



An extended hedonic motivation adoption model of TikTok in higher education

Xinjie Deng¹ · Zhonggen Yu¹

Received: 3 December 2022 / Accepted: 20 March 2023 / Published online: 30 March 2023

© The Author(s), under exclusive licence to Springer Science+Business Media, LLC, part of Springer Nature 2023

Abstract

As information technologies develop, social networking services have gradually gained attention from both researchers and practitioners. However, little is known about the technology adoption of social networking from the perspective of hedonic motivation. For this purpose, this study applied the hedonic motivation system adoption model (HMSAM) to TikTok and incorporated two innovative factors, i.e., perceived boredom and personal innovativeness. Via structural equation modeling (SEM), this study used SmartPLS 4.0.8 to analyze 246 valid responses from Chinese university students via an online survey. The results showed that the research model was adequate for the adoption of TikTok. Curiosity and perceived boredom significantly mediated the positive relationships between perceived ease of use and behavioral intention. Additionally, the educational level moderated the relationship between joy and focused immersion. The results of this study provided insights for future researchers and innovative teaching.

Keywords Hedonic motivation system adoption model (HMSAM) · TikTok · Perceived ease of use · Perceived boredom · Personal innovativeness

1 Introduction

The advancement of information technologies promoted the development of social network services in the twenty-first century. TikTok (Fig. 1) as a short video platform has experienced growing popularity across the world since its launch in 2016. As of September 27th 2021, TikTok has reached over one billion

✉ Zhonggen Yu
yuzhonggen@blcu.edu.cn; 401373742@qq.com

Xinjie Deng
1255811529@qq.com; 202121198711@stu.blcu.edu.cn

¹ Faculty of Foreign Studies, Beijing Language and Culture University, 15 Xueyuan Road, Haidian District, Beijing 100083, China

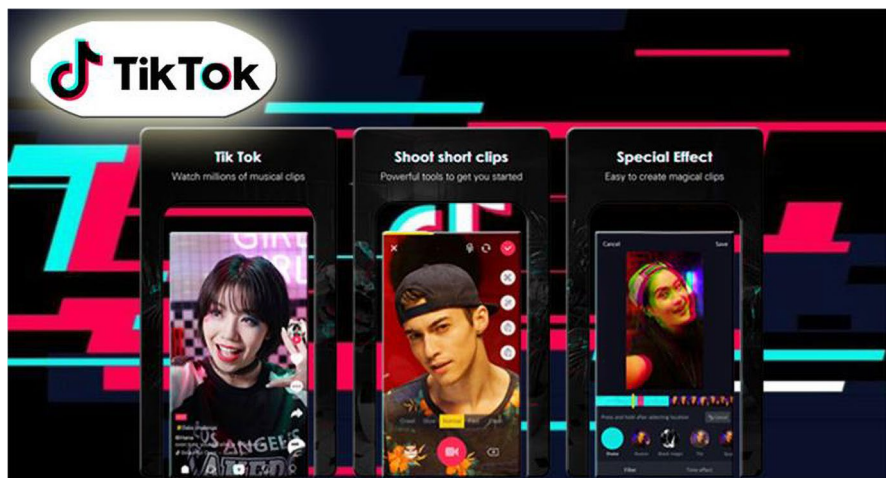


Fig. 1 The screenshot of TikTok (<https://tiktokapp.cc/>; www.tiktok.com)

monthly active users worldwide (TikTok, 2021). TikTok, also known as Douyin in China, is characterized by music videos between 15 and 60 s long (Zeng & Kaye, 2022) on various topics ranging from fashion to sports. Since the mission of TikTok is to “inspire creativity and bring joy” (TikTok, 2021), people from different countries use TikTok to learn, laugh, and connect themselves to the outside world. TikTok users can interact with the application by sharing, liking, commenting on, and even imitating original videos (Montag et al., 2021).

Although TikTok is usually a platform for entertainment, it can also serve as a pedagogical tool in different disciplines and learning contexts. TikTok can offer a place and space for higher dance education and shed light on post-humanist thinking in artistic practices (Heyang & Martin, 2022). Similarly, through music and movement, TikTok can meet the requirements of sports science courses, thus promoting students’ motivation, creativity, and curiosity (Escamilla-Fajardo et al., 2021). In chemistry education, TikTok videos can improve undergraduate students’ learning interest and engagement (Hayes et al., 2020). The technological features of TikTok, i.e., instantaneity, interactivity, mobility, and multimodality, also contributes to online informal language learning (Lee, 2022).

While previous studies explored the educational use of TikTok, few of them further examined the role of intrinsic motivation in TikTok use. Intrinsic motivation could be defined as the doing of an activity because of inner satisfaction rather than external inducement (Ryan & Deci, 2000). In the context of technology adoption, intrinsic motivation could prompt students to perceive the potential benefits of technology (Sun & Gao, 2020). Intrinsic motivation was also a significant factor to influence college students’ continuance intention in blended learning (Yang et al., 2022). Therefore, this study aimed to identify an extended

TikTok adoption model based on the hedonic-motivation system adoption model (HMSAM) by including personal innovativeness and perceived boredom.

2 Literature Review

2.1 Theoretical framework

The hedonic system acceptance model (HSAM) (van der Heijden, 2004) was essentially a variation of the technology acceptance model (TAM). The TAM (Davis, 1989) was used to predict and explain users' acceptance of information systems. Two salient constructs in the model were perceived ease of use (PEOU) and perceived usefulness (PU). Since Venkatesh (2000) added perceived enjoyment (i.e., joy) which was a type of intrinsic motivation to TAM, many studies have paid attention to the role of intrinsic motivation in technology acceptance research (e.g., van der Heijden, 2004). HSAM involved PEOU and joy to represent intrinsic motivation, and included PU to measure extrinsic motivation. PU and joy were two significant mediators in the relationship between PEOU and behavioral intention to use cinema websites (van der Heijden, 2004).

Based on van der Heijden's (2004) model, Lowry et al. (2013) further proposed the hedonic-motivation system adoption model (HMSAM). The latter considered both intrinsic motivation and cognitive absorption. Flow theory, as the conceptual basis of cognitive absorption (Lowry et al., 2013), well explained involvement and concentration in the context involving intrinsic motivation. This theory believed that if individuals were internally motivated, they would logically experience immersion and be absorbed in their ongoing activities (Guo & Poole, 2009; Lee, 2010). Flow theory was thus frequently used to extend existing models, such as the technology acceptance model (TAM) (Lee, 2010) and the unified theory of acceptance and use of technology (UTAUT) (Zhou, 2011). The final HMSAM consisted of seven constructs, i.e., perceived ease of use (PEOU), perceived usefulness (PU), curiosity, joy, control, focused immersion (FI), and behavioral intention to use (BIU).

The HMSAM was designed and applicable for hedonic motivation systems, including video games, online shopping, virtual worlds, and social networking (Lowry et al., 2013; van der Heijden, 2004). Among previous studies, Oluwajana et al. (2019) used HMSAM to investigate students' acceptance of gamified learning environments. Likewise, HMSAM was also applied to Kahoot!, which was a game-based student response system (Palos-Sanchez et al., 2022). Drawing upon HMSAM, researchers focused on both American and Chinese consumers' mobile shopping intentions (Ertz et al., 2022). Furthermore, perceived enjoyment and subjective well-being were integrated with the HMSAM to explain consumers' continued intention to use virtual reality for tourism (Kim & Hall, 2019). However, little was known about users' hedonic motivation and adoption of social networking. This study thus focused on TikTok use for learning to further understand the acceptance of social networks among students in higher education institutions.

