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THE MODERATION EFFECT OF TEACHERS' EXPERIENCE AND BIOGRAPHY ON THEIR INTENTION TO USE THE GAMIFICATION IN ONLINE LEARNING ACTIVITIES

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ABSTRACT

The world is rapidly moving toward implementing different technological innovations and the Internet in learning by providing effective educational platforms. These can significantly aid teachers in helping students achieve the set learning objectives and enhance students' academic performance. In Saudi Arabia, the Ministry of Education has launched the "Future Gate Program" project as one of the national transformation initiatives toward realising digital education for several purposes. This study investigates the impact of the teachers' biography (age, gender) and experience on their intention to use gamification throughout other performance factors by implementing the 'Future Gate' application in learning. This study considers two theoretical frameworks, including UTAUT2 and TTF, to develop the proposed model in this study, which investigates the moderation effect of teachers' experience and biography on their intention to use gamification in online learning activities. The quantitative research design has examined teachers' perceptions about their intention to adopt the Future Gate platform. Moreover, using a cross-sectional statistical modelling technique, Structural Equation Modelling (SEM) is used to assess the relationship between the study's constructs. The results showed that 'age' has a significant, negative moderating effect on 'Habit and Intention to Use' ($ß = -0.365$, t-value = 4.690, p-value <0.001). Likewise, the effect of 'Performance Expectancy' on 'Intention to Use' is negatively moderated by the respondents' experience ($ß = -0.129$, t-value = 2.165, p-value = 0.031). However, gender showed no significant moderating effect between the independent variables of the study (PE, EE, SI, HM, and H) and Intention to Use. Accordingly, teachers' intention to use showed a significant negative impact due to their age and habit. Also, previous experience with performance expectations negatively influences the intention to use.

Keywords: *Education, Technology, Distant Learning, Hedonic Motivation, Saudi Arabia, Tablet, Gamification, Structural Equation Modelling, Future-Gate Platform.*

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1. INTRODUCTION

The current utilisation of various motivational approaches in teaching and learning has increased students' excitement and involvement in the classroom. Using certain activities or strategies mainly depends on how a teacher manages students' interaction and performance. According to Stupnisky et al. [1], instructors' motivation for teaching can be used as the main predictor of their utilisation of teaching the best practices. In addition, the positive intention of individuals toward technology is the core factor for technology use in different contexts, such as the mobile learning approach [2], [3], e-learning systems [4], [5], banking [6], [7], and many more. Furthermore, several studies were conducted to encourage teachers' use of technology, as it is argued that when teachers use innovative technologies and strategies, they can deliver efficient teaching to their students.

Our world is rapidly moving toward implementing technological innovations and the Internet in the learning process by providing various educational platforms which assist teachers in making students achieve the desired learning objectives and enhance students' academic performance. Worldwide, the European Union (EU) has launched the Digital Education Action Plan (2021-2027). The renewed EU policy initiative sets out a common vision of high-quality, inclusive, and accessible digital education in Europe. It primarily aims to support the adaptation of the education and training systems of Member States to the digital age. The Action Plan, adopted on Sept. 30 2020, is a call for greater cooperation at the European level on digital education, particularly to address the challenges of the COVID-19 pandemic and provide golden opportunities for the education and training community (teachers, students), policymakers, academia, and researchers at the national, EU, and international level [8].

One new online and e-learning technique is gamification which refers to applying game design principles to non-game situations [9]. Gamification is a motivational service designed to provide game-like experiences, commonly affecting user behaviour [10], [11]. It offers game-design elements and principles in non-game contexts [10], [12]. Gamification commonly uses various gamification techniques to enhance individuals' participation/engagement, productivity, flow, learning, crowdsourcing, etc. [13]. Several previous studies were conducted to determine the influence of gamification techniques on users' practice behaviour in many contexts. Zichermann and Cunningham [14] asserted that incorporating gamification techniques into the teaching process of a lesson can potentially improve learners' abilities. This is because gaming techniques can result in a higher level of learners' commitment and motivation to a particular involved learning task [15]. The application of gamification in school teaching and learning has received much attention over the past few years [16]–[18]. This is because motivating young students to practice has become more complex, primarily when learning is partially carried out online via the learning management system [19], [20]. Marín et al. [21] reported the potential of using gamification in school classes from the teachers' perspectives. Most previous studies reported different results concerning gamification in stimulating students' motivation and engagement in the classroom and their academic achievement or performance.

Nevertheless, individual and contextual differences may influence users' intention to use gamification techniques in teaching. A review of previous studies asserted the role of gamification techniques in improving group members' abilities to effectively comprehend digital content and understand a specific area of study [22], [23]. The main types of rewards used in the gamification activity consist of points [24], leader board, achievement badges filling a progress bar or providing the user with virtual currency. In addition, assigning rewards to an individual can be linked to his/her level of accomplishment in the game, which is visible to other game members who participate in the same learning activity or task [25]. This study investigates the effect of teachers' biography (age, gender) and experience on their intention to use gamification throughout other performance factors using the application 'Future Gate' in the Kingdom of Saudi Arabia as a case study.

