Integrating Media Richness Theory and Technology Acceptance Model to Study the Learning Outcomes of Air Quality Education App

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Abstract

In recent years, the rapid expansion of digital media has revolutionized educational materials by incorporating engaging multimedia elements and gamification principles. These advancements in technology have transformed digital learning into a gamified experience, enhancing the creation and utilization of learning materials. The primary aim of this study was to develop a predictive model for measuring learning outcomes in the Air Quality Education (AQE) app. The study results revealed that the most influential factor affecting learning outcomes was Learning Outcome (R^2 = 0.673), followed by Behavioral Intention (R^2 = 0.541), Practicability (R^2 = 0.456), Use Attitude (R^2 = 0.431), and Entertainment (R^2 = 0.328). The proposed model accounted for an impressive 67.29.8% of the variability in predicting learning outcomes. These research findings emphasize the significance of Behavioral Intention and Practicability as crucial factors in designing predictive models for learning outcomes within the AQE app. Furthermore, the study highlights the users' strong emphasis on interface media richness and user experience design elements, indicating the need for their prioritized attention and enhancement. By focusing on these aspects, developers can heighten players' expectations for interactive media elements and enable them to achieve a more immersive gaming experience through a user-friendly and interactive interface design.

Keywords: Air quality education, Augmented reality app, Technology acceptance model, Involvement

1 Introduction

In recent years, augmented reality (AR) technology has made significant strides, prompting numerous studies on its efficacy and value in educational settings. Research has shown a wide range of applications for AR, spanning medical care, education, leisure and entertainment, the military, and industry [1]. The continual advancements in portable device hardware and software, such as smartphones, tablet computers, and wearable devices, have significantly reduced the technical challenges associated with AR development. Consequently, the creation of AR app content has accelerated, particularly in entertainment and education [2]. Users can now experience augmented reality through smartphones or tablet computers, enriching their real-world experiences.

A prominent example of successful AR application in entertainment is Pokémon-GO, introduced by the Japanese Pokémon Company in July 2016. This game employs AR technology to merge virtual characters with real scenes, transforming real map paths into in-game map objects displayed on the device screen. Pokémon-GO has gained tremendous popularity and attention from users [3] and has even demonstrated positive effects on the social anxiety of children [4].

Furthermore, a study released by the International Agency for Research on Cancer (IARC) in 2013 established a link between outdoor air pollution and an increased incidence of cancer, particularly lung cancer. Air pollution-related diseases ranked among the top 10 causes of death in 2017. The Environmental Protection Administration reported that since December 2016, there have been 80 days in southern Taiwan with unhealthy air levels, comprising 95% of the total days. The central and northern regions have also experienced a significant number of days with poor air quality. These figures highlight the gradual rise in long-term exposure to air pollution, leading to adverse health outcomes and premature deaths.

In summary, this study aims to achieve three primary goals:

(1) Establishing an AQE App Learning System to Assess Learning Effectiveness.

(2) Constructing an AQE App Learning Outcomes Prediction Model.

(3) IPMA Analysis of AQE App Learning Effectiveness Design.

2 Related Works

2.1 The Relationship between Media Richness, Entertainment and Practicability

Media Richness Theory, also known as Information Richness Theory [5], pertains to a medium's ability to convey information effectively. Trevino (1987) [5]

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posited that different media possess unique characteristics, leading to diverse communication effects and purposes [6]. Dass and Kumar (2018) [6] considered computers as a communication medium that offers immediate feedback, multiple cues, language diversity, and personalized focus [7]. Wang, Hsieh, and Song (2012) [8] proposed that users' perception of entertainment is positively influenced by the richness of communication software within the perceptual medium. Sullivan (1999) [9] emphasized the significance of interactivity, such as website-user dialogues, enabling reciprocal interactions and user responses to the information and content provided by websites [10]. Coyle & Thorson (2001) [11] suggested that interactivity positively affects website usefulness, website attitude, and attitude-behavior consistency.

In summary, this study incorporates the hypotheses of media interactivity from Media Richness Theory as follows:

H1: Media richness positively influences entertainment.

H2: Media richness positively influences use attitude.

H3: Media richness positively influences practicability.

2.2 The Relationship between Entertainment, Use Attitude and Behavioral Intentions

Behavioral attitude refers to an individual's positive or negative perceptions of engaging in a behavior and is primarily influenced by behavioral beliefs and outcome evaluations [12-13]. Subjective norm refers to the influence of significant others or important individuals on an individual's behavior or opinion about a specific behavior, and is primarily determined by normative beliefs and motivation [14-15]. According to Fishbein and Ajzen (1975) [16], attitude and subjective norm are identified as the two most crucial factors in determining behavioral intentions.

The characteristics of enjoyment constructs have also been applied in behavioral research [17], and they are considered to have a subjective and personal component [18-19]. When it comes to system use, the higher the user's perceived enjoyment of the decision system, the greater their intention to adopt it [20].

In summary, this study suggests the following hypotheses:

H4: Entertainment has a positive influence on use attitude.

H6: Entertainment has a positive influence on behavioral intentions.

2.3 The Relationship between Practicability, Use Attitude and Behavioral Intentions

According to the Technology Acceptance Model (TAM), users' attitudes toward a system are influenced by perceived ease of use and perceived usefulness. Furthermore, their behavioral intentions are influenced by both attitudes and perceived usefulness, with perceived usefulness also impacting perceived ease of use [21]. This model has been widely applied in various studies on technology acceptance behavior, and its hypotheses have been validated multiple times [22-23].

Therefore, this study includes the hypotheses of TAM, which are outlined below:

H5: Practicability has a positive influence on use attitude.