2.2 Research model and hypotheses

Perceived ease of use (PEOU) and perceived usefulness (PU) were two essential elements in technology acceptance research and models. PEOU was defined as the extent to which users believed that interacting with a certain system would require little effort, and PU referred to the degree to which individuals thought that using a particular system would improve their learning efficiency or job performance (Davis, 1989). However, hedonic systems were not designed for productivity goals. PU in the HMSAM emphasized hedonic aspects instead of a utilitarian function, thus focusing on the usefulness of pursuing pleasure (Gu et al., 2010; Lowry et al., 2013). Many previous studies have identified the positive relationship between PEOU and PU in different research models from both utilitarian (e.g., Alyoussef, 2021; Yu, 2020) and hedonic (e.g., Oluwajana et al., 2019; Palos-Sanchez et al., 2022) perspectives. Therefore, the authors proposed the following hypothesis.

H1. Perceived ease of use positively and significantly affects perceived usefulness in TikTok use at the 0.05 level.

Curiosity, a subconstruct of cognitive absorption, indicated the extent to which users' experience with a specific system aroused their sensory and cognitive curiosity (Agarwal & Karahanna, 2000). Curiosity was derived from flow theory (Csikszentmihalyi, 1990) and was deemed as an important feature of intrinsic motivation. PEOU of instant messaging technology significantly influenced Kuwait university students' curiosity (Rouibah & Hamdy, 2009). Other studies on game-based systems also verified the positive relationship between PEOU and curiosity (Oluwajana et al., 2019; Palos-Sanchez et al., 2022). The authors thus presented the following hypothesis.

H2. Perceived ease of use positively and significantly affects curiosity in TikTok use at the 0.05 level.

Control measured the extent to which users perceived that they were in charge of the interaction with systems (Agarwal & Karahanna, 2000). Specifically, individuals with a high level of control could skillfully either adapt the interaction to their needs or interrupt the experience (Lowry et al., 2013). It was found that if a system was easy to manipulate, users would be in control of the interaction (Oluwajana et al., 2019). When people used technology tools with ease, their confidence and self-efficacy increased. Consequently, users were likely to control their interactions (Lowry et al., 2013). Therefore, the authors formulated the following hypothesis.

H3. Perceived ease of use positively and significantly affects control in TikTok use at the 0.05 level.

Joy, also termed as heightened enjoyment in the HMSAM, referred to "the pleasurable aspects of the interaction" with systems (Agarwal & Karahanna,

2000, p. 673). It was usually described as being enjoyable and fun. PEOU positively predicted joy when students used gamification tools such as Kahoot! (Palos-Sanchez et al., 2022) and storyboards (Lowry et al., 2013). In the mobile shopping context, PEOU was a significant antecedent to perceived enjoyment, contributing to the enjoyable experience (Chang & Chen, 2021; Ertz et al., 2022). Thus, the following hypothesis was proposed.

H4. Perceived ease of use positively and significantly affects joy in TikTok use at the 0.05 level.

Boredom was a negative deactivating emotion frequently occurring with enjoyment (Dewaele & Li, 2021). It was defined as an unpleasant psychological state where people were in low physical and cognitive activation and thus wanted to escape from ongoing activities (Li, 2021). The under-stimulation theory (Larson & Richards, 1991) believed that repetitive stimuli resulted in the lack of arousal and involvement. According to the control-value theory, boredom may result from a low level of value and control over tasks (Pekrun, 2006). The integration of perceived boredom (PB) and the HMSAM followed Lowry et al.'s (2013) suggestions that future research could examine the effect of emotions on hedonic motivation system acceptance. Based on these considerations, the authors proposed the following hypothesis.

H5. Perceived ease of use negatively and significantly affects perceived boredom in TikTok use at the 0.05 level.

Behavioral intention to use (BIU) was conceptualized as the degree to which people consciously established plans to perform or not to perform particular future behavior (Warshaw & Davis, 1985). Many acceptance models have investigated the antecedents of BIU. Among them, PU was the most studied and common one (Palos-Sanchez et al., 2022; Ruangkanjanases et al., 2020). University students' hedonic motivation significantly influenced their continued use intention of travel applications (Zhou et al., 2022). In the HMSAM, curiosity and joy were another two positive predictors of BIU (Ertz et al., 2022; Lowry et al., 2013). This study attempted to introduce an additional predictor, i.e., perceived boredom. Therefore, the following hypotheses were determined.

H6. Perceived usefulness positively and significantly affects behavioral intention to use TikTok at the 0.05 level.

H7. Curiosity positively and significantly affects behavioral intention to use TikTok at the 0.05 level.

H8. Joy positively and significantly affects behavioral intention to use TikTok at the 0.05 level.

H9. Perceived boredom negatively and significantly affects behavioral intention to use TikTok at the 0.05 level.

Focused immersion (FI) referred to a state of flow where individuals were totally engaged in their tasks and ignored other attentional demands (Agarwal & Karahanna, 2000). During the COVID-19 pandemic period, customers' hedonic motivation positively influenced their flow when they used live-streaming shopping applications (Zhao & Bacao, 2021). In virtual reality tourism, perceived enjoyment was an important antecedent of both visitors' and non-visitors' flow state (Kim & Hall, 2019). The HMSAM also confirmed that curiosity, control, and joy were three determinants of FI (Lowry et al., 2013; Oluwajana et al., 2019). Moreover, individuals with a high level of boredom showed a deficit in sustained attention (Malkovsky et al., 2012). Thus, the authors presented the following hypotheses.

H10. Curiosity positively and significantly affects focused immersion in TikTok use at the 0.05 level.

H11. Control positively and significantly affects focused immersion in TikTok use at the 0.05 level.

H12. Joy positively and significantly affects focused immersion in TikTok use at the 0.05 level.

H13. Perceived boredom negatively and significantly affects focused immersion in TikTok use at the 0.05 level.

Personal innovativeness (PI) was defined as the willingness of a person to try out any new system or information technology (Agarwal & Prasad, 1998). The diffusion of innovation theory (Rogers, 1995) posited that people held different attitudes toward new things and did not adopt an innovation simultaneously. PI, when integrated into the TAM, significantly exerted a positive influence on PEOU in students' mobile learning (Joo et al., 2014). Similarly, teachers' PI contributed to the prediction of their PEOU and behavioral intention to adopt emerging technologies (Akar, 2019). PI was also incorporated into the UTAUT model to explore Indonesian students' mobile learning (Sidik & Syafar, 2020). Although PI was a critical construct for understanding the acceptance of technology innovations, it remained underexplored (Agarwal & Prasad, 1998) and was not included in the HMSAM. The authors thus formulated the following hypothesis. Based on previous studies and hypotheses development, the final research model was proposed in Fig. 2.

H14. Personal innovativeness positively and significantly affects perceived ease of use in TikTok at the 0.05 level.

3 Methods

3.1 Participants and procedures

The participants of this study were students from higher education institutions in China with the experience of using TikTok. The researchers obtained ethical approval from their organizations before data collection. A convenience sampling method was used

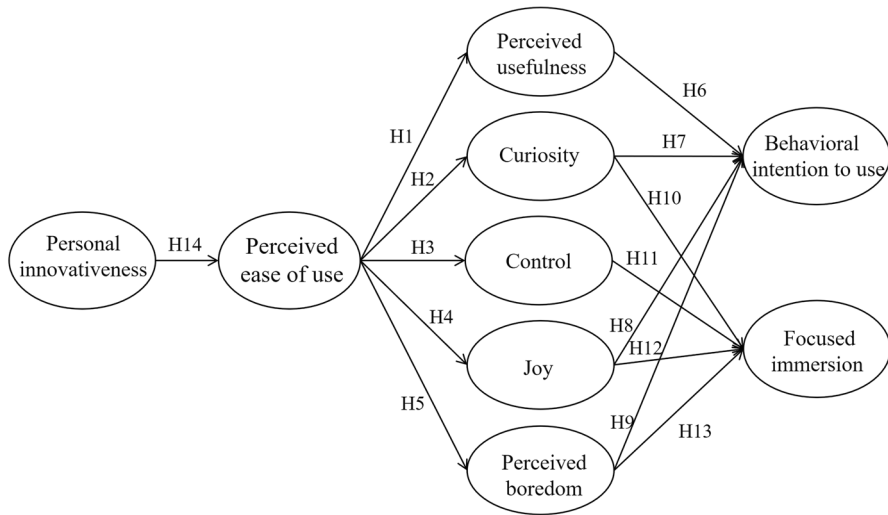


Fig. 2 The proposed research model

both online and offline at the first author's university. The participants were informed about the confidentiality policy and instructions to fill in the survey.

