technology characteristics dimension of TTF refers to the capabilities of a technology to support the task requirements. These capabilities can include the functionality of the technology, the ease of use of the technology, and the compatibility of the technology with the user's skills and knowledge. For example, a technology that is highly functional and easy to use would have different technological characteristics than a technology that is less functional and more difficult to use.

Goodhue and Thompson[11] proposed that TTF can be measured as the degree of overlap between the task requirements and the technology characteristics, and when task, technology, and individual characteristics are aligned, a high level of task-technology fit is achieved. When this is achieved, the technology can effectively support the task requirements based on user characteristics, leading to improved user performance.

TTF has been applied to numerous different contexts, including e-commerce[12], healthcare[13], and education[14], and has been successfully used to explain people's decision to make use of different types of technologies, such as social media[15], mobile applications[16], and smart devices[17]. Overall, TTF is a well-established theory that has been supported by empirical research.

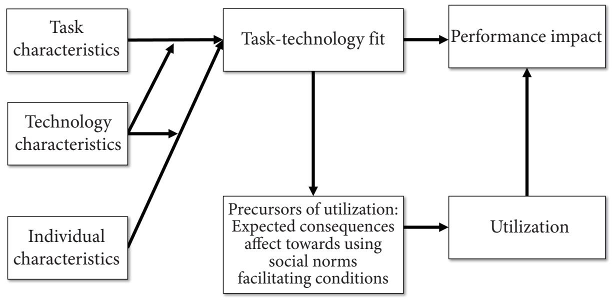

Fig. 2 Technology-to-performance chain.

The theory provides a useful framework for understanding how the fit between tasks and technologies can influence user performance.

1.3 Technology self-efficacy

Technology self-efficacy (TSE) is a key concept in the field of information systems and psychology, which draws its theoretical foundation from Bandura's[18] theory of self-efficacy. Self-efficacy, in general, refers to the extent to which a person believes that they are capable of performing a task or achieving a goal. It plays an important role in determining the individual's behavior, thoughts, and motivation. When applied to technology, self-efficacy becomes "technology self-efficacy". It refers to a person's belief in their capability to achieve a goal or perform a task involving the use of technology such as a piece of software, device, or mobile application.

The concept of technology self-efficacy was developed and applied to the field of information systems by Compeau and Higgins[19]. They defined technology self-efficacy as "the belief in one's capabilities to use a piece of technology to achieve a specific task or goal" and found that technology self-efficacy influenced individual's computer use both directly and indirectly through its effects on outcome expectations. This definition of technology self-efficacy is state oriented, meaning that the perception is formed based on his or her judgment immediately before the task performance[20].

This concept has been used to understand and predict technology acceptance and usage, as it influences a user's behavior toward technology. It has been used to understand various phenomena in the technology domain and has been found to be an important factor determining a user's intention to accept and use online health information systems[21], mobile health applications[22], as well as mobile self-assessment technology[23].

1.4 Digital alliance

Therapeutic alliance is a concept in psychotherapy that refers to the collaborative relationship between therapist and client[24], and is considered to be one of the key factors affecting the success of therapeutic intervention. Based on the concept of therapeutic alliance, digital alliance (DA) refers to the collaborative relationship between a user and a digital health intervention or tool[25]. It is thought to be important for the success of digital health interventions, just as therapeutic alliance is important for the success of psychotherapy. As in therapeutic alliance, a good digital alliance requires that the technology and user share a common goal, agree on that the tasks assigned are relevant in helping achieve these goals, and establish a positive relationship of mutual trust, acceptance, and confidence.

Early research in this area focused on digital technologies facilitating the provision of mental health services by professionals such as communication technologies like e-mail, chat, and telemedicine. These research found that the therapeutic alliance in e-therapy was comparable to in-person therapy, with the quality of the alliance affecting the therapy outcome[26]. More recent research in this area has focused on applying the concept of digital alliance to unguided digital applications for mental healthcare. Based on this scenario, one of the key differences between a piece of technology and a therapist is the ability to proactively foster a sense of empathy and bond between the technology and the user. With advances in technology, the application of human computer interaction theories such as persuasive design and computer science techniques such as affective computing, digital technologies have begun to take on more human like characteristics, helping to address this limitation[27]. Existing studies support the importance of digital alliance in encouraging user adherence and engagement, and suggest that digital alliance is an important factor to be considered when designing and implementing digital health interventions[28].

