Acceptance of Virtual Reality in Trainees Using a Technology Acceptance Model

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Table of Contents

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Abstract

Background: Virtual reality (VR) technologies have demonstrated therapeutic usefulness across a variety of healthcare settings. However, graduate medical education (GME) trainee perspectives on VR acceptability and usability are limited.

Objective: The primary aim of this study was to apply a hybrid technology acceptance model (TAM)/United Theory of Acceptance and Use of Technology (UTAUT) model to evaluate factors that predict the behavioral intentions of GME trainees to use VR for patient anxiolysis. The secondary aim was to assess the reliability of the TAM/UTAUT.

Methods: Participants were surveyed in June 2023. GME trainees participated in a VR experience used to reduce perioperative anxiety. Participants then completed a survey evaluating demographics, perceptions, attitudes, environmental factors, and behavioral intentions that influence adoption of new technologies.

Results: 202 of 1540 GME trainees participated. 198 participants were included in the final analysis (12.9% participation rate). Perceptions of usefulness, ease of use, and enjoyment, social influence and facilitating conditions predicted intention to use VR. Age, past use, price willing to pay, and curiosity were less strong predictors of intention to use. All confirmatory factor analysis models demonstrated good fit. All domain measurements demonstrated acceptable reliability.

Conclusions: This TAM/UTAUT demonstrated validity and reliability for predicting GME trainees' behavioral intentions to use VR as a therapeutic anxiolytic in clinical practice. Social influence and facilitating conditions are modifiable factors that present opportunities to advance VR adoption, such as fostering exposure to new technologies and offering relevant training and social encouragement. Future investigations should study the model's reliability within specialties in different geographic locations.

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None

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as fostering exposure to new technologies and offering relevant training and social encouragement. Future investigations should study the model's reliability within specialties in different geographic locations.

Keywords: Virtual reality, technology assessment, graduate medical education, anxiolysis

Introduction

The technology acceptance model (TAM) is the leading theoretical framework for evaluating consumer adoption of new technologies.[1–3] The model assesses variables such as perceptions of usefulness, ease of use, and attitudes towards technologies as indicators for intention to use.[1,4] Since the original 1989 model, TAMs have been applied across a wide range of technologies and with high predictive reliability. In 2010, a TAM successfully predicted factors indicative of health informatics acceptance.[2] The TAM framework has since characterized behaviors and attitudes toward several healthcare innovations, including digital health services, contact tracing, and adverse event reporting systems.[5–8]

Virtual reality (VR) is a new class of technologies involving head-mounted devices that have a variety of healthcare applications, including as a therapeutic adjunct for anxiolysis and as an educational tool for medical training.[9–20] A modified TAM assessed consumers' perceived enjoyment, age, curiosity, past use, and willingness to pay for VR.[21] In 2023, this VR TAM was applied to pediatric healthcare clinicians with strong validity and high reliability.[22] Beyond the conventional variables of TAM, the United Theory of Acceptance and Use of Technology (UTAUT) model adds socio-environmental variables such as social influence and facilitating conditions as predictive factors.[23] UTAUT proponents believe that conventional TAM's lack of these factors limit their generalizability, and instead opt for models that also include UTAUT social variables.[23,24]

Despite VR's therapeutic usefulness, widespread clinical adoption is lacking. Barriers include lack of technical skills, organizational cultures that are slow to adopt new technologies, and perceived usefulness to care.[25,26] Because residency and fellowship experiences influence future patient care delivery, understanding perceptions of VR as adjunct therapy is important in early-career professionals.[27] Identifying factors associated with technology adoption creates opportunity for sustainable and effective implementation.[28] However, graduate medical education (GME) trainee perspectives on VR acceptability and usability are limited.

Given the importance VR will play in future healthcare delivery, a hybrid TAM/UTAUT that predicts utilization among GME trainees was developed. The primary aim modeled factors that predict the behavioral intentions of GME trainees' use of VR as an anxiolytic adjunct. The secondary aim assessed the reliability of the TAM/UTAUT measurements for modeling use in the healthcare context.