This study addresses a significant literature gap in integrating advanced technologies and teaching strategies in secondary education. Applying UTAUT2 and TTF models contributes to understanding technology adoption and utilisation in Saudi Arabia. The findings benefit decision-makers, enabling them to provide support and allocate time for gamification implementation. Integrating UTAUT2 and TTF models enhances our understanding of factors influencing teachers' technology use. This novel integration yields insights into predicting technology adoption by teachers.

Moreover, this research develops a comprehensive model of factors influencing teachers' use of gamified teaching. Insights into teachers' perceptions inform the Ministry of Education, guiding decisions, rules, and guidelines for effective gamification use in education. In summary, this study fills a crucial research gap, advances knowledge on technology adoption, and benefits educational decision-makers and policymakers in Saudi Arabia.

In line with Saudi Arabia's vision of 2030, released on Mar. 3 2017, the Minister of Education in Saudi Arabia, Dr Ahmed Al-Issa, launched the 'Future-Gate Program' project as one of the national transformation initiatives towards implementing digital education for several purposes. Tatweer Educational Technologies Company developed Future Gate as a Learning Management System (LMS) platform for 7-12 grades. This platform is an innovative environment for teachers and students to promote their teaching and learning practices [26]. The Future Gate project has been applied to 300 schools in the Kingdom, where all administration duties and teachers' practices are linked to Riyadh, Jeddah, Dammam, Alahsa, Alqassim, Onaizah, and Aseer. This innovative project includes 3789 male and 3903 female teachers, with 7692 teachers in Saudi schools. The third phase of this project was launched in 2019-2020 while using the system by schools in KSA [27]. In the Future Gate platform, gamification techniques are added to all the teachers' activity page learning activities. The main goals of integrating gamification techniques are to help teachers create an interactive learning environment that motivates the students, offer content electronically, and use images and anemography. These concerted efforts are part of the development plan by the Saudi Ministry of Education to consolidate information provided to students and facilitate student retrieval in the future. In addition, the use of gamification tools is an attempt to replace the traditional method by enabling learners at a younger age to acquire the necessary skills and promote their use of technology in learning. Table 1 illustrates the main tools incorporated into the Future Gate program [28].

Table 1 Gamification use in Future Gate in Saudi Arabia

Tool	Strategy
E-Course and its activities	Students can return to the course when needed, understand it, and apply activities before attending the class.
Wiki	Students can apply a cooperative education strategy through the wiki and participate in brainstorming sessions.
Interactive content and interactive homework	It makes learning active and attractive to students by allowing them to practice self-learning.
Discussion through the default class	Provides strategy of dialogue, discussion, brainstorming, and problem-solving with the peer group in the presence of the experienced teacher
Activities	Offers active learning strategy, problem-solving, and brainstorming
Choose by voting	Helps to vote on certain learning matters within a group
Points, Badges, and Leaderboard	Offers gamification elements to motivate students to better performance

2. THEORETICAL FRAMEWORK

The Unified Theory of Acceptance and Use of Technology (UTAUT2) was founded by [29], who empirically investigated the potential of using eight models to provide a unified theory of acceptance to describe users' use of innovative technology. Venkatesh et al. [30] proposed the UTAUT2 after a comprehensive assessment of eight prominent models used in user acceptance of technology. The results showed that certain constructs from previous models could be used to construct a unified view of users' acceptance, thus shaping the UTAUT2 model. Meanwhile, Task Technology Fit (TTF) was proposed by Goodhue and Thompson (1995) to understand the association between information systems and users' performance and provide some insights into how technology may impact users' involvement when technology provides specific features and support, which fit the requirement of a task. While the concept of TTF is a vital user evaluation construct in predicting the utilisation of a particular technology, the UTAUT2 model focuses on user perception of the technology. The TTF and UTAUT2 are significant models in the information system domain to explain the user behaviour of using information systems/information technology [31]. Zhou et al. [32] proposed an integrated model that considers both technology perceptions and the match of technology and task features. The authors proposed three routes for connecting UTAUT2 and TTF. Therefore, this study aims to consider the theoretical framework of UTAUT2 and the theoretical framework of TTF to develop the proposed study model to investigate the effect of teachers' biography and experience, as shown in Figure 1.

