BEHAVIORAL INTENTION AND ADOPTION OF AR/VR TECHNOLOGIES: INSIGHTS FROM MEDICAL STUDENTS IN TÜRKİYE USING UTAUT

Kazım Dağ
Ministry of Education, Gaziantep, Türkiye

Sinan Çavuşoğlu*
Bingöl University, Bingöl, Türkiye

Ferhat Aslan
Gaziantep Islamic Science and Technology University, Gaziantep, Türkiye

ABSTRACT

This study examines the extent to which augmented reality (AR) and virtual reality (VR) technologies are adopted, using the Unified Theory of Acceptance and Use of Technology (UTAUT) as a framework and focusing on behavioral intention. This research aims to evaluate medical students' perceptions of AR and VR technologies in light of the effects of the COVID-19. The study population consisted of students enrolled in medical faculties in Türkiye, and convenience sampling was used for sample selection. Data were collected using both online and offline tools, and Smart PLS 4 (Partial Least Squares) statistical software was used for the analyses. The analysis results revealed that performance expectations, effort expectations, facilitating conditions, hedonic motivation, and price value had positive effects on individuals' attitudes. By contrast, social influence and habit had no statistically significant impact on attitudes. It was determined that individuals' attitudes positively impact behavioral intention. These findings underscore the significance of emphasizing user-friendly and motivating elements to encourage the adoption of AR and VR technologies among students studying in the field of health.

Keywords: Augmented Reality, Virtual Reality, Behavioral Intention, Unified Theory of Acceptance and Use of Technology.

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* Corresponding author: Bingöl University, Bingöl, Turkey, sinankys42@gmail.com

1. INTRODUCTION

The COVID-19 has posed significant global challenges across economic, social, and medical domains. VR and AR technologies are seen as effective tools to support COVID-19 response and prevention (Saleem et al., 2023). The rise of big data, social media, and mobile technologies has accelerated the development of VR/AR applications (Patel et al., 2024). Technological advances have enabled timely information exchange and allowed healthcare systems to adopt virtual methods for patient care during COVID-19 (Jacobs, 2010; Webster, 2020). These tools have also enhanced students' practical skills and academic performance by offering engaging, flexible, and accessible learning environments (Tsou et al., 2006).

According to data from the World Health Organization (WHO), as of March 2020, over 90% of medical education institutions worldwide had either completely suspended face-to-face instruction or transitioned to remote learning. In Türkiye, clinical rotations in medical faculties were suspended for an average of 4-6 months, resulting in a 60-75% reduction in bedside practice hours for medical students (Rose, 2020). This interruption, particularly the loss of access to anatomy laboratories during the preclinical phase and the limitation of simulation opportunities in clinical skills labs, led to a reported 15-20 point decrease in learning outcomes (Özdemir et al., 2022). Moreover, infrastructure-related challenges and lack of interaction during the adaptation to remote learning platforms led approximately 40% of students to report a loss of motivation, while 35-40% indicated experiencing learning difficulties (Telli & Altun, 2020; Bozkurt, 2020). This situation has highlighted the urgent need to develop AR/VR-based hybrid models to ensure the sustainability of the practically oriented components of medical education, which hold critical social and public significance, and to maintain student performance.

VR has been used to simulate infection transmission and human behavior to enhance skill development and safety. It has also supported telehealth during the pandemic. AR, widely applied in healthcare, marketing, and education, enables high-resolution communication, remote collaboration, and visualization of abstract concepts. However, VR has been more prominent than AR in emergency responses to infectious diseases, mainly for education and training (Asadzadeh et al., 2021). During COVID-19 lockdowns, AR effectively supported visualization, explanation, and narration (Papagiannis, 2020).

The UTAUT model provides a comprehensive theoretical framework to explain the cognitive and social factors influencing individuals' adoption of new technologies (Venkatesh et al., 2003). It has been widely applied across diverse domains, such as education, healthcare, and organizational settings, to investigate technology acceptance. Recent studies also demonstrate that UTAUT offers strong explanatory power in the context of augmented and virtual reality adoption. For instance, Chen et al. (2025) found that UTAUT variables effectively predicted medical students' acceptance of VR-based simulations. Similarly, Huang et al. (2016) reported that performance expectancy and hedonic motivation significantly influenced users' attitudes toward AR in educational environments. In addition, Sagnier et al. (2020) emphasized the role of social influence and facilitating conditions in predicting VR adoption. Thus, the UTAUT framework is particularly well-suited for analyzing the adoption of AR/VR technologies in medical education, especially in the context of shifting instructional modalities during the COVID-19 pandemic.