Methods

Context and Setting

This study was conducted in 2023 at Stanford Hospital and Lucile Packard Children's Hospital Stanford (Stanford University, Stanford, CA). Oculus Go (Meta Inc., Menlo Park, CA) VR headsets displayed the application Pebbles the Penguin (Stanford Chariot Program, Stanford, CA). This third-person perspective application displays a head controlled cartoon penguin sliding down a mountain collecting colorful objects for points. The application is intuitive, continues in perpetuity, and is successfully used to reduce perioperative and procedural anxiety.[10,29,30]

The Stanford GME department includes over 1,000 residents and fellows and over 100 training programs. The inclusion criteria were postgraduate medical trainees in any year of a Stanford residency or fellowship program. Exclusion criteria were individuals with nausea, motion sickness, seizure disorders, and active illness. The Stanford University Internal Review Board approved a waiver of consent. No financial payments were provided for participation.

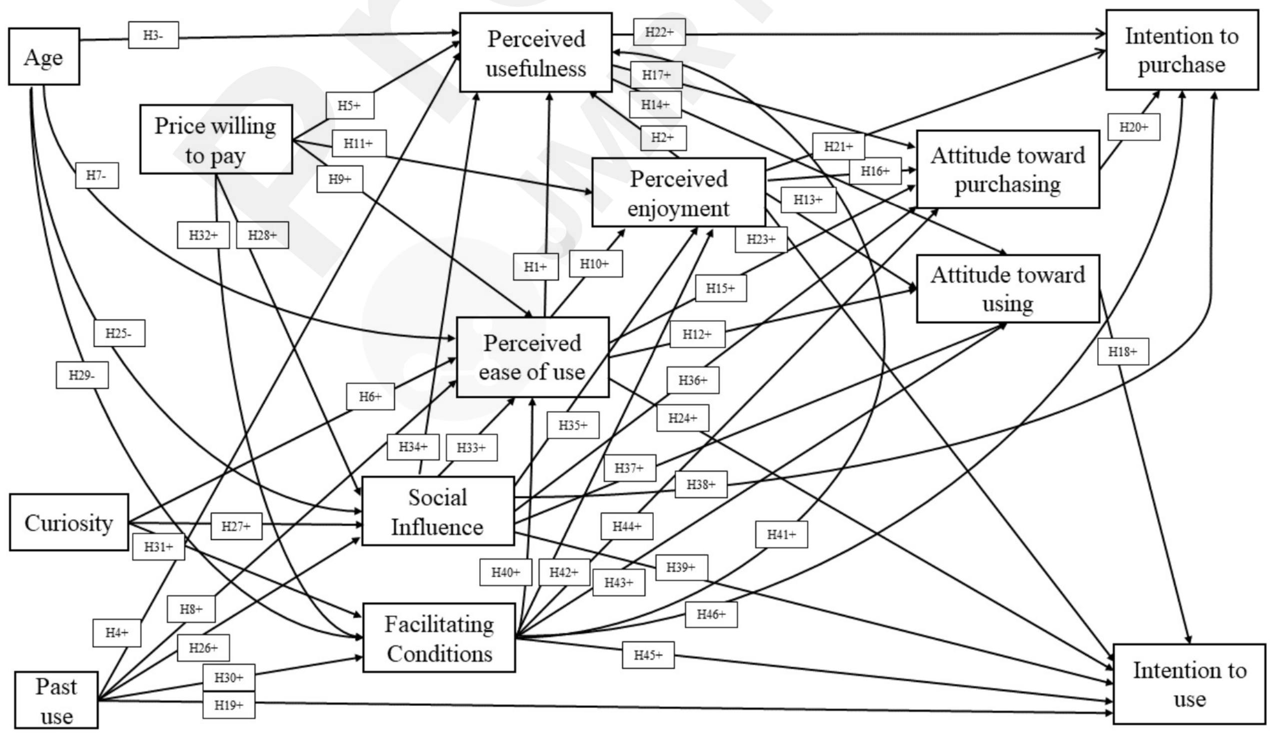
Intervention

Trained research assistants (RAs) recruited volunteer participants in resident and fellow break rooms, outside cafeterias, and in patient care areas of the hospitals. Upon enrollment, RAs provided participants with descriptions of the clinical use of the VR experience as well as gameplay instructions. Participants completed a demographic survey before playing Pebbles the Penguin for two minutes. Following the VR experience, participants completed a survey adapted for healthcare professionals derived from previous VR TAM/UTAUT models (Supplementary Appendix A).[21–23]