H7: Practicability has a positive influence on behavioral intentions.

H8: Use attitude has a positive influence on behavioral intentions.

2.4 The Relationship between Behavioral Intentions and Learning Outcome

Behavioral intention serves as a valuable tool for examining the connection between attitude and behavior across different usage scenarios. Changes in behavioral attitude, subjective scope, and perceived behavior control can lead to variations in behavioral outcomes [24-25]. Fujita-Starck (1994) [26] emphasized the importance of enhancing learning satisfaction to improve learning effects. Additionally, the strength of behavioral intention (BI) positively impacts learning outcomes [25]. Based on these insights, this study proposes the following hypothesis:

H9: Behavioral intentions have a positive influence on learning outcomes.

2.5 Moderator Variable

The moderator variable is defined as the extent to which the relationship between a predicted variable and the outcome variable is influenced when systematically manipulated [27]. Product involvement refers to the level of personal engagement that occurs when product categories align with individuals' intrinsic values and self-concept, influenced by contextual factors and personal interests [8, 28]. Variations in involvement levels can impact consumers' decision-making patterns regarding product perceptions [29]. Gender differences, particularly concerning the extent of technology use and acceptance, have been identified as moderators of these effects [30-32]. González-Gómez et al. (2012) [33] examined the influence of gender differences on attitudes toward learning with an AR app and aimed to identify areas of teaching that require improvement to enhance satisfaction among both male and female students. Based on the above findings, it can be inferred that gender differences may have an impact on the behavioral intention of AR app users. With these insights, this study proposes the following hypotheses:

H10: Gender differences have an moderating effect on learning outcomes.

H11: Involvement has an moderating effect on learning outcomes.

3 Methods

3.1 The AQE App Design

This study introduces a framework for the development of AR games, with a specific focus on designing digital course instruction for the learning outcomes of an air quality education app (Figure 1). The design process comprises two main aspects: the design transfer process for digital courses and the AR app design process for teaching AQE.

The description of the AQE app design flow is as follows:

Development and Design Procedure for Integrating Course Content:

(1) Analysis: Conduct an analysis of the demand, teaching content, tasks, and potential impact. For example, before preparing the textbook, it is crucial to analyze the learners'

existing knowledge, their grasp of subject knowledge, and the teaching content. Additionally, understanding the information and sequence of each theme is essential.

(2) Design: (a) Teaching objectives: Clearly define teaching objectives using measurable verbs. (b) Teaching strategy: Ensure that the presentation of course content achieves the desired effect.

(3) Development: (a) Decision scheme in the design stage. (b) Accuracy of theme-related content. (c) User-friendly interface. (d) Evaluation and revision of the textbook. (e) User testing. (f) Consideration of hardware and software compatibility. (g) System operation.

(4) Implementation: (a) Establish content. (b) Verify the accuracy of theme-related content. (c) Design interaction and interface. (d) Quality control. (e) Implement usage tests for users. (f) Assess software and hardware performance. (g) Ensure server operation and login page functionality.

(5) Evaluation: (a) Assess if study objectives have been achieved. (b) Determine if target users are utilizing the textbook for learning. (c) Identify any difficulties encountered by textbook users. (d) Evaluate learners' feedback and satisfaction. (e) Identify areas for improvement.

(6) Maintenance: Adjustments and corrections to the textbook are made based on the evaluation results, and users are informed once the updates are implemented.

