Students' Behavioral Intentions Toward Teachers' Use of Augmented Reality in Higher Education: Insights from the UAE

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***Abstract*—This research examines a Unified Theory of Acceptance and Use of Technology (UTAUT2)-model derived method to identify variables influencing students' behavioral intention towards the use of augmented reality by university teachers in the UAE. Although social influence was insignificant with implications that UAE students are utility and usability oriented rather than peer/teacher influence. Performance expectancy, effort expectation, facilitating conditions, flexibility, hedonic motivation, and self-efficacy significantly influenced Augmented Reality (AR) adoption by strongly predicting AR adoption based on the results from an analysis of data on 308 students using Partial Least Squares Structural Equation Modeling (PLS-SEM). Findings highlight the need for the development of user-friendly, entertaining AR technologies for building self-efficacy and institutional facilitation (e.g., training, infrastructure) support. policy recommendations to policy makers and educators are presented in the study for accelerating adoption and further extend UTAUT2 by demonstrating its applicability in UAE's AR learning environment.**

***Keywords*—augmented reality, behavioral intentions, higher education, Unified Theory of Acceptance and Use of Technology (UTAUT2), contextual factors**

I. Introduction

Institutions are increasingly adopting technology to support learning and teaching processes [1]. Real, actual, genuine, humorous, and inspiring learning environments can be created as a result of technological developments [2]. As augmented reality has the potential to transform human-computer interaction [3] and is still gaining popularity in education [4–7], this study is all about AR education. Augmented Reality (AR) is described as a "step between reality and virtual reality for the sake of education" [8]. AR provides a composite view by projecting a user's viewpoint of the real world onto a computer-generated image, allowing users to interact with virtual goods by fusing virtual data with the real world [9, 10]. Merging worlds makes AR "augmenting reality instead of displacing it" [11]. This is a revolutionary ed-tech offering engaging and interactive learning experiences that enhance student retention and engagement [12]. AR is being integrated into classrooms globally to bridge the difference between theoretical concepts and real-world applications, promoting increased understanding and creativity among learners [13, 14]. Literature has proven that AR improves learning outcomes in the form of visual and experiential learning, particularly for subjects of Science, Technology, Engineering, and Mathematics (STEM) [15, 16]. Despite this, its adoption at universities is uneven, with technical constraints, prohibitive costs, as well as educator and student resistance being formidable obstacles [17, 18].

Technology and innovation in education are also a characteristic of national development plans such as Vision 2021 and the National Innovation Strategy in the United Arab Emirates (UAE) [19, 20]. These plans aim to establish the UAE as a world leader in education through innovative technologies such as AR to deliver graduates fit for the future [21, 22]. The UAE's investment in smart classrooms and digital infrastructure has created a rich soil for AR adoption, yet not much is understood about students' perception and response to the technology [23, 24]. Understanding students' behavioral intentions toward AR is essential in order to integrate it effectively in higher education. Behavioral intentions, which are influenced by perceived usefulness, ease of use, and social influence, take a central place in technology adoption [25, 26]. Cultural and contextual considerations in the UAE could also shape these intentions, and therefore it is important to examine students' perceptions [27, 28]. The use of Augmented Reality (AR) in universities has attracted much attention around the world because it offers the possibility of improving learning processes by using interactive and immersive technologies [29, 30].

However, research on AR adoption in the context of the United Arab Emirates (UAE) remains limited, particularly in terms of how students perceive and respond to the technology [21, 24]. While the UAE has invested significantly in educational technology as part of its Vision 2021 and National Innovation Strategy, there is a notable lack of empirical studies that investigate the drivers of students' behavioral intentions towards AR in higher education [19, 20]. Past studies on AR in education have primarily focused on its technical use and potential benefits, such as increased engagement and learning outcomes [13, 31]. However, quantitative research that examines students' behavioral intentions is scarce, which are crucial for the successful implementation and adoption of AR in classrooms [32, 33]. Behavioral intention, mediated by perceived ease of use, perceived usefulness, and social influence, plays an important role in the adoption and success of emerging

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technologies [25, 34]. Without a strong understanding of such influences, the UAE's educationists and policymakers may not be able to capitalize on AR optimally to harness its full potential in higher learning. Although research indicates that AR has the potential to enhance student academic self-efficacy, there is limited research on the contextual determinants (task value, learning space and characteristics of technology) in which AR is implemented within educational settings and how this influences student academic self-efficacy.

This is an essential area of study since the usage of augmented reality in educational settings is quickly growing. It is also argued [35] that the use of technology in teaching has resulted in an increase in classroom layout modifications, with traditional rows of desks and chairs being replaced by a range of furniture that can be configured in a variety of ways to facilitate teaching and learning. Nonetheless, schools are unable to provide funding for adjustable furniture to enhance children' learning experiences. As a result, the goal of this research is to look at the contextual aspects that influence students' academic self-efficacy while utilizing augmented reality. In order to achieve this goal, two study questions were addressed: 1) What are the primary predictors of academic self-efficacy in the usage of AR? 2) Do contextual variables accurately predict intents to utilize AR? The justification for this research includes its dual contribution to practice and academia. The research provides practical insight to educators and policymakers in the UAE regarding what affects students' behavioral intentions towards Augmented Reality (AR), thereby enabling the development of strategic strategies towards improving AR adoption among higher education. Through empirical examination of a theoretical model with special focus on AR and student behavior intervention, the study contributes both to practice and theory.

