

Investigating the Factors Influencing Augmented Reality Adoption in Blended Learning Environments for Mechanical Engineering Degree Students at the University of Malta

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Abstract—This study investigates the acceptance and utilization of Augmented Reality technology among mechanical engineering students in higher education at the University of Malta, utilizing the Unified Theory of Acceptance and Use of Technology model and the Community of Inquiry framework. The research was conducted in three phases: developing lecture scenarios incorporating AR elements, delivering these scenarios, and analyzing the data using structural equation modelling with SPSS and AMOS. Findings reveal that Performance Expectancy, Effort Expectancy, Hedonic Motivation, and Cognitive Presence significantly influence Behavioral Intention, while Social Influence, Habit, and Price Value do not. Moreover, Facilitating Conditions and Behavioral Intention significantly influence Use Behavior. Most notably, Cognitive Presence from the COI framework emerges as a critical element, highlighting the significance of fostering learners' cognitive engagement to promote AR technology adoption in blended learning environments.

Keywords—augmented reality, technology acceptance, higher education, engineering education, Unified Theory of Acceptance and Use of Technology (UTAUT), community of inquiry

I. INTRODUCTION

Augmented Reality (AR)-based technology represents a transformative tool in the educational landscape, offering innovative ways to enhance learning and teaching. AR is a technology that combines real-world content captured by IP cameras with virtual, computer-generated elements, usually through devices such as tablets, smartphones or AR glasses [1]. Contrary to Virtual Reality (VR), which engages users in a completely virtual world, AR enriches the real world by overlaying digital information onto it [2]. Augmented Reality (AR) was specifically chosen for this study due to its unique ability to enhance student engagement and comprehension. Several studies show that AR applications positively impact learning and such technology has been effectively integrated across various educational levels, disciplines, and settings, offering multiple benefits for students. Amongst the highly cited benefits posed by AR include enhancing learners' engagement and motivation, enabling the visualization of abstract or complex concepts, offering hands-on learning experiences, encouraging collaboration and social learning, assisting students to develop digital skills, and preparing them for future careers in a technology-driven world [3].

The concept of AR has been around since the 1950s, with early developments in the fields of computer graphics and user interface design. However, it wasn't until the early 21st century, with the advent of advanced smart mobile devices and robust software platforms, that AR became accessible to the general public and viable for educational applications [4]. Madden *et al.* [5], singles out the year 2010 as an inflection point towards the exponential growth of AR in education which concurrently coincided with the emergence of mobile AR technology. Another two significant drivers which pushed the use of AR in education in the past decade included the launch of Google Glass in 2014 and the release of 2016 Pokémon Go game [6]. Gazon *et al.* [7], argue that these factors combined highlighted AR technologies, drawing the attention of developers worldwide to create educational AR applications. Moreover, new MAR systems have been created that do not require users to have programming skills. With access to these resources, teachers and students can easily create their own MAR learning artefacts and interact with digital objects in various formats [8]

Notwithstanding the extensive research work focusing on AR in education highlighting the positive outcomes, Kljun *et al.* [3], the use of this technology in educational institutions is still in its early stages, especially when compared to the more established studies on technologies like multimedia and web-based platforms in education. Moreover, a review carried out by Prieto *et al.* [9], reveals that the current studies on educational AR applications are still rather 'shallow'. Additionally, the proposed study assumes greater significance when considering that studies on the use of AR focusing on tertiary learners are still limited. A study conducted by J. Gazon *et al.* [10], indicates that the majority of the studies on the use of AR in education focus on secondary education (32.8%), followed by primary education (32.7%) and lastly, and tertiary level learners (29.5%).

Hence, while research on educational AR is still emerging, a significant gap exists in understanding the factors that influence students' willingness to adopt AR in their learning processes. Specifically, there is limited exploration of how these factors intersect with the ongoing paradigm shift toward student-centered learning, grounded in constructivist pedagogy. While constructivist approaches emphasize designing learning environments that foster deep understanding and lifelong learning, research often overlooks

how these pedagogical shifts affect students' adoption of new technologies like AR [11]. This gap is crucial, as many studies focus primarily on the technical aspects of AR, neglecting the student's learning needs and behavioral intentions. Understanding these factors is essential for educators to effectively integrate AR into curricula, ensuring its potential translates into meaningful educational outcomes. These arguments along with the limited information on AR integration in Maltese Higher Education institutions provide a clear rationale and strengthen the justification for conducting the current study.

Within this context, this study aims to investigate the learners' behavioural intentions towards the use of AR-based technology. The key objectives include (1) identifying the factors that influence students' intentions to adopt AR technology in their learning processes, (2) exploring the relationships which emerge from among these factors and (3) lastly evaluating the influence of each element on the learners' behaviour intention.

In this study, the AR-based technology was implemented in a blended learning environment setting. B. Tomlinson and C. Whittaker [12], defines blended learning as the combination of in-person teaching with computer-based technologies, including both online and offline activities and materials. Another highly cited definition of blended learning is that suggested by Graham [13], who defined as the combination of face-to-face instruction with computer-mediated instruction. Chien *et al.* [14], even coined the term Augmented Reality-based Blended Learning (ARBL) to describe a pilot study that combined traditional face-to-face classroom instruction with the use of MAR technology. The decision to carry out this study within a blended learning environment rather an exclusive online environment stems from the different studies which suggest that blended learning results in improved learning outcomes and increased motivation, with the potential to enhance learner-focused teaching and learning initiatives [15].