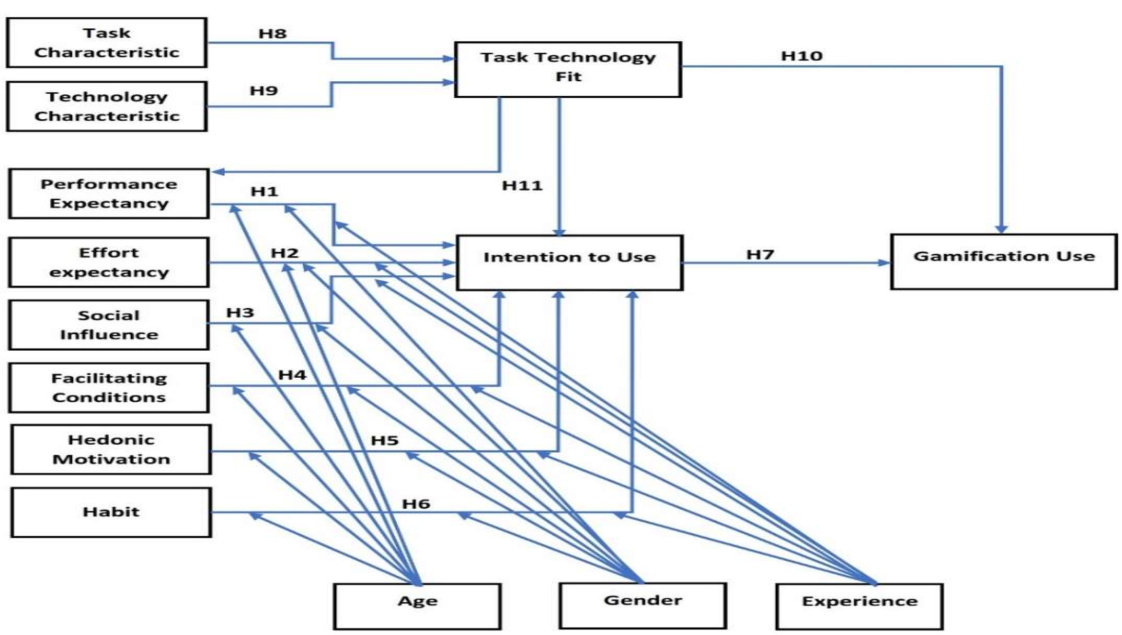

Figure 1 Theoretical Framework

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3. METHODOLOGY

This study employed the quantitative research design to examine the extent of teachers' perceptions about their intention to adopt the Future Gate platform in the learning process. A questionnaire survey was distributed via Google Forms through emails to investigate a large sample of teachers' perceptions and achieve more reliable results [33]. The Future Gate project has been applied to 300 schools in Saudi Arabia; the project started in 2017 and involved more than 7692 teachers. According to Schumacker and Lomax [34], the sample size for a Structural Equation Modelling (SEM) study can range between 10 to 20 respondents per variable. Thus, in this study, the number of participants – having 13 variables including age, gender, and experience, and considering the highest number of cases per variable – is calculated to range between 130 to 260. Structural Equation Modelling (SEM) was used in this study to assess the relationship between the study's constructs by using a cross-sectional statistical modelling technique. Moreover, factor analysis, path analysis, and regression analysis were performed to determine the accuracy and suitability of the constructs. The SEM analysis has been performed using SEM-Partial Least Square (PLS-SEM) to assess the reflective measurement model (to measure the internal consistency reliability, convergent validity, and discriminant validity); and the structural model parameters coefficient of determination (R^2), path coefficients, effect size (f^2), and predictive relevance (Q^2) [35].

This study analysed survey data using SPSS, which generated descriptive statistics and facilitated data cleaning. Structural Equation Modeling (SEM) was then used to assess relationships between constructs outlined in the research hypotheses. Factor analysis, path analysis, and regression were performed to validate construct accuracy, addressing research questions 1 and 2 on performance, effort expectancy, social influence, and hedonic motivation.

SEM was chosen for confirmatory analysis and evaluation model validity. It aids the understanding of structural relationships in diverse contexts, combining factor analysis and multiple regression to explore relationships between observed variables and latent constructs. SEM estimates path coefficients, capturing interdependence among variables. Endogenous variables represent dependent variables, while exogenous variables are independent.

Two models were used for relationship assessment. The measurement model establishes theoretical relationships specific to a context, while the structural model demonstrates interrelationships between constructs. The SEM model addresses research questions 3, 4, and 5, examining the effect of TTF on behavioural intention and usage of gamification and investigating mediating effects of age, gender, and experience.

4. ANALYSIS OF RESULTS

4.1 Data and Model Validation

The total number of participants involved in this study is 328. Three variables related to the participant's demographic characteristics were used, including gender, age, and teachers' experience gained in the Future Gate platform. Male participants showed a higher percentage of participation than females (55.49% vs. 44.51%), while the highest percentage of participation involved those aged 31-35 years with 35.06%, followed by 20-25 years (27.74%). Regarding the participants' experience in using the Future Gate platform, the highest percentage of participation included those with six months of experience (28.96%), followed by 18 months (28.35%), 24 months (27.44%), and 12 months (15.25%), as shown in Table 1.

