The acceptance of social media video for knowledge acquisition, sharing and application: A comparative study among YouTube Users and TikTok users' for medical purposes

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CHRONICLE	ABSTRACT
	YouTube and TikTok have gained increasing recognition as social network sites to support online knowledge acquisition, sharing, and application via social media platforms in the medical field. This study examines which aspect of TikTok and YouTube stimulates doctors, nurses, and any other YouTube and TikTok in the medical setting, to rely on them as sources of knowledge acquisition and sharing to keep their medical repertoire updated. A hybrid model is designed to investigate users' acceptance of YouTube and TikTok as social media platforms. The model focuses on four main external factors: content richness, innovativeness, satisfaction, and enjoyment. These factors are connected with two TAM constructs which are perceived ease of use and perceived usefulness. The results have shown that both YouTube and TikTok are affected by PEOU, PU, personal innovativeness, flow theory, and content richness. Both social media networks provide up-to-date sources described as useful, enjoyable, and relevant. Nevertheless, the comparative results have shown that YouTube has deeply influenced users' medical perception and knowledge compared to TikTok. It is created for the very mere purpose of socialization and self-expression. In contrast, YouTube is used for educational and non-educational purposes due to the type of uploaded content and time management. Therefore, TikTok developers and influencers should initiate highly specialized videos and create content that raises awareness of medical field issues.

1. Background

YouTube and TikTok are Social Network Sites (SNSs) that are common social media platforms (Al-Maroof, Alshurideh, Salloum, AlHamad, & Gaber, 2021; Al-Skaf, Youssef, Habes, Alhumaid, & Salloum, 2021; Almazrouei, Alshurideh, Al Kurdi, & Salloum, 2021; Alyammahi, Alshurideh, Kurdi, & Salloum, 2021). Social sites have changed the internet world and methods of communication. People's life is affected by the shared videos and exchanged experiences (AlQudah, Salloum, & Shaalan, 2021; Chatzoglou, Chatzoudes, Ioakeimidou, & Tokoutsi, 2020; Dawud & Nikolic, 2020). Recently, technology

users in the health domain rely heavily on social network sites (Ahmed, Alshurideh, Al Kurdi, & Salloum, 2021). For instance, YouTube comes as the second most popular website, a source of knowledge in medical education.

Similarly, TikTok has emerged as an application that has a micro-video feature. Micro-video sets it apart from YouTube that has long videos. The Chinese government used short videos to spread the news about COVID19. The short videos play a critical role in assessing the relation between the government and the Chinese citizen. It urges Chinese people to use micro-videos which led to the emergence of TikTok is a popular platform. Hence, TikTok is seen as the top app that offers short video socialization in China and is considered a front for spreading various topics in new media (Al-Maroof, Salloum, Hassanien, & Shaalan, 2020; Wang & Fu, 2020; Zhu, Dong, Qi, & Deng, 2021).

Even though these two platforms have offered great opportunities to their users in sharing and exchanging data (Mhamdi, Al-Emran, & Salloum, 2018; Salloum, Al-Emran, & Shaalan, 2016; Salloum, Maqableh, Mhamdi, Al Kurdi, & Shaalan, 2018), there is little intention to compare these two platforms and investigate each type's effectiveness as a learning source in the medical field that urges its users to accept the technology (Aburayya et al., 2020; Alghizzawi et al., 2018; Alhashmi, Salloum, & Abdallah, 2020; Alhashmi, Salloum, & Mhamdi, 2019; Alshurideh, 2018; Salloum, Al-Emran, Abdallah, & Shaalan, 2017; Salloum, Mhamdi, Al Kurdi, & Shaalan, 2018). Accordingly, based on a conceptual model built to assess users' acceptance, this study examines what factors can significantly stimulate users to benefit from these two platforms.

To build a comprehensive model, certain external factors account for certain features related to these two platforms. For instance, content richness is chosen to investigate certain aspects of the social media platform, including the richness of the content, the time limitation and the up-to-date information. Other factors are related to the users' themselves, including their degree of enjoyment, readiness to accept new technology (level of innovativeness), and users' satisfaction. In short, the study intends to investigate the differences among users in using TikTok and YouTube, putting in mind that TikTok has appeared as new technology which stands in contrast with the lengthy videos available on the YouTube platform. One of the most important features is the time limitation and the availability of up-to-date information quickly. TikTok seems to be a more facilitating platform for users to reflect their prior knowledge and capture new information or feedback than YouTube, which tends to lack many of the newly implemented features in TikTok. To the best of our knowledge, the literature review never compares these two platforms in the medical setting, which is based on a developed conceptual model that aims to contrast the effectiveness of these two platforms.