Although there are conceptual and review studies in the literature on the potential of AR and VR technologies in education (Yuksekdag, 2021; Küçük et al., 2015; Asadzadeh et al., 2021), empirical studies that specifically examine the negative impacts of the COVID-19 on medical education and investigate the capacity of these technologies to mitigate such effects remain extremely limited. However, COVID-19 has caused significant disruptions in both theoretical and practical components of medical education, weakening learning outcomes and creating critical gaps in training healthcare professionals. In this context, exploring how AR/VR technologies can be utilized to partially compensate for the loss of clinical practice is of strategic importance—from the standpoint of technological advancement and for ensuring the quality and continuity of healthcare services. Therefore, this study aims to address the empirical gap in the literature and contribute to the development of digital transformation policies in post-COVID-19 medical education. It seeks to generate timely and applicable findings relevant to educational sciences and the healthcare domain. In this study, based on the Unified Theory of Acceptance and Use of Technology (UTAUT), the factors influencing the adoption of augmented reality (AR) and virtual reality (VR) technologies are examined specifically in the context of medical students. In particular, the focus is placed on students' attitudes toward these technologies and the impact of these attitudes on their behavioral intentions. Within the framework of the model, variables, such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, and price value, are empirically tested for their effects on attitude. This study sets out a comprehensive analysis of the psychological and environmental factors shaping the adoption process of AR/VR technologies in relation to the shifting educational dynamics brought about by COVID-19.

2. LITERATURE REVIEW

2.1. Augmented Reality and Virtual Reality

Virtual reality (VR) creates a fully digital environment isolated from the real world, allowing users to interact with 3D spaces via devices like headsets and sensors (Wibawanto et al., 2016). Augmented reality (AR) overlays virtual objects in the real world, blending physical and digital environments for interactive experiences (Azuma, 1997).

Augmented reality (AR) has a strong potential to enhance meaningful learning and knowledge transfer, particularly in basic medical sciences and surgical training (Yuksekdag, 2021). It supports the acquisition of both explicit and implicit knowledge (Pernas et al., 2010). As information technologies become more prevalent in education, they facilitate access to learning materials and supplementary resources (Li & Liu, 2023). AR is increasingly used in medical technologies, offering practical benefits, such as improved efficiency, foresight, and rapid results in professional settings (Venkatesan et al., 2021). By overlaying virtual objects in the real world, AR is gaining significance in healthcare education (Kamphuis et al., 2014). Research also shows that AR enhances learning outcomes, social skills, and overall training quality (Dalili Saleh et al., 2021).

2.2. Adoption and Use of AR and VR in Medical Education

Virtual reality (VR) and augmented reality (AR) are increasingly used in medical education as effective digital learning tools (Aslan & Erdoğan, 2017; Boulton et al., 2018). Technologies like Google Glass, which uses smart cameras to track eye movements, allow practical lessons to be recorded and viewed remotely, as adopted by Radboud University Medical Center (Kamphuis et al., 2014). Studies show that AR enhances anatomy learning more effectively than traditional methods (Silva et al., 2017; Di Serio et al., 2013). VR and AR technologies also support detailed surgical training and global health education through immersive tools like 360-degree videos (Curiscope, 2023).

AR enhances patient safety by enabling 3D visualization of objects, allowing learners to explore from multiple perspectives and learn through trial and error (Thomas et al., 2010). It is also effective in pre-hospital care and clinical decision-making training for medical students (Munzer et al., 2019). VR plays a key role in preparing healthcare professionals for crises, such as pandemics, by simulating complex medical scenarios, including infectious diseases and disasters (Ngo et al., 2016). Asadzadeh et al. (2021) categorized the use of VR/AR during COVID-19 into four areas: potential applications, clinical aspects, telecommunications, and education. VR systems were developed to support patients with various conditions (e.g., multiple sclerosis, Parkinson's, chronic pain, anxiety, stroke rehabilitation), helping to mitigate the pandemic's clinical impact.

2.3. Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT was developed by integrating multiple models such as TRA, TAM, TPB, IDT, and SCT (Williams et al., 2015). Initially proposed by Venkatesh et al. (2003), it was later extended to UTAUT 2 with seven key factors influencing intentions and behaviors: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit (Venkatesh et al., 2012; Surya et al., 2021).

According to Venkatesh et al. (2003), Performance Expectancy (PE) refers to the belief that technology improves job performance, while Effort Expectancy (EE) relates to the ease of use. Social Influence (SI) reflects the perceived pressure from important others to use technology and Facilitating Conditions (FC) indicate the belief in the availability of organizational and technical support. Hedonic Motivation (HM) is the enjoyment derived from using technology, and Price Value (PV) refers to the perceived trade-off between benefits and costs. Habit is defined as the automatic behavior developed through repeated use (Escobar-Rodríguez & Carvajal-Trujillo, 2014).

The UTAUT model has been widely applied to explain user acceptance across various technological contexts. Recent studies have demonstrated its effectiveness in understanding the adoption of innovative technologies, such as augmented reality (AR) and virtual reality (VR). For instance, Al-Emran and Granić (2021) found that performance expectancy and hedonic motivation significantly influenced users' intentions to adopt AR-based mobile learning applications in higher education. Similarly, research on VR adoption (Singh & Lee, 2009; Shen et al., 2022) has revealed that effort expectancy and facilitating conditions are critical determinants of users' attitudes and behavioral intentions. Chen et al. (2025) applied the UTAUT framework to investigate medical students' attitudes toward AR-supported anatomy learning systems in healthcare, showing that UTAUT variables significantly predicted technology acceptance. In this regard, the present study integrates the UTAUT model with AR/VR technologies and the transformed medical education environment shaped by COVID-19, thereby offering a theoretically grounded and empirically novel contribution to the literature.