Table 2 Respondents' Demographic Characteristics

Respondents' Profile	Freq.	Percentage %	Cumulative Percentage %
Gender			
Male	182	55.49	55.49
Female	146	44.51	100
Total	328	100	
Age			
20-25	91	27.74	27.74
26-30	67	20.43	48.17
31-35	115	35.06	83.23
More than 35	55	16.77	100
Total	328	100	
Experience			
Six months	95	28.96	28.96
12 months	50	15.25	44.21
18 months	93	28.35	72.56
24 months	90	27.44	100
Total	328	100	

Furthermore, Skewness and Kurtosis were measured to determine the normality of the data. Table 2 shows that data has a normal distribution with Skewness and Kurtosis values less than 2 and 7 (or -2 and -7), respectively [36]. Additionally, the data showed no outliers or missing values. This showed that the collected data is suitable for further analysis and model measurement.

Table 3 Normal distribution of study constructs

Variables	Skewness	SE	Kurtosis	SE
Task characteristics	.604	.135	-.572	.268
Technology characteristics	1.114	.135	1.827	.268
Task technology fit	.210	.135	-1.025	.268
Performance Expectancy	.395	.135	-.357	.268
Effort Expectancy	1.357	.135	4.035	.268
Social influence	1.385	.135	2.997	.268
Facilitating Conditions	-.153	.135	-.891	.268
Hedonic motivation	.615	.135	-.086	.268
Habit	-.060	.135	-.410	.268
Intention to use	1.297	.135	4.790	.268
Gamification use	-.031	.135	-.210	.268

Outside measurements and the structural/internal model were also evaluated. Internal consistency reliability, indicator reliability, convergent validity, and discriminative validity are the critical statistical characteristics of the measurement model [37]. The model's internal consistency should satisfy the standardisations and standards of academic research environments. Each construct's overall composite dependability (CR) should minimally obtain a threshold of 0.70 [38]. Except for the Facilitating Conditions, which were removed from the study, the composite reliability for all components in this study is more than 0.70. The indicator reliability of the measurement model was evaluated by determining the loading values for the items of the constructs of more than 0.50 [39]. In this study, all the items of constructs obtained loading values of more than 0.50. The loading values for items of constructs ranged between 0.503- 0.963, as shown in Table 3.

Table 4 Indicator reliability for items of constructs

		Dimensions									
Constructs	**Qs**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
EffortExpec1	1	0.810									
	2	0.833									
	3	0.759									
	4	0.503									
Badges	1		0.532								
Leader board	2		0.638								
Points	3		0.849								
Habit	1			0.534							
	2			0.669							
	3			0.899							
	4			0.623							
Hed Motiv	1				0.581						
	2				0.556						
	3				0.963						
Intent use	1					0.838					
	2					0.822					
	3					0.750					
Performexp	1						0.724				
	2						0.762				
	3						0.631				
	4						0.674				
Social Inf	1							0.864			
	2							0.920			
	3							0.759			
TaskCharac	1								0.837		
	2								0.666		
	3								0.738		
	4								0.779		
TaskTechFit	1									0.765	
	2									0.559	
	3									0.606	
	4									0.607	
	5									0.560	
TechCharac	1										0.820
	2										0.731
	3										0.845

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The convergent validity was assessed using a measurement model to determine the average variance extracted (AVE). The standard value of AVE should be equal to or higher than 0.50 for the constructs of the study [40]. The AVE of the constructs of the present study is higher than 0.50. Although some AVE values are less than the margin of 0.50, these values are considered acceptable since Cronbach's Alpha values are within the accepted range as recommended by [41]. One of the essential validation criteria is discriminant validity, which is evaluated by determining the standard measures, such as Fornell and Larcker's criterion, cross-loadings, and heterotrait-to-monotrait. Discriminant validity is determined using Fornell and Larcker's criteria [42]. As displayed in Table 4, the values of Fornell and Larcker's criteria for each concept are greater than the squares of correlations with latent variables, except for the TTF.

Table 5 Fornell and Larcker's criterion of constructs

	EE	GU	Hab	HM	IU	PE	SI	TAC	TTF	TEC
EE	0.736									
GU	0.383	0.613								
Hab	0.246	-0.045	0.677							
HM	0.556	0.356	0.473	0.679						
IU	0.518	0.382	0.327	0.483	0.804					
PE	0.184	0.193	0.150	0.219	0.111	0.700				
SI	0.587	0.315	0.143	0.316	0.504	0.224	0.850			
TAC	0.048	-0.050	0.347	0.099	0.317	0.283	0.283	0.758		
TTF	0.172	0.069	0.286	0.073	0.309	0.317	0.294	0.596	0.594	
TEC	-0.066	-0.285	0.255	-0.004	0.004	0.252	0.147	0.614	0.612	0.800
	Effort Expectancy (EE), Gamification Use (GU), Habit (Hab), Hedonic Motivation (HM), Intention to Use (IU), Performance Expectancy (PE), Social Influence (SI), Task Characteristics (TAC), Task-Technology Fit (TTF), Technology Characteristics (TC) (TEC).									