2. Literature Review

Previous studies on YouTube and TikTok have focused on different crucial factors that affect the acceptance of these two applications both in educational (Al-Maroof, Alfaisal, & Salloum, 2020) and non-educational settings. Within the educational setting, researchers have focused on both YouTube and TikTokas a learning tool (Al Kurdi, Alshurideh, Nuseir, Aburayya & Salloum, n.d.; Al-Maroof, Arpaci, Al-Emran, Salloum, 2021; Habes, Salloum, Alghizzawi, & Mhamdi, 2019; Salloum, n.d.). The final purpose of these studies is to investigate the effect of different factors, including motives and benefits, on the acceptance of TikTok and YouTube by users, especially students and educators. In a study by (Jung & Lee, 2015), the researchers have investigated the factors that affect YouTube usage by students and educators from Japanese and American universities. The study is based on a conceptual model where UTAUT is used. Similarly, other studies have focused on the conceptual model of TAM to achieve different objectives such as to investigate the motives behind using YouTube for procedure learning, the benefits behind using YouTube as a tool for teaching and learning, the effect of ads towards purchasing a service and the influence of student social media usage on the acceptance of e-learning platforms (Alghizzawi et al., 2019; Dehghani, Niaki, Ramezani, & Sali, 2016; DeWitt et al., 2013; Lee & Lehto, 2013).

Within non-educational settings, YouTube and TikTok are investigated to explain their effects in a far-forth setting from universities and schools. YouTube comments have been under analysis in research by (Siersdorfer, Chelaru, Nejdl, & San Pedro, 2010), who investigated the influence of sentiment expressed in comments. Likewise, a study by (Omar & Dequan, 2020) has emphasized that TikTok acceptance can be measured using the conceptual model of Uses and Gratifications (U&G) to investigate the effect of TikTok on personality traits and users' motivation. A similar study in China has investigated the effect of technical characteristics on consumers' intention to use TikTok (Han & Zhang, 2020). Table 1 summarises most of the common studies that focused on accepting these two applications for educational and non-educational settings.

Based on the previous discussions, this study has deviated from all previous studies to compare two platforms used as the source of learning. Thus, the present study aims to measure the effectiveness of different social media platforms in assessing users' knowledge in the medical field. The learning content that is provided by these two different platforms helps in developing the missing knowledge so users can benefit from that learning content easily and in a short time. To achieve the previously designed aim, the current study develops a conceptual framework to measure users' acceptance of two different social platforms: YouTube and TikTok. Besides, the study aims to create a comparison between these two platforms. Recently researchers have started making a distinction between extrinsic and intrinsic tasks. The former refers to the information system

that supports inherent goal achievement. On the other hand, the latter is a kind of task used instrumentally to get various out of the scope information where users can share and watch videos voluntarily (Gefen & Straub, 2000; Ryan & Deci, 2000).

Table 1
Educational and Non-Educational Settings in the Literature Review.

Author(s)	Acceptance Model	Sample	Type of Social Platform	The objective of the Study	Setting Type
(I. Jung & Lee, 2015)	Unified Theory of Acceptance and Use of Technology (UTAUT)	Five hundred and sixty-nine students and 56 educators from Japanese and American universities	You Tube	To predict and compare factors influencing YouTube acceptance	Educational Setting
(D. Y. Lee & Lehto, 2013)	Technology Acceptance Model (TAM)	432 respondents engaged in procedural learning	You Tube	To investigate the motives behind using YouTube for procedure learning	Educational Setting
(Siersdorfer et al., 2010)	SentiWordNet thesaurus, a lexical WordNet-based resource	6 million comments on 67,000 YouTube videos	You Tube	To investigate the influence of sentiment expressed in comments	Non-Educational Setting
(Dehghani et al., 2016)	TAM	Students studying at the Sapienza University of Rome.	You Tube	To investigate the effect of ads on purchasing a service	Educational Setting
(DeWitt et al., 2013)	N/A	20 experts (instructors and lecturers) in a different specialization	You Tube	To investigate the benefits of the use of YouTube as a tool for teaching and learning	Educational Setting
(Alghizzawi et al., 2019)	A modified Technology Acceptance Model	410 graduate and postgraduate students	Facebook YouTube and Twitter	To explore the influence of student social media usage on the acceptance of e-learning platforms	Educational Setting
(Mir & Ur REHMAN, 2013)	Perceived credibility (PC) and Perceived usefulness (PU)	231 university students from Islamabad	You Tube	To investigate the effects of the number of posts, views, and reviews (QPVR) on users' acceptance	Educational Setting
(Omar & Dequan, 2020)	Uses and Gratifications (U&G)	385 TikTok users	TikTok	To investigate the effect of TikTok on personality traits and users' motivation	Non Educational setting
(Han & Zhang, 2020)	TAM	295 people in China	TikTok	To investigate how new technical characteristics affect consumers' intention to use	Non-Educational Setting