Data were collected using an online survey from October 9, 2022 to November 6, 2022. The researchers distributed the survey to their students through an online platform named Questionnaire Star during the 10-min break. The first author also posted messages in mainstream social software to recruit participants, including WeChat, QQ, Weibo, TikTok, and Xiaohongshu (an Instagram-like lifestyle app in China). Once respondents finished the survey, they would receive either a participation reward or a corresponding gift. A total of 277 students were willing to participate in this study and submitted their informed consent. The researchers excluded 31 invalid questionnaires and analyzed the remaining 246 responses. Therefore, the valid response rate was 88.9%. Table 1 provides the profile of participants.

Table 1 The profile of participants

Item	Category	Frequency	Percentage (%)
Gender	Male	105	42.68
	Female	141	57.32
Educational level	Bachelor	143	58.13
	Master	92	37.40
	Doctor	11	4.47
Frequency of using TikTok	Always	63	25.61
	Often	68	27.64
	Sometimes	49	19.92
	Seldom	66	26.83
Total		246	100.00

3.2 Instruments

The researchers used the back-translation method and designed the questionnaire in both English and Chinese to avoid misunderstanding. They also invited 10 TikTok users and 3 professors to complete the survey before data collection. Based on their suggestions, the researchers optimized and improved the questionnaire regarding wording, format, numbering, and sequence of the items.

The final version of the questionnaire consisted of two parts. The first part included the willingness of participating in the survey, gender, educational level, and frequency of using TikTok. The second part was made up of 34 items (see [Appendix](#) in supplementary files) to measure the nine constructs included in the proposed research model: PEOU (4 items), PU (5 items), curiosity (3 items), control (3 items), joy (4 items), perceived boredom (4 items), PI (4 items), BIU (3 items), and FI (4 items). All items in the second part were measured using five-point Likert scales adapted from previous studies (Agarwal & Karahanna, 2000; Bieleke et al., 2021; Lowry et al., 2013; Venkatesh, 2000).

3.3 Data analysis

This study adopted partial least squares structural equation modeling (PLS-SEM) to test the research model. PLS-SEM was suitable for theory development and highly complex models with many constructs (Hair et al., 2012). This study included nine constructs and mediating effects, aiming to develop a theoretically comprehensive model by introducing boredom theory. PLS-SEM was also especially useful for investigating relatively new phenomena (Chin & Newsted, 1999), such as learning in TikTok. Thus, the researchers employed SmartPLS 4.0.8 (Ringle et al., 2022) to analyze measurement and structural models. The analysis of PLS-SEM results involved two stages (Sarstedt et al., 2014). The first stage examined the measurement model by reliability and validity. The second stage evaluated the structural model by predictive relevance, significance of path coefficients, indirect effects, and moderating effects.

4 Results

4.1 Measurement model assessment

To examine the reflective measurement model, the researchers performed an ordinary PLS-SEM algorithm to obtain indicator loadings first (Table 2). Loadings greater than 0.70 revealed that the construct could explain over 50% of the indicator's variance (Sarstedt et al., 2014). Since the loadings of FI1 and PU4 were far below 0.70, the researchers decided to delete the two items. After deletion, all factor loadings were higher than 0.70 and significant at the 0.05 level, indicating acceptable item reliability (Chin, 1998). Following Hair et al.'s guidelines (2019), the researchers also assessed internal consistency reliability using Cronbach's alpha

Table 2 Reliability and convergent validity of the measurement model

Construct	Item	Factor loading	Cronbach's alpha	Composite reliability (CR)	Average variance extracted (AVE)
Behavioral intention to use (BIU)	BIU1	0.947*	0.931	0.931	0.879
	BIU2	0.939*			
	BIU3	0.926*			
Control (CTL)	CTL1	0.891*	0.782	0.907	0.681
	CTL2	0.791*			
	CTL3	0.791*			
Curiosity (CUR)	CUR1	0.876*	0.872	0.876	0.796
	CUR2	0.928*			
	CUR3	0.871*			
Focused immersion (FI)	FI1 (deleted)	0.216	0.716	0.746	0.635
	FI2	0.734*			
	FI3	0.868*			
	FI4	0.783*			
Joy (JOY)	JOY1	0.897*	0.910	0.924	0.790
	JOY2	0.940*			
	JOY3	0.920*			
	JOY4	0.789*			
Perceived boredom (PB)	PB1	0.822*	0.788	0.829	0.608
	PB2	0.866*			
	PB3	0.708*			
	PB4	0.709*			
Perceived ease of use (PEOU)	PEOU1	0.772*	0.791	0.821	0.611
	PEOU2	0.702*			
	PEOU3	0.799*			
	PEOU4	0.847*			
Personal innovativeness (PI)	PI1	0.874*	0.894	0.898	0.760
	PI2	0.908*			
	PI3	0.826*			
	PI4	0.876*			
Perceived usefulness (PU)	PU1	0.875*	0.848	0.872	0.685
	PU2	0.832*			
	PU3	0.851*			
	PU4 (deleted)	0.605*			
	PU5	0.746*			

* $p < 0.05$

and composite reliability (CR). The Cronbach's alpha and CR for each construct exceeded the recommended threshold, i.e., 0.70. The third step was to evaluate the convergent validity. The average variance extracted (AVE) of all constructs were

greater than the minimum acceptable value of 0.50, suggesting a satisfactory level of convergent validity.

The fourth step was to measure discriminant validity using three statistical criteria. First, cross-loadings required that factor loadings of each component item belonging to its corresponding construct should be higher than those of other constructs (Urbach & Ahlemann, 2010). Second, as shown in Table 3, the discriminant validity met the Fornell-Larcker criterion (Fornell & Larcker, 1981) that square root of each construct's AVE was larger than inter-construct correlation between the same construct and all the others. However, this metric received criticism because variance-based SEM methods may overestimate factor loadings and underestimate structural model relationships (Henseler et al., 2015). The third criterion was thus proposed.

The heterotrait-monotrait ratio (HTMT) was an estimate of the correlations. It was the average of the item correlations across constructs relative to those within the same construct (Henseler et al., 2015). The threshold value would be set at 0.90 if constructs were conceptually similar, and a threshold value of 0.85 was suggested when constructs were distinct. Since perceived usefulness (PU) focused on hedonic aspects, it was reasonable that PU was slightly similar to joy. Therefore, the HTMT ratio (Table 4), ranging from 0.120 to 0.909, generally validated the discriminant validity of this study.