The remainder of this article is outlined to provide an introduction to Students' Behavioral Intentions Toward Teachers' Use of Augmented Reality in Higher Education. In the next section an explanation on the development of our conceptual model and seven hypotheses, each of which is explicated in terms of context factors, strategies, and student behavioral intention to AR use. The study then describe AR in education and the analytical approach used. In section four of the study the results is evaluated and reviewed, then thereafter the study is ended with a discussion of our findings and the supply of implications for theory, practice, and future research.

A. Augmented Reality in Education

In order to create an immersive and interactive learning environment, AR technology superimposes digital data, such as images, videos, or 3D models, onto the physical world [36]. AR has been used at the higher-education level with various courses ranging from medical school, where the human body is visualized by students through AR, to engineering, where the use of AR simulation enables learning about complex equipment [37, 38]. For example, medical school anatomy courses such as Anatomy 4D may be able to allow students to navigate extremely detailed 3D representations of the human body, while HP Reveal enables instructors to provide AR-interactive instructions. These programs demonstrate the potential of AR filling the gap between theoretical underpinnings and practical application and how abstract concepts could be better made comprehensible [39].

The benefits of AR learning are well-known as Augmented Reality (AR) promotes learner engagement by delivering dynamic and attractive learning opportunities that entice students to dive deeper into the content [40]. Because AR enables students to interact with virtual products and conduct experiments in a safe environment, it promotes interactive learning and the development of critical thinking and problem-solving abilities [41]. Furthermore, augmented reality has been found to improve visual and spatial learning, allowing students to acquire and remember complicated information [42]. Despite all of these advantages, there remain significant challenges to solve before AR may be extensively employed in higher education. Adoption at institutions with low budgets is hindered by technological challenges, such as the necessity for high-quality hardware and software [38]. Another obstacle to entry, especially for individuals with low financial means, is the expense of the equipment and the content production process [43]. Teachers' and students' opposition is sometimes caused by a lack of information about augmented reality or a reluctance to deal with what they see as a "flashy new technology" with limited uses [44].

Previous research identifies certain barriers to AR uptake in the UAE context, e.g., cultural resistance against immersive technology [45], mismatches between public-private institution readiness [46], and persisting infrastructure issues in periphery regions [47]. Moreover, the study doesn't situate its findings in the global AR adoption trend by omitting comparative analysis with innovation-leading education systems like South Korea's nation-wide AR curriculum integration [48] or Singapore's blended reality program [49], which could reveal transferable approaches to further advance AR in the UAE. The critique also understates emerging concerns over AR pedagogic trade-offs, such as dangers of cognitive overload in STEM disciplines [50] or equity problems with device-dependent learning [51] issues particularly relevant to the UAE's multicultural student cohorts. Including such comparative and critical perspectives, as seen in the latest meta-analyses [52, 53], would not only extend the theoretical contribution of this study but also its applied value for UAE policymakers dealing with AR's uneven environment for global adoption.

B. Behavioral Intentions in Educational Technology

According to the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), a number of critical variables influence behavioral use intention of educational technology, including perceived ease of use, perceived usefulness, social influence, and facilitating conditions [54, 55]. Perceived ease of use refers to how easy they feel it is for them to utilize technology, while perceived utility refers to how much students believe a technology, such as Augmented Reality (AR), would improve their learning performance [45]. Social influence, e.g., peer and teacher attitudes, and facilitation conditions, e.g., institutional and access to resources, also significantly influence behavioral intentions [56]. Cultural and contextual factors further shape these forces in the UAE since the UAE's collectivist culture and power distance would enhance the influence of social influence and empower people in technology adoption [57]. Also, the UAE focus on innovation and technology-based education, as presented in Vision 2021, provides a distinctive context where facilitators, including government support and institutional investment, play a major role in the probability of AR adoption [19].

II. Theoretical Framework and Hypothesis Development

To this purpose, the universal Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model is presented to investigate students' behavioral intents in relation to instructors' use of augmented reality (AR) in UAE higher education. To expand the model for this investigation, additional components and external variables were added to the original UTAUT2 framework, and hypotheses were developed accordingly. The key determinants of student adoption intentions are the following UTAUT2 constructs: performance expectation, effort expectancy, social influence, enabling circumstances, hedonic motivation, price value, and habit. Perceived benefits have also been included, as well as compatibility and self-efficacy, to extend the model to be more relevant to AR adoption in higher learning institutions. The primary latent variables (constructs) researched here are defined and placed within the study scope. The corresponding manifest variables where these measures were found had also been well selected from literature and adapted according to the individual educational context of AR adoption at university campuses. Likewise, Fig. 1 represent the conceptual model with all the construct.

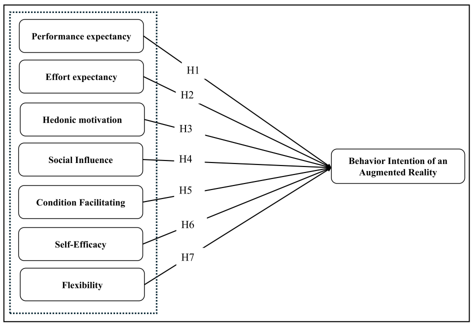

Fig. 1. Conceptual model.

A. UTAUT2 Model as a Theoretical Framework

The current research uses the UTAUT2 model to validate students' behavioral intention determinants for the use of Augmented Reality (AR) by instructors in UAE higher education. The UTAUT2 model has been extensively used to evaluate technological acceptability in a variety of fields, making it an appropriate theory for our investigation. [58] conducted a comprehensive assessment of 650 UTAUT2-based research, highlighting its importance as a theoretical approach for understanding technology adoption in a variety of situations, including people, organizations, technologies, and tasks. Its predecessor, UTAUT, is regarded as one of the most comprehensive theories in information systems research, giving insights on technology acceptance across numerous use cases. UTAUT2 defines behavioural intention in terms of Performance Expectation (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Circumstances (FC), Hedonic Motivation (HM), Price Value (PV), and Habit (HT). As a sophisticated theory, the UTAUT2 model provides a solid framework to investigate students' intention to utilize AR as an instructional tool in terms of the motivational and contextual drivers of their adoption choices.