2 Hypotheses Development

The primary research question that this study aims to answer is how task-technology fit influences a student's decision to make use of mental health technologies, and considers the roles of the technology acceptance model, technology self-efficacy, and digital alliance in this process. Figure 3 illustrates our proposed model. The relationships described within the model were hypothesized in order to answer our research question and are consistent with existing research.

Task-technology fit and technology self-efficacy are two different but interrelated constructs within the field of technology acceptance and use. While task-technology fit is a concept that refers to the degree to which a particular technology can support a user in performing a specific task, technology self-efficacy refers to an individual's belief in their ability to use a specific technology. There is a significant relationship between TTF and technology self-efficacy. For example, perceived task-technology fit can enhance a user's belief in their ability to use that technology (technology self-efficacy). This is because when a technology is perceived as being capable of supporting a task effectively, users may feel more confident in their ability to use it[11]. Existing studies support this, showing that TTF and TSE are correlated, that they tended to go together, and that TTF significantly impacts TSE even after controlling for other factors such as computer anxiety and prior experience with computers[29]. We thus propose the following hypothesis:

H1: Task-technology fit positively relates to technology self-efficacy.

Perceived usefulness (PU) is a fundamental construct in TAM and can be defined as how much a person believes that their performance can be improved via the use of a piece of technology. When a technology fits the tasks at hand well, it is perceived as more useful because it can support the tasks more effectively, thus enhancing the user's performance[11]. This alignment between the technology's capabilities and the user's tasks can lead to higher productivity, making the technology more valuable to the user. Consequently, the user perceives the technology as being more useful[30]. In Ref. [31], Dishaw and Strong[31] studied a model integrating TTF with TAM and found that task-technology fit directly impacts perceived usefulness. Their findings suggest that a better fit between tasks and technology capabilities increases users'

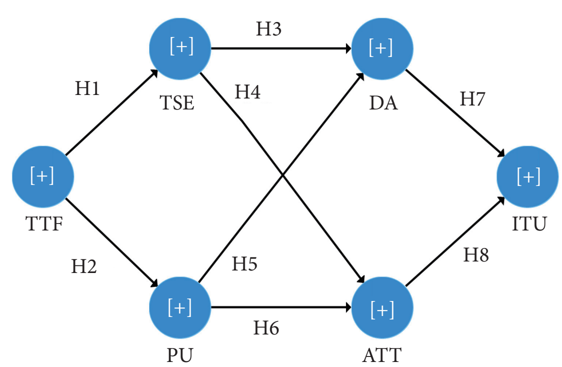

Fig. 3 Proposed research model.

perception of the technology's usefulness, which in turn influences their intention to use (ITU) the technology. We thus propose the following hypothesis:

H2: Task-technology fit positively relates to perceived usefulness.

The core requirements for a successful digital alliance are a shared goal, relevant tasks, and a positive bond. As people with high technology self-efficacy are more likely to use technology to support them in completing various tasks, they are able to perceive how technology and its use is relevant to their goals. In addition to being able to relate more positively with technology[32], such people are also more likely to be open to new technologies and to adopt them quickly[33]. On the other hand, people with low technology self-efficacy may be reluctant to use technology, or they may use it ineffectively. This can hinder digital alliances, as these individuals may not be able to see the value in technology with relation to their task and may also be more negative about its use. One particular study also showed that users with a higher technological self-efficacy, were less likely to be put off by technical challenges, and even when faced with such challenges, were able to troubleshoot and resolve technical issues, thus maintaining the continuity of the therapeutic alliance[34]. We thus propose the following hypothesis:

H3: Technology self-efficacy positively relates to digital alliance.

In the original TAM, attitude was defined as a person's feelings towards performing technology related behaviors and can be thought of as a person's overall evaluation of technology, including but not limited to their beliefs about the usefulness, enjoyment, and ease of use of technology. For example, having higher levels of technology self-efficacy can help reduce technology-related anxiety, thereby fostering more positive attitudes toward technology use. People who are confident in their ability to use technology may experience less anxiety or fear about using it[35]. Another way in which technology self-efficacy has been shown to affect attitude is by enhancing performance expectancy. Individuals who believe that they can use technology effectively perceive less risk associated with its use[36], are more likely to believe it can help improve their performance and see it as beneficial[37]. We thus propose the following hypothesis:

H4: Technology self-efficacy positively relates to attitude.