In the present study, the user acceptance process is driven by TAM, which is the most significant model (Davis, 1989), where perceived usefulness and perceived ease of use can contribute to the extrinsic type of motivation. The current study extends the TAM to include additional constructs: users' satisfaction, personal innovativeness, and content richness that significantly add to the learning content of both YouTube and TikTok (Ong & Lai, 2006; Pituch & Lee, 2006; Sánchez & Hueros, 2010).

3. Development of Research Hypotheses and the conceptual Model

3.1 Content Richness

The content richness is learning resources that facilitate the acquisition and application of knowledge. Whenever the content richness is sufficient, the users are more willing to accept the technology. Content richness has three main important constructs, which are relevance, sufficiency, and timeliness. Relevance refers to how the shared content is useful, whereas sufficiency refers to how the shared content is complete and expresses a unified concept. The last construct, timeliness, refers to the technology's ability to provide its users with the latest development information within the required content (Wulf, Schillewaert, Muylle, & Rangarajan, 2006; Jung, Perez-Mira, & Wiley-Patton, 2009; Tung & Chang, 2008). Content richness has been proved to be a clear direction with technology acceptance. De Wulf et al. (2006) points out that there is a positive impact of content on user's acceptance of technology. Other previous studies tackle the aspect of content richness, concluding that the higher the content richness is, the higher the users' satisfaction and usefulness, hence, technology acceptance. For instance, Jung et al., 2009 & Park, Son, & Kim (2012) argue that whenever the content richness is high, the usefulness of the technology will be high as well. In terms of timeliness, previous studies have shown that out of date content is less useful. Therefore, time-critical elements affect users' perception of the technology. Accordingly, it is hypothesized that:

H₁: *Content richness has a positive impact on users' satisfaction.*

3.2 Flow Theory

The term flow is originally defined as a sense of control, involvement, and enjoyment. Whenever users feel that the technology provides full enjoyment, users will be ready to use it consistently. Accordingly, when users' thoughts, attention, behavioural repertoire are activated, the activation raises certain positive feelings, contributing to the flow experience of using technology (Csikszentmihalyi, 1988; Fredrickson, Tugade, Waugh, & Larkin, 2003; Hung, Chou, & Ding, 2012). When the users start experiencing the flow, the time passes so quickly, and they become intrinsically motivated. Hence, it creates a sort of consistent online flow. The consistent flow is defined as continuous interactivity that appears as a consequence of pleasant, enjoyable, immersed, and insolvent experiences (Hoffman & Novak, 1996, 2009). Lately, flow experience has been added to IT adoption systems such as e-learning, the Internet, and entertainment. It can be seen as the total assortment without self-consciousness whenever technology is used (Ang, Zaphiris, & Mahmood, 2007). Thus, flow theory can work as a predictor in technology adoption. The following hypothesis is formed:

H₂: *Flow experience (FLO) positively impacts the perceived ease of using YouTube and TikTok (PEOU).*
H₃: *Flow experience (FLO) positively impacts the perceived usefulness of YouTube and TikTok (PEOU).*