2.4. Attitude

Attitude is defined as a psychological tendency that reflects an individual's favorable or unfavorable evaluation and willingness to use a specific technology (Hussein, 2017). According to Ajzen and Fishbein (1980), attitude represents an individual's general assessment of whether performing a particular behavior is good or bad. Within the UTAUT 2 framework, attitude may serve as an indirect but pivotal mediator of behavioral intention. As Kim et al. (2009) have shown, a strong attitude toward system use fully mediates the effect on behavioral intention, while a weak attitude results in partial mediation. In the context of this study, attitude is considered a central construct that influences whether medical students are likely to adopt AR/VR technologies in their learning processes. Given that AR/VR-based environments are introduced to compensate for clinical skill deficiencies during and after COVID-19, students' positive attitudes toward these technologies directly enhance their behavioral intentions to use them. Therefore, this study conceptualizes attitude as a mediating variable shaped by performance expectancy, effort expectancy, and hedonic motivation, thereby forming an indirect pathway influencing behavioral intention in AR/VR adoption.

2.5. Behavioral Intention

Behavioral intention refers to an individual's readiness to perform a specific behavior and is considered the most immediate antecedent of actual behavior when an appropriate intention measure is obtained (Ajzen & Fishbein, 1980). In the context of technology adoption, behavioral intention is widely recognized as a critical predictor of actual system use (Venkatesh et al., 2003). According to Davis et al. (1989), the successful implementation of any information system is contingent upon users' willingness to adopt and use the system. In this study, behavioral intention is operationalized as medical students' expressed willingness or plan to engage with AR/VR applications in digital learning environments.

Unlike generic technology adoption studies, this research uniquely contextualizes behavioral intention within the post-COVID-19 transformation of medical education, where access to physical clinical training remains partially restricted. Hence, students' intention to use AR/VR is not merely a theoretical construct but a reflection of their adaptive strategies in acquiring clinical competencies through immersive technologies. The measurement of behavioral intention in this study specifically captures students' likelihood of voluntarily using AR/VR tools for educational purposes, such as virtual anatomy labs or simulated patient interactions, which are increasingly positioned as vital supplements to traditional clinical exposure.

3. THEORETICAL FRAMEWORK

3.1. Unified Theory of Acceptance and Use of Technology (UTAUT) and Attitude (ATT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2012) includes dimensions, such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit, to explain individuals' behavioral intentions. It is supported by theoretical frameworks like the Theory of Reasoned Action (Ajzen & Fishbein, 1980), the Theory of Planned Behavior (Ajzen, 1990), and the belief-attitude-intention model (Madrigal, 2001). Examining medical students' perceptions of AR and VR technologies through the UTAUT model and their attitudes is a relevant and emerging research area.

Performance expectancy is defined as "the degree to which an individual believes that using the system will support gaining achievements in job performance" (Venkatesh et al., 2003: 447). VR and AR increase students' learning performance by simultaneously using all senses during comprehensive learning and simulated reality facilitated by the "learning by doing effect" (Soo et al., 2018). It is seen that the more knowledgeable a person is about a behavior, the more the person develops a positive attitude toward being careful about performing the behavior (Kim et al., 2016). Hence, awareness of AR and VR will affect attitude. UTAUT states that the effect of performance expectancy on behavioral intention is strong (Venkatesh & Zhang, 2010). Therefore, the following hypothesis was proposed:

H_1: Performance expectancy positively affects the students' attitudes to using AR/VR applications for educational purposes.

Effort expectancy is defined as the "degree of ease associated with using the system" (Venkatesh et al., 2003). Perceived usefulness, attitude and behavioral intention to use the virtual environment were significant among students (Singh & Lee, 2009). Attitudes towards system use and perceived ease of use have an effect on behavioral intention. Systems whose interfaces are simple, easy and user-friendly are perceived as systems conducive to people in their work (Kim et al., 2009). Therefore, it is expected that students' attitudes towards AR/VR applications will be positive if they have the perception that their use will help them perform better and that these applications are effortless and easy to use (Shen et al., 2022). It is assumed that students thinking they can easily use AR and VR applications will positively affect their attitude. Therefore, the following hypothesis was proposed:

H_2: Effort expectancy positively affects the students' attitudes to using AR/VR applications for educational purposes.