In the context of digital alliance, perceived usefulness can be seen as the degree to which people believe that using digital technologies will help them to achieve their goals. If a user perceives the technology as useful, they are not only more likely to perceive benefits from using the technology[38], they are also more likely to be satisfied with the digital interactions and maintain the continuity of the alliance[39]. When studying personal health informatics, perceived usefulness of the technology was found to directly affect the user's engagement and satisfaction, both of which are necessary for effective digital alliances in health-related contexts[40]. In such situations when the technology is seen as reliable and beneficial, it can foster trust which is crucial for the success of digital alliances[41]. We thus propose the following hypothesis:

H5: Perceived usefulness positively relates to digital alliance.

When individuals perceive a piece of technology as useful, they are more likely to form a positive attitude towards it. The more they believe that the technology can improve their performance or productivity, the more favorable their attitude towards using it[1]. This can have a significant impact on a user's decision to adopt and use technology[42]. In addition, after the adoption of a technology, studies have shown that as long as the technology continues be perceived as useful by demonstrating utility and enhancing task performance, the user's attitude will remain positive, encouraging its continued use[39]. Numerous studies support the influence of perceived usefulness on attitude in the digital healthcare domain. For example, studies have shown that patients who perceived an electronic health record (EHR) patient portal as useful for managing their healthcare information were more likely to have a positive attitude towards using it[43], while home care patients who perceived a web-based technology for self-management as useful for managing their health likewise demonstrated a more positive attitude towards its use[44]. We thus propose the following hypothesis:

H6: Perceived usefulness positively relates to attitude.

Digital alliance can positively impact intention to use in several ways. First, digital alliance can help to create a shared understanding of the benefits of using technology. Users who are aware of the potential benefits of using technology are more likely use make use of it to achieve their goals[38]. A strong digital alliance can also enhance satisfaction and positive user experiences[45], which can subsequently enhance the intention to use a technology. If users are satisfied and have positive experiences with the alliance, their likelihood of intending to continue using the technology increases[46]. These relationships have been shown to be applicable to the healthcare domain. For example, patients who perceive a strong therapeutic alliance, also perceive digital health interventions as more effective or efficient, increasing their intention to use digital health technologies[26]. A strong alliance also translates to increase patient engagement and experience, which in turn leads to an increased intention to use digital health technologies[47]. We thus propose the following hypothesis:

H7: Digital alliance positively relates to intention to use.

The impact of attitude on intention to use in TAM is based on the theories put forth by the theory of planned behavior (TPB), one of the core theories upon which TAM is based. In TPB, the formation of attitude is based on two components, the belief that an action will result in an outcome, and how desirable the expected outcome is. One example of this is the relationship between a positive attitude towards technology and enjoyment. A person with a positive attitude towards a technology is likely to enjoy using technological tools[48]. This enjoyment can impact the person's intention to use, making them more likely to want to use the technology and can also make them more likely to persist with the technology even if they encounter challenges. This impact of attitude on intention to use has been demonstrated in numerous technological domains such as e-banking[49], e-learning[50], and mobile health applications[51]. In all instances, it was shown that a positive attitude towards the technology significantly predicted the intention to use it. We thus propose the following hypothesis:

H8: Attitude positively relates to intention to use.

Based on the direct effect and the indirect effect of all of the variable constructs discussed above, this study suggests that task-technology fit might have an indirect effect on intention to use via technology self-efficacy, digital alliance, and perceived usefulness and attitude. We thus propose the following additional hypotheses:

H9: Technology self-efficacy and digital alliance jointly mediate the relationship between task-technology fit and intention to use.

H10: Technology self-efficacy and attitude jointly mediate the relationship between task-technology fit and intention to use.

H11: Perceived usefulness and digital alliance jointly mediate the relationship between task-technology fit and intention to use.

H12: Perceived usefulness and attitude jointly mediate the relationship between task-technology fit and intention to use.

