UTAUT Model for Digital Mental Health Interventions: Factors Influencing User Adoption

Mohammed Alojail
Management Information System Department, College of Business Administration, King Saud University, Riyadh, Saudi Arabia

***Abstract*—The impact of digital revolution on mental health therapies is examined in this research. As explained in the paper, the delivery of mental healthcare is being revolutionized by digital transformation, which is providing creative answers to the problems associated with mental health illnesses. But knowing and managing user approval is crucial to the effective integration of digital transformation approaches into mental health therapies. To investigate user's acceptance regarding digital transformation in Mental Health therapies, this study outlines a modeling-based method based on a well-established Unified Theory of acceptability and Use of Technology theory, abbreviated as UTAUT. This study delves into the base constructs of Expected Performance, Expected Effort, Social Influence, Conditions facilitating the use of proposed solution, Hedonic Motivation, and Value for Money, utilizing the UTAUT model as a framework. By employing Structural Equation Modelling (SEM) in a thorough study, the goal of this research is to identify statistical correlations that impact user acceptance dynamics. To offer context-specific insights, this article also delves into digital mental health solutions, including teletherapy platforms, mood monitoring smartphone applications, and virtual reality-based exposure therapy. This study enhances accessibility, engagement, and results for people seeking mental health care by providing a deeper knowledge of user acceptability, which aids in the creation and roll-out of digital mental health solutions.**

Keywords*—*Digital transformation; mental health interventions; UTAUT model; TAM; SmartPLS; user acceptance; hypothesis testing

I. Introduction

The integration of digital technologies in healthcare represents a transformative shift, offering profound opportunities for enhanced patient care, improved clinical outcomes, and optimized healthcare delivery processes [1][2]. Within this realm of transformation, mental health interventions are at the forefront, leveraging various digital solutions to address the multifaceted challenges associated with mental health disorders [4]. Digital transformation in mental healthcare includes innovations such as teletherapy platforms, mobile applications for mood monitoring, virtual reality-based exposure therapy, and online support communities. These advancements hold significant promise in extending the accessibility of mental health services, reducing associated stigma, and empowering individuals to actively manage their mental health [4]. A central component of the success of digital mental health interventions is user acceptance, which reflects the degree to which individuals perceive a technology as useful, user-friendly, and worth adopting [3]. Navigating user acceptance dynamics is crucial for the effective implementation and uptake of these interventions across diverse user populations. Unified Theory of Acceptance and Use of Technology (UTAUT) model offers a robust framework for testing factors which effect user acceptance within the context of digital transformation. The UTAUT model, proposed by Venkatesh et al. [6], integrates key constructs from various other new technology acceptance theories, like Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), and Innovation Diffusion Theory (IDT) [3]. According to this model, user acceptance is influenced by core constructs such as Performance expectation, Expected Effort, Influence of Social Life, Conditions facilitating the use of proposed solution, Hedonic Motivation, and Value for Money. These constructs encompass the usefulness through perception, ease of use, social norms, organizational support, and cost-effectiveness linked to adopting a technology.

While the UTAUT model has seen widespread application in various contexts, its utility within the domain of digital mental health interventions remains underexplored. This paper is written with an objective to bridge this gap by employing a UTAUT modeling-based approach to investigate user acceptance dynamics specific to digital transformation in mental healthcare. Utilizing Structural Equation Modeling (SEM), this study examines the connection between UTAUT constructs and user acceptance. The insights derived aim to inform the design, implementation, and evaluation of effective digital mental health strategies, ultimately advancing the delivery of evidence-based care to those in need.

A. Motivations and Contributions

Since mental health is a major subject of the current world. It is also seen that the world is moving towards the involvement of more digital transformation driven interventions in various facets of life. Therefore, it was felt prudent that, while the paper is developed diligently towards the development of the solutions – how well these solutions will be accepted by the user group. It was done, because ultimately, it is the users who decide the success or failure of the specific solution. This paper makes an endeavour to analyze the responses from a varied set of people to understand the following parameters:

1) How eager are people to employ a digital transformation driven mental health care intervention in their lives?

2) Is cost a driving factor in this?

3) Will people use the functionality under the peer pressure of friends, family or society?

4) How significant is the user friendliness of the solution to drive its usage?

The paper is divided into the following sections. Section I Lists the Introduction and Section II presents the Literature review followed by Proposed Research Model in Section III.

Section IV describes the Model Validation and Section V Presents the Results and last Section Concludes.

II. Literature Review

At the very onset of this paper, the paper reviews the previous works done on the premise of digital transformation implementation, then it delves into digital transformation acceptance and then into implementation of digital transformation methodologies in mental health scenario.