3.3 Personal Innovativeness

Personal innovativeness is defined as the degree of willingness that users may have to accept technology. In other words, it refers to users' readiness to use and accept new technology. The concept of readiness is embedded within personal innovativeness as an external factor to measure users' acceptance of technology. Personal innovativeness is significantly affected by users' confidence which implies that whenever the degree of confidence is higher, the possibility of accepting the technology is higher too. Furthermore, personal innovativeness is related to technology perception. When the users have a high perception towards accepting technology, the higher their degree of personal innovativeness (Lewis, Agarwal, & Sambamurthy, 2003; Lu, Yao, & Yu, 2005; Rogers, 1995; Serenko, 2008). Notably, Agarwal and Prasad shed light on the fact that personal innovativeness is embedded within the users' cognitive interpretations of technology and risk-taking traits that may exist with some users but not necessarily all of them due to individual differences (Agarwal & Prasad, 1998). Recent studies have shown that personal innovativeness is an influential factor that measures technology adoption in different fields and among different populations because it positively affects technology adoption. Studies have shown that innovativeness has close relation with motivation; that is, highly motivated users are more innovative and ready to accept the risk of trying new technology (Ciftci, Berezina, & Kang, 2021; Du, Ngo, Tran, & Nguyen, 2021; Gupta, 2021; Seyed Esfahani & Reynolds, 2021). Studies by (Cheng & Huang, 2013; Cho, Cheon, Jun, & Lee, 2021)have proven that personal innovativeness directly affects both perceived ease of use and perceived usefulness. The availability of innovativeness makes users evaluate the information system as easy to use and useful. Therefore, the following hypotheses are formed:

H₄: *Personal innovativeness (PI) positively impacts the perceived ease of using YouTube and TikTok (PEOU).*
H₅: *Personal innovativeness (PI) positively impacts the perceived usefulness of YouTube and TikTok (PU).*

3.4 Users' Satisfaction

Users satisfaction refers to the degree where users feel that they are pleased and satisfied in using technology. To many researchers, user satisfaction is an achieved outcome expressed in emotion towards using technology. This implies that users may feel that the technology is satisfying even if they do not prefer it (Liao, Palvia, & Chen, 2009; Szymanski & Hise, 2000; Tan, Yang, & Teo, 2007; Wixom & Todd, 2005). A study by Alshurideh et al. (2012) has pointed out that users' satisfaction positively affects the usage of e-service. A study also by Bavarsad & Mennatyan (2013) has pointed out that users' satisfaction has a positive effect on usage of e-service and is closely related to perceived usefulness and perceived ease of use. A similar conclusion is stated in studies by (Al-hawari & Mouakket, 2010; George & Kumar, 2013; Teo, 2011), where it is argued that users' satisfaction is an influential factor that affects the acceptance of technology.

Furthermore, it has both direct and indirect relations with both perceived ease of use and perceived usefulness. One of the significant conclusions has been confirmed by Liaw (2008), who states that the higher the degree of satisfaction, the higher the tendency to use the technology. Therefore, when the degree of satisfaction is low, the users will not use the technology or accept it. Based on the previous assumption, it is hypothesized that:

H₆: *Users' satisfaction (US) has a positive impact on YouTube and TikTok acceptance.*

3.5 Technology Acceptance Model

The Technology Acceptance Model (TAM) has been used by researchers in studies that intend to examine the acceptance and adoption of technology by users in different fields. It is a critical factor used to measure the successfulness of a system and

the outcomes of specific experience (Agarwal & Karahanna, 2000; Niederhauser & Perkmen, 2010). TAM has two main constructs that influence the socio-technical aspects; hence, it is used to examine users' behavioural intention to use a particular system. The perceived ease of use and perceived usefulness are crucial to understanding users' attitudes or beliefs towards the information system. They can be defined as the degree to which the users believe that the system is free of effort and useful (Davis, 1989). Past literature has focused on these two constructs as crucial factors contributing to the acceptance of technology and the behavioural intention to use it (Al Kurdi, Alshurideh, & Salloum, 2020; M. Alshurideh, Al Kurdi, & Salloum, 2020; Limayem, Hirt, & Chin, 2001; Teo, 2011). Hence, the following hypotheses are formed:

H7: *Perceived ease of use (PEOU)positively impacts the acceptance of YouTube and TikTok.*