The target student population for this study included first, second and third-year students enrolled in higher education mechanical engineering degree programs at the University of Malta. A meta-analysis on the use of AR in different higher educational fields reveals that only 6.6% of studies targeted the use of AR within engineering, manufacturing and construction areas [10]. This result further reinforces the argument that there is still a lot to develop in this field. The research was implemented into three primary phases. The first phase entailed developing several lecturing scenarios which include elements of AR in the lecturing material, secondly, the delivery of these lecturing scenarios and data collection. The third phase included data analysis and interpretation.

II. LITERATURE REVIEW

The research model presented in this research is an amalgamation of the UTAUT 2 model and the COI model. Both models are explained in further detail hereunder:

A. UTAUT2 Model

Researchers have explored various theoretical models to identify factors influencing individuals' behavioral intentions toward technology use. Notable models include the Theory of

Reasoned Action (TRA), the Theory of Planned Behavior (TPB), the Technology Acceptance Model (TAM), the Combined TAM and TPB model (C-TAM-TPB), the Motivational Model (MM), and the Innovation Diffusion Theory (IDT). In certain contexts, these models have been combined or extended with additional factors to better capture the complexities of technology adoption behaviors. Collectively, they account for approximately 30% to 60% of the variance in users' behavioral intentions to use technology [16]. However, in 2003, Venkatesh *et al.* [16], consolidated eight of these models and developed the Unified Theory of Acceptance and Use of Technology (UTAUT) model. UTAUT is a framework devised to predict technology acceptance in organizational settings. The application of the UTAUT model in this study was considered from very early stages given the model explains a higher (70%) percentage of the variation when compared to other models which thus provides an upper explanatory power compared to other relevant models and theories in Information System (IS) and Information Technology (IT) acceptance context.

Since its inception, UTAUT has been utilized by numerous scholars. According to M. Williams *et al.* [17], the UTAUT is among the most commonly utilized models in the field of technology acceptance, focusing on the technological factors that contribute to the successful implementation of information systems. Additionally, a meta-analysis by S. Walldén *et al.* [18], which reviewed 69 published studies, determined that UTAUT is a valid and reliable model, supported by extensive empirical evidence.

B. COI Model

Furthermore, whilst several authors conclude that the use of AR applied in an educational context improves learning performance and the student's cognitive and affective skills, there is a lack of empirical research examining the role of cognition in these interactions that cognition plays in supporting learning in such settings [19]. E. Eldar *et al.* [20], conclude that human action is formed through cognitive processes. Hence, to further enhance the research being conducted, this study adopts the extended UTAUT model proposed by Q. Ruobing and Y. Zhonggen [21]. This model extended the UTAUT model by amalgamating the "Cognitive Presence" construct from the Community of Inquiry Constructs (COI).

The CoI framework, developed by D.R. Garrison, T. Anderson, and W. Archer [22], is a theoretical model designed to structure the learning process in online environments. Grounded in Dewey's (1933) theoretical perspectives, it is characterized as a comprehensive and unified framework for a transactional educational experience, primarily designed to guide and oversee the process of collaborative thinking and learning [23]. This concept asserts that significant learning experience should be based on a reflective investigation process that involves four phases: a triggering event, exploration, integration, and resolution. Later studies have also applied the COI model in blended learning classroom settings, rather than limiting its use exclusively to online learning [24].

Besides the need to carry this study, described in the Introduction, a minor contribution to this study is the

combination of the UTAUT2 model with the COI model, instead of using the original UTAUT model as proposed by Qin and Yu [21]. Research indicates that UTAUT2, with its proposed extensions, significantly enhances the explained variation in behavioral intention (ranging from 56% to 74%) and technology use (ranging from 40% to 52%) when compared to the original UTAUT model [25]. Secondly, whilst the model proposed by Ruobing, and Zhonggen has been applied to an online learning platform, in this study, the model will be applied in a blended learning environment.

Overall, this research approach is believed to foster a more learner-centred focus in the adoption of AR-based learning technology, rather than emphasizing the technical aspects of AR. The amalgamation of the UTAUT2 model and the COI model into one research model is presented in Fig. 1 below. The upper box within the diagram highlights the constructs and hypothesis adopted from the UTAUT 2 model whilst the lower box with a dashed outline highlights the key constructs adopted from the COI model. In the model developed by Qin and Yu [21], the authors also include an additional three constructs i.e. teaching presence, social presence and collaborative learning as key factors influencing cognitive presence. However, these constructs were not considered given that the focus of the study was on highlighting the key factors affecting behaviour intention and subsequently, actual usage. Moreover, excluding these three additional constructs was also essential to keep the questionnaire instrument as concise as possible. The key constructs and the related hypothesis are explained below.

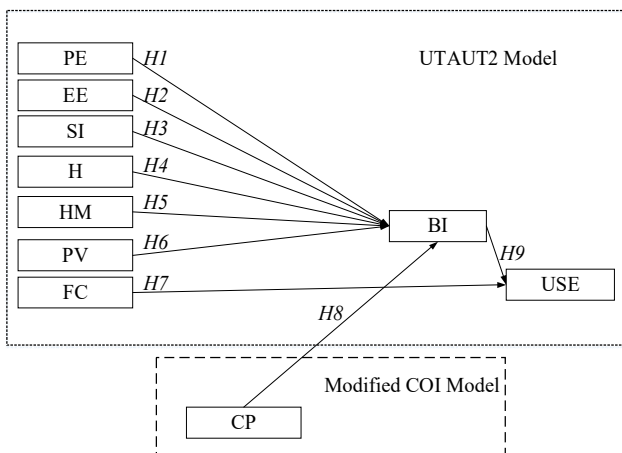


Fig. 1. Extended UTAUT2 research model. adopted from Qin and Yu [21].