Table 5. illustrates all the cross-loadings for the items of constructs used in this study. All loading values output for each item of a specific construct should be higher than other latent values found in other constructs. The blue highlighted values were found to be higher than the values of this item in other constructs. Based on the results in this table, the items and constructs are all acceptable regarding discriminant validity.

Table 6 Cross loadings of discriminant validity

	EE	GU	Hab	HM	IU	PE	SI	TAC	TTF	TEC
EE1	0.810	0.312	0.108	0.410	0.409	0.092	0.419	0.096	0.091	-0.084
EE2	0.833	0.249	0.096	0.364	0.371	0.084	0.372	-0.154	0.111	-0.062
EE3	0.759	0.365	0.297	0.563	0.471	0.148	0.564	0.082	0.283	-0.006
EE4	0.493	0.143	0.245	0.208	0.207	0.310	0.342	0.154	-0.109	-0.059
Badges	-0.033	0.532	0.000	-0.170	-0.194	-0.091	-0.013	0.034	-0.012	-0.008
Leaderboard	0.330	0.638	-0.049	0.140	0.202	0.009	0.315	0.026	0.048	-0.104
Points	0.215	0.849	-0.018	0.242	0.194	0.204	0.144	-0.072	0.044	-0.340
Hab1	0.234	0.015	0.534	0.236	0.160	-0.044	0.117	0.098	-0.091	-0.027
Hab2	0.217	-0.080	0.669	0.278	0.173	-0.042	0.156	0.251	0.258	0.332
Hab3	0.183	-0.020	0.899	0.477	0.330	0.157	0.099	0.284	0.280	0.199
Hab4	0.053	-0.047	0.623	0.207	0.166	0.301	0.030	0.300	0.260	0.172
HM1	0.092	0.080	0.287	0.581	0.121	0.426	0.060	0.149	0.142	0.250
HM2	0.154	0.069	0.307	0.556	0.035	0.361	0.003	0.082	-0.041	0.232
HM3	0.575	0.365	0.426	0.963	0.498	0.111	0.331	0.066	0.048	-0.082
IU1	0.525	0.321	0.322	0.497	0.838	0.109	0.538	0.423	0.331	0.065
IU2	0.336	0.322	0.175	0.347	0.822	0.083	0.290	0.070	0.099	-0.140
IU3	0.334	0.278	0.261	0.270	0.750	0.068	0.321	0.180	0.271	0.045

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	EE	GU	Hab	HM	IU	PE	SI	TAC	TTF	TEC
PE1	-0.042	0.014	0.088	0.162	0.050	0.724	0.126	0.313	0.278	0.380
PE2	0.300	0.346	0.128	0.201	0.184	0.762	0.223	0.070	0.242	-0.069
PE3	0.080	0.185	0.102	0.078	0.040	0.631	0.120	0.172	0.157	0.138
PE4	0.182	-0.080	0.105	0.140	-0.024	0.674	0.141	0.277	0.170	0.325
SI1	0.582	0.302	0.072	0.287	0.482	0.265	0.864	0.151	0.099	0.064
SI2	0.528	0.160	0.146	0.319	0.409	0.148	0.920	0.273	0.226	0.088
SI3	0.365	0.341	0.158	0.192	0.384	0.142	0.759	0.320	0.465	0.241
TAC1	0.026	-0.111	0.279	0.121	0.237	0.187	0.137	0.837	0.438	0.387
TAC2	0.152	0.181	0.203	0.188	0.293	0.233	0.147	0.666	0.359	0.195
TAC3	0.173	0.027	0.279	0.209	0.278	0.258	0.333	0.738	0.352	0.437
TAC4	-0.108	-0.156	0.283	-0.108	0.192	0.202	0.247	0.779	0.587	0.713
TTF1	0.000	-0.053	0.129	-0.153	0.280	0.030	0.231	0.648	0.765	0.589
TTF2	0.113	-0.042	0.171	-0.002	-0.122	0.193	-0.041	0.208	0.559	0.259
TTF3	0.026	0.169	0.227	0.133	0.043	0.549	0.040	0.252	0.606	0.235
TTF4	0.340	0.146	0.240	0.252	0.461	0.104	0.417	0.240	0.607	0.342
TTF5	0.112	0.013	0.142	0.111	0.070	0.241	0.113	0.235	0.560	0.269
TEC1	-0.114	-0.151	0.095	-0.028	0.002	0.333	0.187	0.469	0.381	0.820
TEC2	0.022	-0.339	0.340	-0.053	0.028	-0.001	0.126	0.606	0.508	0.731
TEC3	-0.079	-0.176	0.152	0.060	-0.019	0.297	0.062	0.396	0.546	0.845

Effort Expectancy (EE), Gamification Use (GU), Habit (Hab), Hedonic Motivation (HM), Intention to Use (IU), Performance Expectancy (PE), Social Influence (SI), Task Characteristics (TAC), Task-Technology Fit (TTF), Technology Characteristics (TC) (TEC).