Hypotheses

This TAM/UTAUT applied a validated hypothesis model exploring consumer intention to use VR.[21,22] Perceived ease of use, perceived usefulness, and perceived enjoyment were established in the earliest versions of the TAM and are widely applicable to technology acceptance.[21] Perceptions regarding usefulness, ease of use, and enjoyment positively influence attitudes and behaviors towards purchasing and use.[21] Age is hypothesized to negatively influence perceptions, while other demographic variables such as past use and price willing to pay are hypothesized to positively influence perceptions and intent to use. Curiosity is a positive indicator for perceived ease of use.[21] From the UTAUT model, social influence and facilitating conditions are both expected to have positive influential effects on perceptions, attitudes, and behavioral intentions (Figure 1).[23]

Figure 1. VR TAM/UTAUT Hypothesis Model (adapted from Manis and Choi, 2019; Wang et al., 2023; Kim et al. 2016)



Outcomes

The primary outcome was to determine the predictors and validity of the TAM/UTAUT for adoption of VR as an anxiolytic for patient care among a heterogeneous group of GME trainees. The secondary outcome explored the reliability of the model in the healthcare setting.

Measures

Demographic data collected prior to the intervention included age, gender, race, ethnicity, specialty, years of trainee experience, and prior VR use. The TAM/UTAUT surveyed aspects of perceived usefulness, perceived ease of use, perceived enjoyment, intention to use, intention to purchase, curiosity, attitude toward using, attitude toward purchasing, and price willing to pay. The TAM/UTAUT also included two socio-environmental variables – social influence and facilitating conditions – to address previous limitations of conventional TAMs (Appendix B).

Price willing to pay was measured on a continuous scale from $0 to $1,500. Attitudes toward using and purchasing were each measured using five questions graded on a 5-point sliding scale. Perceived usefulness and perceived ease of use were each measured using five questions graded on a 1-5 Likert scale, ranging from strongly disagree (1), mostly disagree (2), neither agree nor disagree (3), mostly agree (4), and strongly agree (5). The remaining variables were each measured using four questions graded on the same Likert scale (Appendix A). Study data were collected, encrypted, and managed securely using Research Electronic Data Capture (REDCap) tools hosted at Stanford University.[31,32]

Analysis

All elements were analyzed as continuous variables. To assess the predictive validity of the TAM/UTAUT, means and standard deviations were evaluated for each scale. Confirmatory factor analysis (CFA) was conducted using Mplus 8.6 (Muthén & Muthén, 1998-2022) to test the construct validity of different scales. Items over 0.7 were considered satisfactory.[33,34] Each item was tested for a normal distribution. For scales that were normally distributed, the maximum likelihood (ML) estimation method was used. For non-normal scales, a robust maximum likelihood (MLM) method was adopted to estimate the CFA model. The comparative fit index (CFI), root mean square error of approximation (RMSEA), Tucker-Lewis Index (TLI), and standardized root mean square residual (SRMR) evaluated model fit. The CFI and TLI indices were accepted above 0.9.[35,36] The RMSEA and SRMR below .08 indicated acceptable fit.[37,38] The results were interpreted as the difference between each non-reference group.

To assess the secondary outcome of TAM/UTAUT's internal consistency and reliability, each scale was evaluated using Cronbach's alpha and composite reliability. Composite reliability is similar to Cronbach's alpha except that it does not assume each item to be equally weighted and accounts for actual factor loadings. Values were considered acceptable if greater than 0.6.[39]

Results

Demographics

202 of 1540 GME trainees participated (13.1% participation rate). After excluding responses with missing values, 198 participants (12.9% participation rate) were included in the final data analysis (Table 1). The ratio of female to male respondents was 1:1. The average age of all participants was 31.3 years, ranging from 23 to 45 years, with a standard deviation (SD) of 3.5 years. Among the participants, 72 (36.4%) had no prior exposure to VR, 107 (54.0%) had 1-5 experiences with VR, and 19 (9.6%) had 6 or more experiences with VR. The mean number of previous VR exposures was 2.7 ± 4.5. In total, 44 unique specialties and fellowship subspecialties were represented among the participants. The most frequently represented specialties included Pediatrics (32, 16.2%), Internal Medicine (27, 13.6%), and Pathology (20, 10.1%) (Appendix C).