Digital transformation refers to the amalgamation of digital technologies, strategies, and capabilities into various aspects of an organization or industry in order to fundamentally alter its operations and value delivery to stakeholders [5]. It is not merely a matter of adopting new technologies, but rather a holistic reimagining and restructuring of an organization's culture, processes, and customer experiences to align with the evolving demands of the digital age. This phenomenon of digital transformation is not confined to any specific sector or industry. It has had a widespread impact, transforming diverse fields such as finance, healthcare, retail, and manufacturing [6]. While the potential benefits of digital transformation can be substantial, including enhanced competitiveness, customer satisfaction, and long-term sustainability, it also presents significant challenges. These challenges include the need for substantial investment, overcoming resistance to change, and addressing ethical and regulatory issues related to data use.

Conceptualizing Digital Transformation in Organizations the concept of digital transformation transcends the mere adoption of new technologies, encompassing a more holistic and strategic approach to fundamentally reshape how organizations operate and deliver value to their stakeholders [5]. This transformative process involves the integration of digital technologies, capabilities, and innovative strategies across various aspects of the business, from culture and processes to customer experiences [6]. By embracing digital transformation, organizations can reinvent themselves to better align with the evolving demands of the digital age.

While digital transformation has impacted a wide range of industries, from finance and healthcare to retail and manufacturing, the extent of its adoption and the challenges faced can vary significantly across sectors [6]. Organizations that navigate this transformation successfully can reap substantial benefits, including enhanced competitiveness, improved customer satisfaction, and long-term sustainability. However, the path to digital transformation is not without its obstacles, requiring substantial investment, overcoming resistance to change, and addressing complex ethical and regulatory issues related to data utilization [7].

One significant implementation case study of Digital Transformation is the Real Estate Sector.

Realizing the Full Potential of Digital Transformation in Real Estate The real estate sector has historically been slower to embrace the digital revolution compared to other industries, but there is growing recognition of the immense potential for growth and innovation through digital transformation [8]. This discrepancy can be attributed to the deeply entrenched processes and systems that have long defined the upstream and downstream segments of the real estate industry, as well as the disruptive impact of digital technologies on conventional business practices.

Despite this initial hesitation, the real estate sector has witnessed a surge in the adoption of cutting-edge technologies, becoming a topic of increasing interest in relevant research studies [5]. Over the past decade, the pace and scope of innovation have accelerated, driven by a wave of technological advancements, such as cloud and mobile computing, as well as the rising prominence of platform-based business models that have attracted substantial venture capital investment [9].

The mental healthcare sector is undergoing a significant transformation driven by the integration of digital technologies. Digital transformation in this context refers to the adoption and implementation of innovative digital solutions to address the complex challenges associated with mental health disorders [10]. These digital interventions have the potential to revolutionize mental healthcare delivery, enhancing accessibility, engagement, and treatment outcomes for individuals seeking support.

However, the successful integration of digital technologies into mental health interventions is contingent upon understanding and navigating user acceptance. UTAUT model has emerged as a valuable framework for exploring the issues that influence user behaviour towards new technologies [11]. The UTAUT model identifies core constructs, such as Expected Performance, Expected Effort, Social Influence and Conditions facilitating the use of proposed solution, as key determinants of user acceptance and usage behavior.

Recent studies have further expanded the UTAUT model to include additional factors relevant to the context of digital mental health interventions. For instance, Hedonic Motivation, which refers to the intrinsic enjoyment and pleasure derived from using a technology, and Price Value, which considers the perceived cost-benefit ratio, have been incorporated to develop an understanding towards user acceptance dynamics [12].

Structural Equation Modeling (SEM) has emerged as a powerful analytical technique to explain the complex relationships between these UTAUT determinants and user acceptance. By employing SEM, researchers can uncover the intricate interplay between factors such as Expected Performance, Expected Effort, Social Influence and Conditions facilitating the use of proposed solution, and their collective impact on user acceptance and usage behavior.

The existing literature has highlighted the importance of context-specific insights when studying user acceptance of digital mental health interventions. Researchers have delved into the adoption and usage patterns of various digital mental health solutions, including teletherapy platforms, mobile applications for mood monitoring, and virtual reality-based exposure therapy [13]. These context-specific investigations provide valuable insights into the unique challenges and opportunities associated with the integration of digital technologies in mental healthcare.