To determine the measurement model's acceptability, the fit model is considered an essential statistical function to approve the study's measurement model. The evaluation of the goodness of fit depends on the Standardised Root Mean Square Residual (SRMR) value obtained from Smart-PLS outputs. The standard value of SRMR should be equal to or less than 0.08 [43]. The results showed acceptable goodness of fit, where the value of SRMR obtained for the present study model is 0.042, with acceptable values of chi-square (7522.198) and NFI (0.205). Overall, the reliability and validity tests of the measurement model are acceptable. All items and constructs used in the present study are valid and meet the standards of academic research, except for the Facilitating Conditions that violated the assumptions. Therefore, this variable was excluded from the structural equation modelling analysis. The second step is evaluating the structural model of constructs' relationships.

4.2 Structural Model Analysis

The structural model for the independent variable should be evaluated to validate the theoretical contribution to the study objectives. Several statistical coefficients and assumptions should meet the standardisations of academic settings. The coefficient of determination, the path coefficient, hypothesis testing, the moderation connection, multi-group analysis, and mediation are all used in statistics [44]. The coefficient of determination (R^2) shows how the independent factors impact the dependent variable's variance. The results showed that R^2 with a range of 42.7%, Effort Expectancy, Habit, Hedonic Motivation, Performance Expectancy, Social Influence, and Task-Technology Fit describe the usage purpose. Gamification Use is explained by Habit, Task-Technology Fit, and Intention to Use, with a variation of 47.8%. With a variable of 43.3%, the Task-Technology Fit is explained by Technology Characteristics and Task Characteristics. With a variation of 11.3%, the Task-Technology Fit describes Performance Expectancy. The R^2 of all the above models showed predicted adequate acceptance of these models in terms of coefficients of determinations with significant effects (more than 0.26).

Moreover, to assess the multicollinearity of the developed model constructs, the VIF values should be lower than 3.0 [45]. As shown in Table 6, the inner and outer values of VIF are less than 3 for the items and constructs of the research model. As one of the vital model measures, path coefficients are valid and acceptable when the t-values are higher than 1.96, or the mean values of coefficients range between 1 and -1, with significant p values [45]. The developed model constructs showed t-values are higher than 1.96 with significant values less than 0.05, except for the Task-Technology Fit with the Gamification Use and the Habit with Intention to Use, as shown in Figure 2.