Performance Expectancy (PE) is described as the extent to which an individual believes that utilizing the system will enhance their job performance [16]. Studies have consistently shown that PE has a positive influence on determining the UB (user behaviour) of proposed technologies across various research contexts [26–29]. Hence, the first hypothesis in this study has been formulated as follows:

Ho1: PE will have a significant influence on the learners' behavioural intention to use the AR authoring platform.

Effort Expectancy (EE) is described as the perceived ease of using the system [16]. Studies conducted by Paulo *et al.* [26], Venkatesh *et al.* [30] and Lin [31], all confirm a positive relationship between effort expectancy and usage behaviour. Within the scope of this research, these studies indicate that if the learner feels that the AR authoring platform is easy to use

and provides benefits, there is an increased likelihood that the use of the proposed technology is higher. Nevertheless, it should also be noted that other studies particularly those carried out by Madigan *et al.* [27] and Maillet *et al.* [32], have not yielded any significant relationship between EE and UB. These inconsistencies provide an opportunity for further investigation by testing the following hypothesis:

Ho2: EE will have a significant influence on the learners' behavioural intention to use the AR authoring platform.

Social Influence (SI) is defined as the extent to which an individual perceives that significant others (such as colleagues, friends, or authority figures) believe they should adopt a particular technology [16]. Given these conclusions, it is hypothesized that:

Ho3: SI will have a significant influence on the learners' behavioural intention to use the AR authoring platform.

Despite the broad acceptance of UTAUT, Venkatesh *et al.* [30], introduced three additional constructs—habit, hedonic motivation, and price value—into the model, resulting in UTAUT2. In comparison to the UTAUT, these extensions in UTAUT2 significantly improved the variance explained in behavioural intention and technology use. The three additional constructs are defined hereunder:

Habit (H) has been described as the extent to which individuals tend to engage in behaviours automatically due to learned patterns or associating habit with automaticity [30]. Although the concepts are similar, the habit has been measured in two distinct ways: first, as past behaviour and second, as the degree to which a person perceives the behaviour as automatic [33]. These conclusions lay the foundation for the following hypothesis:

Ho4: H will have a significant influence on the learners' behavioural intention to use the AR authoring platform.

Hedonic Motivation (HM) alludes to the enjoyment or pleasure gained from using technology and plays a crucial role in the acceptance and use of technology. In information systems research, this concept, often termed perceived enjoyment, has been demonstrated to directly influence technology acceptance and use [34].

Ho5: HM will have a significant influence on the learners' behavioural intention to use the AR authoring platform.

Price Value (PV). For Venkatesh *et al.* [30], a key comparison between consumer use settings and the organizational use settings for which UTAUT was developed is that consumers typically incur the financial cost of using technology, whereas employees do not. This difference in cost and pricing structure can significantly influence consumers' technology usage.

Ho6: PV will have a significant influence on the learners' behavioural intention to use the AR authoring platform.

Facilitating Conditions (FC) refers to the extent to which an individual believes that the organizational and technical infrastructure is in place to support the use of the system. These conditions have a direct positive influence on the intention to use, though this effect becomes insignificant after initial use. As a result, the model suggests that facilitating conditions exert a significant direct impact on actual usage behavior [16]. Within this context, the following hypothesis has been formulated:

Ho7: FC will have a significant influence on the learners' behavioural intention to use the AR authoring platform.

use behaviour of use AR authoring platform.

Cognitive Presence (CP): As mentioned earlier, the cognitive presence construct has been extracted from the COI model. For Garrison *et al.* [22], cognitive presence is the degree to which learners are able to build and validate meaning through continuous reflection and dialogue within a thoughtful and collaborative learning community. Within the COI model, the Practical Inquiry (PI) model is a framework used to guide and analyze cognitive presence within educational settings, particularly in online and blended learning environments. Within this context, the following hypothesis has been formulated:

Ho8: CP will have a significant influence on the learners' behavioural intention to use the AR authoring platform.

Behavioural Intention (BI): Consistent with the foundational principles of all intention-based models, V. Venkatesh *et al.* [16], predicts that Behavioral Intention (BI) will have a significant positive impact on the learners' usage behaviour (USE) of the AR authoring platform.

Ho9: BI has a significant influence on the learners' actual usage of the AR authoring platform.

III. MATERIALS AND METHODS

A. Participants

The research being conducted will focus on learners enrolled in bachelor mechanical engineering degree programs at the University of Malta. To increase the learners' participation in the study as much as possible it was decided to open the study to all the enrolled mechanical engineering students at the University of Malta in their first ($N = 74$), second ($N = 28$) and third year ($N = 47$) of their studies.

B. Application Design and Content

An important consideration taken during the very early stages of the research was the selection of hardware and software resources to create a robust AR-based learning environment that engages learners and meets educational objectives. The primary hardware needed for AR-based learning environments includes smart devices which can be grouped into tablets, AR glasses or smartphones. The majority of research publications emphasize the latter device due to its widespread availability among students and presents benefits such as portability, encouragement of high social interactivity, and independent operability [35, 36]. Hence, it was decided to opt for smartphones combined with an AR platform which can be easily accessible to students. The AR experimental tool employed in this study is Zapworks which is an online platform developed by Zappar that allows educators to create augmented reality (AR) experiences. This platform offers tools for designing and deploying interactive AR content, including 2D and 3D animations, object recognition, and spatial interactions. T. Serdar suggest that 3D animations help to enhance students' visualization and comprehension rather than 2D views [37]. The Zappar AR app was selected because it is already licensed to the University of Malta, eliminating any associated costs for its use. Additionally, this AR authoring platform is versatile, supporting various devices such as smartphones, tablets, and PCs.