3 Methodology

3.1 Sample

As partial least squares structural equation modelling (PLS-SEM) would be used in our analysis, to calculate the required sample size, the inverse square root method of sample size calculation[52] was applied. Based on this method, adopting a significance level of 5% and a minimum path coefficient of 0.2 as established by Ref. [53], the minimum sample size required this study would be 155. This number also agrees with previous research indicating that samples sizes between 100 and 200 are considered adequate when conducting path modelling[54]. Participants in this study consisted of students from a Singapore university. In total 241 responses were received, of which 178 were valid and used for analysis. No demographic differences were noted between participants which were deemed ineligible and participants that were included for analysis.

3.2 Survey questionnaire

In this study, measurement items were adapted from previously validated constructs as recommended by Ref. [55]. In total, the instrument used in this study consisted of 22 items and employed a 7-point Likert scale ranging from 1—strongly disagree to 7—strongly agree. Of the 22 items, nine technology acceptance model items were adapted from Klopping and McKinney[56], Yu and Yu[57], and Ahadzadeh et al.[58], six therapeutic alliance items were adapted from Goldberg et al.[59], and both the four technological self-efficacy items and three task-technology fit items were adapted from Becker[60]. All items were slightly modified to fit the context of digital mental health technologies.

3.3 Data analysis

Structural equation modelling (SEM) refers to a set of statistical techniques used to measure and analyze the relationship between one or more independent latent variables and one or more dependent latent variables[61]. Two main approaches to SEM are covariance-based SEM (CB-SEM) and PLS-SEM. When considering which approach to use, it is important to take into account numerous factors such as the research objective, nature of the constructs, model complexity, and data characteristics[62]. Given PLS-SEM's robustness when used in conjunction with potentially non-normally distributed data and smaller sample sizes, PLS-SEM was selected as the preferred data analysis approach. In this study, PLS-SEM was carried out using the SmartPLS 3 software. Assessment of the model made use of the recommended two-step process[63]. First, the measurement or outer model was assessed, followed by the structural or inner model.

4 Result

4.1 Measurement model

For the measurement model's internal consistency to be considered reliable, the composite reliability of all constructs within the model needs to have a composite reliability (CR) score between 0.6 and 0.95. As seen in Table 1, the CR for constructs within this study ranged from 0.842 to 0.927. These results show that for this study, the indicators used to represent the proposed constructs have good internal consistency reliability.

For indicators to be considered reliable, they had to present an indicator loading score over 0.5. As seen in Table 1, the indicator

Table 1 Indicator loadings, cronbach's alpha (CA), composite reliability (CR), and average variance extracted (AVE).

Layer	Indicator	Loading	CA	CR	AVE
Attitude	ATT_1	0.870	0.791	0.878	0.706
	ATT_2	0.837			
	ATT_3	0.813			
Intention to use	ITU_1	0.884	0.882	0.927	0.809
	ITU_2	0.932			
	ITU_3	0.882			
Perceived usefulness	PU_1	0.835	0.718	0.842	0.640
	PU_2	0.766			
	PU_3	0.797			
Digital alliance	DTA_1	0.857	0.889	0.916	0.649
	DTA_2	0.855			
	DTA_3	0.847			
	DTA_4	0.818			
	DTA_5	0.626*			
	DTA_6	0.805			
Technology self-efficacy	TSE_1	0.833	0.771	0.854	0.598
	TSE_2	0.553*			
	TSE_3	0.823			
	TSE_4	0.842			
Task-technology fit	TTF_1	0.839	0.738	0.852	0.657
	TTF_2	0.815			
	TTF_3	0.777			

Note: * indicates "considered for removal".

loading scores ranged from 0.553 to 0.932 and so all indicators were shown to be reliable. Depending on the current composite reliability score and AVE score, indicators with loadings below 0.7 should be considered for elimination if doing so would significantly improve the composite reliability and AVE. In our measurement model, two indicators fell into this category (marked with *). However, as the composite reliability and AVE of the impacted constructs were already above the required levels of 0.7 and 0.5, respectively, and the elimination of the indicators did not significantly impact composite reliability and AVE, all indicators were kept as recommended[64]. For convergent validity to be established, the constructs AVE value needs to exceed 0.7. As shown in Table 1, the AVE score for constructs within the model ranged from 0.596 to 0.809. As these values were all above 0.5, the convergent validity of the constructs was confirmed.