By offering a nuanced understanding of user acceptance, this line of research contributes to the design, development and roll-out of effective digital mental health related strategies. Leveraging the insights gained from UTAUT-based studies can help mental healthcare providers and digital health innovators to

design and deploy digital interventions that are more aligned with user needs and preferences, ultimately enhancing accessibility, engagement, and treatment outcomes for individuals seeking mental health support.

Ensuring User Adoption is Key to Successful Digital Transformation. The success of digital transformation initiatives is fundamentally contingent upon user adoption and acceptance of the implemented technological solutions [12]. Recognizing the central role of end-users, organizations must prioritize understanding the factors that drive technology acceptance in order to effectively promote and sustain the usage of their digital innovations. To this end, researchers have developed several conceptual models that provide valuable frameworks for exploring the nuances of user acceptance behavior. These include the extended expectation-confirmation model (EECM), UTAUT and TAM [14]. The EECM is specifically insightful in relation of post-adoption technology usage. This model extends the TAM by integrating expectation-confirmation theory, suggesting that users' ongoing satisfaction and continued usage of a technology are influenced not only by their initial expectations, but also by the degree to which those expectations are confirmed through actual system usage.

Complementing the EECM, the UTAUT model provides a comprehensive perspective on the key indicators of acceptance of technology, including expected performance, expected effort, influence of social life, and conditions that facilitate the situation [6]. Similarly, the TAM focuses on the role of perceived usefulness and perceived ease of use in shaping user attitudes and behavioural intentions towards technology [17]. These frameworks can help organizations develop a more holistic realization of the multifaceted behaviour that influence user acceptance and adoption of mental health related digital innovations.

By leveraging these well-established theoretical models, organizations can design and deploy their digital transformation strategies in a manner that is more closely aligned with user needs, preferences, and ongoing experiences. This user-centric approach is crucial for fostering sustained engagement, driving long-term adoption, and ultimately, realizing the full potential of digital transformation initiatives. While the EECM, UTAUT, and TAM have similarities in studying user acceptance of technology, they also have distinct differences. After reviewing the literature on user acceptance of the system, it became evident that the TAM, UTAUT, and EECM are all relevant frameworks for understanding user acceptance of technology.

Building upon the well-established theory of reasoned action, TAM has emerged as a seminal framework for understanding and predicting user adoption of new technologies is demonstrated [15]. At the core of this model are two key constructs that shape an individual's attitudes, intentions, and ultimately, their usage behavior. The first construct, perceived ease of use (PEOU), reflects the degree to which a user expects the target system to be free of effort and user-friendly [17]. This factor speaks to the intrinsic motivations of the user, as individuals are more likely to embrace technologies that they perceive as intuitive and effortless to navigate. The second construct, perceived usefulness (PU), captures the user's subjective assessment of the likelihood that using a particular system will enhance their performance or productivity within a given context [16]. This extrinsic motivation is a critical determinant of user acceptance, as individuals are more inclined to adopt technologies that they believe will tangibly improve their outcomes or experiences.

By integrating these two core determinants - PEOU and PU - the TAM provides a robust theoretical foundation for analyzing the complex interplay of cognitive, attitudinal, and behavioral factors that shape an individual's technology adoption decisions [15]. This model, grounded in the broader theory of reasoned action, acknowledges that user behavior is not solely driven by personal beliefs and attitudes, but is also influenced by subjective norms and social influences.

The versatility and predictive power of the TAM have made it a widely adopted framework for exploring user acceptance across a diverse range of technological innovations, from enterprise software and mobile applications to e-commerce platforms and smart home devices [6]. By leveraging the TAM, researchers and practitioners can gain valuable insights into the nuanced factors that drive technology adoption, enabling the design and deployment of more user-centric digital solutions.

It has been observes that the previous works done encircling the key words have done only a partial level of analysis, where either TAM, PU or any one acceptance factor is analyzed solely without any cohesion amongst other factors, this has deeply restricted the performance of the solutions in models shown in available literature review.

III. Proposed Research Model

In this paper, examination of the total acceptance model along with some modifications to handle mental health intervention specific tests in the system. In the extant scenario through the proposed models, it has been proposes to contribute a holistic approach towards UTAUT where various critical factors are analyzed in conjunction with other critical factors of the model, such as Societal Conditions, Attitude Towards Use etc. to come to a more effective conclusion at the end of the study.

In the instant case, the following is considered:

Behavioral Intention is taken as the base measure of TAM, which is a concept derived from base UTAUT architecture [6], System Quality (SQ) plays zero role in this solution, as the proposed research paper plays no role in this.