The whole process was initiated with the design and development of the 3D models. For the scope of the study, all the content was developed by the lecturer using 3D CAD modelling software. Once developed, the 3D models were imported into ZapWorks. It was decided that the best way for students to trigger and view the models is through the generation of distinct QR codes. Once the QR code was developed, the AR experience was tested using Android and iOS smartphones. Lastly, the QR codes generated were integrated into various sections of lecturing material provided to the students.

The subject and the selection of the unit/subject for the development of AR-based learning environments was also another careful consideration. The selection of this unit was guided by the fact that it is a subject consistently taught to first-year, second-year, and third-year engineering students. This approach ensures continuity and uniformity across the cohorts, making it a suitable choice for analysis. Opting for a single subject across multiple years also avoids the complexity and variability that would arise from selecting different subjects for each year group, thereby facilitating a more streamlined and comparable evaluation.

As outlined in the Introduction, it was decided to develop demonstrations/lecture plans which incorporate elements of Augmented Reality (AR) into units/subjects related to Engineering Drawing. The first AR-based demonstration focused on "Section Views," was designed specifically for first-year students pursuing a Bachelor of Engineering (honours) in mechanical engineering. The second demonstration delves into the topic of "Working Drawings and Assemblies," targeting second and third-year students enrolled in the Bachelor of Engineering (honours) in mechanical engineering. Both demonstrations also included collaborative exercises where students were divided into small groups and through the use of Zappar AR app were asked to explain how different components interact in the final assembly of a product. This exercise was aimed to promote shared learning and discussion, encouraging students to construct collective knowledge. Following the topic selection, the learning objectives and material for each identified lecture plan were clearly outlined. Identifying the skills and knowledge that learners should acquire through AR-based learning scenarios was essential. The Zappar AR app will allow students to visualize and interact with 3D models, enabling them to understand complex engineering drawings in a more immersive and hands-on manner. This active involvement in learning aligns with the constructivist approach, which prioritizes learning by doing [11].

C. Instrument Development

Data was gathered using a self-administered questionnaire with forty-three statements. Through the survey, a small group of individuals can define the attributes of a larger population. The questionnaire was divided into two sections. The first section, focused on descriptive analysis, included general questions for the participants related to their age group, gender and their level of experience with AR.

The second section of the questionnaire includes the measurement items for all constructs, covering both dependent and independent variables. As explained earlier,

these constructs were adopted and structured based on a thorough review of the UTAUT model and the COI model. The detailed statements, the expected direction of correlation and the sources are listed in Table 1. As indicated in Table 1, the constructs namely, performance expectancy, effort expectancy, social influence, facilitating condition, behaviour intentions and usage behaviour were adopted from the original UTAUT model developed by Venkatesh *et al.* [16]. The three constructs i.e. hedonic motivation, price value, and habit were adopted from the UTAUT2 model [30]. Lastly, the cognitive presence construct was taken from the Community of Inquiry (CoI) framework [22].

The questionnaire presented statements to participants using a five-point Likert scale, ranging from “strongly agree” to “strongly disagree.” Lastly, the item “Other Remarks” section was added to the last part of the questionnaire to enhance the depth, richness, and flexibility of the questionnaire, providing important qualitative insights and helping to ensure that participants’ perspectives are fully captured and allowing the respondents to clarify any responses.

D. Data Collection Methods

This study adopted a quantitative approach through the use of a questionnaire. Following an official invite sent from the Registrar’s Office, engineering students were invited to take part in an AR-based demonstration described in the previous section. The data collection was performed by distributing self-administrated questionnaires following the AR-based demonstration. Data was collected during the last semester of the 2023/2024 academic year. In total, there are 149 registered first, second and third-year engineering students. A sample size of 108 respondents was required to guarantee a 5% margin of error at the 95% confidence level. Thus, at least 108 valid questionnaires were required to fulfil this analysis. Following the demonstration, a total of 118 responses were received which resulted in 109 valid responses after excluding the invalid questionnaires. The response rate is 73.2% and the sample size (109) guarantees a 4.88% margin of error at the 95% confidence level, which is acceptable for Partial Least Squares Structural Equation Modeling (PLSSEM). However, 109 responses are adequate for PLS-SEM, considering that the “10-times rule” method, a commonly used approach for determining minimum sample size in PLS-SEM, suggests that the sample size should be a minimum of 10 times the highest number of inner or outer model links directed toward any latent variable in the model [38]. Google Forms, a cloud-based software for online survey development was used to collect data from the participants. Prior to the survey, participants were required to complete an electronic consent form. The form clearly informed them that they could withdraw from the study at any time without any negative consequences.

E. Evaluation of the Research Model

After completing the research methodology and data collection stages, the next phase involves selecting appropriate data analysis methods and techniques. In this study, Structural Equation Modeling (SEM) was adopted to examine the structural relationships among nine constructs

and the actual usage of the AR-based Zappar learning platform. Adhering to the two-step approach recommended by Hair [39], the study first assessed the measurement model to ensure validity and reliability and then evaluated the structural model to test the research hypotheses and determine the model’s overall suitability.

IV. RESULTS AND DISCUSSION

This section outlines the outcomes of the gathered data across three main subsections followed by a discussion. In the first subsection, descriptive statistics will be presented. As outlined in the previous section, the following two stages present the results emerging from the measurement model analysis and the structural model analysis.