Application of the UTAUT2 model to AR adoption by institutions of higher education is fitting and necessary. Previous research applied UTAUT2 in other areas of modelling technology adoption such as green investment choices, ecologically sustainable behaviours, and electronic e-government [59–61]. Like these applications, UTAUT2 provides a robust framework for understanding the determinants of students' behavioral intentions to learn using AR, i.e., how constructs such as PE, EE, SI, and FC influence their attitudes and perceptions. Therefore, we propose the following hypothesis.

B. Performance Expectancy (PE)

Performance Expectancy (PE) is an influential technology adopter that has been demonstrated to predict user intention in a variety of digital learning contexts [62] (Venkatesh *et al*. 2012). PE is the extent to which students feel that the incorporation of augmented reality (AR) into higher education will improve their learning outcomes and academic performance [58]. In the application of AR, PE is the assessment of students' belief with regard to whether AR would enhance participation, comprehension, and learning retention. To the extent that the students feel that AR is a critical component in the improvement of the learning process, they will be ready to adopt a positive attitude towards its use.

H1: Performance expectancy will positively influence students' behavioral intentions toward teachers' use of augmented reality in higher education.

C. Effort Expectancy (EE)

Another strong technology adopter is Effort Expectancy (EE), which is the perceived ease of using a specific system or tool. EE captures the extent to which students perceive AR technology as easy, convenient, and easy to incorporate into their studies [59]. If AR is discovered to be easy to use and enjoyable to engage with, the potential for its uptake in learning procedures by students is high. However, complex interfaces and usability issues can discourage uptake despite possible benefits to learning. Optimizing usability and accessibility of AR technology helps optimize adoption levels among students, since simplicity of use is one of the principal predictors of the adoption of technology. Consequently, we suggest the following theory:

H2: Effort expectancy will positively influence students' behavioral intentions toward teachers' use of augmented reality in higher education**.**

D. Hedonic Motivation (HM)

Hedonic Motivation (HM) is a major determinant of the acceptance of technology, in this case, learning, where motivation and satisfaction have central driving functions to decide the outcome of learning results [62]. HM is employed to define how much students experience enjoyment and gain intrinsic satisfaction when they use AR in learning [63]. Compared to traditional learning approaches, AR provides interactive and immersive experiences that can potentially render learning enjoyable and thrilling. If students like to learn with AR and find it difficult, they are more likely to embrace it as part of their learning process. Therefore, we propose the following hypothesis:

H3: Hedonic motivation will positively influence students' behavioral intentions toward teachers' use of augmented reality in higher education.

E. Social Influence (SI)

Social Influence (SI) is a widely documented technology acceptance factor, which refers to the degree to which students feel that opinion leaders, teachers, or social groups influence them to adopt AR in learning [62]. In the classroom, students are likely to embrace AR if they see peers and teachers encouraging its adoption or if they experience normative pressure to do so [64]. Furthermore, institutional support and teacher backing can also solidify students' attitudes towards AR as a tool for learning. Thus, we suggest the following hypothesis:

H4: Social influence will positively influence students' behavioral intentions toward teachers' use of augmented reality in higher education.

F. Facilitating Conditions (FC)

Facilitating Conditions (FC) is defined as the resources, technical assistance, and institutional infrastructure that support students in utilizing AR to an optimal level in their tertiary studies [62]. When there is access to good AR labs, internet connectivity, and proper training, students are most likely to form positive attitudes towards the adoption of AR in learning [65]. Though, limited availability of AR tools or institutional backing may hinder adoption even if they are aware of its possibilities. Hence, we suggest the following hypothesis:

H5: Facilitating conditions will positively influence students' behavioral intentions toward teachers' use of augmented reality in higher education.

G. Self-Efficacy (SE)

Self-Efficacy (SE) is a psychological variable used to evaluate the perceived ability of students in using AR effectively in higher education [66]. Self-efficacy describes the extent to which the student possesses self-perceptions of effectively running AR technology independently [67]. Strong self-efficacy generates students to interact with AR-enhanced learning environments because of self-confidence over controlling technicalities. If the students are finding AR challenging, they might be less likely to use it, although it can be very helpful. Therefore, we establish the following hypothesis:

H6: Self-efficacy will positively influence students' behavioral intentions toward teachers' use of augmented reality in higher education.

H. Flexibility (FL)

Flexibility (FL) is a new technology adoption concept that captures the way students see AR as something adjustable and flexible that can facilitate learning at one's own pace [68]. Learning using AR offers the possibility of personalized learning, with learners being able to engage with learning content in the most appropriate manner conducive to their learning and interests. If the students find AR to provide flexibility in accessibility, interaction with content, and learning at their own pace, they will embrace it into their learning processes. Thus, we formulate the following hypothesis:

H7: Flexibility will positively influence students' behavioral intentions toward teachers' use of augmented reality in higher education.

III. Materials and Methods

A. Augmented Reality (AR) Overview

Augmented Reality (AR) places virtual data like image, sound, or text over the actual world to add something more to the users' perception of reality. In contrast to Virtual Reality (VR), which presents a totally fabricated virtual environment, AR mixes virtual data into reality, normally through AR glasses, smartphone, or tablet [69]. Such technology is applied across many industries from education, healthcare, retail to entertainment since it has the potential to develop interactive experiences. AR makes learning possible in education by allowing students to visualize otherwise complex concepts [37]. While AR can do so much, it also has its limitations in the way of technological limitations, the issue of user privacy, and the need for gigantic computational powers [70]. With the development of AR, there needs to be ongoing research and development to address these problems and make it full potential in various areas.