In this study, we made use of three methods, the Fornell-Larker's criterion, cross loadings, and heterotrait-monotrait ratio (HTMT) to evaluate the discriminant validity of constructs in our model. To establish discriminant validity via the Fornell-Larker criterion, the square root of each constructs AVE should be higher than its correlation with other latent constructs, indicating the ability to better explain the variance of its own indicators then the variance of other latent constructs. To establish discriminant validity via cross loadings, the loadings of each indicator on each construct must be analyzed. For discriminant validity to be confirmed, each indicator should load most highly on the construct that they have been assigned rather than other constructs within the model. Lastly, to establish discriminant validity via the heterotrait-monotrait ratio of correlations, the average correlation of indicators across constructs should be below 0.90. All three assessment methods successfully confirmed the discriminant validity of our model.

4.2 Structural model

To determine if the proposed hypotheses are valid, the path coefficients between latent variables need to be assessed. Table 2 shows the path coefficients (B), t-statistics, and significance level for all hypothesized direct relationships in the proposed model. By making use of the results of the path analysis, we can determine if each of the proposed hypothesis is valid or invalid.

In our analysis, we observed that task-technology fit exerted a notable positive influence on both technology self-efficacy (B = 0.551, t = 10.609, and p < 0.001) and perceived usefulness (B = 0.596, t = 11.223, and p < 0.001), thereby validating hypotheses H1 and H2, respectively. Delving into the impact of technology self-

Table 2 Path coefficients, t-statistics, and significance level for all hypothesized direct relationships in the proposed model.

Path	Path coefficient	t-value	p-value
TTF→TSE	0.551	10.609	0.000
TTF→PU	0.596	11.223	0.000
TSE→DA	0.659	11.713	0.000
TSE→ATT	0.307	4.892	0.000
PU→DA	0.188	2.986	0.003
PU→ATT	0.460	6.318	0.000
DA→ITU	0.363	6.004	0.000
ATT→ITU	0.447	6.384	0.000

efficacy, we found it to have a significant positive effect on both digital alliance (B = 0.659, t = 11.713, and p < 0.000) and attitude (B = 0.307, t = 4.892, and p < 0.001), supporting H3 and H4. The relationship between perceived usefulness and digital alliance required a deeper look; while the statistical significance was evident (B = 0.188, t = 2.986, and p = 0.003), the path coefficient was marginally below 0.2. However, the effect size F2 was 0.064, indicating a significant yet small effect, confirming the validity of hypothesis H5. perceived usefulness also exhibited a pronounced positive impact on attitude (B = 0.460, t = 6.318, and p < 0.001), confirming H6. Lastly, both digital alliance (B = 0.363, t = 6.004, and p < 0.001) and attitude (B = 0.447, t = 6.384, and p < 0.001) demonstrated significant positive relationships with intention to use, confirming hypotheses H7 and H8, respectively.

To evaluate hypotheses H9 to H12, we analyze the specific indirect effects found in the model, as shown in Table 3. H9 proposed that both technology self-efficacy and digital alliance act as mediators in the relationship between TTF and ITU. This hypothesis was validated with our findings showing a substantial positive impact of TTF on ITU via these mediators (B = 0.132, t = 5.534, and p < 0.001). Similarly, for H10, the combined mediation of technology self-efficacy and attitude was observed to exert a significant influence on the TTF-ITU relationship (B = 0.075, t = 3.414, and p = 0.001). H11, which posited a joint mediation effect of perceived usefulness and digital alliance, was also validated, albeit with a slightly lower impact (B = 0.041, t = 2.158, and p = 0.031). Finally, H12 demonstrated the powerful mediating effects of perceived usefulness and attitude, showing a consequential impact on the connection between TTF and ITU (B = 0.123, t = 3.593, and p < 0.001). In addition, analysis of the direct effect of TTF on ITU found it to be insignificant (B = 0.098, t = 1.266, and p < 0.101), indicating that the effects of TTF on ITU can be said to be fully mediated by the paths proposed in H9–H12.

4.3 Comparing alternative model

In order to compare our model with the technology acceptance model, structural equation modelling was also applied to two commonly used variants of the technology acceptance model shown in Fig. 4, one with the attitude construct, and one without. As can be seen from the path analysis in both alternate models 1 and 2, the perceived ease of use (PEOU) construct did not have a significantly effect on either the attitude or the intention to use constructs, supporting earlier criticisms of the technology acceptance model question the validity of the perceived ease of use construct in different settings and contexts.

Table 3 Specific indirect effects.