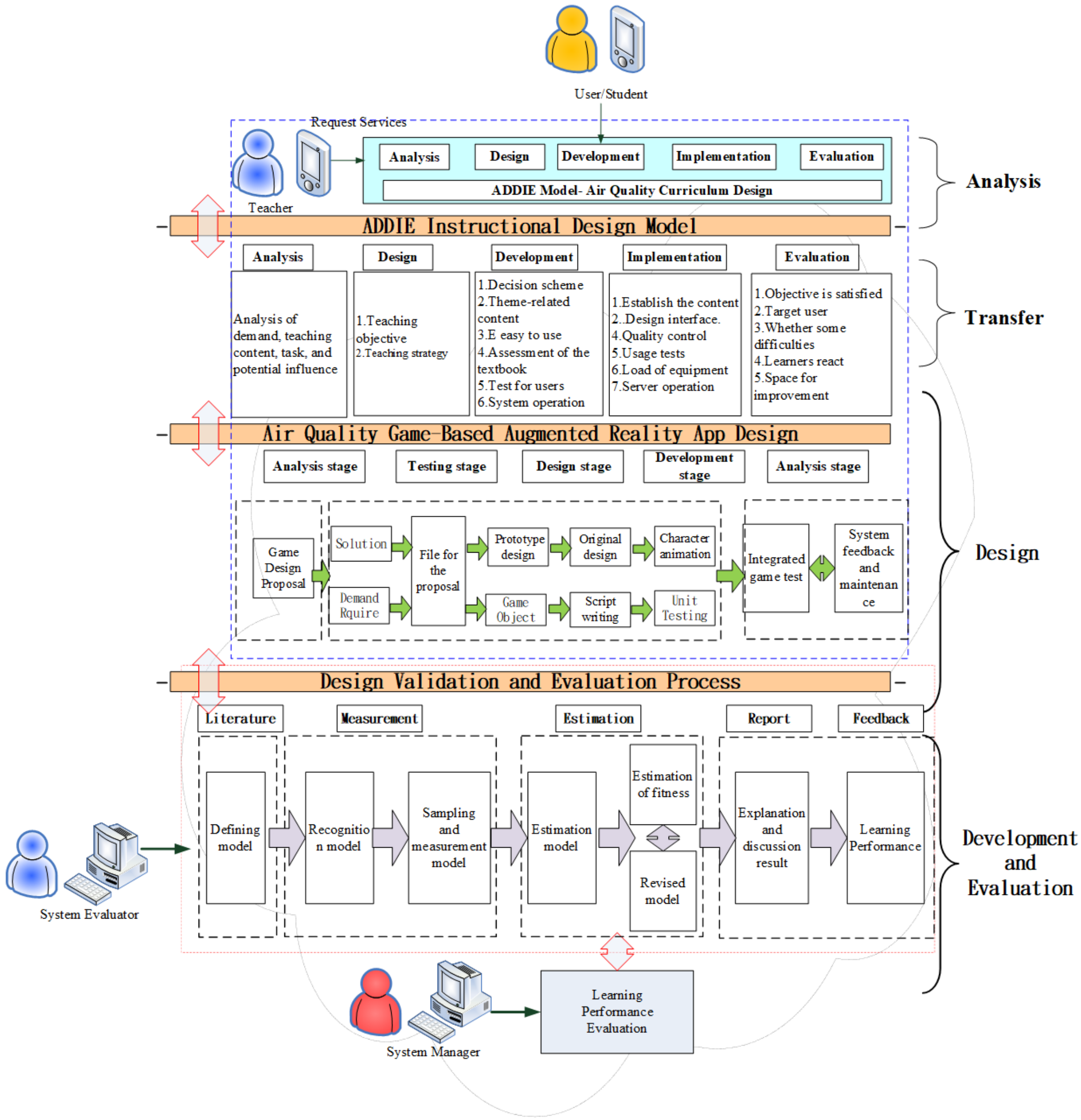

Figure 1. The framework of AQE app design flow

3.2 AQE App Game-based Learning Activities Design

In this study, augmented reality (AR) image recognition technology is utilized to create an interactive game system that blends entertainment and education for teaching purposes. The unit incorporates various sources of pollution represented as images, and 3D models symbolizing these sources are generated. To achieve this, the researcher chooses three common pollutants from each type, totaling nine pollutants, which act as the basis for developing the 3D objects representing the pollution sources (see Table 1).

The app employs instructional explanations and a multimedia 3D screen to capture users' attention. By relating the app's content to users' everyday experiences and incorporating AR Mark design, along with allowing free exploration, the app aims to establish a sense of relevance for the users. Users are encouraged to explore and locate AR Marks within the specified area, scanning them to receive feedback. By adding AR Mark information, users can access different game perspectives, which boosts their learning confidence and broadens their knowledge. Throughout the unit and upon its completion, relevant knowledge information is provided, and a result screen offers feedback for users to reflect on and review, ultimately enhancing learning satisfaction (as depicted in Figure 2 to Figure 5).

Table 1. Design picture of eight sources of pollution for AR image marker

			
A two-wheeled mechanical bicycle traveling on the street is the focus of the design.	A gasoline-powered car traveling on the street is the focus of the design.	Diesel-powered vehicle traveling on the street is the focus of the design.	Canned food is the focus of the design, and the main body of the design is the can imagery.
			
Multiple oil tanks and chimneys add to the pollution imagery.	A thermal power plant with different sizes of exhaust stacks is the focus of the design.	The general tarmac road is regarded as the design image, and the dust on the road surface will be blown up.	The barbecue restaurant surrounded by grease and smoke is the design image.

Figure 2. The learning process of the game tutorial

Figure 3. Multi-media screen to attract attention and arouse curiosity

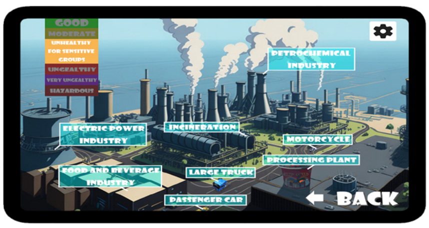

Figure 4. Visible changes of the game after adding AR material

Figure 5. Visible changes of the game after adding information

3.3 Research Framework

Based on the technology acceptance model (TAM) and media richness theory (MRT), this project seeks to incorporate practicability, enjoyment, and media interactivity into an empirical study focused on measuring the use intention of the AR app in AQE teaching activities. Furthermore, the study explores the impact of transnational involvement and gender-based factors. Figure 6 presents the research model proposed for this project, and Table 2 outlines the operational definitions within the research model introduced in this study.