B. Data Collection

The research's cross-sectional design was a suitable method of collecting the current attitudes of AR adoption by students—a reasonable choice given the newness of AR introduction to UAE universities [21]. Stratified random sampling achieved discipline, institution type, and demographic representativeness, allowing generalizability to the UAE's multicultural higher education context [71]. While longitudinal data can potentially tell temporal trends, the cross-sectional design aligns with similar technology-acceptance research [26] and enables policymakers prompt feedback on addressing current implementation challenges. Student sampling favored students exposed to AR tools over real-world applicability at the expense of methodological rigor.

Data was collected by distributing a structured, self-administered questionnaire to 308 student participants. The research instrument, which was aimed at attaining the research goals, was pilot-tested to ensure reliability and ease of use. It was made available both online using email and learning management systems and offline in classrooms for widest coverage. Anonymity was assured to the participants to obtain candid feedback. Data gathering lasted four weeks, with reminders to facilitate follow-up response. Completed responses were cleaned and compiled to remove inconsistencies and ensure integrity to datasets. The technique allowed for the efficient collecting of large-scale data, making it easier to analyze patterns and trends and provided a strong basis for statistical analysis and result interpretation.

C. Description of the Sample

The demographic sample for this study includes 308 UAE students from diverse study fields, institutions, and communities. To characterize the full population, the study uses stratified random sampling to split it into subgroups based on factors such as gender, academic attainment level, and discipline. This sampling technique makes the data more generalizable while simultaneously providing a detailed depiction of each population segment. According to the 10x rule, the sample size is sufficient to fulfill the requirements of Partial Least Squares Structural Equation Modeling (PLS-SEM). This requirement requires the sample size to be 10 times the indicators of the model's most complicated component [72]. The sample size of 308 is appropriate for statistical analysis since the model in question includes 30 indicators, implying that the sample size would be at least 300. This sampling technique not only provides vital insights into students' behavioral intentions about AR adoption in UAE higher education, but it also assures the results' validity and reliability.

The systematic questionnaire was developed on the basis of the established measurement scales in the literature (see Table 1). The study employed stratified random sampling to enlist 308 students in disciplines and institutions in the UAE to represent the general demographic and academic diversity of the target sample (UAE higher education students). This is a boost in generalizability as the sample reflects the major features of the larger population, including gender, academic level, and area of study [71].

Table 1. Used theoretical constructs

Construct	No. of Items	Source
Performance expectancy (PE)	4	[58, 62]
Effort expectancy (EE)	4	[62, 73]
Social influence (SI)	3	[62, 64]
Facilitating conditions (FC)	4	[62, 74]
Hedonic motivation (HM)	4	[62, 63]
Self-efficacy (SE)	3	[67, 75]
Flexibility (FL)	3	[68]
Behavioral intention (BI)	3	[62]

D. *Data Analysis*

Component-based estimate is employed in the Partial Least Squares (PLS) Structural Equation Modelling (SEM) technique used in this study. Since it enables the simultaneous analysis of the measurement and structural models, this approach is suitable [72]. A model may also be tested with a small sample size (n = 65 in this study). SmartPLS (Version 3.2.8), a software tool that enables users to do route modeling with latent variables using the PLS technique, was used for all statistical studies. First, the conceptual model's measurement and structure are assessed. The structural (inner) model illustrates both direct and indirect unobservable links between constructs, while the measurement (outer) model illustrates the linkages between a construct and its related variables (measurement items) [72]. Tests for validity and reliability were conducted in the measurement of the measurement model. A number of techniques, such as Composite Reliability (CR), Cronbach Alphas, Average Variance Extracted (AVE), and/or communality, may be used to examine construct measurement reliability, also known as internal consistency reliability and indicator reliability. AVE and CR are used in this study to assess reliability. Fornell and Larcker (1981) state that AVE should be greater than the threshold value of 0.5 because it calculates the difference between the variance explained by the indicators and the variance explained by measurement errors. The degree to which indicators measure the related idea is reflected in their internal consistency, or CR.

Scales to measure the constructs (e.g., Performance Expectancy, Effort Expectancy) were adapted from the known instruments used in previous studies [62, 67, 75] to ascertain content validity. Relevance and clarity of the items were further ascertained by pilot testing on half of the sample. Reliability was also tested through Cronbach's alpha, with all the constructs well above the recommended minimum of 0.70 [76], excluding Social Influence (α = 0.569), which was retained on theoretical grounds. Composite Reliability (CR > 0.70) and Average Variance Extracted (AVE > 0.50) were also demonstrated for internal consistency and convergent validity [72, 77]. The survey was done in English, the prevailing medium of instruction for UAE higher education, to avoid translation bias.

IV. Result and Discussion

Table 2 correlations capture the strong interrelationships between the key constructs, with a particularly high correlation between Effort Expectancy (EE) and Performance Expectancy (PE) (r = 0.922), which verifies existing literature that ease of use significantly contributes to perceived usefulness in adopting technology (Venkatesh *et al*., 2003). Behavioral Intentions Towards Augmented Reality (BIAR) is most closely related to PE (r = 0.653), and this suggests students' willingness to implement augmented reality in higher education is significantly motivated by performance expectations. Additionally, descriptive statistics presented in Table 3 indicate that observed values for all the measures are normally distributed since values of skewness fall between −2 and 2 [78]. FC, however, has the greatest excess kurtosis (5.01), which is a peaked distribution and could indicate that there exist differences in access to technology resources underlying it. The explanatory power of the structural model was measured using R^2 values and BIAR's R^2 value indicates moderate explanatory power [72].