Table 1. Participant Demographics

Characteristic	Value
Age (years)	31.3 ± 3.5
Sex (n=)	
Male	99 (50.0%)
Female	99 (50.0%)
Race*	
American Indian or Alaskan Native	0 (0.0%)
Asian	64 (32.3%)
Black or African American	11 (5.6%)
Native Hawaiian or Other Pacific	0 (0.0%)
White	112 (56.6%)
More than one race	5 (2.5%)
Prefer not to answer	6 (3.0%)
Ethnicity	
Hispanic or Latino	25 (12.6%)
Not Hispanic or Latino	170 (85.9%)
Unknown /Chose not to disclose	3 (1.5%)
Level of training	
PGY1	57 (28.8%)
PGY2	34 (17.2%)
PGY3	27 (13.6%)
PGY4	21 (10.6%)
PGY5	27 (13.6%)
PGY6 or higher	32 (16.2%)
Previous exposure to VR	
0 times	72 (36.4%)
1-5 times	107 (54.0%)
6-9 times	2 (1.0%)
10-14 times	8 (4.0%)
15-19 times	1 (0.5%)
>=20 times	8 (4.0%)

* Multiple answers allowed

Primary Outcome

For each composite domain, mean and standard deviation of responses were: perceived usefulness (3.498 ± 0.883); perceived ease of use (3.911 ± 0.803), perceived enjoyment (4.349 ± 0.721), intention to use (3.460 ± 1.064), intention to purchase (3.446 ± 0.880), curiosity (3.404 ± 0.908), attitude toward using (3.979 ± 0.751), attitude toward purchasing (3.810 ± 0.801), social influence (2.910 ± 0.729), and facilitating conditions (3.684 ± 0.707). The mean price willing to pay was \$781.36 ± \$375.50 (Appendix D). All responses demonstrated normality, and the MLM estimated the models.

Standardized factors loadings were greater than 0.7 for all items within the perceived usefulness, perceived ease of use, perceived enjoyment, intention to use, attitude toward using, and attitude toward purchasing domains. Two survey items within intention to purchase, one item within curiosity, two items within social influence, and one item with facilitating conditions were below 0.7 (Appendix E). All CFA models demonstrated good fit (CFI .984-1; TLI .968-1; RMSEA 0-.137, SRMR 0-.021) (Appendix F).

Detailed estimates of the path coefficients were calculated (Figure 2a and 2b, Table 2). Most of the relationships between the perception, attitude, and intention domains were significant, except for the influence of perceived enjoyment on attitude toward using and perceived ease of use on intention to use. Perceived ease of use influenced perceived usefulness (*P*<.001), perceived enjoyment (*P*<.001), attitude toward using (*P*=.043), and attitude toward purchasing (*P*=.034). Perceived enjoyment influenced perceived usefulness (*P*<.001), attitude toward purchasing (*P*=.041), intention to purchase (*P* .001), and intention to use (*P*<.001). Perceived usefulness influenced attitude toward using (*P*<.001), attitude toward purchasing (*P*<.001), and intention to purchase (*P*<.001) (Figure 2, Table 2).