4.2 Structural model analysis

Having confirmed the reliability and validity of the measurement model, the researchers first assessed the coefficient of determination (R^2). R^2 indicated the relationship of a construct's variance that could be explained to its total variance, ranging from 0 to 1. The calculation of R^2 was sum of squares due to regression (SSR) divided by total sum of squares (SST). Thus, R^2 could reflect the explanatory or predictive power of a model (Shmueli & Koppius, 2011). The R^2 value of 0.67, 0.33,

Table 3 Fornell-Larcker test of discriminant validity

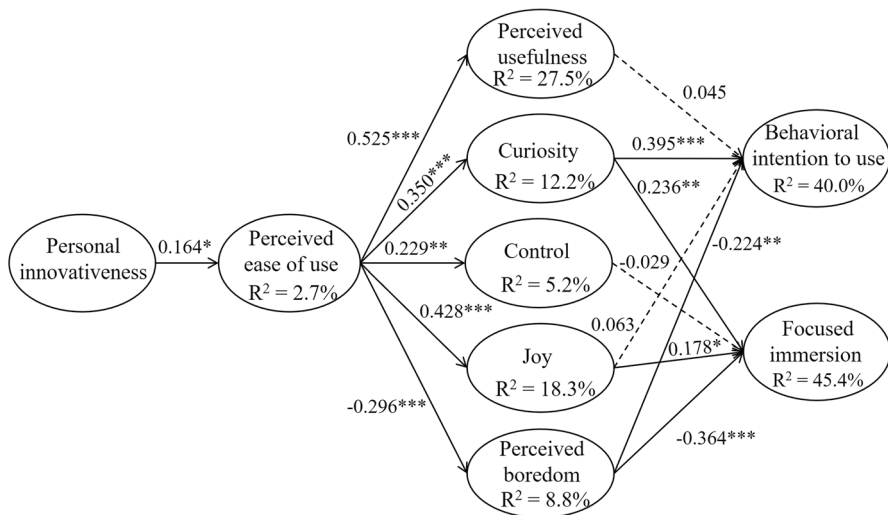
Construct	Correlation of the constructs								
	BIU	Control	Curiosity	FI	Joy	PB	PEOU	PI	PU
BIU	0.937								
Control	0.157	0.825							
Curiosity	0.590	0.035	0.892						
FI	0.408	0.024	0.562	0.797					
Joy	0.506	0.244	0.676	0.560	0.889				
PB	-0.512	-0.005	-0.566	-0.610	-0.630	0.780			
PEOU	0.229	0.229	0.350	0.371	0.428	-0.296	0.782		
PI	0.155	0.092	0.251	0.107	0.125	-0.109	0.164	0.871	
PU	0.453	0.189	0.594	0.559	0.801	-0.553	0.525	0.172	0.828

The diagonal values in bold are square roots of AVEs. BIU: Behavioral intention to use; FI: Focused immersion; PB: Perceived boredom; PEOU: Perceived ease of use; PI: Personal innovativeness; PU: Perceived usefulness

Table 4 Heterotrait-monotrait ratio (HTMT) of discriminant validity

	BIU	Control	Curiosity	FI	Joy	PB	PEOU	PI	PU
BIU									
Control	0.175								
Curiosity	0.654	0.058							
FI	0.493	0.130	0.691						
Joy	0.548	0.283	0.756	0.673					
PB	0.576	0.144	0.655	0.762	0.715				
PEOU	0.247	0.261	0.410	0.465	0.474	0.335			
PI	0.166	0.120	0.285	0.138	0.141	0.134	0.194		
PU	0.511	0.210	0.692	0.685	0.909	0.652	0.582	0.201	

BIU: Behavioral intention to use; FI: Focused immersion; PB: Perceived boredom; PEOU: Perceived ease of use; PI: Personal innovativeness; PU: Perceived usefulness

**Fig. 3** The research model with path coefficients. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

and 0.19 could be considered substantial, moderate, and lower weak (Chin, 1998). Figure 3 presents that the research model explained a minimum of 45.4% of focused immersion and 40.0% of behavioral intention to use TikTok, suggesting moderate explanatory power.

The blindfolding technique was removed in SmartPLS 4, and PLSpredict was recommended for the assessment of predictive power. Following Hair et al.'s (2019) suggestions, the researchers chose to compare the root mean squared error (RMSE), rather than the mean absolute error (MAE), with the benchmark, i.e., the linear regression model (LM) values. After PLSpredict executed tenfold cross-validation 10 times, the results (Table 5) showed that none of indicators

Table 5 The results of PLSpredict

Construct	Item	Q ² predict	PLS-SEM analysis		LM benchmark	
			RMSE	MAE	RMSE	MAE
Behavioral intention to use (BIU)	BIU1	0.019	1.057	0.878	1.070	0.893
	BIU2		1.101	0.908	1.107	0.904
	BIU3		1.168	0.977	1.180	0.967
Control (CTL)	CTL1	0.005	0.993	0.834	1.007	0.842
	CTL2		0.981	0.825	0.995	0.838
	CTL3		1.101	0.883	1.119	0.901
Curiosity (CUR)	CUR1	0.052	0.854	0.604	0.864	0.609
	CUR2		0.946	0.750	0.954	0.760
	CUR3		1.025	0.839	1.029	0.837
Focused immersion (FI)	FI2	0.009	0.865	0.627	0.880	0.636
	FI3		0.882	0.604	0.896	0.614
	FI4		1.087	0.946	1.097	0.947
Joy (JOY)	JOY1	0.010	0.94	0.678	0.954	0.690
	JOY2		0.961	0.679	0.971	0.695
	JOY3		1.009	0.760	1.020	0.765
	JOY4		1.094	0.931	1.100	0.930
Perceived boredom (PB)	PB1	0.007	1.086	0.926	1.098	0.928
	PB2		1.102	0.911	1.119	0.918
	PB3		1.151	0.956	1.156	0.950
	PB4		1.153	0.990	1.168	1.011
Perceived ease of use (PEOU)	PEOU1	0.015	0.635	0.464	0.641	0.470
	PEOU2		0.829	0.571	0.840	0.604
	PEOU3		0.878	0.606	0.893	0.626
	PEOU4		0.672	0.560	0.680	0.565
Perceived usefulness (PU)	PU1	0.018	0.998	0.769	1.012	0.781
	PU2		0.806	0.576	0.817	0.575
	PU3		1.099	0.878	1.110	0.879
	PU5		1.075	0.883	1.086	0.888

yielded greater RMSE values compared to the LM benchmark, which indicated a high predictive power (Shmueli et al., 2019). All the positive Q² values also confirmed the predictive relevance of the model.

The researchers also verified the hypothesized relationships using the PLS-SEM algorithm and bootstrapping techniques. The standardized root mean square residual (SRMR) reflected the approximate model fit. The value of SRMR was 0.065 and lower than 0.08 (Henseler et al., 2016a, 2016b), indicating that the model fit was adequate. Path coefficients explained the strength of the relationship between two constructs, which should exceed 0.10 (Urbach & Ahlemann, 2010).

The resampling technique such as bootstrapping was run to determine the significance, and the number of bootstrap subsamples was set to 5000.

As presented in Table 6, 11 out of 14 hypothesized paths were statistically significant. Perceived ease of use positively affected perceived usefulness ($\beta=0.525$, $p<0.001$), curiosity ($\beta=0.350$, $p<0.001$), control ($\beta=0.229$, $p<0.01$), and joy ($\beta=0.428$, $p<0.001$), which supported H1, H2, H3, and H4. In contrast, perceived ease of use negatively predicted perceived boredom ($\beta=-0.296$, $p<0.001$), supporting H5. Perceived usefulness ($\beta=0.045$, $p>0.05$) and joy ($\beta=0.063$, $p>0.05$) did not significantly affect behavioral intention, which rejected H6 and H8. However, curiosity ($\beta=0.395$, $p<0.001$) and perceived boredom ($\beta=-0.224$, $p<0.01$) were significant predictors of behavioral intention, supporting H7 and H9. Likewise, curiosity ($\beta=0.236$, $p<0.01$), joy ($\beta=0.178$, $p<0.05$), and perceived boredom ($\beta=-0.364$, $p<0.001$) also significantly predicted focused immersion, which validated H10, H12, and H13. Nevertheless, control failed to significantly affect focused immersion ($\beta=-0.029$, $p>0.05$), thus rejecting H11. Personal innovativeness positively influenced perceived ease of use ($\beta=0.164$, $p<0.05$), which supported H14.

4.3 Mediating analysis

The researchers performed the mediation analysis with a 95% confidence interval using the bias-corrected and accelerated bootstrap method. Among the mediating relations in the research model, 10 mediation paths were significant (Table 7).