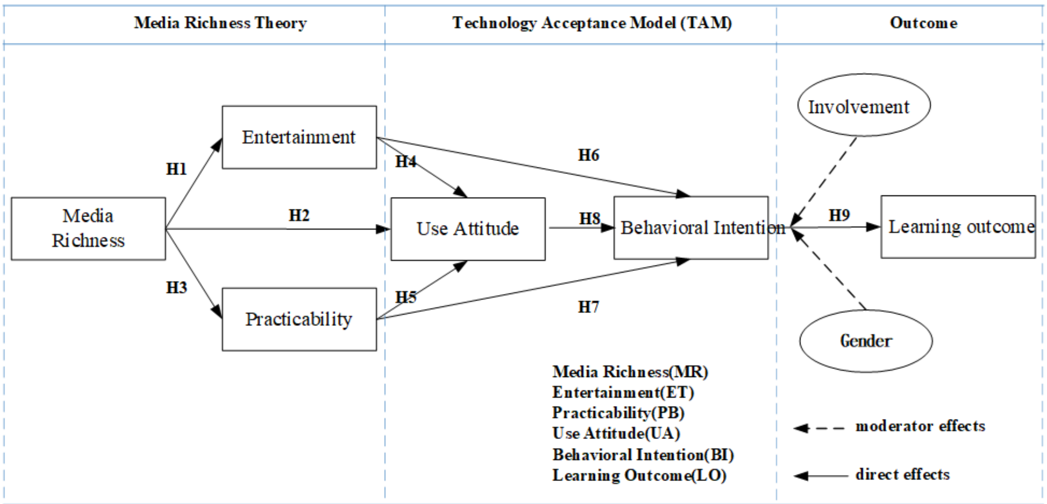

Figure 6. The framework of AQE app learning outcomes predict model

Table 2. Definition of conceptual operation

Variable	Operational definition	Item	Source
Media rich interactivity	This aspect pertains to the level of user engagement and interaction enabled by the media. It encompasses features that encourage active participation, such as multimedia elements, interactive interfaces, and responsive feedback systems.	The visual design of the app is very beautiful. On the whole, the design of the interface for app users is good. App users have good interactivity with other app users. App users can establish a relationship with other app users via the app.	[11]
Entertainment	Entertainment plays a pivotal role in conceptual operation, as it reflects the ability of media content to captivate and amuse users. Content that entertains often fosters a positive user experience and encourages continued engagement.	The app is equipped with many interesting functions. The function of the app makes me feel pleased. The app interests me.	[34]
Practicability	The practicability of media content considers how useful and applicable it is to users' needs and goals. Highly practical content tends to align with users' interests and can address their specific requirements effectively.	The app provides what I want. On the whole, I believe the app is useful. The app is easy to use. The app is easy to use and understand.	[35-36]
Attitude of use	This factor refers to users' emotional and psychological dispositions when engaging with media. A positive attitude of use often leads to enhanced satisfaction and increased likelihood of recurrent interactions.	On the whole, I like using the app. I give positive comments on the app.	[37]
Behavioral intention	The intention of use refers to the purpose or goal that drives users to interact with media content. Understanding users' intentions is essential for creating tailored experiences that cater to their unique motivations.	I will continue to use the app in the future. I will continue to use the app in spite of other similar alternatives. Are you willing to recommend the app you use to other people?	[37]
Involvement	Involvement measures the depth of users' immersion and connection to the media. Higher levels of involvement are linked to more profound user experiences and sustained interest.	I feel it meaningful when engaged in technology education activities. When engaged in technology education activities, I feel excited. Technology education activities make me feel meaningful. Technology education activities are attractive and I feel my own value when participating in this activities.	[29]
Gender differences	Recognizing gender differences in conceptual operation is vital as it sheds light on how men and women may perceive and interact with media content differently. This understanding can lead to more inclusive and relevant designs.	Basic population variable.	The definition of the project operation.

3.4 The Definition of Conceptual Operation

In this section, we delve into the definition of conceptual operation, focusing on several key aspects that play a significant role in shaping user experiences. These aspects are media rich interactivity, entertainment, practicability, attitude of use, intention of use, involvement, and gender differences. Conceptual operation refers to the underlying principles and mechanisms that govern the interactions between users and media content. To better understand this concept, we must explore the following factors (see Table 2). By considering these crucial aspects of conceptual operation, content creators, designers, and developers can craft media experiences that resonate with users, enhancing engagement and overall satisfaction.

3.5 Sampling Design

This study adopts a survey approach to collect data, utilizing both online and physical sampling methods. The distribution channels include BBS and Facebook. Additionally, physical sampling is conducted in colleges and universities located in Kaohsiung, Taiwan, to ensure the sample's representativeness. To streamline the data collection process, a convenience sampling method is employed, involving the distribution of questionnaires to students at universities and colleges who actively use the AR app for teaching activities related to AQE Game-based learning.

4 Result

4.1 Descriptive Statistics of the Sample

A total of 147 valid questionnaires were collected for this study, with 75 of them completed by males and 72 by females. Males accounted for 61.4% of the valid sample. Regarding the age distribution of the users, those below 26 years old accounted for 38.5% of the valid sample, users aged 26-35 accounted for 28.2%, users aged 36-45 accounted for 17.9% of the total sample, and users aged 46-55 accounted for 11.1% of the total sample. Therefore, it can be observed that the users of the AQE app are primarily concentrated in the younger demographic. In terms of weekly usage frequency, the majority of users (53.8% of the valid sample) reported using the app 2-3 times per week. Regarding the duration of each usage session, the highest percentage (53.8% of the valid sample) reported using the app for 30-60 minutes per session.

4.2 Reliability and Validity Analysis of the Measurement Model

The reliability analysis results of this study are presented in Table 3, where all factor loadings were found to be significant ($p = 0.001$) and greater than 0.5. The composite reliability values ranged from 0.856 to 0.961, all exceeding 0.8. The AVE values ranged from 0.715 to 0.875, all surpassing 0.5. Therefore, this study met the aforementioned three conditions. The factor loadings for all items ranged from 0.703 to 0.963, reaching the significant level at $p = 0.05$, thus demonstrating convergent validity [38]. As shown in Table 3, the square roots of the AVE values for all variables were higher than the correlations between variables. Table 4 displayed that the individual item loadings for each variable were higher than their loadings in other variables. Thus, the variables in this study demonstrated acceptable reliability and validity [39-40].