A. Descriptive Statistics

The initial section of the results aims to present demographic data. As shown in Table 1, the significant majority of respondents were male (72.48%). This outcome sheds light on the persistent issue of gender gap in engineering education. The gender gap refers to the substantial imbalance between the number of men and women entering, studying, and working in engineering fields. This result is consistent with other studies, suggesting that female students are also underrepresented in local engineering education programs [40].

Table 1. Respondents’ demographic data (N=109)

Question	Options	Frequency	%
Gender	Male	79	72.48
	Female	30	27.52
	Prefer not to say	0	0
Age Group	Below 20	55	50.46
	21 to 30	54	49.54
	31 to 40	0	0
	41 to 50	0	0
	51 plus	0	0
Estimate the level of experience with AR	No experience	45.00	41.28
	Novice	50.00	45.87
	Intermediate	13.00	11.93
	Expert	1.00	0.92

The next demographic result relates to the age group. Data shows that 50.46% are below the age of 20 whilst 49.54% fall within the age bracket of 21 to 30. This result was expected given that first-year students are usually around 18–19 years old, as they often enter university directly after completing sixth-form. Second-year students tend to be 19–20 years old while third-year students are typically 20–21 years old. Lastly, the students were asked about their level of experience using AR. The results strongly indicate that an overwhelming majority of students (87%) have little to no experience with AR. The student’s lack of familiarity with technology reinforces the need for training. Thus, it is crucial that before assessing the effectiveness of AR technology, students are presented with structured training sessions to develop the technical skills and confidence necessary to interact effectively with AR tools.

B. Measurement Model Analysis

The primary step of the structural equation modelling involves the assessment of the measurement model particularly the determination of convergent and discriminant

validity. Validation of the dataset is crucial in addressing potential biases, as it ensures the accuracy, consistency, and representativeness of the data used in the methodology. Several tests were carried out to ensure the convergent validity and reliability of the measurement model. Listed in Table 2, the tests conducted include Factor Loadings (FL), Cronbach's Alpha (α), Average Variance Extracted (AVE) and Composite Reliability (CR). The initial result in Table 1 is Factor Loadings which represent the relationship between observed variables and their corresponding latent variables. They indicate how much each observed variable contributes to a particular factor, essentially quantifying the strength and direction of the association. Loadings of 0.5 or higher are often considered satisfactory, with values above 0.7 being preferable. Hair *et al.* [38], advise opting for loadings higher 0.708 as it is considered acceptable because it demonstrates that the construct explains over 50% of the variation in the indicator, ensuring satisfactory item reliability. A closer look at the results achieved shows that one item CP1, has a factor loading lower than 0.708. However, CP1 was still considered since the result is still considered a good loading, suggesting a strong association.

Reliability analysis using Cronbach's Alpha (α) comes next. The reliability test measures the degree to which the constructs being studied are consistent in what it is intended to measure. A Cronbach's alpha value of 0.7 or higher is generally considered acceptable in most scientific research studies [38]. From Table 2, it can be observed that the Alpha value of the latent variables exceeds 0.7 thus, suggesting adequate internal consistency. Composite Reliability (CR) is also a measure of internal consistency in scale items. According to Hair *et al.* [38], CR is often preferred in SEM because it takes into account the actual loadings of indicators and provides a more accurate representation of a construct's reliability, especially when the indicators do not have equal loadings. Values ranging between 0.70 to 0.95 are generally regarded as satisfactory to good. A reliability of 0.95 or higher suggests that the individual items are measuring the same concept, making them redundant. The conclusions from Table 2 show that the CR values exceed the recommended level of 0.7 and are less than 0.95.

Another important step in CCA is the assessment of convergent validity which can be measured using the Average Variance Extracted (AVE). AVE is obtained by averaging the indicator reliabilities of a construct. This metric is a measure of how well indicators of a specific latent variable correlate with each other, showing that they are indeed measuring the same construct demonstrating whether the items used can reflect a construct [41]. The criterion for AVE is the value should be 0.5 or higher [38]. The results in Table 1 show that the AVE values for all constructs are higher than 0.5 thus indicating evidence of good convergent validity.

To investigate factorial validity the KMO (Kaiser-Meyer-Olkin) and Bartlett's test of sphericity were performed. The KMO evaluates the overall adequacy of the data for factor analysis, while Bartlett's test examines whether the variables in the dataset are sufficiently correlated to justify proceeding with factor analysis. If the KMO value exceeds 0.7 and the Bartlett's p-value is smaller than the 0.05 level of significance indicate that the latent factor structure has

factorial validity. Generally, a KMO value of 0.80 or higher is considered very good for assessing data suitability for factor analysis [38]. Factor analysis carried out on the collected data yielded a KMO value (0.8) and a Bartlett's p-value ($p < 0.001$) which implies that both conditions are satisfied.

Table 2. Convergent validity and reliability of measurement model

Const.	Items	FL (> 0.708)	Cronbach's Alpha ($\alpha > 0.7$)	CR (CR > 0.7)	AVE (AVE > 0.5)
PE	PE 1	0.842	0.857	0.915	0.782
	PE 2	0.918			
	PE 3	0.891			
EE	EE 1	0.837	0.886	0.921	0.745
	EE 2	0.909			
	EE 3	0.884			
	EE 4	0.820			
SI	SI 1	0.823	0.836	0.902	0.754
	SI 2	0.895			
	SI 3	0.885			
H	H 1	0.861	0.892	0.934	0.825
	H 2	0.933			
	H 3	0.928			
HM	HM 1	0.833	0.886	0.929	0.815
	HM 2	0.932			
	HM 3	0.939			
PV	PV 1	0.884	0.855	0.912	0.776
	PV 2	0.906			
	PV 3	0.851			
CP	CP 1	0.666	0.931	0.924	0.597
	CP 2	0.770			
	CP 3	0.850			
	CP 4	0.843			
	CP 5	0.741			
	CP 6	0.794			
	CP 7	0.833			
	CP 8	0.731			
	CP 9	0.735			
	CP 10	0.767			
	CP 11	0.744			
BI	BI 1	0.825	0.876	0.924	0.802
	BI 2	0.913			
	BI 3	0.935			
USE	USE 1	0.895	0.895	0.935	0.827
	USE 2	0.899			
	USE 3	0.934			
FC	FC 1	0.711	0.792	0.877	0.641
	FC 2	0.843			
	FC 3	0.857			
	FC 4	0.784			