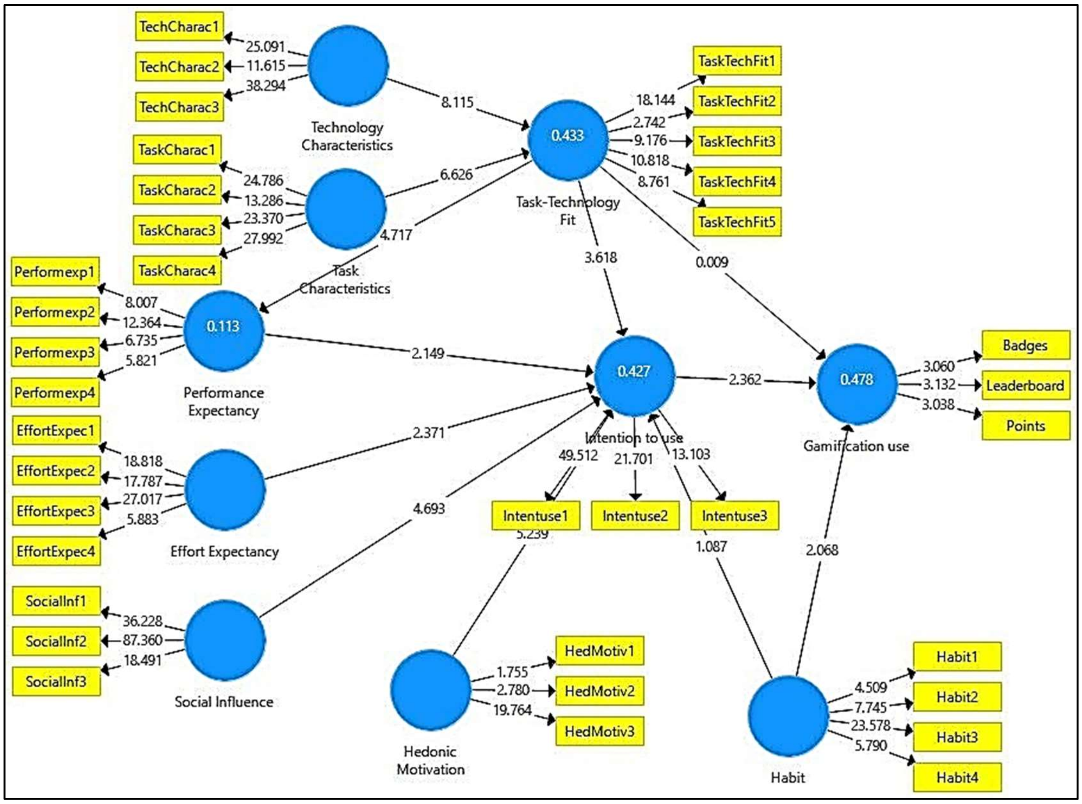

Figure 2 Constructs of the structural model

4.3 Moderators Effects

The moderation of variables should be observed between the dependent and independent variables, positively or negatively influencing the outcomes. The moderation alluded to the interactions played by the third variable, which significantly influenced the dependent variable [46] The moderator is included in structural equation modelling either as a categorical variable (like gender) or a quantitative variable (like age and experience). In the moderation analysis, assume that the dependent variable, independent variable, and moderators are referred to as Y, X, and M, respectively. M should moderate the relationship between Y and X. This moderation is changeable depending on the theoretical contribution and statistical outcomes. Three main statistical parameters, which should be evaluated, include significance, type of relationship, and path coefficient. The Multi-group moderation analysis is used in this study to assess the influence of moderators on the association between the independent and dependent variables and test the study's hypotheses. Intention to Use represents the study's dependent variable, whereas the independent variables in this study are Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, and Habit. The moderators are gender, age, and experience of the Future Gate platform.

The results showed that:

a. Gender showed no significant moderating impact between the independent variables (PE, EE, SI, HM, and H) and Intention to Use.
b. Only age has a significant moderating effect on Habit and Intention to Use. There is a negative moderation effect of Age between Habit and Intention to Use (ß = - 0.365, t-value = 4.690, p-value <0.001), i.e., the Age

factor limits the predictive impact of Habit on Intention to Use.

c. Experience in the Future Gate platform showed a significant moderation effect with the Performance Expectancy and Social Influence on Intention to Use. The influence of Performance Expectancy on Intention to Use is shown to be negatively moderated by the respondents' experience (ß = -0.129, t-value = 2.165, p-value = 0.031), i.e., a high level of experience in the Future Gate platform reduces the strength of the impact of Performance Expectancy on Intention to Use. Besides, experience positively moderates Social Influence on Intention to Use (ß = 0.242, t-value = 4.644, p-value <0.001). As demonstrated in Table 6, a high familiarity level with the Future Gate platform increases the predictive impact of Social Influence on the respondents' Intention to Use it.

Table 7 Moderators of the model

Moderators	Hypotheses of moderators	Std coefficient	t-value	*p*-value
Gender	Gender*Hedonic Motivation → Intention to Use	-0.093	1.503	0.133
	Gender*Performance expectancy → Intention to Use	-0.005	0.066	0.948
	Gender*Social Influence → Intention to Use	0.048	0.654	0.513
	Gender*Effort Expectancy → Intention to Use	0.087	1.020	0.308
	Gender*Habit → Intention to Use	0.206	1.021	0.308
Age	Age*Effort Expectancy → Intention to Use	0.109	1.482	0.139
	Age*Habit → Intention to Use	-0.365	4.690	0.000
	Age*Hedonic Motivation → Intention to Use	0.381	1.49	0.137
	Age*Performance expectancy → Intention to Use	-0.132	1.692	0.091
	Age*Social Influence → Intention to Use	0.148	1.448	0.148
Experience	Experience*Effort Expectancy → Intention to Use	0.106	1.377	0.169
	Experience*Habit → Intention to Use	-0.151	1.925	0.055
	Experience*Hedonic Motivation →Intention to Use	0.022	0.319	0.750
	Experience*Performance expectancy → Intention to Use	-0.129	2.165	0.031
	Experience*Social Influence → Intention to Use	0.242	4.644	0.000

Thus, the only significant mediators obtained from the study outcomes are supported. The significant mediators are (i) Intention to Use and (ii) Task Technology Fit. Meanwhile, gender failed to moderate the independent factors' effects on the dependent variable. The effect of Habit on Intention to Use showed a moderating effect on age. The predicted moderating impact for Performance Expectancy and Social Influence on Intention to Use was validated by experience with the Future Gate platform.