Table 6 The results of hypothesis testing

Hypothesis	Path	Path coefficient	T statistics	p value	95% confidence interval		Results
					Lower	Upper	
H1	PEOU $\rightarrow$ PU	0.525	8.900	0.000	0.408	0.637	Accepted
H2	PEOU $\rightarrow$ Curiosity	0.350	4.390	0.000	0.184	0.495	Accepted
H3	PEOU $\rightarrow$ Control	0.229	3.403	0.001	0.103	0.361	Accepted
H4	PEOU $\rightarrow$ Joy	0.428	6.265	0.000	0.287	0.553	Accepted
H5	PEOU $\rightarrow$ PB	-0.296	4.321	0.000	-0.425	-0.157	Accepted
H6	PU $\rightarrow$ BIU	0.045	0.494	0.622	-0.122	0.231	Rejected
H7	Curiosity $\rightarrow$ BIU	0.395	5.062	0.000	0.228	0.533	Accepted
H8	Joy $\rightarrow$ BIU	0.063	0.637	0.524	-0.134	0.254	Rejected
H9	PB $\rightarrow$ BIU	-0.224	2.938	0.003	-0.376	-0.075	Accepted
H10	Curiosity $\rightarrow$ FI	0.236	3.112	0.002	0.088	0.384	Accepted
H11	Control $\rightarrow$ FI	-0.029	0.487	0.626	-0.148	0.092	Rejected
H12	Joy $\rightarrow$ FI	0.178	2.058	0.040	0.006	0.344	Accepted
H13	PB $\rightarrow$ FI	-0.364	5.217	0.000	-0.503	-0.233	Accepted
H14	PI $\rightarrow$ PEOU	0.164	2.575	0.010	0.064	0.295	Accepted

BIU: Behavioral intention to use; FI: Focused immersion; PB: Perceived boredom; PEOU: Perceived ease of use; PI: Personal innovativeness; PU: Perceived usefulness

Table 7 Significant mediating effects of the research model

Path	Indirect effect	Standard deviation	T statistics	<i>p</i> value	95% confidence interval	
					Lower	Upper
PEOU → Curiosity → BIU	0.125	0.039	3.194	0.001	0.060	0.216
PEOU → PB → BIU	0.066	0.027	2.485	0.013	0.022	0.128
PEOU → Curiosity → FI	0.075	0.035	2.144	0.032	0.022	0.160
PEOU → PB → FI	0.108	0.034	3.176	0.002	0.051	0.184
PI → Curiosity → BIU	0.079	0.031	2.572	0.010	0.027	0.151
PI → Curiosity → FI	0.048	0.024	2.011	0.044	0.011	0.104
PI → PEOU → PU	0.085	0.038	2.241	0.025	0.013	0.158
PI → PEOU → Joy	0.069	0.032	2.163	0.031	0.013	0.135
PI → PEOU → PB	-0.048	0.022	2.138	0.033	-0.097	-0.011
PI → PEOU → Curiosity	0.051	0.026	1.996	0.046	0.010	0.108

BIU: Behavioral intention to use; FI: Focused immersion; PB: Perceived boredom; PEOU: Perceived ease of use; PI: Personal innovativeness; PU: Perceived usefulness

Curiosity ($B=0.125$, 95% CI [0.060, 0.216]) and perceived boredom ($B=0.066$, 95% CI [0.022, 0.128]) were two significant mediators of the relationship between PEOU and BIU. They also significantly mediated the effect of PEOU on FI ($B=0.075$, 95% CI [0.022, 0.160]; $B=0.108$, 95% CI [0.051, 0.184]). The results also confirmed the mediating role of curiosity between PI and BIU ($B=0.079$, 95% CI [0.027, 0.151]), and between PI and FI ($B=0.048$, 95% CI [0.011, 0.104]). The effect of PI on hedonic aspects (i.e., PU, joy, and curiosity) was significantly mediated by PEOU.

4.4 Multigroup analysis

The researchers also performed permutation multigroup analysis to investigate moderating roles of gender and educational level. All participants in this study were divided into male and female in terms of gender. Regarding educational level, master and doctor were merged into one category because of the small sample size of the doctor category. Before multigroup analysis, measurement invariance of composite models (MICOM) should be examined in three steps, i.e., configural invariance, compositional invariance, and the equality of composite mean values and variances (Henseler et al., 2016a, 2016b). In step 1, configural invariance was established (Table 8). In step 2, correlations of all constructs in both groups of gender or educational level were not significantly lower than one, indicating that compositional invariance was established (Henseler et al., 2016a, 2016b). In step 3, the 95% confidence interval of differences in mean values and variances generally included the original difference, which suggested that the composite mean values and variances were equal.

The permutation multigroup analysis showed the absence of the moderating effect of gender. Relationships in the research model did not vary with gender.

Table 8 The results of the three-step MICOM procedure

Moderating variable	Construct	Step 1 Configu- ral invari- ance	Step 2			Step 3a			Step 3b				
			Original correla- tion	<i>p</i> value	Compo- sitional invariance	Original difference	95% CI	<i>p</i> value	Equal means	Original difference	95% CI	<i>p</i> value	Equal variances
Gender (Male vs. Female)	BIU	Yes	1.000	0.923	Yes	-0.064	[-0.259, 0.250]	0.624	Yes	0.339	[-0.319, 0.304]	0.034	No
	CTL	Yes	0.999	0.978	Yes	-0.071	[-0.258, 0.245]	0.579	Yes	0.229	[-0.338, 0.308]	0.163	Yes
	CUR	Yes	0.999	0.166	Yes	-0.138	[-0.257, 0.251]	0.287	Yes	0.508	[-0.421, 0.394]	0.017	No
	FI	Yes	0.998	0.724	Yes	0.060	[-0.253, 0.253]	0.647	Yes	0.313	[-0.436, 0.414]	0.148	Yes
	JOY	Yes	1.000	0.252	Yes	-0.193	[-0.262, 0.256]	0.142	Yes	0.362	[-0.422, 0.421]	0.098	Yes
	PB	Yes	0.999	0.657	Yes	0.002	[-0.254, 0.250]	0.985	Yes	0.252	[-0.351, 0.334]	0.145	Yes
	PEOU	Yes	0.994	0.362	Yes	-0.012	[-0.248, 0.247]	0.936	Yes	0.456	[-0.565, 0.569]	0.142	Yes
	PI	Yes	0.996	0.362	Yes	0.062	[-0.257, 0.249]	0.623	Yes	-0.043	[-0.311, 0.296]	0.788	Yes
	PU	Yes	0.999	0.571	Yes	-0.083	[-0.257, 0.253]	0.519	Yes	0.258	[-0.496, 0.494]	0.312	Yes

Table 8 (continued)

Moderating variable	Construct	Step 1 Configu- ral invari- ance	Step 2		Step 3a			Step 3b					
			Original correla- tion	<i>p</i> value	Compo- sitional invariance	Original difference	95% CI	<i>p</i> value	Equal means	Original difference	95% CI	<i>p</i> value	Equal variances
Educational level (Bach- elor vs. Master and doctor)	BIU	Yes	1.000	0.549	Yes	-0.210	[-0.253, 0.248]	0.102	Yes	0.17	[-0.294, 0.318]	0.265	Yes
	CTL	Yes	0.889	0.068	Yes	0.023	[-0.251, 0.255]	0.852	Yes	-0.227	[-0.305, 0.332]	0.165	Yes
	CUR	Yes	1.000	0.557	Yes	-0.217	[-0.255, 0.255]	0.096	Yes	-0.023	[-0.398, 0.412]	0.914	Yes
	FI	Yes	0.996	0.453	Yes	-0.121	[-0.253, 0.239]	0.344	Yes	0.089	[-0.416, 0.419]	0.678	Yes
	JOY	Yes	0.999	0.159	Yes	-0.087	[-0.248, 0.252]	0.498	Yes	0.145	[-0.399, 0.431]	0.502	Yes
	PB	Yes	0.998	0.601	Yes	0.098	[-0.255, 0.248]	0.447	Yes	0.106	[-0.330, 0.342]	0.543	Yes
	PEOU	Yes	0.988	0.145	Yes	-0.228	[-0.256, 0.253]	0.079	Yes	0.545	[-0.580, 0.549]	0.061	Yes
	PI	Yes	0.999	0.796	Yes	0.139	[-0.254, 0.253]	0.282	Yes	-0.179	[-0.306, 0.305]	0.251	Yes
PU	Yes	0.999	0.705	Yes	-0.169	[-0.255, 0.255]	0.200	Yes	0.169	[-0.469, 0.511]	0.496	Yes	

MICOM: Measurement invariance of composite models; BIU: Behavioral intention to use; CTL: Control; CUR: Curiosity; FI: Focused immersion; JOY: Joy; PB: Perceived boredom; PEOU: Perceived ease of use; PI: Personal innovativeness; PU: Perceived usefulness

However, the relationship between joy and focused immersion was moderated by the educational level (original difference = 0.378, $p < 0.05$). It indicated that the extent to which the interaction with TikTok was enjoyable differently influenced users' ability to be engrossed in videos according to the educational level. Undergraduate students were more likely to concentrate on their learning because of joy than postgraduate students.