Figure 2a. TAM/UTAUT Results – significant estimates

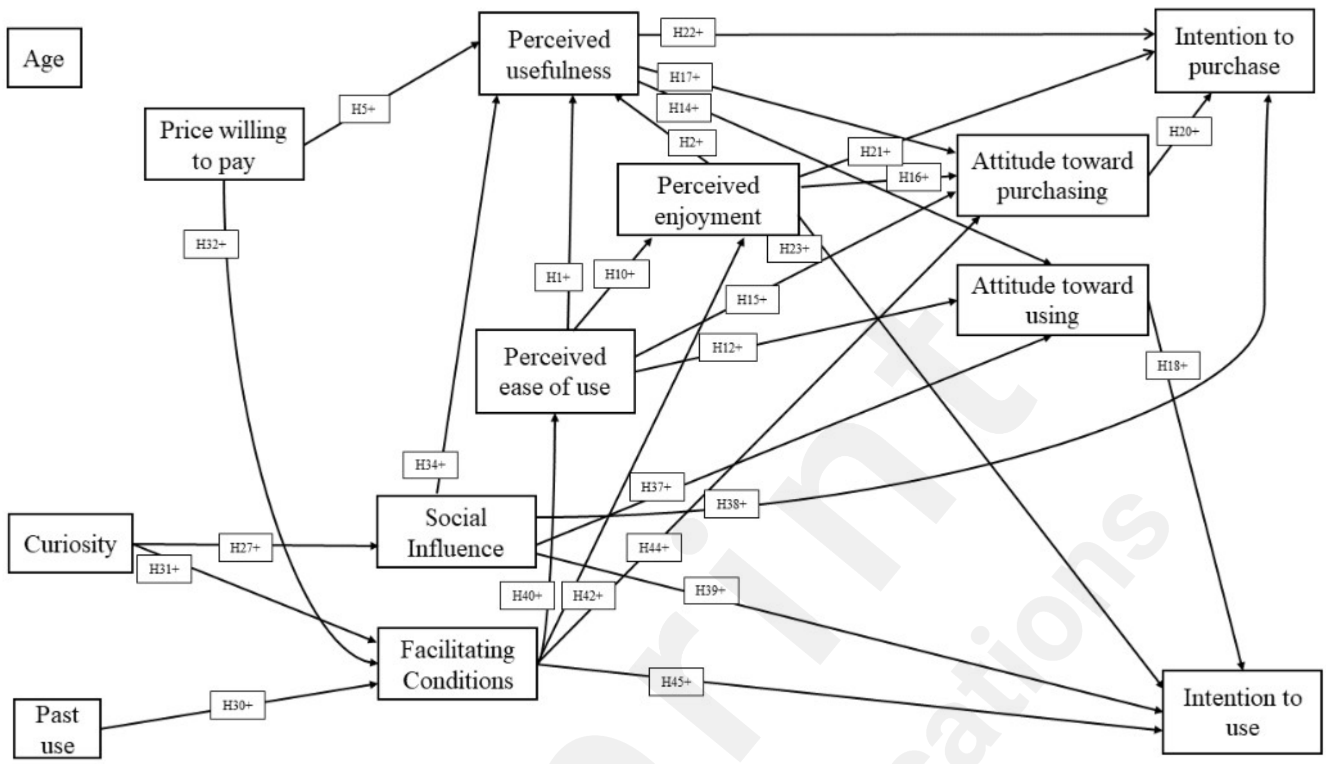


Figure 2b. TAM/UTAUT Results – non-significant estimates

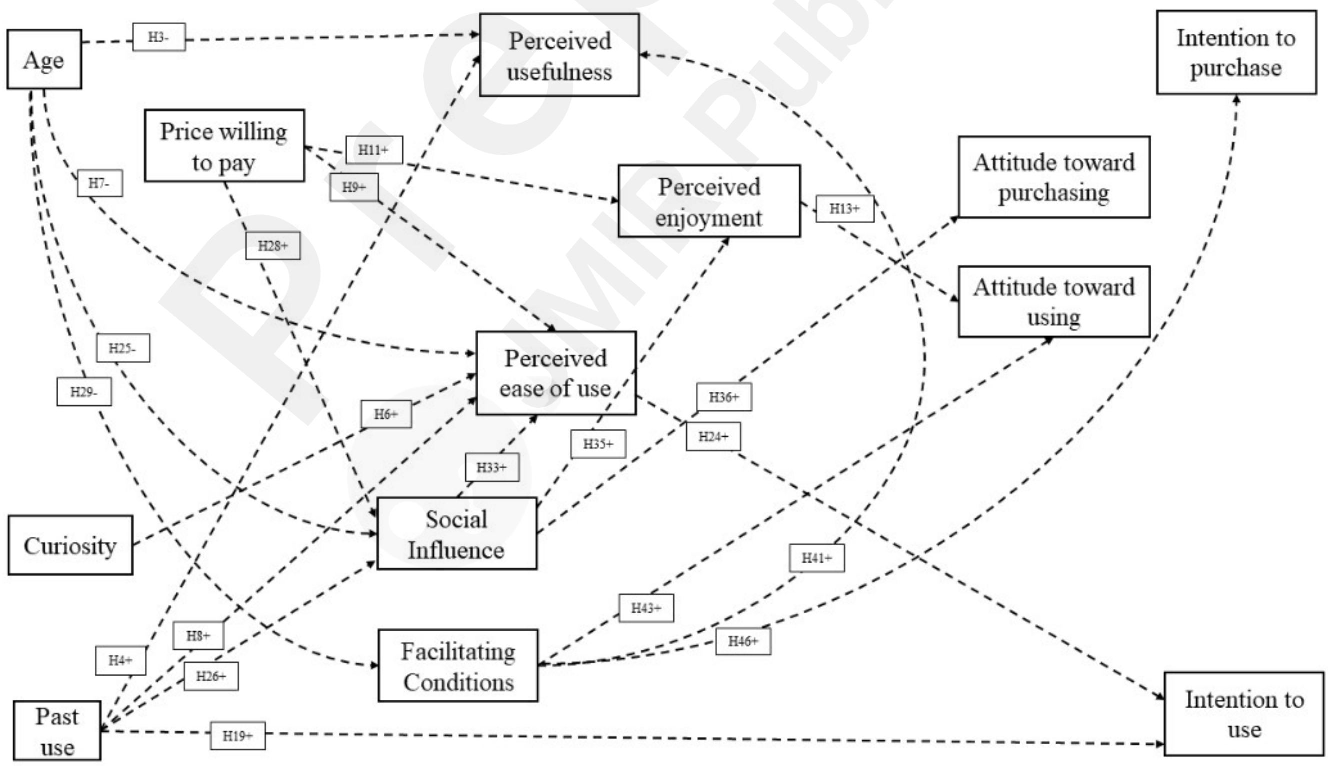


Table 2. Standardized Estimates of the TAM/UTAUT

	Predictor	Outcome	*β*	*P*	95% CI
H1	Perceived ease of use	Perceived usefulness	.258**	<.001	[.135, .381]
H2	Perceived enjoyment	Perceived usefulness	.299**	<.001	[.169, .430]
H3	Age	Perceived usefulness	-.082	.108	[-.182, 0.18]
H4	Past use	Perceived usefulness	.058	.258	[-.042, .158]
H5	Price willing to pay	Perceived usefulness	.147**	.005	[.045, .250]
H6	Curiosity	Perceived ease of use	-.053	.438	[-.187, 0.81]
H7	Age	Perceived ease of use	-.054	.402	[-.179, .072]
H8	Past use	Perceived ease of use	.067	.292	[-.058, .193]
H9	Price willing to pay	Perceived ease of use	.034	.606	[-.096, .164]
H10	Perceived ease of use	Perceived enjoyment	.427**	<.001	[.318, .535]
H11	Price willing to pay	Perceived enjoyment	.035	.518	[-.072, .142]
H12	Perceived ease of use	Attitude toward using	.146*	.043	[.005, .287]
H13	Perceived enjoyment	Attitude toward using	.104	.179	[-.048, .256]
H14	Perceived usefulness	Attitude toward using	.276**	<.001	[.130, .422]
H15	Perceived ease of use	Attitude toward purchase	.157*	.034	[.012, .302]
H16	Perceived enjoyment	Attitude toward purchase	-.162*	.041	[-.318, -.006]
H17	Perceived usefulness	Attitude toward purchase	.369**	<.001	[.221, .517]
H18	Attitude toward using	Intention to use	.316**	<.001	[.205, .426]
H19	Past use	Intention to use	-.032	.488	[-.122, .058]
H20	Attitude toward purchase	Intention to purchase	.309**	<.001	[.204, .414]
H21	Perceived enjoyment	Intention to purchase	.199**	.001	[.080, .318]