H8: *Perceived usefulness (PU) has a positive impact on the acceptance of YouTube and TikTok*
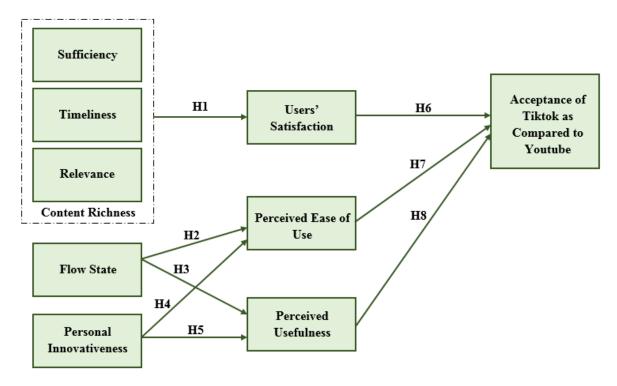

Fig. 1. Research Model

4. Research Methodology

4.1 Data collection

As a deductive technique, the cross-sectional design was adopted in this descriptive-analytical investigation. The study's data-collecting tool was an online questionnaire that employed a self-administered technique to gather information from healthcare employees in the United Arab Emirates (UAE), especially in the Emirate of Dubai. This examination research was conducted in a healthcare clinic in Dubai, with participation from seven primary healthcare clinics and five hospitals; the study lasted two months, from February 25th, 2021, to April 29th, 2021. The questionnaire link was distributed to health care employees via official emails and social media channels such as WhatsApp. Various healthcare providers were addressed for data collection, including administrative employees (registration, quality, receptionists, and administrative supports) and clinical staff (physicians, nurses, and allied health professionals) working at the selected hospitals and healthcare facilities, since these individuals may provide vital information concerning healthcare provision within healthcare. The study department delivered 600 questionnaires, where the respondents responded against 542questionnaires, which illustrates a 90 percent response rate. Nonetheless, certain values were missed in 58 completed questionnaires. Consequently, they were excluded. Hence, 542questionnaires completed in all respects were considered effective by the survey team. The inclusion of respondents' was attributed to the fact that they can contribute significantly to this study's usefulness whenever the respondents encounter any difficulty implementing technology; administrative support extends their help in providing more efficient and user-friendly tools. In contrast, the wide-ranging experiences of administrative support help the respondents in the adoption of new technologies. The respondents may find such an application through social media or their friends, but they could not experience its first-hand usage. As proposed by Krejcie & Morgan (1970), acceptable sample size was constituted by the cumulative number of 542 valid responses since 306 respondents make up the estimated sample size for a population of 1500, which is significantly

lower than the sample size of 542 respondents. Thus, the sample size for this study will be evaluated with the help of Structural Equation Simulation (SEM) (Chuan & Penyelidikan, 2006), which will subsequently be used to substantiate the hypothesis. The established theories mainly drive the hypotheses; however, they were often assisted with the concept of The Internet of things (IoT) context. The SEM, the SmartPLS Version (3.2.7), was employed to test the measurement model. The final path model has been utilized for further evaluation.

4.2 Personal /Demographic Information

The assessment of the personal/demographic data is shown in Table 2. The females and males' students were found to be 57% and 43%, respectively. The respondent's age was between 18 and 29 years for 23% of the respondents, while 77% of respondents were above 29 years. Maximum respondents were qualified and having university degrees. Further, 76% of individuals obtained a bachelor's degree, and 16% acquired a master degree, while the doctoral degree was earned by 8% of the respondents. As per Al-Emran & Salloum (2017), the researchers considered the "purposive sampling approach" due to its ease while contacting the respondents since they are happy to volunteer. This study sample was designed by the students from various medical centres in different age groups; they studied various programs at different levels.

Moreover, the IBM SPSS Statistics ver. 23 was used to measure the demographic data. Table 2 illustrates the comprehensive demographic data of the respondents.

Table 2
Demographic data of the respondents.

	Factor	Frequency	Percentage
Gender	Female	310	57%
	Male	232	43%
Age	Between 18 to 29	126	23%
	Between 30 to 39	246	46%
	Between 40 to 49	110	20%
	Between 50 to 59	60	11%
Education qualification	Bachelor	414	76%
	Master	86	16%
	Doctorate	42	8%

4.3 Study Instrument

To validate the hypothesis, a survey instrument was declared by this research. The survey contained 29 more items aiming to measure the eleven constructs in the questionnaire. Table3 incorporated the sources of these constructs. The researchers refined the questions from previous studies to enhance their relevance.