5 Discussion

This study aimed to establish an acceptance model of TikTok system based on the HMSAM and examine students' behavioral intention and focused immersion. The results revealed that the HMSAM was applicable and suitable for social networking, and 11 of the 14 hypotheses were finally supported. Curiosity and perceived boredom significantly mediated the relationship between perceived ease of use and two dependent variables. Gender could not moderate any relationships in the model, while the educational level moderated the relationship between joy and focused immersion.

Perceived ease of use (PEOU) significantly influenced perceived usefulness (PU), curiosity, control, joy, and perceived boredom. The results were consistent with previous studies (e.g., Chang & Chen, 2021; Oluwajana et al., 2019; Palos-Sanchez et al., 2022), which implied that the ease of use of TikTok increased learners' hedonic benefits. Without complex procedures and instructions to cope with, users could focus on their experience and feelings, e.g., joy and perceived boredom. Users' attention could also be free to explore novel interactions (Lowry et al., 2013), thus stimulating users' curiosity. In contrast, if TikTok was difficult to use, students had to take much time or energy to get familiar with the system and struggle to control their interactions. Gradually, they may feel frustrated and bored to overcome the initial barrier.

Personal innovativeness (PI) was a significant antecedent of PEOU, supporting the findings of Joo et al. (2014). Innovativeness, a positive attitude toward technology, contributed to an increase in technology readiness (Chang & Chen, 2021). This personal characteristic encouraged users to actively try out new technology and experiment with the newly-launched system although they may encounter some technical and operational issues. For that reason, individuals with a higher level of innovativeness were more risk-taking (Sidik & Syafar, 2020) and easier to interact with TikTok than those who refused emerging applications. It was reasonable that innovative learners perceived TikTok as easy to use.

The main predictors of behavioral intention to use (BIU) TikTok were curiosity and perceived boredom. This suggested that either the presence of curiosity or the absence of perceived boredom was a motivation for students to adopt TikTok-assisted learning. However, the results did not completely confirm the influence of PU and joy, unlike other studies (Lowry et al., 2013; Palos-Sanchez et al., 2022). The possible reason was that they focused on the game-based response system (Palos-Sanchez et al., 2022) or actual games (Lowry et al., 2013). The game per se was enjoyable and interesting, while not all educational videos were entertaining. Furthermore, since PU in the HMSAM placed emphasis on pleasure, a similar situation occurred with PU.

Similarly, the main predictors of focused immersion (FI) were curiosity, joy, and perceived boredom, which was in line with Palos-Sanchez et al. (2022). Students would bury themselves in videos if TikTok provoked curiosity, improved enjoyment, and prevented boredom. Educational videos on TikTok were usually accompanied by detailed explanations and background music, which might be more interesting and diverting than words. Students did not need to burn much energy to understand, contributing to absorption and immersion. Nevertheless, the findings also showed that control did not significantly predict FI. It meant that whether users could control their interactions with TikTok, they might still be deeply intrigued by educational videos. This was caused mainly because TikTok could automatically play the next video even if users did nothing, facilitating sustained attention.

The effect of PEOU on BIU and FI was fully mediated by curiosity and perceived boredom, corroborated by Oluwajana et al. (2019). TikTok boasted the algorithm of personalized recommendations based on previous videos users watched. Users were likely to receive the video that suited their tastes. However, they would never guess what exactly the next video was about until the next video played, stimulating their curiosity. The ease of use allowed different kinds of interactions with TikTok, e.g., giving a like, commenting, following, and posting, encouraging to avoid boredom that resulted from simply browsing similar videos. Users thus concentrated on educational videos and wanted to continue using TikTok application for learning.

The results shed light on the role of TikTok in improving higher-order thinking skills. Technology could potentially develop students' higher-order thinking skills (Nussbaum et al., 2021) such as problem-solving skills, critical thinking skills, and creative thinking skills (Priyaadharshini & Sundaram, 2018). The aim of TikTok was to stimulate creativity, which was a vital element in the problem-solving process (Nussbaum et al., 2021) and the enhancement of students' creative thinking. Curiosity could support information seeking, question asking, and deeper learning, which were three mechanisms for the development of scientific thinking (Jirout, 2020). Since deep learning approaches directly influenced higher-order thinking skills (Lee & Choi, 2017), students should be encouraged to do critical analyses rather than repetition after watching the same series of Tik Tok videos.

This study also examined the moderating effect of both gender and educational level. Gender was not a significant moderator, indicating that relationships among variables were not moderated by gender. The reason might be that most educational videos on TikTok were designed and available for both males and females. The educational level moderated the relationship between joy and FI. The possible explanation might come from different learning styles and approaches. The learning styles of most undergraduate students were auditory-reading and auditory-kinesthetic types. However, compared with undergraduate students, graduate students were more likely to be unimodal learners and adopt deep and strategic learning approaches (Samarakoon et al., 2013). They systematically acquired professional knowledge by reading books and journal articles, attending academic lectures, and writing papers. They were probably not accustomed to enjoying short videos with fragmented information and failed to gain pleasure, thus not being involved in TikTok videos.

6 Conclusion

6.1 Major findings

This study developed an adoption model of TikTok system by incorporating two constructs into the HMSAM, i.e., perceived boredom and personal innovativeness. The results showed that the proposed research model was adequate for the adoption of TikTok. Perceived innovativeness significantly and positively influenced perceived ease of use. Additionally, curiosity and perceived boredom mediated the positive relationships between perceived ease of use and behavioral intention and between perceived ease of use and focused immersion. Multigroup analysis revealed that the educational level moderated the relationship between joy and focused immersion.

6.2 Limitations of this study

Although this research shed light on TikTok adoption, there were still some limitations in this study. First, this study was conducted among Chinese university students. The results should be generalized to other countries with caution. Second, this study used cross-sectional data to validate the research model. However, students' perceptions and feelings may change over a period of time with the advancement of technology. Third, the research model only explained 40.0% of the total variance of behavioral intention to use TikTok. Other potential factors may also influence behavioral intention and focused immersion.

6.3 Implications for future research

This research provided some valuable theoretical implications. First, this study validated the theoretical framework, i.e., the HMSAM, in the context of TikTok-assisted learning in the university. Future research could investigate the adoption of other social media platforms, e.g., Facebook and Twitter. Learners in other phases such as high school students should also be considered. Second, perceived usefulness in the HMSAM was pleasure-oriented, which did not focus on students' performance. Researchers in the future are thus expected to compare pleasure-focused and performance-focused usefulness in one model. Third, researchers could enrich and expand the HMSAM by introducing other influencing factors or theories, such as the expectation confirmation theory. Future studies could also examine the effect of other moderating variables, e.g., age, frequency of using the application, and learning content, on behavioral intention and focused immersion. Researchers in the future are also expected to further explore other differences between undergraduate and graduate students in the use of TikTok.