H22	Perceived usefulness	Intention to purchase	.243**	<.001	[.107, .380]
H23	Perceived enjoyment	Intention to use	.273**	<.001	[.149, .397]
H24	Perceived ease of use	Intention to use	.089	.135	[-.028, .207]
H25	Age	Social influence	.001	.985	[-.130, .132]
H26	Past use	Social influence	.062	.351	[-.068, .192]
H27	Curiosity	Social influence	.313**	<.001	[.187, .439]
H28	Price willing to pay	Social influence	.121	.071	[-.010, .253]

H29	Age	Facilitating conditions	-.103	.118	[-.233, .026]
H30	Past use	Facilitating conditions	.138*	.035	[.010, .266]
H31	Curiosity	Facilitating conditions	.228**	<.001	[.100, .357]
H32	Price willing to pay	Facilitating conditions	.207**	.002	[.077, .336]
H33	Social influence	Perceived ease of use	.098	.173	[-.043, .238]
H34	Social influence	Perceived usefulness	.253**	<.001	[.145, .362]
H35	Social influence	Perceived enjoyment	.112	.053	[-.002, .226]
H36	Social influence	Attitude toward purchase	.113	.086	[-.016, .243]
H37	Social influence	Attitude toward using	.212**	.001	[.087, .337]
H38	Social influence	Intention to purchase	.165**	.002	[.061, .268]
H39	Social influence	Intention to use	.180**	.001	[.073, .287]
H40	Facilitating conditions	Perceived ease of use	.389**	<.001	[.255, .523]
H41	Facilitating conditions	Perceived usefulness	.022	.734	[-.104, .148]
H42	Facilitating conditions	Perceived enjoyment	.291**	<.001	[.170, .413]
H43	Facilitating conditions	Attitude toward using	.090	.194	[-.046, .225]
H44	Facilitating conditions	Attitude toward purchase	.260**	<.001	[.123, .397]
H45	Facilitating conditions	Intention to use	.139*	.019	[.023, .255]
H46	Facilitating conditions	Intention to purchase	.111	.054	[-.002, .224]