Table 3
Measurement Items

Constructs	Items	Instrument	Sources
YouTube and TikTok acceptance	AU1	Using Youtube is highly preferred for knowledge acquisition in the medical environment.	(Davis, 1989; Rai & Selnes, 2019; Venkatesh, Morris, Davis, & Davis, 2003)
	AU2	Using TikTok is highly preferred for knowledge acquisition in the medical environment.	
	AU3	Using TikTok is more preferred than Youtube.	
Users' Satisfaction	US1	In general, my experience with Youtube as a doctor was satisfactory.	(Oliver, 1981)
	US2	In general, my experience with TikTok satisfied all my needs as a doctor.	
	US3	In general, my experience with TikTok is more satisfactory than on Youtube.	
Perceived Ease of Use	PEOU1	I think that Youtube is easy to use among doctors.	(Huang, Huang, Huang, & Lin, 2012; Larsen, Sørebø, & Sørebø, 2009)
	PEOU2	I think that TikTok is easy to use among doctors.	
	PEOU3	I think that TikTok can replace Youtube due to its ease of use.	
Perceived Usefulness	PU1	I think that Youtube helps in acquiring and sharing medical information among doctors.	(Huang et al., 2012; Larsen et al., 2009)
	PU2	I think that Youtube improves my desire to get new medical information regularly.	
	PU3	I think that TikTok helps in acquiring and sharing medical information among doctors.	
	PU4	I think that Youtube improves my desire to get new medical information regularly.	
	PU5	I think that TikTok is more useful than Youtube in the application of the acquired knowledge.	
Content Richness	REL1	Youtube provides doctors with sufficient content for knowledge acquisition, sharing, and application.	(De Wulf et al., 2006)
	REL2	TikTok provides doctors with sufficient content for knowledge acquisition, sharing, and application.	
	REL3	TikTok is rich with medical content as compared with Youtube.	
	TIM1	Youtube has the latest medical information that can be shared and applied medically.	
	TIM2	TikTok has the latest medical information that can be shared and applied medically.	
	TIM3	TikTok's short videos are more satisfactory than Youtube's long videos in sharing medical knowledge.	
	SUF1	Youtube has provided doctors with sufficient medical information whenever they need it.	
	SUF2	TikTok has provided doctors with sufficient medical information whenever they need it.	
	SUF3	TikTok has more sufficient medical information than Youtube.	
Personal Innovativeness	PI1	As a doctor, I am ready to use TikTok's new technology as compared to Youtube.	(Mun, Jackson, Park, & Probst, 2006)
	PI2	As a doctor, I accept the innovativeness of TikTok as compared to Youtube.	
	PI3	I am usually hesitant to use TikTok as new technology as compared to Youtube.	
Flow State	FLO1	I feel completely engaged when I use Youtube.	(Bilgihan, Okumus, Nusair, & Bujisic, 2014; M.-C. Lee & Tsai, 2010)
	FLO2	I feel completely engaged when I use TikTok.	
	FLO3	I think that TikTok keeps me more focused as compared to Youtube.	

4.4   A pilot study of the questionnaire

The reliability of the questionnaire items was tested through a pilot study, which contained nearly 100 students randomly picked from the chosen population. As per the decision, the sample size was confined to 1000 students, which was 10% of the complete sample size with reference to the research; the main results include the pilot study, where pilot participants were the part of the main study; however, these people became the source of data collection. The IBM SPSS Statistics ver. 23 and the Cronbach alpha test were applied to examine internal reliability from the pilot study. Consequently, the researchers obtained acceptable outcomes for measurement items. In addition, the reliability coefficient equal to 0.70 is assumed as acceptable when this trend of analysis is focused on research studies (Nunnally & Bernstein, 1978). For the subsequently mentioned 7 measurement scales, the Cronbach alpha values are given in Table 4.

Table 4
Cronbach's Alpha values for the pilot study (Cronbach's Alpha ≥ 0.70)

Constructs	Cronbach's Alpha.
AU	0.896
US	0.883
PEOU	0.879
PU	0.806
CONT	
REL	0.749
TIM	0.798
SUF	0.832
PI	0.856
FLO	0.812

Note: AU, YouTube, and TikTok acceptance; the US, Users' Satisfaction; PEOU, Perceived Ease of Use; PU, Perceived Usefulness; Content Richness (REL, Relevance; TIM, Timeliness; SUF, Sufficiency); PI, Personal Innovativeness; FLO, Flow Experience.