4.3 Path Coefficient Testing and Model Predictive

PLS analysis was conducted on the structural model to evaluate the explained variance (R^2), standardized path coefficients (β), and t-values, which are primary indicators for assessing the model's goodness-of-fit (Chin, 1998) [38]. The results of the structural model analysis are presented in Figure 7. In the analysis of the complete model, the path coefficient between MR and ET was 0.531 ($t = 6.213$), indicating high significance and supporting hypothesis H1, which states that an increase in MR of the AQE app corresponds to an increase in ET. The path coefficient between MR and UA was 0.394 ($t = 2.758$), demonstrating a higher level of significance and partially supporting hypothesis H2, suggesting that a strong MR of the AQE app is related to an increase in users' perception of UA. The path coefficient between MR and PB was 0.621 ($t = 8.123$), exhibiting a higher level of significance and supporting hypothesis H3, indicating that an increase in MR of the AQE app corresponds to an increase in users' perception of PB. The path coefficient between ET and UA was 0.325 ($t = 3.254$), showing higher significance and supporting hypothesis H4, indicating that an increase in ET of the AQE app corresponds to an increase in users' perception of UA. The path coefficient between PB and UA was 0.395 ($t = 5.698$), displaying higher significance and supporting hypothesis H5, indicating that an improvement in PB of the AQE app corresponds to an increase in users' perception of UA. The path coefficient between ET and BI was 0.425 ($t = 5.214$), revealing higher significance and supporting hypothesis H6, suggesting that an increase in ET of the AQE app corresponds to an increase in players' behavioral intention (BI) towards the app. The path coefficient between PB and BI was 0.231 ($t = 1.967$), demonstrating higher significance and supporting hypothesis H7, suggesting that the better the PB of the AQE app, the higher the players' BI towards the app. The path coefficient between UA and players' BI was 0.354 ($t = 3.956$), displaying significance and supporting hypothesis H8, indicating that the higher the UA of the AQE app, the higher the players' BI towards the app. Hypothesis H9, stating that the higher the BI of the AQE app, the higher the players' LO, was supported with a path coefficient of 0.596 ($t = 6.740$), demonstrating higher significance.

The effect sizes were evaluated based on the general guidelines proposed by Cohen (1988) [41]. As seen in Table 5, the average effect sizes for all variables are greater than 0.15, indicating a medium effect. In assessing predictive relevance, in addition to examining the observed values, researchers should also check the Stone-Geisser values. According to Table 5, the GoF value in this study is 0.68, which exceeds 0.36, indicating an excellent model fit [42].

Table 3. Reliability and validity analysis

	Mean	STD	Factor loading	CR	Cronbach's α	AVE	BI	ET	UA	PB	MR	LO
BI	5.455	1.115	0.945	0.961	0.945	0.875	**0.930**					
ET	5.075	1.315	0.895	0.956	0.925	0.775	0.634	**0.880**				
UA	4.855	1.215	0.755	0.816	0.795	0.715	0.654	0.554	**0.850**			
PB	5.175	1.115	0.775	0.826	0.705	0.755	0.564	0.374	0.860	**0.840**		
MR	4.985	1.415	0.895	0.876	0.775	0.695	0.504	0.444	0.754	0.780	**0.860**	
LO	4.698	1.364	0.845	0.856	0.784	0.745	0.564	0.547	0.64	0.711	0.784	**0.871**

Table 4. Factor loadings analysis of variables

	BI	ET	UA	PB	MR	LO
BI 1	**0.963**	0.573	0.573	0.513	0.443	0.443
BI 2	**0.963**	0.613	0.613	0.523	0.443	0.443
BI 3	**0.923**	0.603	0.583	0.543	0.473	0.473
ET 1	0.463	**0.773**	0.523	0.443	0.443	0.443
ET 2	0.513	**0.813**	0.503	0.383	0.393	0.393
ET 3	0.513	**0.813**	0.523	0.403	0.483	0.483
UA1	0.513	0.513	**0.933**	0.253	0.423	0.423
UA2	0.453	0.433	**0.903**	0.313	0.333	0.333
UA3	0.693	0.523	**0.883**	0.453	0.463	0.463
PB1	0.243	0.363	0.393	**0.703**	0.233	0.233
PB 2	0.243	0.103	0.273	**0.713**	0.153	0.153
PB 3	0.453	0.333	0.463	**0.773**	0.633	0.633
PB 4	0.443	0.383	0.543	**0.723**	0.503	0.503
MR1	0.273	0.153	0.363	0.383	**0.763**	0.233
MR2	0.543	0.543	0.643	0.713	**0.873**	0.153
MR3	0.313	0.283	0.523	0.403	**0.853**	0.633
MR4	0.343	0.303	0.593	0.523	**0.873**	0.503
LO1	0.543	0.543	0.643	0.713	0.643	**0.829**
LO2	0.313	0.283	0.523	0.403	0.523	**0.885**
LO3	0.343	0.303	0.593	0.523	0.593	**0.883**

Table 5. Total effect and model fit indicator

	ET			PB			UA			BI			LO			IPMA			Model fit indicator		
	(D)	(I)	(T)	(D)	(I)	(T)	(D)	(I)	(T)	(D)	(I)	(T)	(D)	(I)	(T)	(I)	(P)	R^2	f^2	Q^2	*GoF*
MR	0.531	-	0.531	0.621	-	0.621	0.394	0.173	0.567	-	0.365	0.365	-	0.218	0.218	0.65	56.12	-	-	-	0.68
ET	-	-	-	-	-	-	0.325	-	-	0.425	0.115	0.54	-	0.318	0.318	0.46	61.86	0.328	-	0.13	
PB	-	-	-	-	-	-	0.395	-	0.395	0.231	0.139	0.37	-	0.221	0.221	0.33	57.09	0.456	-	0.18	
UA	-	-	-	-	-	-	-	-	-	0.354	-	0.354	-	0.211	0.211	0.28	60.55	0.413	0.19	0.26	
BI	-	-	-	-	-	-	-	-	-	-	-	-	0.596	-	0.596	0.34	55.55	0.541	0.21	0.43	
LO	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.673	0.25	0.46	