Therefore, a system is designed where the following are considered:

H1: Perceived Usefulness (PU)

H2: Perceived Ease of Use (PEOU)

H3: Social Influence/ Social Impact (SI)

H4: Facilitating Conditions (FC)

H5: Attitude Towards Use (ATT)

TAM is centered around two main constructs that shape an individual's acceptance and usage of technology, which are Perceived Usefulness (PU) which refers to "the degree to which a person believes that using a particular system would enhance

their job performance" and Perceived Ease of Use (PEOU) which is defined as "the degree to which a person believes that using a particular system would be free of effort" [17]. These two main units, PU and PEOU, are influenced by external variables and in turn affect the user's "attitude toward using (ATT)" and "behavioral intention to use (BI)". The model presumes that the perceived ease of use and usefulness mediate the relationship between these independent variables and the actual system usage behavior. The validity of the TAM model has been extensively demonstrated across a wide range of fields and disciplines, including healthcare, technology related to assistive care, social networking, e-shopping, internet, computer, online public services, and entertainment [17].

Notably, the TAM has been widely applied in the context of technology acceptance and adoption among the population. Researchers have explored the use of TAM in various technological contexts relevant to the youth, such as social network related works & digital well-being related interventions and more [18].

The versatility and predictive power of the TAM have made it a leading framework for understanding the factors that drive technology acceptance, enabling researchers and practitioners to design and deploy more user-centric digital solutions.

Fig. 1 shows a graphical representation of the proposed hypothesis.

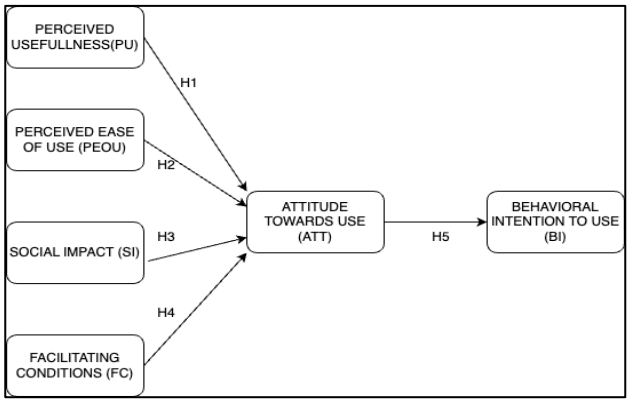

Fig. 1. Research model.

Most crucial parameter for our proposed research model is Attitude to Use (ATT) and its subsequent factorem Behavioral Intention to Use (BI). These factors help in influencing user experience with information technology, encompassing aspects like ease of use, accessibility, and reliability [19]. This study integrates BI as an independent variable within the TAM framework to explore its influence on perceived ease of use (PEOU) and perceived usefulness (PU) of the use case (U) of "Using Digital Transformation based interventions in Mental Health". Understanding this relationship is vital for assessing the impact of ATT and BI on both PEOU and PU, ultimately influencing user behavioral intentions towards user acceptance.

A. Hypothesis Development

The hypothesis formulated for this subject research model are as follows:

1) H1. Perceived usefulness of the use case "Using Digital Transformation based interventions in Mental Health" has a positive effect on the ATT & BI.

2) H2. Perceived Ease of Use of the use case "Using Digital Transformation based interventions in Mental Health" has a positive effect on the ATT & BI.

The degree to which an individual feels that utilizing a certain technology will enhance their quality of life is known as Perceived Usefulness (PU). Perceived Ease of Use (PEOU) is the degree to which a person believes that using a technology involves no effort.

Most studies employing the Technology Adoption Model (TAM) approach make the assumption that there is a relationship between a product's adoption and usage patterns and consumers' evaluations of its utility. This suggests that people are more likely to adopt new technology when they believe it to be beneficial or has clear advantages.

The Technology Acceptance Model (TAM) states that an individual's opinion of a technology's usefulness influences their assessment of its value. A thorough evaluation of the variables impacting healthcare professionals' adoption of information and communication technology (ICT) revealed that the PEOU and PU of the system were the two most crucial components. These two components made up the majority of the original TAM [20].

H3. Social Influence/Social Impact of the use case "Using Digital Transformation based interventions in Mental Health" has a positive effect on the ATT & BI.

The degree to which friends, family, peers, and carers feel something will affect someone's decision to use new healthcare technology, either favourably or unfavourably, is known as social influence [6].

Previous studies ([21] & [22]) have shown how important social impact is when deciding whether or not to utilise technology for ageing in place. Peers, relatives, kids, and professional caretakers for the elderly are all potential sources of social influence.

H4. Facilitating Conditions of the use case "Using Digital Transformation based interventions in Mental Health" has a positive effect on the ATT and BI.