An integral test conducted in Measurement Model analysis is Discriminant Validity. This test assesses whether constructs or variables that should theoretically be unrelated are, in fact, distinct from one another. It demonstrates that a test or measurement is unique to a particular concept, showing low correlations with different, unrelated constructs. Achieving high discriminant validity is crucial for ensuring that measurements are specific and not simply overlapping with other variables, strengthening the validity of research findings. Fornell-Larcker Criterion is one of the common methods used to check for Discriminant Validity which is established if the AVE square root for each construct is higher than its correlations with other constructs. The criterion requires all diagonal loadings (AVE square root) to be greater than their vertical counterparts. In Table 3, all bold diagonal loadings exceed the vertical loadings, indicating that the items in each construct are measured distinctly from items in other

constructs. Thus, the criterion for discriminant validity is satisfied.

Table 3. Discriminant validity of model using the Fornell-Larcker

	PE	EE	SI	FC	HM	PV	H	CP	BI	USE
PE	0.88									
EE	0.396*	0.863								
SI	0.300*	0.429**	0.868							
FC	0.422*	0.709**	0.301**	0.801						
HM	0.331**	0.220*	0.082	0.320**	0.903					
PV	-0.03	-0.18	-0.15	-0.169	-0.153	0.881				
H	0.209*	0.295**	0.247**	0.363**	0.022	0.012	0.908			
CP	0.444**	0.340**	0.291**	0.335**	0.368**	-0.057	0.168	0.772		
BI	0.600**	0.452**	0.228*	0.527**	0.571**	-0.138	0.187	0.540**	0.896	
USE	0.288**	0.094	0.071	0.304**	0.178	0.013	0.241*	0.236*	0.298**	0.91

* $p < 0.05$; ** $p < 0.01$

After conducting the CR and DV tests, the fitness of the resulting model was evaluated using AMOS. Table 4 provides a summary of the primary fit measures, the recommended criteria for each, and the achieved scores. All criteria fall within the recommended ranges.

Table 4. Model fit summary for the final measurement model

Fit Index	Recommended Criteria	Measurement Model
Chi-square (χ^2)	>0.05	0.107
RMSEA	<0.05	0.044
CFI	>0.95	0.964
TAG	>0.95	0.973
SUMMER	<0.05	0.045

The R^2 value or coefficient of determination indicates the percentage of the variance in the dependent variable that is explained by an independent variable in the regression model [38]. Hair *et al.* [38], suggest that values of R^2 ranging from 0.75, 0.5 and 0.25 can be considered as substantial, moderate and weak. From Table 5, it can be observed that the R^2 value for BI is 0.589 meaning that the structural equation model can explain 58.9% of the variance in students' behaviour intention to use AR in blended learning. The second R^2 value of 0.509 implies that 50.9% of the variance in the students' actual usage of AR for blended learning can be explained through the BI and FC constructs.

Table 5. Coefficients of determination of the dependent variables

Construct	R^2	Result
BI	0.589	Moderate
USE	0.509	Moderate

C. Structural Model Analysis

The outcomes from Table 6, depicted in Fig. 2, indicate that out of nine, six hypotheses emerged as significant.

Table 6. Results of Hypothesis Testing

Hyp.	Path	Standard part coef. β	P	Result
H1	BI $\leftarrow$ PE	0.271	<0.001	Supported
H2	BI $\leftarrow$ EE	0.171	0.008	Supported
H3	BI $\leftarrow$ SI	0.027	0.669	Rejected
H4	BI $\leftarrow$ H	0.025	0.722	Rejected
H5	BI $\leftarrow$ HM	0.240	<0.001	Supported
H6	BI $\leftarrow$ PV	-0.007	0.863	Rejected
H7	USE $\leftarrow$ FC	0.266	0.031	Rejected
H8	BI $\leftarrow$ CP	0.175	0.006	Supported
H9	USE $\leftarrow$ BI	0.310	0.022	Supported