Note. ** *P*< .01, * *P*<.05. CI = Confidence Interval

Curiosity influenced social influence (*P*<.001) and facilitating conditions (*P*<.001), but not perceived ease of use (*P*=.438), as originally hypothesized (Figure 2, Table 2).

Price willing to pay influenced perceived usefulness (*P*=.005) and facilitating conditions (*P*=.002). There was no relationship between price willing to pay and perceived ease of use, perceived enjoyment, or social influence (Figure 2, Table 2).

Age and past use did not predict any outcomes, with the exception of a relationship between past use and facilitating conditions (*P*=.035) (Figure 2, Table 2).

Social influence was a predictor of perceived usefulness (*P*<.001), attitude toward using (*P*=.001), intention to purchase (*P*=.002), and intention to use (*P*=.001). There was no relationship between social influence and perceived ease of use, perceived enjoyment, or attitude toward purchase. Facilitating conditions influenced perceived ease of use (*P*<.001), perceived enjoyment (*P*<.001), attitude toward purchasing (*P*<.001), and intention to use (*P*=.019), but did not influence perceived usefulness, attitude toward using, or intention to purchase (Figure 2, Table 2).

Secondary Outcome

All scales demonstrated acceptable reliability, as determined by Cronbach's alpha and composite reliability values. Cronbach's alpha results ranged from .753 to .962, and composite reliabilities ranged from .756 to .962 (Table 3).

Table 3. Reliability of the Measurement Tools

Variable	Cronbach's α	Composite Reliability
Perceived Usefulness	.952	.952
Perceived Ease of Use	.915	.916
Perceived enjoyment	.924	.918
Intention to use	.951	.952
Intention to purchase	.876	.877
Curiosity	.753	.756
Attitude toward using	.937	.937
Attitude toward purchasing	.962	.962
Social influence	.865	.861
Facilitating conditions	.818	.828

Note. The third item in the curiosity scale was deleted in the data analysis because it affects the reliability (if not deleted, Cronach's alpha would be 0.578) and the loading of this item is very low in CFA (i.e., the relationship between this item and the curiosity factor is weak).

Discussion

Principal Results

The TAM/UTAUT predicted behavioral intentions associated with clinical VR utilization within this group of GME trainees. Attitude toward purchasing, perceived enjoyment, perceived usefulness, and social influence were predictors of intention to purchase, while attitude toward using, perceived enjoyment, social influence, and facilitating conditions were predictors of intention to use. Contrary to our hypothesis, perceived ease of use was not a predictor of intention to use. However, perceived ease of use predicted perceived enjoyment and attitude toward using; these latter two elements are effective mediators between perceived ease of use and intention to use. With respect to the secondary aim, all TAM/UTAUT scales demonstrated good construct validity and reliability. This contributes to a growing body of evidence that TAMs and UTAUTs are appropriate modeling techniques to characterize technology adoption within healthcare settings.

The VR-TAM that informed the tested model predicted that curiosity, age, past use, and price willing to pay all influenced perceived ease of use in the consumer market.[21] In contrast, this population of early career physicians indicated that curiosity, age, past use, and price willing to pay were not predictors of perceived ease of use. In addition, age and past use did not predict perceived usefulness. These results suggest that the previously hypothesized barriers to new technology adoption, such as older age or lack of prior exposure, do not affect GME trainees' perceptions of ease of use or usefulness. The majority of trainees were 40 years or younger and had previous VR experience, compared to the older mean age of faculty physicians. Given that GME trainees are more likely to be on the adoptive side of the "digital divide," personal characteristics are less influential factors for predicting technology use.[40]

This TAM/UTAUT demonstrated that price willing to pay was a predictor of perceived usefulness and facilitating conditions. These domains acted as mediators for predicting attitudes towards purchasing and using, and intention to use, with implications for future adoption. VR is relatively affordable compared to other anxiolytics, especially as commercial equipment costs continue to decrease and healthcare VR applications expand.[9,41–43] As the difference between cost and price willing to pay continue to downtrend, there will be an increasing financial justification to apply VR in clinical settings from the perspective of GME trainees.