(D) = Direct effect; (I) = Indirect effect; (T) = Total effect; GoF = $\sqrt{\overline{communality} \times \overline{R}^2}$

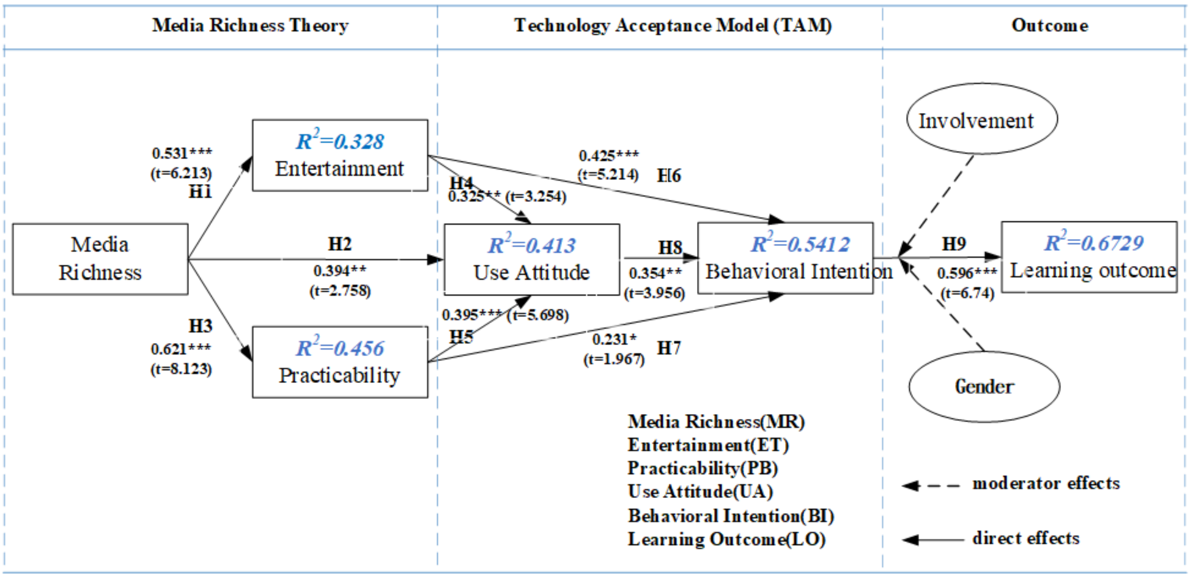

Figure 7. The path coefficient testing of AQE app learning outcomes pridict model

4.4 Importance-Performance Matrix Analysis (IPMA)

The IPMA (Importance-Performance Map Analysis) was utilized to extend the PLS-SEM results [43]. According to the IPMA, players highly value media interactivity but are not highly satisfied with it. Therefore, when designing or improving the app, special attention should be given to this aspect. Design strategies and considerations should be implemented to enhance the level of media interactivity in the app. As depicted in Figure 8, Media richness is located in the "Concentrate here" area, indicating high importance but low performance. This suggests that interface and user experience design elements need to be prioritized for improvement, and further design strategies should be employed to enhance players' satisfaction with media interactivity elements. By incorporating well-designed interactive interfaces, players can become more deeply engaged in the app's usage context.