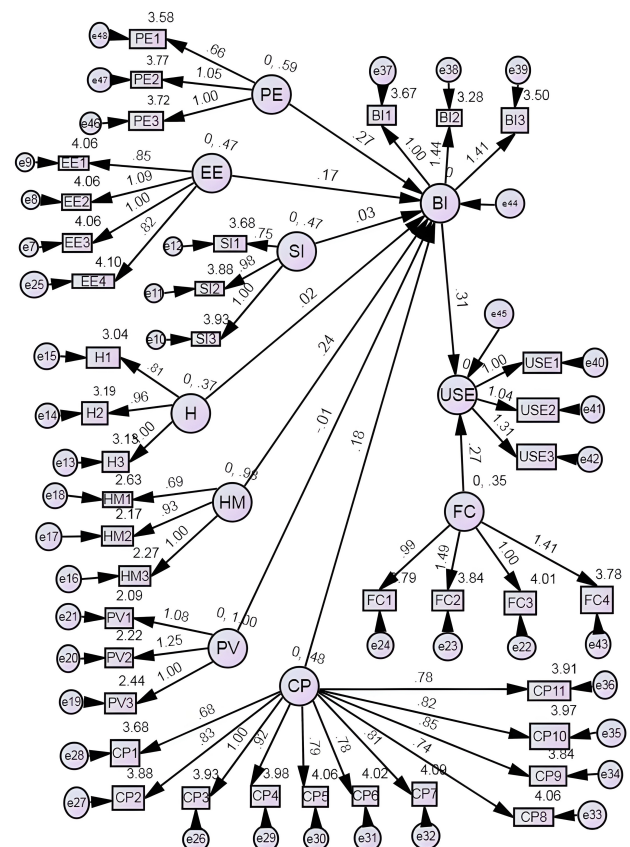


Fig. 2. Path diagram of structural equations model.

The UTAUT model guided the design and testing of a structural equation model (SEM), using survey data collected from a representative sample of students. The related hypotheses and potential explanations are further outlined hereunder:

H01: PE will have a significant influence on the learners' behavioural intention to use the AR authoring platform.

The primary result of this research confirms the hypothesis that Performance Expectancy (PE) exhibit a significant positive relationship with Behaviour Intention (BI). This variable has the highest regression coefficient (β) of 0.271 at a significance level of less than 0.001. This result aligns with various other studies that adopted the UTAUT model and focused on other educational technological instruments [42]. Marto [43], applied the UTAUT model to assess the use of AR in archaeological sites and also concluded similar results.

The validation of this hypothesis is crucial, as it lays the foundation for future research work in this area. Further research on using AR in education is futile if students believe the adopted AR technology won't enhance their work performance or productivity. Thus, confirming this hypothesis suggests that the perceived utility of AR technology in education is a key factor in influencing whether or not students intend to engage with it. The results show that the students' perceived benefits are high, thus they are more likely to show a strong intention to use AR technology.

Ho2: EE will have a significant influence on the learners' behavioural intention to use the AR authoring platform.

The results indicate that there is a significant relationship between Effort Expectancy (EE) and Behaviour Intention (BI) when using AR authoring platform ($\beta = 0.171$, $p < 0.05$). This result is also in line with similar studies on education technology [42]. Rather than the UTAUT model, Jang *et al.* [44], used the Technology Acceptance Model (TAM) to examine AR and VR as essential tools for learning. His study also reveals that Perceived Ease of Use (PEU), a similar construct to Effort Expectancy, emerged as a strong and significant predictor. In practical terms, the affirmation of this hypothesis suggests that the easier students perceive the technology to use, the they are more likely to adopt it. Hence, in reality, it is essential to ensure that the AR-based technology is user-friendly i.e. designed to be simple, intuitive and easy to follow. This result underlines the importance that technological complexity can be viewed as a barrier hindering students from using the technology. Lastly, this result suggests that providing training or guidelines on how to use them can be vital to enhance students' intention.

Ho3: SI will not have a significant influence on the learners' behavioural intention to use the AR authoring platform.

The variable 'Social Influences' exhibits an insignificant positive relationship with the dependent variable. The regression coefficient for this variable is 0.27 and a p-value of 0.669. Unexpectedly, this result seems to go against the trend in other research studies. A meta-analysis conducted shows that from 71 studies on the UTAUT model, SI influence emerged as a significant predictor in 54 studies. In practical terms, this outcome shows that the encouragement or opinions of others, like peers, instructors, or societal norms, don't have a meaningful effect on whether students intend to adopt the technology. In an educational setting, this suggests that students might be more influenced by personal motivations or perceived ease of use and usefulness of the technology itself rather than by external social pressures or expectations.

Ho4: FC will have a significant influence on the learners' use behaviour of use AR authoring platform.

Facilitating conditions were found to enhance students' use of the AR authoring platform. This variable has a regression coefficient of 0.266 and a p-value of 0.031 level ($p < 0.05$). This result reveals that students are more likely to engage with the AR authoring platform when they perceive that the necessary resources and technical support are accessible. In preparation for the demonstration scenarios, it was ensured that the barcodes used to activate the AR authoring platform 3d models were fully functional and also the students were provided with training and assistance on to how to use Zappar

AR. Thus, to further encourage the use of AR technology, educational institutions should provide training, documentation, and technical assistance as needed. Additionally, it is important to have supportive and knowledgeable staff available at all times to help students navigate any challenges they may face.

Ho5: HM will have a significant influence on the learners' behavioural intention to use the AR authoring platform.

The independent variable 'Hedonic Motivation' exhibited the second strongest significant positive relationship with the dependent variable. In the final regression model, this variable had the second highest regression coefficient i.e. 0.240 at a significance level of 0.001. This result confirms the hypothesis and adds hedonic motivation as a predictor of the student's intention to use AR technology. The significance of this relationship implies that the enjoyment or pleasure that students derive from using the AR authoring platform has a meaningful and measurable impact on their decision to adopt and use that technology. Essentially, this indicates that entertainment value of the technology is a key factor influencing the students' behaviour.

Ho6: PV will have a significant influence on the learners' behavioural intention to use the AR authoring platform.

Price value is one of the three hypotheses which is not statistically significant with behaviour intention. The regression coefficient for this variable is -0.007 and a p-value of 0.863. The results show that the perceived cost-benefit ratio of AR technology does not strongly influence the students' intention to use it. In reality, the fact that the AR authoring platform is freely available to students, with costs covered by the educational organization, is a prime factor contributing to this result. According to Raman and Don [45], price is considered an important factor where consumers have to bear the cost associated with the purchase of devices and services. In essence, if a technology is free, students may focus more on the other factors outlined in this section, rather than the price value. This could explain why price value isn't a significant predictor of users' intention to use it in studies where the technology is available at no cost.