5. DISCUSSION

The study examined the impact of moderators on the main factors of the UTAUT2 model, which is integrated into the task technology fit. As Venkatesh et al. [30] proposed, gender, age, and experience are the principal moderators. Harris [47] determined the influence of the demographic moderators (age, gender, and experience) by determining the direct and interaction effects. However, Harris did not investigate the impact of the participants' demographics as significant moderators for his UTAUT2 model. Similarly, Pultoo et al. [48] found that experience is the only significant moderator between effort expectancy and intention to use, but it is insignificant for age in their study. Huang [49] also reported that age with facilitating conditions and gender with habit is the main moderators in their UTAUT2 model. However, gender has no effect as a significant moderator with UTAUT2 variables. Khechine et al. [50] also found that age is a crucial moderating variable between Performance Expectancy and Facilitating Conditions. The study showed a significant negative impact of age with Habit

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effects on the Intention to Use, consistent with Martins et al. [51]. In other words, the Age factor limits the predictive impact of Habit and Intention to Use; in this context, the older the teacher is, the less the intention to gamify in the Future Gate platform. It also tends to weaken the strength of Habit. The findings indicated that Experience in Future Gate significantly moderates the influence of Social Influence and Intention to Use. In other words, the respondents' experience enhanced the predictive relationship between Social Influence and Intention to Use. If the participants are more experience, the impact of Social Influence on Intention to Use will be enhanced. This finding showed that higher levels of expertise combined with more social influence could increase the instructor's intention to adopt new technologies in the learning process in Saudi Arabia. The findings by Martins et al. [51] consolidated this conclusion. On the other hand, the findings showed an insignificant moderating effect of gender between the independent variables (Hedonic Motivation, Performance Expectancy, Social Influence, Effort Expectancy, and Habit) and Intention to Use. The results are consistent with the findings of Huang [49] findings as the authors reported that gender has no significant effect as a moderator using the UTAUT2 model. Furthermore, age showed no significant influence on Effort Expectancy, Hedonic Motivation, Performance Expectancy, Social Influence, and Effort Expectancy, supported by Martins et al. [51]. Finally, the last moderator (Experience) showed an insignificant impact on Hedonic Motivation, Performance Expectancy, Effort Expectancy, and Habit, possibly due to the lack of training in using the Future Gate platform among the study population.

The present study has limitations in methodological procedures, specifications, and generalisation. Methodologically, it is recommended to use an intervention program to measure the improvement in teachers' intention to use and actual practice (Hassenfeld et al., 2020). Involving supervisors and academics from the educational platform would also enhance the assessment of teachers' performance. Specifications pose challenges as the study could not differentiate between various gamification applications and lacked literature on differences among gamification elements. Additionally, the study could not analyse specific class types or education levels. Generalisation is hindered by unequal sample sizes, preventing a comparison among regions, and a larger sample size of teachers would improve the study's validity. The study also did not evaluate student levels due to variations in abilities and interactions with teachers. In summary, limitations include methodological procedures, specifications, and generalisation, with recommendations for intervention programs involving supervisors and academics, addressing gamification variations, specifying class and education levels, and considering sample size, regions, and school levels for better generalisation.

Therefore, recommendations for future work include applying the model to specific subject areas like English, Mathematics, Science, and other disciplines to gain a deeper understanding of the factors influencing gamification use among teachers. Exploring the model's applicability in different school categories, such as primary schools and schools for gifted students, or comparing gamification use between schools for girls and boys, would provide valuable insights. Implementing intervention programs in e-learning platforms like Future Gate can yield more accurate findings on the factors influencing gamification adoption. Increasing awareness among teachers, students, and parents about the benefits of technology applications is essential for practical integration into pedagogical systems. Future research should consider employing qualitative studies to identify and address obstacles, needs, and necessary support for gamification use, contributing to improving teachers' practices and enhancing students' performance in educational settings.

6. CONCLUSION

The rapid integration of technology and the Internet in education has revolutionised learning worldwide. In Saudi Arabia, the Ministry of Education's "Future Gate Program" is part of the nation's digital education transformation initiatives. This study investigated how teachers' biography (age, gender) and experience influence their intention to use gamification within the Future Gate online learning platform.

Using the UTAUT2 and TTF frameworks, a quantitative research design collected teachers' perceptions of adopting Future Gate. Structural Equation Modeling (SEM) analysed the relationships between constructs.

Findings revealed that age negatively moderated the relationship between habit and intention to use gamification, indicating older teachers may face challenges adopting new methods ($ß = -0.365$, $p <$

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0.001). Experience negatively moderated the effect of performance expectancy on intention to use, suggesting previous experience influences teachers' perceived usefulness (ß = -0.129, p = 0.031). Gender did not show a significant moderating effect.

Addressing age-related barriers and supporting habit formation is crucial to promote gamification adoption. Training and support to enhance performance expectations can increase teachers' willingness to embrace gamification.

Hence, targeted interventions should leverage teachers' experiences while addressing age-related challenges. Raising awareness about technology's benefits in education is vital. By implementing these recommendations, stakeholders can create a digitally empowered education system that maximises gamification's potential, enhancing teaching practices and student outcomes.

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