Social influence is "the degree to which an individual perceives the belief of important people for the individual that the individual should use the new system" (Venkatesh et al., 2003). UTAUT argues that the impact of social influence on behavioral intention is governed by gender, age, voluntariness, and experience. The effect of social influence on individual behavior occurs through three basic mechanisms: adaptation, internalization and identification (Venkatesh & Davis, 2000). Another study confirmed that social influence is important among all employees and stated that it affects attitude (Venkatesh & Zhang, 2010). In other words, depending on the social influence, the attitude affects the behavioral intention and creates the intention to recommend (Finn et al., 2009). Therefore, the following hypothesis was proposed:

H_3: Social influence positively affects the students' attitudes to using AR/VR applications for educational purposes.

Facilitating conditions are defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system" (Venkatesh et al., 2003). Facilitating conditions are often referred to as resource factors, such as time and money, and technology, related to compliance issues that affect usage (Taylor & Todd, 1995). In other words, facilitating conditions are factors in environmental factors that influence a person's perception of how easy or difficult it is to perform a task. For example, the use of technology in the context of workplace technology use is believed to include the availability of training and the provision of support. This variable was tested in a series of technology acceptance studies and found to have a significant impact on technology acceptance (Taylor & Todd, 1995). Therefore, the following hypothesis was proposed:

H_4: Facilitating conditions positively affects the students' attitudes to using AR/VR applications for educational purposes.

Hedonic motivation is defined as "entertainment or pleasure derived from using a technology" (Venkatesh et al., 2012). Hedonic motivation is related to students' perception that digital learning is beneficial since it facilitates students' activities/tasks (Shen et al., 2022) by establishing a relationship between entertainment and the efficiency and effectiveness of the digital learning experience (Barak et al., 2016). For this reason, it shows that it will benefit students to develop positive attitudes towards AR and VR applications and to use them for learning purposes by influencing the hedonic motivation attitude. Therefore, the following hypothesis was proposed:

H_5: Hedonic motivation positively affects the students' attitudes to using AR/VR applications for educational purposes.

Price value refers to the "cognitive trade-off between consumers' perceived benefits of apps and the monetary cost of using them" (Venkatesh et al., 2012). In other words, it is the cognitive comparison done by consumers between the perceived benefits of applications and the monetary cost of using them (Escobar-Rodríguez & Carvajal-Trujillo, 2014). Price value is accepted as an important indicator in predicting user behavior (Huang & Kao, 2015). Medical students will likely develop a positive attitude towards their education, as it will increase the perceived usefulness of accessing these technology applications at a reasonable price. Therefore, the following hypothesis was proposed:

H_6: Perceived price value positively affects the students' attitude to using AR/VR applications for educational purposes.

Habit is defined as "people's tendency to automatically perform certain behaviors after learning" (Venkatesh et al., 2012). AR and VR can improve habits, providing a complete experience in the learning process. It is considered that AR and VR can offer a safe environment for students to experiment (Bucea-Manea-Tonis et al., 2020), affecting their attitude. Since learning in virtual environments can be completed faster and without much difficulty, technology makes the learning process more straightforward and more comfortable (Tsou et al., 2006). Therefore, in this environment, students' habits may have an impact on their attitudes because students tend to automatically perform behaviors after learning (Escobar-Rodríguez & Carvajal-Trujillo, 2014). Therefore, the following hypothesis was proposed:

H_7: Habit positively affects the students' attitudes to using AR/VR applications for educational purposes.

3.2. Attitude and Behavioral Intention (BI)

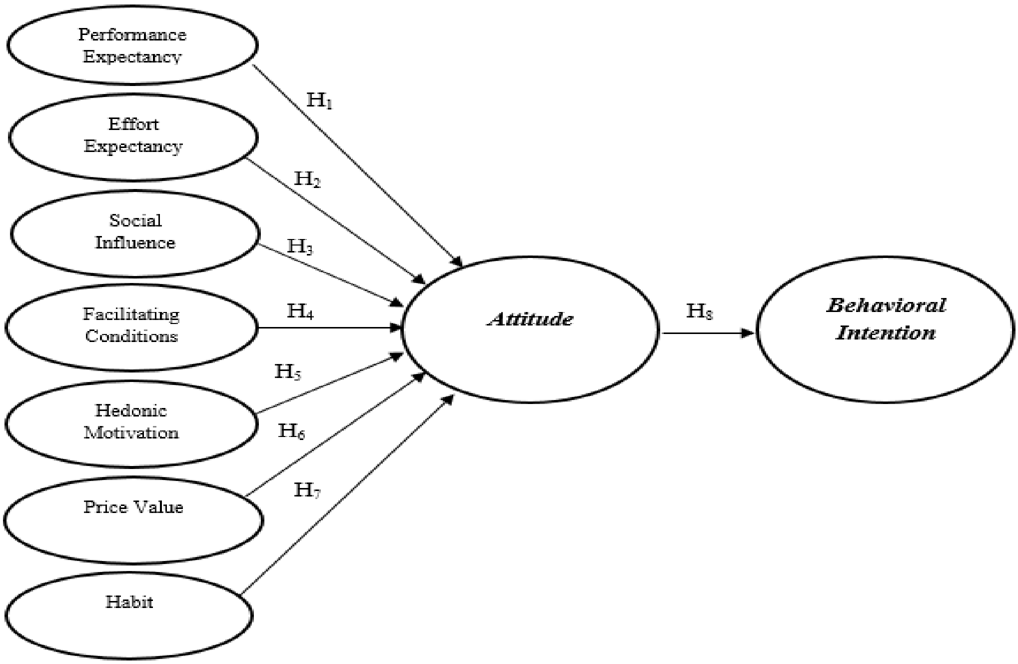
Behavioral intention is shaped by perceived usefulness and attitude toward technology use, with attitude partially mediating the effects of perceived ease of use and usefulness (Kim et al., 2009). Attitude, a key predictor of behavior (Fishbein & Ajzen, 1975; Ki & Hon, 2012), significantly influences IT usage (Yang & Yoo, 2004; Davis et al., 1989). It is also considered a strong determinant of future behavior (Lindenmann, 2002; Hussein, 2017; Ajzen, 1991). Positive attitudes enhance behavioral intention and actual use, while negative attitudes may hinder adoption (Pan, 2020; Demetriadis et al., 2003). Given its critical role, attitude is a significant factor in system use (Kim et al., 2009), and UTAUT effectively explains behavioral intention (Venkatesh & Zhang, 2010). Therefore, the following hypothesis is proposed:

H_8: Students' attitudes towards using digital learning environments positively affect their behavioral intention to use AR/VR applications for educational purposes.

4. METHODOLOGY

This study was conducted based on UTAUT to determine the effects of medical students' perceptions of AR and VR applications on behavioral intention during COVID-19. The population of this research is medical students. Figure 1 below presents the proposed research model.

Figure 1: Proposed Research Model



4.1. Population

According to data from the Council of Higher Education, in 2024, there are 122,687 students enrolled in medical faculties across Türkiye (Higher Education Information Management System, 2024). Since it was not feasible to reach the entire population, a non-probability sampling method, specifically, convenience sampling, was employed in this study. This method was chosen due to practical limitations in accessing participants through probabilistic sampling, given the intensive academic schedules and limited availability of medical students in the post-COVID-19 context. The target group of medical students was reached through both online (via Google Forms) and offline (printed questionnaires) channels, with participation based on voluntary consent. This approach allowed for the collection of valid and reliable data under constraints of time, resources, and accessibility.

Hair et al. (2019) stated that there should be at least five participants for each observed expression. Thus, a population size that meets the requirement for nine structures consisting of 32 statements was targeted. The population size of 425 people was evaluated based on the data in the questionnaire. However, due to constraints probability sampling methods were deemed impractical, such as limited time, restricted access to medical students, and the intense academic schedules in the post-COVID-19 context. A total of 10 evaluations were excluded for failing to answer multiple mandatory questions or containing inconsistent answers (e.g., contradictory answers to similar questions), and the analyses were conducted on 415 valid surveys.

4.2. Scales

To ensure the validity and reliability of the questionnaire, a pilot study was conducted with a small sample of 30 medical students before the main data collection. Based on feedback from the pilot test, minor linguistic revisions were made to clarify the meaning of some items, while the overall structure of the scale was preserved. Internal consistency (Cronbach's alpha) values were examined and within acceptable reliability thresholds across all subdimensions. The questionnaire used in the study was created after the pilot test application to explain the demographic characteristics of the participants and the statements in the research model. The variables added to the questionnaire for the research model were composed of expressions to measure performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, attitude and behavioral intention. Table 1 shows the variables and expressions related to the variables.

Table 1: Variables and Statements

Variables	Statements	Source
Performance Expectancy	I find using AR/VR useful in my daily life. Using AR/VR increases my chances of achieving the things that matter to me. Using AR/VR helps me to get things done faster. Using AR/VR increases my efficiency.	Venkatesh et al. (2003)
Effort Expectancy	It is easy for me to learn how to use AR/VR. My interaction with AR/VR is easy and understandable. I find using AR/VR easy. Mastering (competence) using AR/VR is easy for me.	Venkatesh et al. (2003)
Social Influence	People who are important to me think I should use AR/VR. People who influence my behavior think I should use AR/VR.. People whose opinions I value prefer to use AR/VR.	Venkatesh et al. (2003)
Facilitating Conditions	I have the necessary tools and resources to use AR/VR. I have the necessary knowledge to use AR/VR. AR/VR is compatible with other technologies I use. I can get help from others when I have difficulty using AR/VR.	Venkatesh et al. (2003)
Hedonic Motivation	AR/VR is fun to use. AR/VR is enjoyable to use. AR/VR is very entertaining to use.	Kim et al. (2005)
Price Value	AR/VR is reasonably priced. AR/VR has good value for money. At the current price, AR/VR provides good value.	Dodds et al. (1991)
Habit	It is a habit for me to use AR/VR. I am addicted to using AR/VR. I must use AR/VR. It is only natural for me to use AR/VR.	Limayem & Hirt (2003)
Attitude	I like the idea of using AR/VR in my studies. AR/VR applications make learning interesting. I like learning using AR/VR applications. My general opinion about AR/VR applications is positive.	Shen et al. (2022)
Behavioral Intention	I intend to use AR/VR applications for my future work. I think I will use AR/VR applications for my learning experiences. I plan to use AR/VR applications frequently.	Shen et al. (2022)

All statements used in this study were directed to the participants on a five-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (5).