Consistent with this, Tamilmani *et al.* [46], conducted a meta-analysis of the UTAUT2 empirical studies on the role of "Price Value" in understanding consumer technology adoption. The author reports that, out of 79 empirical studies on UTAUT2, only 41% included price value, while the remaining 59% omitted the construct from their research models. The primary reason for exclusion was that the studies focused on technologies like mobile applications and social networking sites, which are freely available to users.

Ho7: H will not have a significant influence on the learners' behavioural intention to use the AR authoring platform.

Another independent factor which exhibits an insignificant correlation with behaviour intention is Habit. This variable has a regression coefficient of 0.235 and is statistically insignificant at the 0.722 level. In more practical terms, the result suggests that students may not rely on their previous experiences with similar technologies when deciding to adopt the AR authoring platform. The non-confirmation of this hypothesis was anticipated, as the descriptive statistics showed that over 87% of the students reported having little to

no experience with AR technology. Hence, this result further reinforces the need for training and support. In this context, educators will play an important role in educating students about the new technology rather than assuming familiarity with past tools. Additionally, this result underscores the need to create a more engaging user experience to encourage behavioural intention, rather than depending on established habits. Ain *et al.* [47], indicate that another possible explanation for the insignificant relationships of 'habit' in mandatory settings, such as the demonstration scenario, is that students may have engaged in educational activities due to external pressure, driven by extrinsic motivation rather than intrinsic motivation.

Ho8: CP will have a significant influence on the learners' behavioural intention to use the AR authoring platform.

The last significant independent factor to exhibit a strong correlation with the behaviour intentions when considering the AR authoring platform was Cognitive Presence. This variable has a regression coefficient of 0.175 and a p-value of 0.006. Although this result is similar to the conclusion reached by Qin and Yu [21], their model was applied to an online learning platform. In this study, however, the model was applied in a blended learning environment, thus confirming that the amalgamation of the UTAUT2 and COI models can also be considered in such a learning setup. The confirmation of this hypothesis is also aligned with the results of a study conducted by Akyol and Garrison [48]. Interestingly, the study shows that within a COI framework, students in both online and blended courses achieved high levels of cognitive presence and strong learning outcomes.

Ho9: BI has a significant influence on the learners' actual usage of the AR authoring platform.

Lastly, the results also indicate a significant relationship between Behaviour Intention and Actual Usage. This variable has a regression coefficient of 0.310 at a significance level of 0.022 ($p < 0.05$). The confirmation of this hypothesis implies that the student's intention to use the AR authoring platform strongly influences whether or not they will use it. Validating this hypothesis is crucial as it closes off the circle of this discussion. This is because if educators or educational organizations want to increase the students' actual usage of AR technology and make effective use of it, they should focus on boosting the users' behavioural intention by enhancing performance expectancy, effort expectancy, addressing social influences and the other constructs discussed in this section. Hence, this relationship renders the model used in this study an invaluable decision-making instrument for incorporating AR authoring platform technology into engineering education, based on students' needs and grounded in sound teaching pedagogies.

V. CONCLUSION

The primary objective of this research is to explore learners' behavioural intentions towards adopting AR-based technology in education has been achieved. The findings reveal that PE, EE, HM, and CP significantly influence BI, while SI, H, and PV do not. The study highlights that the future integration of AR technology in education depends not only on its technical features but also on students' active engagement and perceptions. This was achieved

implementing the objectives set in the Introduction i.e. by identifying the factors that influence students' intentions to adopt AR technology in their learning processes, subsequently, exploring the relationships which emerge from among these factors and lastly evaluating the impact of each factor on the students' behaviour intention.

Theoretical implications include the novel integration of the UTAUT model with the CoI framework for blended learning environments. While the UTAUT-COI model has been validated for online learning contexts, this research extends its application by exploring AR technology's role in blended learning. By combining these frameworks, the study offers a multidimensional perspective that emphasizes factors driving technology acceptance and the critical role of cognitive presence in enhancing learning experiences. This enriched theoretical approach lays a foundation for future studies to investigate the dynamics of these constructs in varied educational settings.

Practical implications suggest that students are motivated to adopt AR technology when it is effectively integrated into the curriculum. The confirmation of the H1 hypothesis shows that students view AR as a tool that can significantly enhance their performance. Moreover, the study underscores the importance of cognitive presence, derived from the CoI model, in shaping students' willingness to use AR technology. Educators and policymakers should prioritize factors that foster cognitive engagement alongside technical attributes to increase adoption rates. Furthermore, AR technology has the potential to improve learning experiences by boosting engagement, comprehension, and collaboration. Identifying and emphasizing key predictors is crucial for the successful implementation of AR in education.

Limitations and future work highlight areas for improvement. The study's focus on mechanical engineering students and its setting at the University of Malta limit its generalizability. Expanding the sample size would enhance the statistical power and reliability of the findings. Qualitative methods, such as interviews and focus groups could further explore variables like HM and CB, offering nuanced insights into the observed phenomena.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Christian Camilleri collected, analyzed the data and wrote the paper. Lawrence Farrugia Caruana is the principal supervisor while Sarah Pule and Carlos Efrén Mora are the co-supervisors. The supervisory team provided guidance throughout the research process. Liberato Camilleri supervised the statistical analysis. All authors reviewed and approved the final version of the manuscript.

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