The UTAUT model elements, social influence and facilitating conditions, were hypothesized to predict behavioral intention to use.[23] The tested model indicated that social influence predicted perceived usefulness, attitude toward using, intention to purchase, and intention to use, while facilitating conditions predicted perceived ease of use, perceived enjoyment, attitude toward purchasing, and intention to use. These results further support these elements as key predictors for intention to use a novel technology.[23] However, in contrast to earlier studies where facilitating conditions was a stronger predictor of adoption than social influence, this TAM/UTAUT demonstrated social influence to be the stronger predictor.[23,24] In addition, this model indicates that social influence predicted intentions to both use and purchase, whereas facilitating conditions only predicted intention to use. One explanation for this incongruity may be that social influence and facilitating conditions are more context-dependent; different settings may engender different relationships between these extrinsic factors and technology adoption. Given that social influence and facilitating conditions are modifiable environmental factors, the positive directionality of their effects on behavioral intentions have strategic implications. Program directors and faculty responsible for educating GME trainees should foster learning environments that provide exposure to new technologies, relevant training and technical assistance, and social encouragement to drive VR adoption.

Limitations

There were several limitations to this investigation. First, trainees interested in VR may have been more likely to volunteer, leading to a selection bias. Second, factors such as perceived ease of use for patients and perceived usefulness to patients may affect attitudes to VR adoption. Future studies should explore patient perceptions as additional elements. Third, GME trainees were analyzed as a single group. A larger sample would have allowed for specialty subgroup analysis. Fourth, given the proximity to several notable technology company headquarters, participants may have stronger subjective norms towards VR compared to trainees in other regions. To improve generalizability, additional studies should enroll trainees in other geographic settings.

Conclusions

This TAM/UTAUT demonstrated validity and reliability for predicting GME trainees' behavioral intentions to use VR as a therapeutic anxiolytic in clinical practice. Perceptions of usefulness, ease of use, and enjoyment predicted intention to use VR. Age, past use, price willing to pay, and curiosity were less strong predictors of intention to use. Social influence and facilitating conditions also strongly predicted behavioral intentions, representing opportunities to advance VR adoption.

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Financial Disclosures

None

Conflicts of Interest

TJC and EYW are on the board of Invincikids, a nonprofit organization that seeks to distribute immersive technologies to improve pediatric care. They receive no compensation for their roles. The Stanford Chariot Program has received philanthropic gifts from Meta, Inc., and Magic Leap, Inc.

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Abbreviations

CFA - Confirmatory Factor Analysis

CFI - Comparative Fit Index

CI - Confidence Interval

FAER - Foundation for Anesthesia Education and Research

GME - Graduate Medical Education

ML - Maximum Likelihood

MLM - Maximum Likelihood Method

RA - Research Assistant

REDCap - Research Electronic Data Capture

RMSEA - Root Mean Square Error of Approximation

SD - Standard Deviation

SRMR - Standardized Root Mean Square Residual

TAM - Technology Acceptance Model

TLI - Tucker-Lewis Index

UTAUT - United Theory of Acceptance and Use of Technology

VR - Virtual Reality

Supplementary Files

Multimedia Appendixes

TAM/UTAUT Survey.
URL: http://asset.jmir.pub/assets/55de14b3431a505cf0e88d4d7c261990.docx

Variables and Items.
URL: http://asset.jmir.pub/assets/dd255e4c9db3152e6267f5897e20f25d.docx

Participant Specialties.
URL: http://asset.jmir.pub/assets/64462e48ae7bef8d994a5e080c36e0bf.docx

Summary of Variables.
URL: http://asset.jmir.pub/assets/33273130f5b643e2b987092a1f49858b.docx

Standardized Factor Loadings in Confirmatory Factor Analysis.
URL: http://asset.jmir.pub/assets/a8e0447f707e7703a29faa8955e25cda.docx

Confirmatory Factor Analysis of Measures.
URL: http://asset.jmir.pub/assets/19f99c139576e1ddd20248b4c6666a8d.docx