The "facilitating conditions" are the extent to which people believe that an organisational and technological infrastructure is in place to support the information system and motivate users to use it. Previous studies have shown that encouraging surroundings, such as training programmes, technical support, and financial aid, have a beneficial influence on people's intents to use smart wearables and assist them in overcoming their reservations about utilising cutting-edge technology.

Using the effort expectation construct in the same model, researchers discovered that while facilitating conditions by themselves—that is, in the absence of any moderator—do not significantly predict intention to use the system, they do so with a strong effect on older workers with more experience when they are moderated by age and experience. Enabling aspects that are considered important for young people include accessibility, price, and the availability of technical assistance.

H5. Attitude towards use of the use case “Using Digital Transformation based interventions in Mental Health” has a positive effect on the BI.

"An individual's positive or negative feelings or appraisal about using a technology" is the definition of attitude factors (ATT) [6]. Prior research indicated that older adults with more favorable attitudes towards technology are more likely to utilize it. Though they may have a good attitude towards the relevant technology, older people may not want to utilize healthcare technology, according to a study, where the attitude towards technology utilization was not statistically significant.

Behavioural intention (BI) is a key component of technology acceptance models (TAM). It refers to the choice to adopt or utilise a technology based on one's attitude towards using it. Research indicates that a person's behavioural desire to utilise technology positively effects how they actually use it. The first TAM referred to BI as "the degree to which an individual has formulated conscious plans to perform or not perform some specified behaviour in future". Therefore, behavioural intention to use technology has been the focus of various research studies in attempt to predict actual technology usage and adoption.

B. Research Methodology

In the healthcare sector, TAM is the most often used and well-liked model [23], and certain correlations found in TAM have consistently been shown to be significant.

TABLE I. MEASUREMENT ITEMS

Construct	Item	Measurements	Reference
	PU1	Medical Care Managing my health will be easier for me if I use a smart wearable.	
Perceived Usefulness	PU2	I believe that using an innovative wearable to track my mental wellbeing willmake my daily life safer.	[6] & [17]
	PU3	By using a mental health tracker, I will live a better life.	
	PEOU1	I think using a smart mental health monitor will be easy to use.	
Perceived Ease of Use	PEOU2	Learning involved to use this app/technology will be easy.	[6] & [17]
	PEOU3	This app/technology will be convenient to use.	
	SI1	Family will approve of my use of a smart mental health monitor.	
Social impact/influence	SI2	My friends will recommend that I use a mental health monitor.	[6] & [17]
	SI3	My friends will approve that I use a mental health monitor.	
	FC1	I will know how to use the app/technology.	
Facilitating Conditions	FC2	Someone will always be there for help, if I encounter any problem during using the app/technology.	[6] & [17]
	FC3	I have sufficient financial means to use this app/technology.	
	ATT1	Using this will have a positive impact on my lifestyle	
Attitude towards use	ATT2	This app/technology will benefit my family life.	[6] & [17]
	ATT3	I feel positive about this app/technology	
	BI1	I would be happy to use a digital health monitor, if I get the opportunity	
Behavioural Intention to Use	BI2	I will use this app/technology for the betterment of my mental health	[6] & [17]
	BI3	I will use this app/technology to increase my quality of life	

Several research changed and added variables to improve the model's predicting ability in light of the pertinent circumstances for optimal results.

The TAM has a weakness in that it disregards social influence and subjective standards because it was designed based on individual ideas. As a result, the original Technology Acceptance Model (TAM), which included just the two predictive variables PU and PEOU, would not be sufficient to explain why older people embrace technology in a hospital setting.

Based on the suggested model, a structured survey was created to collect information from users who have been exposed to Digital medical/consultation for their medical needs on the variables impacting platform adoption. In order to evaluate important dimensions including perceived utility, perceived ease of use, social impact and facilitating conditions, the survey made use of well-established metrics from earlier research (see Table I).

The concept measurement section uses a 5-point Likert scale, with 1 representing strongly disagree and 5 representing strongly agree. Demographic questions regarding age, gender, qualification, nationality, and user type are also included. Nineteen questions comprise the measure of independent and dependent variables, each specifically designed for the use case scenario.

In this section, all of the questions pertaining to the six variables that make up our suggested model were also accessible. Three measures each, derived from measuring items published ([6] and [17]), were used to test variables including perceived utility, perceived ease of use, and intention to utilise digital health wearables. Three questions each from the Venkatesh et al. measuring items were used to measure social influence and facilitating circumstances. To measure each

component of the research model, a five-point Likert scale ranging from strongly disagree to strongly agree was utilized.