5. FINDINGS

5.1. Demographic Findings

The demographic characteristics of the employees participating in this study are examined in Table 2.

Table 2: Demographics of the Participants

Participant Characteristics		N	%
Age Range	17-21	227	54,7
	22-26	161	38,8
	27-31	18	4,3
	32≤	9	2,2
Gender	Male	212	51,1
	Female	203	48,9
Grade	1st Grade	76	18,3
	2nd Grade	49	11,8
	3rd Grade	86	20,7
	4th Grade	98	23,6
	5th Grade	74	17,8
	6th Grade	32	7,7

According to the results obtained from 415 people, 54.7% of the participants (n: 227) were between the ages of 17-21. Considering the participants' gender, 51.1% were male, 48.9% were female. It was determined that 23.6% (n: 98) of the participants were in the 4th grade.

5.2. Data Analysis

In the proposed structural equation model, Smart PLS 4 (PLS-SEM) software was used to measure and estimate structural parameters (Ringle et al., 2015). SmartPLS is a software tool designed to perform structural equation modeling (SEM) using the partial least squares (PLS) approach. SEM has become one of the most widely used second-generation multivariate analysis techniques in social sciences due to its ability to test theoretically grounded linear and hierarchical causal models (Hair et al., 2013). As a prediction-oriented method, PLS emphasizes variance explanation and operates independently of parametric assumptions in estimation processes (Hair et al., 2017). Moreover, it is considered a robust analytical technique regardless of sample size, performing reliably with both small and large datasets (Hair et al., 2011; Majchrzak et al., 2005). In the measurement model, Cronbach's alpha (CA) and rho-A values are used to determine reliability, composite reliability (CR) is used to calculate internal consistency, and factor loadings and average variance extracted (AVE) values are used to determine convergent validity. Fornell-Larcker criterion and Heterotrait-Monotrait Ratio (HTMT) tests were applied to determine discriminant validity. The structural model was determined using multi-collinearity analysis and variance inflation factor (VIF) and path analyses.

5.3. Measurement Model Results

CA, rho-A, and CR values were calculated to assess reliability, as CA alone may underestimate reliability (Leguina, 2015; Garson, 2016; Mustofa et al., 2022). Values above 0.70 indicate reliability (Fornell & Larcker, 1981; Hair et al., 2019). Initially, some constructs showed very high internal consistency (>0.95), suggesting item redundancy. Items with outer loadings below 0.70 or high inter-item correlations were removed. After refinement, all constructs met reliability thresholds, confirming the model's reliability (see Table 3).

Factor loads and AVE values were calculated to calculate the convergent validity of the variables. It was determined that the factor loads of the statements (Kaiser, 1974) and the AVE values of the variables (Hair et al., 2019) were above 0.50, thus ensuring the convergent validity of the research model. The results are shown in Table 3.

Table 3: Reliability and Validity

Variable	**Statement**	**Factor Loads**	**CA**	**rho_A**	**CR**	**AVE**
Performance Expectancy			0.93	0.94	0.95	0.84
	Performance 1	0.945				
	Performance 2	0.924				
	Performance 3	0.863				
	Performance 4	0.945				
Effort Expectancy			0.91	0.92	0.94	0.86
	Effort 2	0.952				
	Effort 3	0.917				
	Effort 4	0.914				
Social Influence			0.90	0.91	0.95	0.91
	Social 1	0.959				
	Social 3	0.952				
Facilitating Conditions			0.92	0.92	0.95	0.86
	Facilitating 2	0.953				
	Facilitating 3	0.922				
	Facilitating 4	0.914				
Hedonic Motivation			0.89	0.89	0.95	0.90
	Hedonic 1	0.953				
	Hedonic 3	0.954				
Price Value			0.91	0.91	0.95	0.92
	Price 1	0.959				
	Price 3	0.961				
Habit			0.93	0.93	0.95	0.83
	Habit 1	0.931				
	Habit 2	0.935				
	Habit 3	0.885				

	Habit 4	0.896				
Attitude			0.93	0.93	0.95	0.88
	Attitude 1	0.941				
	Attitude 3	0.937				
	Attitude 4	0.943				
Behavioral Intention			0.91	0.91	0.94	0.85
	Intention 1	0.913				
	Intention 2	0.947				
	Intention 3	0.909				

Discriminant validity in PLS-SEM was assessed using the Fornell-Larcker criterion and HTMT analysis. As shown in Table 4, the square root of AVE (italicized values) for each construct exceeded its correlations with other constructs, confirming discriminant validity (Garson, 2016). The threshold value of the proposed HTMT analysis is 0.90 (Henseler et al., 2015) if the Fornell-Larcker criterion is correct and the road model contains very similar structures. According to this rule, there is no HTMT value exceeding the threshold value. It was determined that the proposed model met the discriminant validity criteria by Fornell-Larcker and HTMT analysis (Table 4).