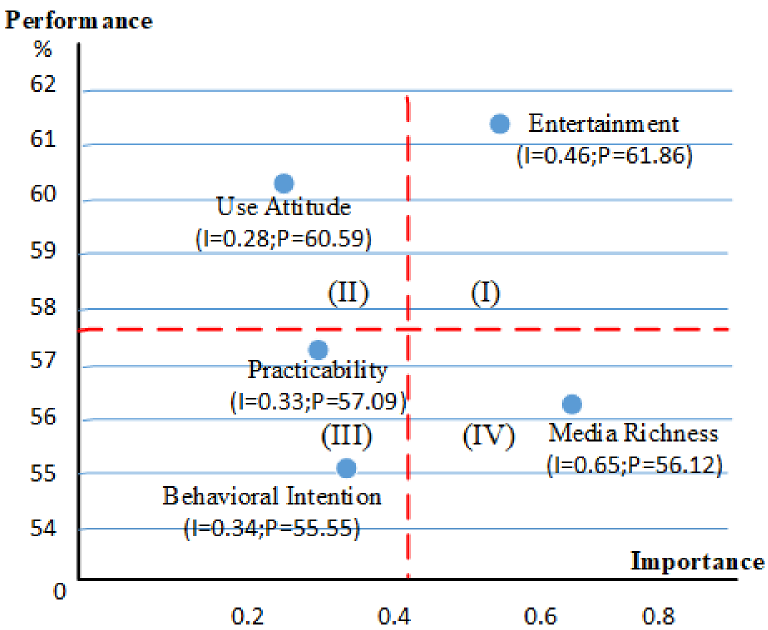

Figure 8. The IPMA of AQE app learning outcome

The IPMA (Importance-Performance Map Analysis) was utilized to extend the PLS-SEM results [43]. The IPMA table (as shown in Table 5) allows for the numerical distribution of the importance and performance of AQE app's learning effectiveness to be plotted (as in Figure 8), providing explanations of managerial implications for different regions (quadrants). (1). Quadrant I represent items that are of high importance and high performance, and it is termed as the "Keep up the good work" area. This indicates that players highly value the Entertainment aspect (I=0.46, P=61.86) and are also highly satisfied with it. When designing the AQE app, it is crucial not only to maintain the existing advantages but also to further enhance its entertainment value. Therefore, this area becomes the primary core competitiveness to consider during the design process. (2). Quadrant II represents items with low importance but high performance, and it is referred to as the "Possible overkill" area. This means that players do not attach significant importance to the Use Attitude (I = 0.28, P = 60.59) aspect, yet they are highly satisfied with it. In the design phase, resources can be adjusted and reallocated to other more important variables to reduce costs. (3). Quadrant III represents items with both low importance and low performance, categorizing them as the "Low priority" area. This indicates that AQE system users do not attribute much importance and satisfaction to Practicability (I = 0.33, P = 57.09) and Student Behavioral intention (I = 0.34, P = 55.55). Therefore, designers need not invest too much effort into these aspects. (4). Quadrant IV represents items that are of high importance but low performance, termed as the "Concentrate here" area. This reveals that AQE app users highly value Media richness but are not very satisfied with it. Thus, during the design process, priority should be given to improvement in this area, implementing appropriate design strategies to enhance the Media richness design level of AQE. As shown in Figure 8, Media richness falls into Quadrant IV, which indicates it is an area of high importance but low performance. This implies that the Media richness design element needs to be addressed and improved as a priority, considering further design strategies to immerse users more deeply into the usage context through a well-designed Media richness interface.

4.5 The Moderation Effects of AQE Involvement

The results of the analysis revealed that the interaction effect between "Behavior intention" and "Involvement" on the path coefficient of "Learning outcome" was 0.192, with a t-statistic of 2.864, indicating statistical significance ($p < 0.01$). This suggests that "Involvement" has a positive moderating effect on the relationship between "Behavior intention" and "Learning outcome." The main effect accounted for 0.6729 of the variance, while the addition of the moderation effect through interaction explained 0.712 of the variance. The effect size of the moderation effect was 0.0391, indicating a low positive moderation effect of the level of student involvement ("Involvement") on the relationship between "Behavior intention" and "Learning outcome." On the other hand, the moderation effect of "Gender" on the relationship between "Behavior intention" and "Learning outcome" did not reach statistical significance ($p > 0.05$), suggesting no moderation effect. The researcher further divided "Involvement" into high and low groups based on plus/minus one standard deviation from the mean and conducted a simple slope analysis to examine the moderation effect. As shown in Figure 9, student "Involvement" has a positive moderating effect on "Behavior intention" and "Learning outcome," with higher slopes for university students with high "Involvement" compared to those with low "Involvement".

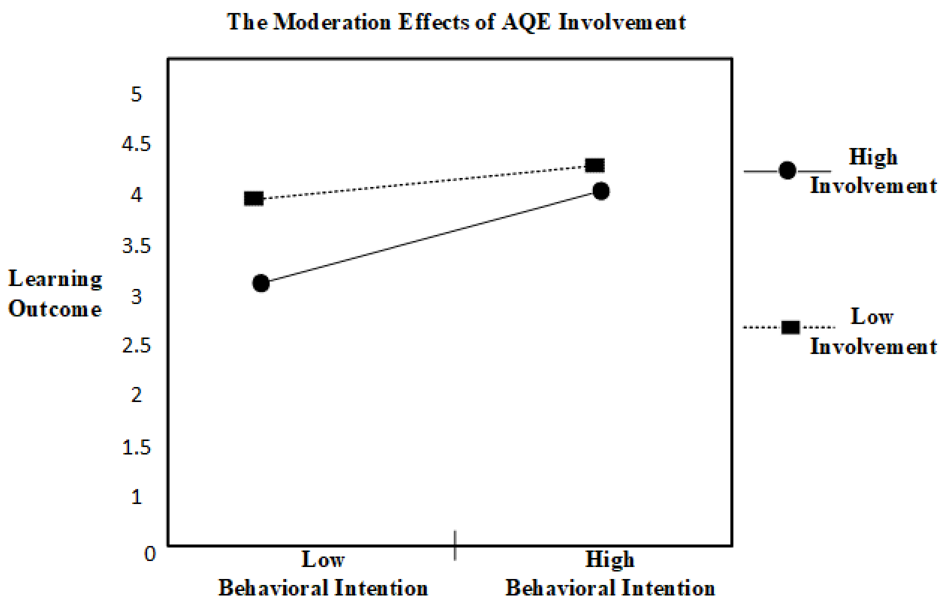

Figure 9. The moderation of involvment and behavioal intention

4.6 Evaluation of Learning Outcomes

This study employed a quasi-experimental design, dividing participants into an experimental group and a control group, and conducted pre-tests, post-tests, and follow-up tests. The experimental group used the AQE app, while the control group received traditional learning instruction. The teaching experiment lasted for 18 weeks, with the first 12 weeks considered the experimental period and the following 6 weeks as the follow-up observation period. The experimental group consisted of 147 college students (75 males and 72 females) who underwent gamified air quality education using the AQE app. After each AQE unit, students received feedback and revisions from the system, which could be adjusted and provided feedback. According to the quasi-experimental design analysis of learning outcome differences (Table 6), there was no significant difference in scores between the experimental and control groups in the pre-test. However, in the later stage after the experiment, the average score for the experimental group was 87, while the control group scored 76, indicating a significant difference in learning outcomes between the two groups (F=18.25*). Therefore, the results of this study confirm a significant improvement in learning outcomes with the use of the AQE app.