This study helped practitioners better understand the adoption of social network tools such as TikTok. Video makers are advised to determine a clear topic and include interesting elements to ensure usefulness and kindle viewers' curiosity. Both users and the platform should provide different music to suit the content. Developers

should attach importance to improving the ease of use of emerging technologies and simplify the interaction process (Chang & Chen, 2021), e.g., registering an account. The results of this study also provided insights into innovative learning and teaching. Teachers could consider learners' intrinsic motivation and properly integrate TikTok into activities to help students enjoy learning and develop higher-order thinking skills. The critical role of personal innovativeness reminded teachers to consciously encourage students to be positive about new technologies. Moreover, the moderating role of the educational level implied that teachers in higher education institutions should adopt different teaching strategies. For example, teachers could enhance undergraduate students' joy of learning to help them keep focused.

In addition, social media companies tend to attract users' attention through highly immersive services (Montag et al., 2019), e.g., endless and personalized content. However, it was the immersive design that may result in problematic use, i.e., TikTok addiction (Montag et al., 2021). Teachers should control the extent to which students adopt TikTok to complete tasks, guide them to use it in moderation, and request parents' cooperation when necessary. Future research could explore the problematic use of social media tools and propose appropriate solutions.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s10639-023-11749-x>.

Authors' contributions Xinjie Deng: Methodology, Investigation, Editing, and Writing-Original Draft. Zhonggen Yu: Conceptualization and Funding acquisition.

Funding This work is supported by 2019 MOOC of Beijing Language and Culture University (MOOC201902) (Important) "Introduction to Linguistics"; "Introduction to Linguistics" of online and offline mixed courses in Beijing Language and Culture University in 2020; Special fund of Beijing Co-construction Project-Research and reform of the "Undergraduate Teaching Reform and Innovation Project" of Beijing higher education in 2020-innovative "multilingual+" excellent talent training system (202010032003); The research project of Graduate Students of Beijing Language and Culture University "Xi Jinping: The Governance of China" (SJTS202108); The Fundamental Research Funds for the Central Universities, and the Research Funds of Beijing Language and Culture University (22YCX017); and the Research Project of the 8th Education and Teaching Reform in Dali University (2022JGY08-129).

Data availability We make sure that all data and materials support our published claims and comply with field standards.

Declarations

Conflict of interest/Competing interests We have no conflicts of interest to declare that are relevant to the content of this article.

References

- Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. *Mis Quarterly*, 24(4), 665–694. <https://doi.org/10.2307/3250951>
- Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information Systems Research*, 9(2), 204–215. <https://doi.org/10.1287/isre.9.2.204>

- Akar, S. G. M. (2019). Does it matter being innovative: Teachers' technology acceptance. *Education and Information Technologies*, 24(6), 3415–3432. <https://doi.org/10.1007/s10639-019-09933-z>
- Alyoussef, I. Y. (2021). Factors influencing students' acceptance of m-learning in higher education: An application and extension of the UTAUT model. *Electronics*, 10(24), 3171. <https://doi.org/10.3390/electronics10243171>
- Bieleke, M., Gogol, K., Goetz, T., Daniels, L., & Pekrun, R. (2021). The AEQ-S: A short version of the achievement emotions questionnaire. *Contemporary Educational Psychology*, 65, 101940. <https://doi.org/10.1016/j.cedpsych.2020.101940>
- Chang, Y. W., & Chen, J. H. (2021). What motivates customers to shop in smart shops? The impacts of smart technology and technology readiness. *Journal of Retailing and Consumer Services*, 58, 102325. <https://doi.org/10.1016/j.jretconser.2020.102325>
- Chin, W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295–336). Lawrence Erlbaum Associates.
- Chin, W. W., & Newsted, P. R. (1999). Structural equation modeling analysis with small samples using partial least squares. In R. Hoyle (Ed.), *Statistical Strategies for Small Sample Research* (pp. 307–341). Sage Publications.
- Csikszentmihalyi, M. (1990). *Flow: The psychology of optimal experience*. Harper and Row.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *Mis Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
- Dewaele, J. M., & Li, C. C. (2021). Teacher enthusiasm and students' social-behavioral learning engagement: The mediating role of student enjoyment and boredom in Chinese EFL classes. *Language Teaching Research*, 25(6), 922–945. <https://doi.org/10.1177/13621688211014538>
- Ertz, M., Jo, M. S., Kong, Y., & Sarigollu, E. (2022). Predicting m-shopping in the two largest m-commerce markets: The United States and China. *International Journal of Market Research*, 64(2), 249–268. <https://doi.org/10.1177/14707853211023036>
- Escamilla-Fajardo, P., Alguacil, M., & Lopez-Carril, S. (2021). Incorporating TikTok in higher education: Pedagogical perspectives from a corporal expression sport sciences course. *Journal of Hospitality Leisure Sport & Tourism Education*, 28, 100302. <https://doi.org/10.1016/j.jhlste.2021.100302>
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.2307/3151312>
- Gu, J. C., Fan, L., Suh, Y. H., & Lee, S. C. (2010). Comparing utilitarian and hedonic usefulness to user intention in multipurpose information systems. *Cyberpsychology Behavior and Social Networking*, 13(3), 287–297. <https://doi.org/10.1089/cyber.2009.0167>
- Guo, Y. M., & Poole, M. S. (2009). Antecedents of flow in online shopping: A test of alternative models. *Information Systems Journal*, 19(4), 369–390. <https://doi.org/10.1111/j.1365-2575.2007.00292.x>
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. <https://doi.org/10.1108/EBR-11-2018-0203>
- Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science*, 40(3), 414–433. <https://doi.org/10.1007/s11747-011-0261-6>
- Hayes, C., Stott, K., Lamb, K. J., & Hurst, G. A. (2020). “Making every second count”: Utilizing TikTok and systems thinking to facilitate scientific public engagement and contextualization of Chemistry at home. *Journal of Chemical Education*, 97(10), 3858–3866. <https://doi.org/10.1021/acs.jchemed.0c00511>
- Henseler, J., Hubona, G., & Ray, P. A. (2016a). Using PLS path modeling in new technology research: Updated guidelines. *Industrial Management & Data Systems*, 116(1), 2–20. <https://doi.org/10.1108/IMDS-09-2015-0382>
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2016b). Testing measurement invariance of composites using partial least squares. *International Marketing Review*, 33(3), 405–431. <https://doi.org/10.1108/IMR-09-2014-0304>
- Heyang, T., & Martin, R. (2022). Teaching through TikTok: A duoethnographic exploration of pedagogical approaches using TikTok in higher dance education in China and Norway during a global pandemic. *Research in Dance Education*. <https://doi.org/10.1080/14647893.2022.2114446>
- Jirout, J. J. (2020). Supporting early scientific thinking through curiosity. *Frontiers in Psychology*, 11, 1717. <https://doi.org/10.3389/fpsyg.2020.01717>