Data was gathered using an online survey tool. The poll was sent to 500 people at random in Saudi Arabia, and 239 of them answered. Participation was completely optional. Three days later, a follow-up email reminder was issued in an attempt to increase participation. 56 valid replies—or a 23.3% response rate—were obtained after the data was cleaned to remove incomplete or incorrect responses as well as to detect and exclude biased respondents. Therefore, then total sample size is 295.

Male and female participants in the research sample showed comparable levels of involvement, according to Table II's findings. The age distribution of the participants was found to be variable, with 42.37% of the individuals lying between the 30- to 39-year-old age ranges. Moreover, 15.25% of the population was under 30, 10.17% was over 50, and 21.2% of the population was between the ages of 40 and 49.

TABLE II. DEMOGRAPHIC DATA

		N=295	%
Gender	Male	166	56.27%
	Female	129	43.73%
Age	Younger than 30	95	32.20%
	30 – 39	125	42.37%
	40 – 49	45	15.25%
	Above 50	30	10.17%
Occupation	Teaching	95	32.20%
	Engineering	121	41.02%
	Medical	52	17.63%
	Govt.	25	8.47%
	Others	2	0.68%
Education	Below High School	2	3.20%
	High School	16	10.30%
	Diploma	85	7.10%
	Bachelor’s	121	63.50%
	Postgraduate	71	16.00%
Income	> 1000$ & < 5000 $	101	34.24%
	> 5000$ & < 10000$	129	43.73%
	> 10000$	65	22.03%
Expense	> 1000$ & < 5000 $	48	16.27%
	> 5000$ & < 10000$	212	71.86%
	> 10000$	35	11.86%
Existing ailment	Yes	114	38.64%
	No	145	49.15%
	Cannot disclose	36	12.20%

The study model was validated using the partial least squares (PLS) method, which is based on structural equation modelling. First, the paper uses measurement analysis, which comprised factor loading, the average variance extracted (AVE), Cronbach alpha, and path coefficient, to assess the internal consistency and validity of our study model.

This paper also confirmed the association between various variables. This paper uses SmartPLS 3 in our investigation to examine the information gathered.

The validity of the convergence and accuracy of the measurement model were evaluated. Internal reliability is verified using Cronbach's alpha test, and consistency of internal validity indication of >0.7 is deemed suitable. A summary of the loadings, SMC, composition reliability, AVE, and Cronbach's alpha can be seen in Table III.

IV. MODEL VALIDATION

The converging validity hypothesis was supported by the composite reliability coefficients (CR) and average variance extracted (AVE) values, both of which were more than 0.65. The loading, variance inflation factors (VIF) and AVE values of our variables meet the criteria for convergent validity, and Cronbach’s alpha (CA) values show that they are internally consistent. A resampling technique called cross-validation is used to get almost unbiased estimates of model performance without compromising sample quantity.

The model validation findings at each of the measurement locations are shown in Tables III-V.

TABLE III. FACTOR LOADING AND RELIABILITY TEST

Construct	Item	Loading	VIF	SMC	CR	AVE	CA
Perceived Usefulness	PU1	0.871	2.37	0.8			
	PU2	0.912	2.62	0.82	0.93	0.81	0.88
	PU3	0.821	2.4	0.8			
Perceived Ease of Use	PEOU1	0.921	3.33	0.87	0.94	0.84	0.9
	PEOU2	0.932	3.76	0.89			
	PEOU3	0.881	2.35	0.79			
Social impact/influence	SI1	0.882	2.38	5.37	0.92	0.8	0.87
	SI2	0.873	2.17	4.79			
	SI3	0.917	2.76	8			
Facilitating Conditions	FC1	0.891	2.14	0.79	0.92	0.79	0.87
	FC2	0.899	2.47	0.89			
	FC3	0.873	2.19	0.91			
Attitude towards use	ATT1	0.894	2.29	0.79			
	ATT2	0.893	2.38	0.79	0.92	0.79	0.87
	ATT3	0.893	2.36	0.75			
Behavioral Intention to Use	BI1	0.899	2.43	0.89			
	BI2	0.922	3.01	0.81	0.93	0.82	0.89
	BI3	0.891	2.79	0.79			

TABLE IV. DISCRIMINANT VALIDITY (FORNELL-LARCKER)

Item	PU	PEOU	SI	FC	ATT	BI
PU	**0.869**					
PEOU	0.614	**0.925**				
SI	0.768	0.593	**0.883**			
FC	0.673	0.794	0.627	**0.898**		
ATT	0.798	0.731	0.654	0.714	**0.883**	
BI	0.662	0.612	0.624	0.649	0.718	**0.926**