To demonstrate internal consistency and convergent validity, the construct measures' reliability was verified using Composite Reliability (CR) and Average Variance Extracted (AVE) [72]. Table 4 shows that all constructs have CR values more than 0.7 and AVE values greater than 0.5, which falls below the recommended reliability threshold [77]. The highest CR value is set for Performance Expectancy (PE) at 0.957, reflecting high internal consistency, while the lowest value is set for Social Influence (SI) at 0.781, which, although lower, is still sufficient. The constructs all have sufficient Cronbach's alpha values too, with PE showing the highest reliability (0.941), further confirming the measurement model's consistency. Discriminant validity was tested by using the [77] Fornell-Larcker criterion (see Table 5), which ensures each construct has more variance in common with its indicators than with any other construct [78]. Additionally, cross-loadings appear in Table 6, wherein each indicator loads most highly upon its own construct, reinforcing discriminant validity and reducing multicollinearity concerns.

Table 2. Correlations

	BIAR	EE	FC	FLX	HM	PE	SE	SI
BIAR	1	0.661	0.313	0.372	0.379	0.653	0.273	0.376
EE	0.661	1	0.244	0.297	0.262	0.922	0.189	0.308
FC	0.313	0.244	1	0.24	0.313	0.222	0.136	0.347
FLX	0.372	0.297	0.24	1	0.198	0.298	0.175	0.196
HM	0.379	0.262	0.313	0.198	1	0.235	0.305	0.759
PE	0.653	0.922	0.222	0.298	0.235	1	0.169	0.298
SE	0.273	0.189	0.136	0.175	0.305	0.169	1	0.239
SI	0.376	0.308	0.347	0.196	0.759	0.298	0.239	1

Table 3. Descriptives statistics

	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness	Cramér-von Mises test statistic
BIAR	2.81	1.04	1.00	−0.02	−0.69	3.46
EE	−3.69	1.00	1.00	0.70	−0.98	2.68
FC	−4.28	1.60	1.00	5.01	−1.66	3.84
FLX	−3.03	1.61	1.00	0.12	−0.16	4.96
HM	−3.69	1.89	1.00	2.01	−0.52	4.19
PE	−3.30	0.94	1.00	1.00	−1.14	3.36
SE	−2.80	1.86	1.00	0.14	−0.62	2.59
SI	−3.51	1.86	1.00	1.10	−0.63	2.51

Table 4. Construct validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
BIAR	0.831	0.83	0.899	0.749
EE	0.898	0.899	0.929	0.766
FC	0.796	0.831	0.866	0.622
FLX	0.866	0.889	0.918	0.788
HM	0.703	0.776	0.816	0.54
PE	0.941	0.941	0.957	0.849
SE	0.674	0.674	0.825	0.615
SI	0.569	0.566	0.781	0.548

Table 5. Descriminant validity fornell larcker creterion

	BIAR	EE	FC	FLX	HM	PE	SE	SI
BIAR	**0.866**							
EE	0.661	**0.875**						
FC	0.313	0.244	**0.789**					
FLX	0.372	0.297	0.24	**0.888**				
HM	0.379	0.262	0.313	0.198	**0.735**			
PE	0.653	0.722	0.222	0.298	0.235	**0.921**		
SE	0.273	0.189	0.136	0.175	0.305	0.169	**0.784**	
SI	0.376	0.308	0.347	0.196	0.659	0.298	0.239	**0.74**

Table 6. Cross loading

	BIAR	EE	FC	FLX	HM	PE	SE	SI
BIAR1	0.92	0.51	0.274	0.309	0.336	0.541	0.223	0.323
BIAR2	0.857	0.586	0.215	0.341	0.226	0.631	0.197	0.274
BIAR3	0.817	0.61	0.32	0.312	0.417	0.52	0.284	0.374
EE1	0.561	0.86	0.189	0.258	0.252	0.757	0.184	0.284
EE2	0.613	0.852	0.193	0.279	0.22	0.781	0.111	0.229
EE3	0.553	0.882	0.221	0.256	0.234	0.792	0.17	0.267
EE4	0.583	0.907	0.251	0.245	0.212	0.894	0.199	0.3
FC1	0.297	0.26	0.858	0.242	0.232	0.259	0.058	0.206
FC2	0.157	0.121	0.671	0.094	0.355	0.103	0.188	0.237
FC3	0.235	0.155	0.699	0.182	0.177	0.133	0.179	0.443
FC4	0.267	0.201	0.902	0.203	0.275	0.171	0.058	0.237
FLX1	0.278	0.217	0.241	0.834	0.204	0.213	0.151	0.169
FLX2	0.32	0.268	0.209	0.911	0.187	0.21	0.215	0.166
FLX4	0.379	0.297	0.198	0.916	0.148	0.35	0.109	0.186
HM1	0.114	0.066	0.154	0.177	0.51	0.042	0.228	0.288
HM2	0.337	0.243	0.275	0.093	0.899	0.22	0.225	0.78
HM3	0.254	0.207	0.206	0.211	0.557	0.168	0.312	0.27
HM4	0.333	0.201	0.261	0.159	0.885	0.197	0.187	0.723
PE1	0.608	0.814	0.181	0.246	0.229	0.907	0.18	0.274
PE2	0.632	0.834	0.189	0.314	0.211	0.904	0.125	0.259
PE3	0.575	0.879	0.212	0.278	0.215	0.938	0.131	0.278
PE4	0.588	0.871	0.236	0.256	0.209	0.936	0.189	0.288
SE1	0.199	0.145	0.13	0.053	0.211	0.103	0.829	0.174
SE2	0.221	0.141	0.147	0.086	0.258	0.108	0.862	0.186
SE3	0.216	0.154	0.042	0.264	0.24	0.182	0.643	0.196
SI1	0.294	0.25	0.226	0.12	0.663	0.284	0.093	0.814
SI2	0.279	0.225	0.304	0.268	0.196	0.2	0.245	0.585
SI3	0.248	0.195	0.231	0.03	0.832	0.16	0.193	0.798