Path	Path coefficient	t-value	p-value
TTF→TSE→DA→ITU	0.551	10.609	0.000
TTF→TSE→ATT→ITU	0.596	11.223	0.000
TTF→PU→DA→ITU	0.659	11.713	0.000
TTF→PU→ATT→ITU	0.307	4.892	0.000

The results of analysis of all three models can be seen in Table 4. As can be seen from Table 4, when comparing our proposed model to the two alternate TAM-based models, our proposed model demonstrated higher variance explained (R^2 = 0.505) and higher predictive power (Q^2 = 0.400). In evaluating the fit of our proposed model against alternate specifications, we employed the Akaike information criterion (AIC), Bayesian information criterion (BIC), and Hannan–Quinn criterion (HQ). Lower values in these metrics indicate a more favorable trade-off between model fit and complexity[65].

Based on these, our proposed model also demonstrated better model selection criteria scores (AIC = −120.012, BIC = −110.467, and HQ = −116.141) compared to alternate model 1 (AIC = −91.631, BIC = −85.268, and HQ = −89.051) and alternate model 2 (AIC = −58.370, BIC = −48.825, and HQ = −54.499). This indicates that our model demonstrates a superior balance of fit and parsimony, is more likely to be the best model for a given dataset and is more likely to be the "true" model. This supports the utility of our model in explaining a user's intention to make use of mental health tools and suggests that it may offer more accurate out-of-sample predictions.

5 Discussion

Our study set out to understand how technology self-efficacy and digital alliance may help explain and predict the impact design in the form of TTF that can have on the intention to use digital mental health technologies among university students. The findings shed light on the interplay of TTF, technology self-efficacy, perceived usefulness, digital alliance, and attitude, and how these factors influence the acceptance and usage of such technologies among university students. The importance of technology self-efficacy, as indicated by our results, aligns with the evolving perspective on technology acceptance models. The traditional TAM, developed in the early 1980s for workplace settings, emphasized ease of use as a significant factor. However, the technology landscape has significantly changed since then. Today's "digital natives", like our study participants, are accustomed to a world surrounded by technology and are proficient in its use. As such, the importance of ease of use diminishes and the role of technology self-efficacy has been brought forth. Our findings corroborate this shift with technology self-efficacy significantly affecting digital alliance and attitude, underlining the importance of individuals' confidence in their

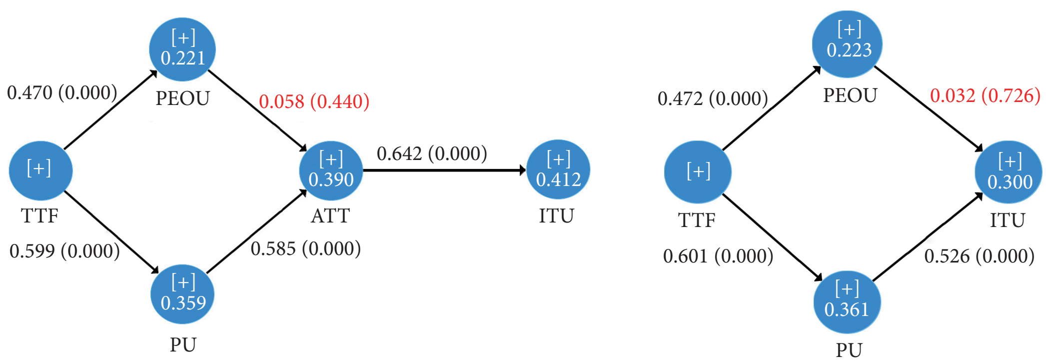

Fig. 4 Alternate model 1 (TAM with ATT) and alternate model 2 (TAM without ATT).

Table 4 Model comparison.

Model	R^2	Q^2	AIC	AICu	AICc	BIC	HQ	HQc
Proposed model	0.505	0.400	−120.012	−116.987	60.219	−110.467	−116.141	−115.856
TAM	0.412	0.328	−91.631	−89.620	88.507	−85.268	−89.051	−88.899
TAM (without ATT)	0.300	0.238	−58.370	−55.344	121.861	−48.825	−54.499	−54.214

Note: AICu: unbiased Akaike information criterion. AICc: corrected Akaike information criterion. HQc: corrected Hannan–Quinn information criterion.

ability to use the technology. This new perspective implies that technology acceptance extends beyond the mere usability of a system, to the user's personal capabilities and their relationship with the technology—a relationship we encapsulate in the term "digital alliance".