Table 6. Analysis of learning outcome differences in quasi-experimental design

		Pre-test (Week 1~5)		Post-test(Week 6~12)		Follow-up test (Week 13~18)		F
Group	Gender	Mean	SD	Mean	SD	Mean	SD	
Experimental group (n=73)	M=37, F=36	71	13	87	8	88	10	18.25*
Control group (n=74)	M=38, F=36	73	11	76	13	75	14	0.212

5 Conclusion and Recommendations

5.1 Discussion

The results of this study have provided support for all nine proposed hypotheses, each of which exhibited a high level of significance.

The relationship between media richness, entertainment, and practicability aligns with the perspectives of Wang, Hsieh, and Song (2012) [8], who argued that when users perceive a higher level of media richness in an information system, their perception of entertainment also increases. Additionally, Coyle and Thorson (2001) [11] found that interactivity positively impacts the practicability of information systems, contributing to the formation of more favorable attitudes towards the system and behavioral consistency. These findings are consistent with the research conducted by Wang, Hsieh (2012) [8] and Coyle and Thorson (2001) [11].

The relationship between entertainment, use attitude, and behavioral intentions is in line with the research perspective of Hirschman and Holbrook (1982) [44], who asserted a positive correlation between entertainment and both use attitude and behavioral intentions. According to system users' perspective, when they perceive a higher level of "enjoyment" in an information system, their intention to adopt it also increases. This finding is consistent with the studies conducted by Holbrook (1982) [44].

The relationship between practicability, use attitude, and behavioral intentions aligns with the Technology Acceptance Model proposed by Davis (1989) [37]. In this model, individual behavioral performance is influenced by behavioral intentions, which can be influenced by personal attitudes and subjective norms. Additionally, perceived usefulness can also impact perceived ease of use. Therefore, the findings of this study are consistent with Davis (1989) [37], indicating that the system usage behavior is determined by behavioral intentions, and behavioral intentions are jointly influenced by attitudes and perceived usefulness, with attitudes being influenced by both perceived usefulness and perceived ease of use.

The relationship between behavioral intentions and learning outcomes aligns with the findings of Davis (1989) [37]. According to Davis (1989) [37] Technology Acceptance Model, users' attitudes toward a system are influenced by perceived ease of use and perceived usefulness, while users' behavioral intentions are influenced by attitudes and perceived usefulness. This model has been widely applied in various studies on technology acceptance behavior, and its assumptions and inferences have been validated multiple times [22]. Therefore, the findings of this study are consistent with the results of Davis's Technology Acceptance Model (1989) [37], highlighting the influence of attitudes and perceived usefulness on behavioral intentions and their subsequent impact on learning outcomes.

5.2 Conclusion

There are several other criteria available for evaluating the model's usefulness, which can serve as reference points to assess the overall quality of the model. Based on the results of this study, the total effect and explanatory power ($R^2 = 0.6729$) of the overall positive path coefficients indicate a high level of explanatory ability for the PB, ET, and MR dimensions in relation to UA, BI, and LO. Additionally, the goodness-of-fit index (GoF = 0.68) of the structural model in this study meets the maximum fit level proposed by Cohen (1988) [41], indicating good evaluation and predictive capabilities of the model. Moreover, the inclusion of the path from PB to UA in the research model increased the explained variance (from 32.8% to 67.29%) with an effect size (f^2) of 0.25, indicating a moderate effect size. Similarly, the inclusion of the path from ET to BI also increased the explained variance (from 41.3% to 51.12%) with an effect size of 0.21, demonstrating a moderate effect size and indicating predictive relevance between the path model and the respective construct [41].

The research model not only demonstrates predictive capabilities for the learning outcome of the AQE app but also exhibits excellent overall model evaluation criteria and research fit. As a result, all nine hypotheses proposed in this study received significant support. This suggests that in the design of the AQE app, comprehensive consideration of PB, ET, MR, and UA factors can lead to a high level of user adoption intention. It is worth noting that this study goes beyond the focus on model predictive capabilities and further explores IPMA analysis. A significant finding in the study is that users highly value the interface and user experience design elements of MR but express low satisfaction. This indicates a need for prioritized attention and improvement, along with the implementation of further design strategies to enhance players' expectations of the media interactivity element. This will allow players to have a more engaging gaming experience through user-friendly interactive interface designs.

5.3 Limitations and Future Research Suggestions

This study has identified several limitations and proposes potential future research directions that merit consideration. Firstly, it should be noted that the study relied solely on existing scales from the literature as measurement tools and did not undertake expert interviews or qualitative research to explore any potential deficiencies in the theoretical constructs. Additionally, the representativeness of the sample in the quantitative survey is limited. Therefore, when investigating the factors influencing the learning outcomes of the AQE app, the following potential future research directions are worth exploring:

Conduct Practical-Oriented Research: In addition to drawing from existing literature, conducting further in-depth qualitative interviews with industry experts can provide valuable insights into the key factors influencing the behavioral intentions of digital creative apps. This approach can significantly enhance the predictive power of the model and offer a more comprehensive understanding of the app's effectiveness.

Extend the Research Model: While this study was grounded in theoretical perspectives, it is advisable to incorporate qualitative research, such as expert interviews, in the subsequent stages of research to address the limitations of quantitative studies. Moreover, extending the research model to include moderating factors like gender and involvement levels can offer valuable insights into whether involvement has a moderating effect on intention to use. This knowledge can aid in optimizing resource allocation and maximizing the benefits derived from the AQE app.

By considering and pursuing these potential research directions, future studies can further enrich our understanding of the AQE app's impact on learning outcomes and contribute to its continuous improvement and effectiveness.

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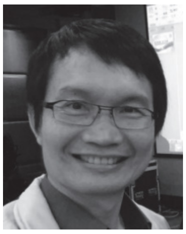

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