A. Structural Model Analysis

We examined the given hypotheses after establishing the measurement model's validity. Five constructs, Effort Expectancy (EE), Facilitating Conditions (FC), Flexibility (FLX), Hedonic Motivation (HM), and Performance

Expectancy (PE) significantly influence students' behavioral intentions toward teachers' use of augmented reality (BIAR) in higher education, according to the structural model analysis results, which are shown in Table 4. The positive correlation between EE and BIAR ($T = 2.251$, $p = 0.024$) indicates that students will utilize AR-based learning tools more if they feel that they are easy to use, as established in prior UTAUT2 research [62]. Likewise, FC also has a substantial impact ($T = 2.16$, $p = 0.031$), once again affirming the imperative nature of institutional support, technology-related infrastructure, and access to resources in impacting students' intention towards adopting AR in all higher education institutions [65]. The importance of FLX ($T = 2.889$, $p = 0.004$) also indicates that students appreciate the option to control the pace of their learning and look at content as they please, which makes them more inclined to embrace AR technology. Furthermore, HM ($T = 2.055$, $p = 0.040$) indicates that the intrinsic enjoyment of AR applications contributes positively to Students' behavioral intentions becoming consistent with research stressing the significance of hedonic incentive in technology adoption (Hew *et al.*, 2020). Also, PE ($T = 2.168$, $p = 0.030$) supports the evidence that students are likely to adopt AR if they feel it is in their learning achievements and academic performance interest [58].

On the contrary, it is found that Self-Efficacy (SE) marginally contributes to BIAR ($T = 1.861$, $p = 0.063$), i.e., students' belief in their capability for AR adoption contributes to adoption but less predictively than other indicators. This result partially supports hypothesis H6, suggesting that although self-efficacy will be significant, external factors like usability and perceived benefits will play a stronger role in influencing behavioral intention [67]. Social Influence (SI), however, is not significant ($T = 0.275$, $p = 0.784$), and hypothesis H7 is rejected. The finding of SI as not being a strong predictor of AR adoption intentions in the UAE contradicts the majority of UTAUT2-guided studies in Western contexts [62] and warrants further cultural investigation. Future research suggests that this could be a sign of the uniqueness of the UAE's higher education environment, where technology adoption decisions are less peer-influenced and more personalized [45]. UAE emphasis on independent learning initiatives within Vision 2021 [19] and worldwide applicability of independent digital learning content might have also disempowered teacher/peer authority as conventionally exercised. That the same study itself has a teacher-driven (not student-driven) adoption focus for AR can explain variance as well, to the extent that students would perceive AR adoption as institutional instructions instead of peer-mediated choice [79].

Although Self-Efficacy (SE) was statistically significant but to a moderate degree, its sub-optimal magnitude is in line with emerging evidence that learners from technologically enriched cultures like the UAE could overestimate basic digital literacy [46]. Widespread promotion of government-funded digital literacy schemes (National Innovation Strategy, for instance) may have created a baseline level of self-efficacy such that SE differences were no longer indicative of intention to use ubiquitously present technologies like AR. However, more recent studies caution that such an impact is possibly entry-level AR app-specific since more advanced applications continue to be strongly SE dependent [16]. This suggests the need for intensified training initiatives – a specification that could be addressed by future UAE studies through differentiating between basic and advanced AR tools. This would imply that student uptake of AR in tertiary education is not influenced by teacher or peer but to a limited extent, in contrast to traditional UTAUT2 model anticipation [62]. Maybe due to the presence of other significant motivators for the students such as personal gain and usability prior to social persuasion upon using AR for their learning procedures

1) Path coefficients and significance levels

As shown in Table 7, the path coefficients indicate the strength and significance of the relationships between the model's constructs.

Table 7. Total effect

	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P-Values	Remarks
EE ≥ BIAR	0.125	2.251	0.024	Accepted
FC ≥ BIAR	0.04	2.16	0.031	Accepted
FLX ≥ BIAR	0.047	2.889	0.004	Accepted
HM ≥ BIAR	0.07	2.055	0.040	Accepted
PE ≥ BIAR	0.129	2.168	0.030	Accepted
SE ≥ BIAR	0.047	1.861	0.063	Accepted
SI ≥ BIAR	0.067	0.275	0.784	Rejected

2) R^2 values for behavioral intentions

Table 8. R square

	R-square	R-square adjusted
BIAR	0.532	0.521

Table 8 reveals that behavioral intentions towards instructors' use of augmented reality (BIAR) have an overall R^2 value of 0.532 and an adjusted R^2 value of 0.521. This means that the independent variables in the model can explain 53.2% of the variance. According to [62], behavioral intention studies based on the UTAUT2 model explain 40-70% of the variance, indicating moderate to high explanatory power.

3) Predictive relevance

As shown in Table 9 Predictive MV Summary, Q^2predict values of (0.308–0.397) ensure the model has sufficient predictive power since higher than zero values indicate predictive relevance [80]. In addition, smaller values of PLS-SEM RMSE and MAE compared to linear regression (LM) and indicator-based approach (IA) indicate that PLS-SEM makes better predictions.