Table 4: Discriminant Validity Results

Variable	1	2	3	4	5	6	7	8	9
Fornell-Larcker Criterion									
Performance Expectancy	*.920*								
Effort Expectancy	.843	*.928*							
Social Influence	.464	.361	*.956*						
Facilitating Conditions	.679	.619	.421	*.930*					
Hedonic Motivation	.599	.503	.385	.547	*.953*				
Price Value	.436	.348	.217	.378	.397	*.960*			
Habit	.678	.563	.531	.614	.610	.431	*.912*		
Attitude	.812	.755	.411	.706	.626	.448	.643	*.940*	
Behavioral Intention	.717	.630	.313	.507	.445	.341	.530	.624	*.923*
HTMT Criterion									
Performance Expectancy									
Effort Expectancy	.889								
Social Influence	.503	.397							
Facilitating Conditions	.730	.672	.461						
Hedonic Motivation	.651	.552	.425	.599					
Price Value	.471	.379	.239	.437	.397				
Habit	.724	.607	.577	.661	.665	.467			
Attitude	.867	.814	.446	.759	.682	.483	.688		
Behavioral Intention	.773	.687	.344	.553	.489	.371	.573	.674	

Note: *Values written in italics represent the square root of the average variance extracted (√AVE).*

The goodness of fit for this research model was assessed using Chi-square, SRMR, and NFI. The Chi-square was 7176.452, SRMR was 0.058 (below the 0.08 threshold), and NFI was 0.57, close to 1 (Hu & Bentler, 1999; Hair et al., 2013). These values indicate an acceptable model fit. The measurement model tests were completed following these results, and the structural model evaluation began.

5.4. Structural Model Results

After assessing the measurement model, the structural model was analyzed to evaluate its predictive ability and the relationships between latent variables (Hair et al., 2017). This internal model evaluation begins with checking for linearity issues, followed by examining correlations and path coefficients. VIF values, shown in Table 5, indicate no linearity or common method bias since all scores were below the threshold of 3 (Kock, 2015).

Following the evaluation of VIF values, effect size (f^2) values were examined in the structural model analysis. The f^2 coefficient indicates the contribution of exogenous variables to the explained variance of endogenous variables (Hair et al., 2013). According to Cohen (1988), an effect size between 0.02 and 0.15 is considered small, between 0.15 and 0.35 is medium, and above 0.35 is large. Upon examining the results, it was observed that the effect sizes were generally at a low level. The effect size results are presented in Table 5.

Table 5: Structural Equation Model Results

Hypothesis		*ß*	*S.S.*	*t-value*	*p-value*	f^2	*VIF*
Model							
H_1	Performance Expectancy>>>Attitude	0.343	0.093	3.679	0,000	*0.091*	*2.379*
H_2	Effort Expectancy>>>Attitude	0.217	0.075	2.910	0,004	*0.051*	*2.846*
H_3	Social Influence>>>Attitude	-0.011	0.024	0.436	0,663	*0.002*	*1.455*
H_4	Facilitating Conditions>>>Attitude	0.209	0.056	3.695	0,000	*0.078*	*2.127*
H_5	Hedonic Motivation>>>Attitude	0.146	0.040	3.678	0,000	*0.044*	*1.843*
H_6	Price Value>>>Attitude	0.068	0.028	2.376	0,018	*0.013*	*1.322*
H_7	Habit>>>Attitude	0.047	0.043	1.095	0,274	*0.004*	*2.462*
H_8	Attitude>>>Behavioral Intention	0.624	0.050	12.439	0,000	*0,639*	*1.000*

According to the results of the structural equation model, it was determined that performance expectancy, effort expectancy, facilitating conditions, hedonic motivation and price value positively affected attitude. Therefore, hypotheses H_1, H_2, H_4, H_5 and H_6 were confirmed. However, the results showed that social influence and habit do not affect attitude. In this respect, hypotheses H_3 and H_7 were not confirmed. On the other hand, it was determined that attitude positively affected behavioral intention. In this regard, the hypothesis H_8 was confirmed.

6. RESULTS AND RECOMMENDATIONS

This research was conducted to analyze the factors affecting medical students using AR and VR applications, utilizing UTAUT in the context of the COVID-19. According to the research results, six of eight hypotheses were supported.

This study found that performance expectancy positively influences students' attitudes toward using AR/VR for education, consistent with previous research (Escobar-Rodríguez & Carvajal-Trujillo, 2014; Ali et al., 2016; Singh & Lee, 2009). Students believe AR/VR enhances learning efficiency, especially through interactive and visual features that clarify abstract concepts. Effort expectancy positively affects attitudes, as ease of use encourages adoption (Yusoff et al., 2011; Ali et al., 2016).