- Joo, Y. J., Lee, H. W., & Ham, Y. (2014). Integrating user interface and personal innovativeness into the TAM for mobile learning in Cyber University. *Journal of Computing in Higher Education*, 26(2), 143–158. <https://doi.org/10.1007/s12528-014-9081-2>
- Kim, M. J., & Hall, C. M. (2019). A hedonic motivation model in virtual reality tourism: Comparing visitors and non-visitors. *International Journal of Information Management*, 46, 236–249. <https://doi.org/10.1016/j.ijinfomgt.2018.11.016>
- Larson, R. W., & Richards, M. H. (1991). Boredom in the middle school years: Blaming schools versus blaming students. *American Journal of Education*, 99(4), 418–443. <https://doi.org/10.1086/443992>
- Lee, M. C. (2010). Explaining and predicting users' continuance intention toward e-learning: An extension of the expectation-confirmation model. *Computers & Education*, 54(2), 506–516. <https://doi.org/10.1016/j.compedu.2009.09.002>
- Lee, Y. J. (2022). Language learning affordances of Instagram and TikTok. *Innovation in Language Learning and Teaching*. <https://doi.org/10.1080/17501229.2022.2051517>
- Lee, J., & Choi, H. (2017). What affects learner's higher-order thinking in technology-enhanced learning environments: The effects of learner factors. *Computers & Education*, 115, 143–152. <https://doi.org/10.1016/j.compedu.2017.06.015>
- Li, C. C. (2021). A control-value theory approach to boredom in English classes among university students in China. *Modern Language Journal*, 105(1), 317–334. <https://doi.org/10.1111/modl.12693>
- Lowry, P. B., Gaskin, J. E., Twyman, N. W., Hammer, B., & Roberts, T. L. (2013). Taking “fun and games” seriously: Proposing the hedonic-motivation system adoption model (HMSAM). *Journal of the Association for Information Systems*, 14(11), 617–671. <https://ssrn.com/abstract=2177442>
- Malkovsky, E., Merrifield, C., Goldberg, Y., & Danckert, J. (2012). Exploring the relationship between boredom and sustained attention. *Experimental Brain Research*, 221(1), 59–67. <https://doi.org/10.1007/s00221-012-3147-z>
- Montag, C., Lachmann, B., Herrlich, M., & Zweig, K. (2019). Addictive features of social media/messenger platforms and freemium games against the background of psychological and economic theories. *International Journal of Environmental Research and Public Health*, 16(14), 2612. <https://doi.org/10.3390/ijerph16142612>
- Montag, C., Yang, H. B., & Elhai, J. D. (2021). On the psychology of TikTok use: A first glimpse from empirical findings. *Frontiers in Public Health*, 9, 641673. <https://doi.org/10.3389/fpubh.2021.641673>
- Nussbaum, M., Barahona, C., Rodriguez, F., Guentulle, V., Lopez, F., Vazquez-Uscanga, E., & Cabezas, V. (2021). Taking critical thinking, creativity and grit online. *Educational Technology Research and Development*, 69(1), 201–206. <https://doi.org/10.1007/s11423-020-09867-1>
- Oluwajana, D., Idowu, A., Nat, M., Vanduhe, V., & Fadiya, S. (2019). The adoption of students' hedonic motivation system model to gamified learning environment. *Journal of Theoretical and Applied Electronic Commerce Research*, 14(3), 156–167. <https://doi.org/10.4067/S0718-18762019000300109>
- Palos-Sanchez, P. R., Saura, J. R., & Velicia-Martin, F. (2022). A case study on a hedonic-motivation system adoption model in a game-based student response system. *International Journal of Human-Computer Interaction*. <https://doi.org/10.1080/10447318.2022.2121801>
- Pekrun, R. (2006). The control-value theory of achievement emotions: Assumptions, corollaries, and implications for educational research and practice. *Educational Psychology Review*, 18(4), 315–341. <https://doi.org/10.1007/s10648-006-9029-9>
- Priyaadharshini, M., & Sundaram, B. V. (2018). Evaluation of higher-order thinking skills using learning style in an undergraduate engineering in flipped classroom. *Computer Applications in Engineering Education*, 26(6), 2237–2254. <https://doi.org/10.1002/cae.22035>
- Ringle, C. M., Wende, S., & Becker, J.-M. (2022). SmartPLS 4. Boenningstedt: SmartPLS. <https://www.smartpls.com>. Accessed 4 Nov 2022.
- Rogers, E. M. (1995). *Diffusion of innovation*. Free Press.
- Rouibah, K., & Hamdy, H. (2009). Factors affecting information communication technologies usage and satisfaction: Perspective from instant messaging in Kuwait. *Journal of Global Information Management*, 17(2), 1–29. <https://doi.org/10.4018/jgim.2009040101>
- Ruangkanjanases, A., Hsu, S. L., Wu, Y. J., Chen, S. C., & Chang, J. Y. (2020). What drives continuance intention towards social media: Social influence and identity perspectives. *Sustainability*, 12(17), 7081. <https://doi.org/10.3390/su12177081>
- Ryan, R. M., & Deci, E. L. (2000). Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary Educational Psychology*, 25(1), 54–67. <https://doi.org/10.1006/ceps.1999.1020>

- Samarakoon, L., Fernando, T., Rodrigo, C., & Rajapakse, S. (2013). Learning styles and approaches to learning among medical undergraduates and postgraduates. *BMC Medical Education*, 13, 42. <https://doi.org/10.1186/1472-6920-13-42>
- Sarstedt, M., Ringle, C. M., Smith, D., Reams, R., & Hair, J. F. (2014). Partial least squares structural equation modeling (PLS-SEM): A useful tool for family business researchers. *Journal of Family Business Strategy*, 5(1), 105–115. <https://doi.org/10.1016/j.jfbs.2014.01.002>
- Shmueli, G., & Koppius, O. R. (2011). Predictive analytics in information systems research. *Mis Quarterly*, 35(3), 553–572. <https://doi.org/10.2139/ssrn.1606674>
- Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing*, 53(11), 2322–2347. <https://doi.org/10.1108/EJM-02-2019-0189>
- Sidik, D., & Syafar, F. (2020). Exploring the factors influencing student's intention to use mobile learning in Indonesia higher education. *Education and Information Technologies*, 25(6), 4781–4796. <https://doi.org/10.1007/s10639-019-10018-0>
- Sun, Y. Y., & Gao, F. (2020). An investigation of the influence of intrinsic motivation on students' intention to use mobile devices in language learning. *Educational Technology Research and Development*, 68(3), 1181–1198. <https://doi.org/10.1007/s11423-019-09733-9>
- TikTok. (2021). Thanks a billion! *TikTok Newsroom*. <https://newsroom.tiktok.com/en-us/1-billion-people-on-tiktok>. Accessed 1 Nov 2022.
- Urbach, N., & Ahlemann, F. (2010). Structural equation modeling in information systems research using partial least squares. *Journal of Information Technology Theory and Application*, 11(2), 2. <https://aisel.aisnet.org/jitta/vol11/iss2/2>.
- van der Heijden, H. (2004). User acceptance of hedonic information systems. *Mis Quarterly*, 28(4), 695–704. <https://doi.org/10.2307/25148660>
- Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research*, 11(4), 342–365. <https://doi.org/10.1287/isre.11.4.342.11872>
- Warshaw, P. R., & Davis, F. D. (1985). Disentangling behavioral intention and behavioral expectation. *Journal of Experimental Social Psychology*, 21(3), 213–228. [https://doi.org/10.1016/0022-1031\(85\)90017-4](https://doi.org/10.1016/0022-1031(85)90017-4)
- Yang, H., Cai, J., Yang, H. H., & Wang, X. C. (2022). Examining key factors of beginner's continuance intention in blended learning in higher education. *Journal of Computing in Higher Education*. <https://doi.org/10.1007/s12528-022-09322-5>
- Yu, Z. G. (2020). Extending the learning technology acceptance model of WeChat by adding new psychological constructs. *Journal of Educational Computing Research*, 58(6), 1121–1143. <https://doi.org/10.1177/0735633120923772>
- Zeng, J., & Kaye, D. B. V. (2022). From content moderation to visibility moderation: A case study of platform governance on TikTok. *Policy and Internet*, 14(1), 79–95. <https://doi.org/10.1002/poi3.287>
- Zhao, Y. Y., & Bacao, F. (2021). How does gender moderate customer intention of shopping via live-streaming apps during the COVID-19 pandemic lockdown period? *International Journal of Environmental Research and Public Health*, 18(24), 13004. <https://doi.org/10.3390/ijerph182413004>
- Zhou, T. (2011). Understanding mobile Internet continuance usage from the perspectives of UTAUT and flow. *Information Development*, 27(3), 207–218. <https://doi.org/10.1177/0266666911414596>
- Zhou, T., Song, Y., & Zhou, P. (2022). Continued use intention of travel apps: From the perspective of control and motivation. *Technology Analysis & Strategic Management*, 34(6), 703–716. <https://doi.org/10.1080/09537325.2021.1916457>

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.