However, the results show that students' behavioral intentions to adopt AR in higher education are significantly influenced by effort expectancy (H1, T statistic = 2.251, $p = 0.024$), facilitating conditions (H2, T statistic = 2.16, $p = 0.031$), flexibility (H3, T statistic = 2.889, $p = 0.004$), hedonic motivation (H4, T statistic = 2.055, p = 0.040), performance expectancy (H5, T statistic = 2.168, p = 0.030), and self-efficacy (H6, T statistic = 1.861, p = 0.063). These results suggest that students' intention to use AR in the classroom is higher when they think they have sufficient self-efficacy and institutional support, as well as when they see AR technology as practical, adaptable, enjoyable, and simple. This is further illustrated in Fig. 2. Result of the Structural Path Model indicating the path with hypothesis for each of the construct in the model. Additional details can be found in Appendix Fig. A1, which presents the original SmartPLS output.

Table 9. Predictive MV summary

	Q²predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE	IA_RMSE	IA_MAE
BIAR1	0.308	0.816	0.516	0.877	0.562	0.98	0.751
BIAR2	0.371	0.879	0.57	0.93	0.562	1.108	0.813
BIAR3	0.397	0.567	0.424	0.522	0.373	0.73	0.622

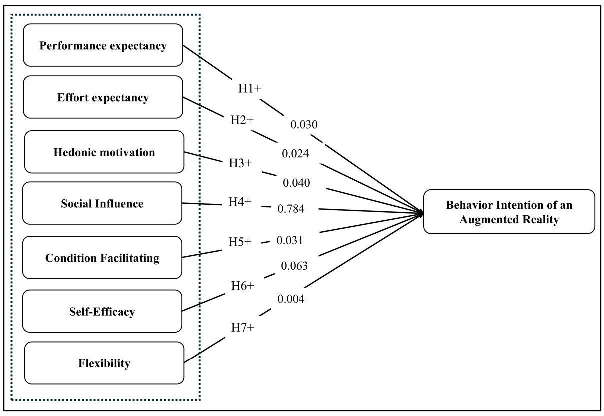

Fig. 2. Results of the structural path model.

V. DISCUSSION

The findings show a trend of UAE universities' t AR adoption—practical students' needs over social factors. In a nation going wholeheartedly for technology-driven education in terms of Vision 2021, students consistently assess AR tools as per their helpfulness (performance expectancy) and simplicity of use (effort expectancy), which is reflective of the UAE culture of efficiency and resourcefulness. The surprising absence of social influence reaffirms this pragmatism: in contrast to collectivist learning environments where adoption is peer-induced, UAE learners' esteem utilitarian usefulness, as found in prior technology adoption research in achievement contexts [62]. But the muted presence of self-efficacy indicates an unaddressed conflict—although students feel that they are competent in general with AR, use remains superficial without formal training, an absence also noted in early e-learning adoption [54].

Consistent with other research, this study demonstrates that students' intention to use augmented reality (AR) in educational contexts is positively impacted by effort expectancy, enabling environments, hedonic incentive, and perceived ease of use. As with other studies that highlighted the importance of perceived size ease of use as a factor in technology acceptability [54, 62], effort expectancy was also shown to be a significant predictor. If it is convenient for students to use AR, they will definitely develop positive attitudes towards using it in learning environments [59]. This verifies that technological devices must be designed with user-friendly interfaces to comfortably fit into learning environments [81]. Likewise, facilitating conditions were a significant factor, showing that availability of resources, technical assistance, and institutional preparedness have great impacts on students' behavioral intentions which is in line with [82, 83]. Hedonic motivation was also an important predictor, showing that enjoyment and involvement of students in AR-enhanced learning are positively linked to their intention to use the technology.

Prior studies have also established that interactive and immersive learning spaces enhance performance and motivation among students [40, 84]. The engagement opportunity allowed by AR can facilitate the enhancement of higher cognitive processing and knowledge retention, based on prior studies on gamified learning spaces [85]. Conversely, social influence was not a good predictor of behavior intention, as opposed to the earlier research where teacher support and peer support were major determinants of technology acceptance [42]. Such disparity suggests that AR adoption would be an internal force rather than an external pressure. The study also confirms that perceived utility is a significant motivation for technology adoption, supporting the significance of performance expectancy in affecting students' behavioral intention [42]. Students are more inclined to use Augmented Reality (AR) as a learning tool if they understand how, it might improve their performance. The Technology Acceptance Model (TAM), which states that perceived utility directly affects technology adoption, is consistent with this [54, 55]. Furthermore, the prediction was significantly influenced by self-efficacy, indicating that students' conviction in using AR and executing it correctly affects acceptance [75, 85].

This is in agreement with findings that suggest greater technological self-efficacy among students is more likely to find them employ technology-based learning resources [86]. The non-significant effect of task value, however, contradicts earlier research which suggests a positive correlation between learning task importance perception and technology use [87]. This contradiction occurs due to the novelty of AR technology, which may override students' inner satisfaction with learning processes in affecting behavioral intentions [84]. Effectively, the study corroborates the set of evidence substantiating the flexibility of learning contexts [85, 88]. AR's ability to deliver individualized and adaptive learning experiences remains a driving factor for learners' adoption of the technology. That evidence is confirmed by the existence of a likelihood that students would desire to engage with adaptive and autonomous learning technologies regardless of learning need [89]. The findings' implications highlight the need to make AR applications congruent with the learning habits and support systems of students in the institution. Together, these results form a three-dimensional picture: UAE students will embrace AR, but universities have to meet their demand for seamless, value-rich experiences with multitiered support that builds trust. This story doesn't just recount the findings; it puts the spotlight on rollout—visionary AR design that harmonizes with the UAE's collaborative culture of ambition and self-directed learning.