Digital alliance, based upon the concept of therapeutic alliance, was introduced as a novel variable in this study, and was found to significantly affect the intention to use, indicating that a positive, cooperative relationship between the user and the technology can foster acceptance and usage. This finding is particularly pertinent for the adoption of digital mental health technologies among university students. Students may need to feel aligned with the technology that they are using for their mental health, trusting that the technology can effectively aid their therapeutic journey. The strong influence of technology self-efficacy on digital alliance and attitude is particularly noteworthy. As mental health is an inherently personal matter, students' confidence in their ability to use digital mental health technologies effectively will likely play a substantial role in determining whether they form a positive relationship with these technologies (digital alliance) and develop favorable attitudes towards their use. Our research model demonstrates that both attitude and digital alliance significantly influence the intention to use digital mental health technologies, with these two factors together accounting for a substantial 50.4% of the explained variance in technology use intentions.

A more detailed examination of the total effect of each variable on intention to use uncovers some intriguing insights. Despite its recognized importance in technology acceptance models, perceived usefulness exhibited the lowest total effect (path correlation of 0.274) on intention to use, compared to task-technology fit, technology self-efficacy, digital alliance, and attitude. The study's indirect effect analysis revealed a crucial mediation role of technology self-efficacy, perceived usefulness, digital alliance, and attitude in the relationship between TTF and intention to use, while analysis of the impact of task-technology fit reveals a moderate correlation to working alliance, attitude and intention to use, and a high correlation to technology self-efficacy and perceived usefulness, further highlighting its importance.

6 Limitation

The participants in this study were drawn exclusively from university students, a group generally characterized by a higher education level and greater technological proficiency. While this allowed for an in-depth exploration of this specific demographic, it may limit the applicability of the findings to broader populations. The insights gained may not accurately reflect the perspectives, experiences, or behaviors of individuals with different educational backgrounds or technological competencies. Future research might consider including more diverse educational and technological strata to widen the scope and relevance of the findings.

In this current study, while the sample size meets the requirement for PLS-SEM, it should be noted that a larger sample size would offer additional statistical power and robustness, allowing for a more confident interpretation of the results. Moreover, increasing the sample size would permit the application of other modelling methods such as CB-SEM, which necessitates a larger sample. Future studies should consider employing a more extensive sample to enhance the methodological diversity and analytical robustness, further enriching the understanding of the research question.

7 Conclusion

Our investigation into the impact of perceived task-technology fit, technology self-efficacy, and digital alliance on the intention to use digital mental health technologies among university students has led to several pivotal discoveries. Firstly, while TTF does not directly correlate with usage intentions, its influence is made evident through the mediation of technology self-efficacy and perceived usefulness. These findings spotlight the profound shift from the early technology acceptance models, emphasizing that in today's digital age, it is not just about a technology's ease of use but about the user's confidence and relationship with the technology—a bond we term "digital alliance".

The introduction of the concept of digital alliance, grounded in therapeutic alliance, emerged as a crucial factor in determining usage intentions. It underscores the necessity for users, especially university students, to perceive and trust technology as a reliable partner in their therapeutic journey. The substantial impact of technology self-efficacy on forming this positive digital alliance reiterates the personal nature of mental health and the need for confidence in utilizing digital tools effectively. Notably, while perceived usefulness is a cornerstone in traditional technology acceptance models, its effect was found to be relatively muted in our study, with other factors like TTF, digital alliance, and attitude having more pronounced influences on intention to use.

From a research standpoint, our incorporation of digital alliance into technology acceptance models signifies an essential step in understanding our ever-evolving relationship with digital tools. Practically speaking, software designers must prioritize achieving an optimal task-technology fit. It is clear that the value of a digital tool does not solely rest on its inherent features but also on how closely it aligns with the user's tasks and goals.

In closing, to foster widespread acceptance and use of digital mental health technologies among university students, there is a pressing need to embrace a holistic perspective—one that encompasses task-technology fit, user self-efficacy, perceived utility, digital alliance, and overall user attitudes. The integration of these elements in the design and deployment phases will undoubtedly pave the way for more effective and widely adopted digital mental health solutions in university settings.

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