The analyses showed that the social influence does not affect students' attituded to using AR/VR applications for educational purposes. This finding suggests that the impact of social influence in technology acceptance models can be highly context-dependent. One possible explanation is that students may have limited exposure to AR/VR technologies in their peer or academic environments, preventing the formation of strong social norms or expectations around their use. In the post- COVID-19 context, students may prioritize personal utility and ease of use over external opinions when deciding whether to adopt digital tools. This suggests that AR/VR technologies may still be in an early adoption phase, where social influence has yet to emerge as a dominant factor in shaping user attitudes.

The assumption that facilitating conditions positively affect students' attitudes to using AR/VR applications for educational purposes is supported. This finding suggests that students' access to the necessary resources, the adequacy of technical infrastructure, and institutional support play a significant role in shaping their willingness to adopt such technologies. The obtained results confirmed the hypothesis on the positive correlation between hedonic motivation and the students' attitudes. The results are consistent with the literature (Ali et al., 2016; Singh & Lee, 2009). This suggests that students are inclined to adopt these technologies not only for their functional benefits but also because they find them enjoyable, engaging, and entertaining.

The hypothesis stating that the perceived price value positively affects students' attitudes to using AR/VR applications for educational purposes was also supported. This suggests that students evaluate these technologies based on a cost-benefit analysis, where the perceived educational benefits-such as improved engagement, interactivity, and learning effectiveness-are weighed against the required effort, time, or financial investment. The hypothesis that habit positively affects students' attitudes to using AR/VR applications for educational purposes was not supported. This suggests that AR/VR technologies have not yet become a part of students' routine or habitual use in educational contexts. Habit typically develops through repeated and consistent interaction over time; however, the current use of AR/VR in education remains limited, often confined to project-based or experimental activities. Students may not have had sufficient exposure or continuity in usage for these technologies to form habitual patterns. Therefore, the lack of a significant effect may reflect the early AR/VR adoption stage in education, where habitual use has not yet emerged.

The last hypothesis, "students" attitudes towards the use of digital learning environments positively affect their behavioral intentions to use AR/VR for educational purposes," was also supported. This suggests that a favorable disposition toward digital technologies generally serves as a critical prerequisite for the adoption of innovative and interactive educational tools. The result of this research is consistent with the Unified Theory of Acceptance and Use of Technology. Because UTAUT explains a large part of the variance in behavioral intention to use technology.

6.1. Theoretical and Practical Inferences

This study makes significant theoretical contributions by applying the UTAUT model to the adoption of AR and VR technologies in medical education. While the general validity of UTAUT has been widely supported in the literature, this research extends the framework by specifically examining medical students' perceptions of AR/VR through the lens of attitude. Given the complexity and interactive nature of medical education, the study provides novel insights into the applicability and boundaries of UTAUT in this context. This approach lays a foundation for future research to explore potential moderators and mediators unique to technology adoption processes in medical education.

From a practical perspective, thİS study highlights that AR and VR technologies can be effectively utilized in medical education, particularly in surgical simulations, anatomy teaching, and clinical skills development. These technologies enable students to repeatedly practice complex surgical procedures in risk-free environments, thereby enhancing learning quality. Successful applications include VR-based surgical rehearsal tools and AR-assisted anatomical visualization systems used in surgical simulation centers. To integrate these technologies into curricula, educational institutions need to focus on training instructors, establishing adequate infrastructure, and fostering collaborations with technology providers. The linkage between theoretical and practical findings is established by demonstrating how factors from the UTAUT model, such as attitude, performance expectancy, and effort expectancy, directly influence the adoption of AR/VR in medical education. This connection offers guidance for policymakers and educators in developing strategies to facilitate technology integration.

7. LIMITATIONS AND RECOMMENDATIONS FOR FURTHER STUDIES

The findings of this study should be interpreted in light of several limitations. First, as the data were collected from medical students in Türkiye, the generalizability of the findings may be limited by cultural and educational contextual differences. Further studies conducted in different countries and regions would allow for cross-cultural comparisons and a better understanding of how contextual variables influence the adoption of AR/VR technologies in medical education. Second, reliance on self-reported measures may have introduced biases, such as social desirability or subjective interpretation. Further research could employ qualitative methods, such as interviews or observations, to complement and validate the quantitative findings. Further validation of the measurement instruments across diverse contexts is recommended to strengthen robustness and transferability of the results. Third, the cross-sectional design of this study precludes examination of changes in attitudes or behaviors over time. Longitudinal studies would provide valuable insights into the sustainability and long-term impacts of AR/VR integration in medical education, especially about learning outcomes and skill development.

Finally, practical barriers, such as the high cost of AR/VR technologies, limited access to appropriate hardware, and resistance to adoption from both instructors and students pose significant challenges to the widespread use of these tools in education. Further studies should explore how these barriers can be addressed, for example, through the development of cost-effective solutions, small-scale pilot programs, or structured training and orientation sessions for users. Addressing these practical concerns is crucial to ensuring the realistic and effective implementation of AR/VR technologies in real-world educational settings.

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