A. Contribution to the Theory and Practice

This study specifically combines the UTAUT2 model with the UAE higher education contextual factors (e.g., national innovation plans, cultural orientations towards AR) in an effort to provide some of the recent empirical analysis of student behavioral intentions within the region. Compared to existing AR adoption studies in terms of technical feasibility or global trends, it provides actionable insights to UAE decision-makers by measuring performance expectancy and institutional support as the primary drivers of adoption—and charting the negative facilitator role of social influence, a Western context divergence [44, 62]. Methodological strictness (PLS-SEM under stratified UAE sampling) also differentiates from qualitative/theoretical contributions.

Similarly, theoretically significant by expanding the corpus of research on AR adoption in the United Arab Emirates and confirming TAM and UTAUT in the AR domain. Our study indicated that contextual elements such as learning environment and task value were not predictors of AR adoption, but that technology characteristics and cognitive individual approaches had an impact on students' behavioral intention. This emphasizes the prominence of perceived usefulness in influencing students' intention to use AR technology in line with the appeal for examining user-centric design of AR technology. Our results also point towards investigating the way cognitive strategies merge with AR adoption to establish even stronger theoretical explanations for technology acceptance in learning.

The implication that AR enhances students' academic self-efficacy renders its implication as a change agent in higher education, challenging professors to implement AR-based learning activities in the class. The above findings also legitimize the establishment of systematic training programs to teach educators the competency to implement AR technologies in class. Besides, the positive influence of technology attributes on students' AR usage intention implies that system developers need to prioritize features that are easy to use and enjoyable. It also suggests that investments in AR infrastructure and training for personnel need to be made so that institutions of higher learning have the necessary resources to enable the mass adoption of AR in institutions of higher learning. Furthermore, it extends the UTAUT2 theory by integrating technology-enhanced learning context factors, thereby connecting current educational theories most significantly [66] theory of self-efficacy and [54] Technology Acceptance Model to current AR adoption research. In presenting evidence of how performance expectancy and institutional support are more influential than social influence in the UAE context, it presents culture-enriched extension of these theories underlying them while providing new evidence for employing immersive technologies in teaching.

B. Limitations of the Study and Future Research

Though this study provides insightful results on AR adoption in higher education, some limitations must be mentioned. The sample size is one primary limitation, which could limit the applicability of the findings to a broad population of students. A broader and representative sample across multiple institutions and disciplines could make the findings more credible. In addition, the cross-sectional nature of the study constrains the ability to determine causality between the factors that were examined. Longitudinal research could uncover more about the temporal dynamics of students' perceptions and behavioral intentions toward AR. Future studies would also be well advised to explore qualitative approaches to understanding students' experiences with AR in greater depth, and how contextual factors influence adoption in dynamic learning environments

VI. Conclusion

This study examined the most significant factors affecting students' behavioral intention towards AR adoption in UAE universities, offering theoretical and practical contributions. The findings reveal that the adoption of AR by students was primarily impacted by individual cognition factors (self-efficacy, hedonic motivation) and technology characteristics (performance expectancy, effort expectancy), and remarkably, social influence and task value had insignificant effects. These results validate TAM's and UTAUT's applicability in AR settings while pointing to cultural nuances—UAE students prioritize functional utility and convenience over peer or instructor influence, as the nation is oriented around self-directed, technology-facilitated learning as laid out in Vision 2021.

The study offers three main implications for practice: (1) institutions must invest in high-quality AR hardware and teaching staff development to cope with facilitating conditions; (2) AR tools have to be designed with intuitive interfaces to achieve maximal effort expectancy; and (3) pedagogical integration should aim at active, experiential learning in a bid to leverage hedonic motivation. For future studies, longitudinal research can track how extended AR exposure changes adoption patterns, and qualitative studies can explore why task value—usually of primary interest in learning theories—had minimal impact in this environment. Combining theoretical models with regionally specific evidence, this research not only adds to AR adoption scholarship but also equips UAE educators and policymakers with actionable strategies

Appendix

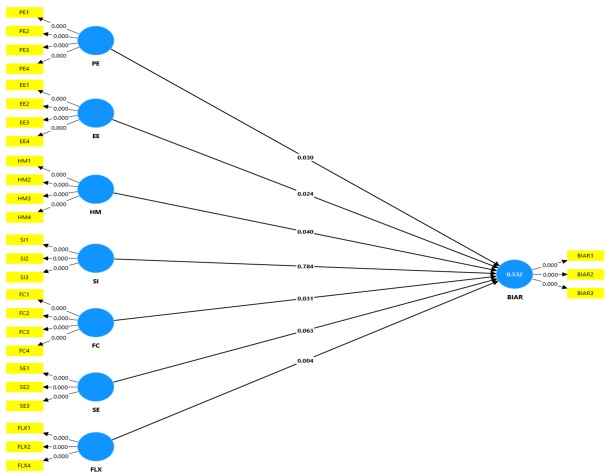

Fig. A1. Original SmartPLS output.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

R. T. A. is a Ph.D. student who designed and conducted the research, analyzed the results, and wrote the manuscript, holding all responsibilities related to it as the corresponding author. The supervisors, N. A. A. and N. L. A., reviewed the work and provided critical feedback and corrections. M. F. A. and L. M. A. contributed to data interpretation and provided technical and editorial support during the manuscript preparation. All authors have read and approved the manuscript for submission.

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