TABLE V. DISCRIMINANT VALIDITY (CROSS LOADINGS)

Item	**PU**	**PEOU**	**SI**	**FC**	**ATT**	**BI**
PU1	**0.896**	0.574	0.711	0.61	0.705	0.647
PU2	**0.904**	0.629	0.675	0.606	0.67	0.618
PU3	**0.896**	0.588	0.657	0.572	0.693	0.601
PEOU1	0.641	**0.924**	0.572	0.757	0.666	0.638
PEOU2	0.592	**0.934**	0.519	0.713	0.629	0.65
PEOU3	0.588	**0.887**	0.508	0.681	0.629	0.562
SI1	0.689	0.518	**0.892**	0.562	0.608	0.543
SI2	0.647	0.489	**0.872**	0.52	0.555	0.619
SI3	0.695	0.554	**0.916**	0.571	0.609	0.576
FC1	0.621	0.724	0.533	**0.89**	0.667	0.629
FC2	0.561	0.656	0.537	**0.899**	0.618	0.528
FC3	0.582	0.706	0.576	**0.874**	0.586	0.562
ATT1	0.717	0.628	0.621	0.62	**0.894**	0.666
ATT2	0.654	0.604	0.585	0.65	**0.893**	0.624
ATT3	0.684	0.646	0.566	0.617	**0.891**	0.627
BI1	0.644	0.659	0.627	0.621	0.655	**0.899**
BI2	0.642	0.612	0.588	0.586	0.657	**0.922**
BI3	0.589	0.577	0.529	0.547	0.629	**0.89**

One of the most often used methods for examining the discriminant validity of measurement models is the Fronell-Larcker criteria. This criteria states that a construct's square root of the average variance it extracts must be larger than the correlation it has with any other construct. Discriminant validity is proven once this requirement is met.

The evaluation of a scale's validity involves determining whether or not it captures the idea of what it is meant to capture. Convergent and discriminant validity are established in order to evaluate construct validity. Convergent and discriminant validity are proven in constructs that are reflectively assessed.

When items in a given measure converge to represent the underlying construct, this is known as convergent validity. The mean of the squared loadings of each indicator connected to a construct is how the AVE is computed. In terms of statistics, convergent validity is proven when the Average Variance Extracted (AVE) value is greater than 0.50.

Discriminant Validity: The purpose of discriminant validity is to determine how unique the study's constructs are. It demonstrates that each research construct has a distinct identity and is not too connected with other study constructs. Three methods are used to establish discriminant validity in SMART-PLS.

Fornell and Larcker Criterion: When discriminant validity is proved, it means that the Sq. When it comes to a certain construct, the root of AVE is larger than its association with every other construct.

Cross Loadings: When compared to other research constructs, an item should have larger loadings on its own parent construct, according to cross loadings.

There are problems with discriminant validity when an item loads more favourably onto a different construct than it does onto its own parent construct. The item may be endangering discriminant validity if the difference in loading smaller than.10 also suggests that it is cross-loading onto the other construct.

The correlations between the constructs are shown by numbers outside of the diagonal, while values in bold indicate the square root of the variance extracted (AVE). PEOU: perceived usability; PU stands for perceived utility, SI for social impact, and FC for facilitating condition. ATT: Usage-related attitude; BI: Intention to utilize behavior.

"Discriminant validity is shown when each measurement item correlates weakly with another construct, except for the ones to which it is theoretically associated,". When analyzing cross-loadings, the researcher looks at each item to determine which ones load heavily on numerous constructions and which ones have high loadings on the same construct [24]. Consequently, to demonstrate discriminant validity at the item level, there must be a significant correlation between items that belong to the same concept and a relatively weak correlation between items that belong to different constructs. Despite its simplicity, this technique lacks empirical evidence and theoretical support [25].

A factor's square root of average variance for each latent variable needs to be greater than the other correlation coefficient in order for it to be deemed significant in terms of discriminant validity. Table V displays the detailed cross-loading data. In Table V, the construct that received the highest weight relative to all other constructs is denoted by bolded numerals.

The results of the investigation show that the conditions for discriminant validity are satisfied. The validity and reliability outcomes of our model are displayed in Tables III–V.

A. Hypothesis Testing and Evaluation

This paper used the Smart PLS 3's bootstrapping module (5000 epochs) to get the path coefficients and t values in order to evaluate our hypothesis. Using the bootstrap technique, subsamples from the observed data were selected at random to verify the data's stability. Perceived usefulness, perceived ease of use, social influence, and enabling condition are the four factors that predict 51.3% of the behaviour intention (R2 = 0.513) and 67.6% of the attitude (R2 = 0.676). The route co-efficient (β) and t statistics were used to examine the association between the variables. Table VI displays the PLS findings for the hypotheses.

TABLE VI. HYPOTHESIS TEST

H	Route	β	t-Value	Comments
Hl	PU to ATT	0.425	4.296**	Supported
H2	PEOU to ATT	0.204	2.136 *	Supported
H3	SI to ATT	0.095	1.285	Not supported
H4	FC to ATT	0.204	2.276*	Supported
HS	ATT to BI	0.716	18.047**	Supported

* $p < 0.05$
** $p < 0.001$

From the above, it is observed that the impact of Social Impact/Influence on the Attitude to Use of Digital Transformation driven interventions in mental health treatment is not supported, therefore, doesn't play any role.

V. RESULTS

This study's primary objective was to look at the elements that affect people' behavioural intention and acceptance of digital transformation-driven mental health therapies, such as wearables or mobile apps.

The two fundamental TAM components of perceived utility and perceived ease of use were supplemented by two additional dimensions in our study: social influence and enabling situation. In this study, which included a rather flexible targeting method for population selection, it is discovered that attitudes towards utilising digital mental health monitors are favourably impacted by perceived usefulness, ease of use, and enabling conditions.

It was demonstrated that attitudes regarding the adoption of digital mental health monitoring were positively impacted by the core TAM qualities of perceived usefulness and perceived ease of use.

In this study, the sample population's attitude towards digital mental health monitoring was strongly impacted by perceived usefulness ($\beta = 0.425$). Similarly, the sample set members' attitude towards utilising digital mental health monitors was positively impacted by their perception of the devices' ease of use ($\beta = 0.200$).

According to the findings, people's attitudes about using digital mental health monitors were favourably correlated with enabling conditions ($\beta = 0.200$), but social influence ($\beta = 0.090$) did not appear to play a significant role in fostering the population's favourable attitudes about using them.

In summary, the research outlines the role that perceived usefulness, perceived ease of use, and facilitating conditions have in supporting attitudes toward mental health support online. While social influence is less prominent, the success of digital transformation of mental health rests on how well these platforms demonstrate alignment with the end-user needs, as well as the ease of access and perceived ease of use associated with these digital technologies. This knowledge can effectively inform the future design and implementation of digital mental health interventions, by focusing on user-centered design, and provide the requisite supporting technical factors to allow for sustained use.

VI. CONCLUSION

Digital mental health monitors must live up to public expectations for usability and practicality in daily life in order to foster good attitudes toward these technologies and promote their usage, taking into account the first two results on perceived utility and perceived ease of use. Moreover, the third result suggests that the population's positive sentiments towards the use of digital wearables may not be significantly influenced by social influence. Friends, relatives, and acquaintances won't have a significant impact on the population's desire to utilise these digital mental health monitors unless they are willing to use the technology themselves.

The public is likely to utilise digital mental health monitors if they obtain technical support and recommendations whenever they require assistance utilising the application or technology, according to the fourth result about enabling conditions.

Finally, it is discovered that the sample population's behavioural intention to utilise digital mental health monitoring was significantly influenced by their opinions. These demonstrated that the population's behavioural intention to utilise digital mental health monitoring is higher among those with a more positive attitude towards using these devices.

Like any other research work, this study is also not free from flaws and is not without restrictions.

The data were gathered from Saudi Arabia, therefore the implementation of this study will require the survey to be done on a global scale. In addition, the sample size was modest given the size of the response received from our survey.

In the future, gathering data is advised should involve a bigger sample size. Furthermore, the term "mental health" is used significantly in the paper and in the survey conducted, therefore it may have acted as a deterrent while filling information as the same may have been a taboo subject. In addition to this, it is also necessary to bind the available principles of UTAUT with modern methodologies that revolve around AI based Surveying and Machin learning processes.

Future researchers are urged to consider other factors in order to present a more thorough and definitive view on the behavioural intention of Saudi Arabian youth to use digital mental healthcare wearables, including age-related characteristics, physical changes, digital literacy, technically savvy—experience with technology—and adoption. This will contribute to a more thorough comprehension of this research. In addition to the above, it is to be noted that, like any other research work, this study also has its own limitations, one major limitation is the usage of relatively old methodology for implementation of UTAUT and other is the geo-specific dataset used for the study which limits the overall effectiveness of the study.

VII. REFERENCES

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