4.5   Survey Structure

The researchers distributed the questionnaire survey. In the United Arab Emirates universities, online surveys were provided to the students (N=500). Furthermore, two famous universities in the UAE, i.e., the British University in Dubai (BUiD) and the University of Fujairah will be considered for data acquisition. A questionnaire survey was provided to these students (Al-Emran & Salloum, 2017). This survey contains three sections.

- The first section focuses on the personal data of the participants.

- The second section contains the five items demonstrating the general question regarding mobile learning systems.

- The third section comprises fifteen items that illustrate the Service quality and Quality of the system.

A five-point Likert Scale will be used to measure the (29 items), and these scales include: strongly agree (5), agree (4), neutral (3), disagree (2), strongly disagree (1).

5.   Findings and Discussion

5.1   Data Analysis

Using the SmartPLS V.3.2.7 software, the data analysis of this study was performed through the partial least squares-structural equation modelling (PLS-SEM) (Ringle, Wende, & Becker, 2015). Researchers employed a two-step assessment approach to investigate the collected data, including the measurement and structural models (Hair, Hollingsworth, Randolph, & Chong, 2017). After key discussions, the PLS-SEM was selected for this study. Initially, PLS-SEM becomes an ideal preference when the researchers desire to establish an existing theory from the available study (Urbach & Ahlemann, 2010). Secondly, the PLS-SEM can effectively handle the exploratory studies containing complex models (Hair, Hult, Ringle, & Sarstedt, 2016). Thirdly, the PLS-SEM analyzes the complete model as one unit before splitting it into fragments (Goodhue, Lewis, & Thompson, 2012). Fourthly, the PLS-SEM offers concurrent analysis for both measurement and structural model, which continuously produces accurate results (Barclay, Higgins, & Thompson, 1995).

5.2   Convergent validity

According to Hair et al. (2017), the construct reliability (including composite reliability (CR), Dijkstra-Henseler's (PA), and Cronbach's alpha (CA)) and validity (including convergent and discriminant validity) were recommended to evaluate the measurement model. The Cronbach's alpha (CA) can be used to determine the construct reliability. Table5 contains the CA values between 0.740 and 0.876. The threshold value, i.e., 0.7, was found less than these figures (Nunnally & Bernstein, 1994). According to Table 5, the composite reliability (CR) contains values between 0.710 and 0.896, higher than the recommended value of 0.7 (Kline, 2015). Rather, construct's reliability should be assessed and reported through the Dijkstra-Henseler's rho (pA) reliability coefficient (Hair et al., 2017). Just like CR and CA, the reliability coefficient ρA should specify values above 0.80 or 0.90 for advanced stages of research and the values of 0.70 or higher in exploratory research (Hair, Ringle, & Sarstedt, 2011; Henseler, Ringle, & Sinkovics, 2009; Nunnally & Bernstein, 1994). Table 5 reveals that for each

measurement construct, the reliability coefficient ρA is above 0.70. These results will substantiate the construct reliability, and ultimately all the constructs were supposed as sufficiently error-free.

The researchers need to test the factor loading and the average variance extracted (AVE) (Hair et al., 2017). Table 5 reveals that the values of all factor loadings remain higher than the suggested value of 0.7. Moreover, according to Table 5, the values yielded by the AVE were between 0.537 and 0.702, which are greater than '0.5', i.e., the threshold value. Based on imminent results, the researchers can successfully achieve convergent validity for all constructs.

5.3 Discriminant validity

The experts have advised measuring the Heterotrait-Monotrait ratio (HTMT) and the Fornell-Larker criterion (Hair et al., 2017). The findings of Table 6 reveal that the Fornell-Larker condition has fulfilled the given requirements since all AVEs and their square roots are higher as compared to their correlation with other constructs (Fornell & Larcker, 1981).

Table 7 depicts the outcomes of the HTMT ratio, which clearly reveals that the threshold value of 0.85 remains greater than each construct (Henseler, Ringle, & Sarstedt, 2015). Thus, the researchers successfully determine the HTMT ratio. These findings help determine the discriminant validity. Concerning its reliability and validity, the analysis results did not find any issues regarding the assessment of the measurement model. Hence, the collected data can further be employed to assess the structural model.

Table 5
Convergent validity results which assure acceptable values (Factor loading, Cronbach's Alpha, composite reliability ≥ 0.70 & AVE > 0.5)

Constructs	Items	Factor Loading	Cronbach's Alpha	CR	PA	AVE
YouTube and TikTok acceptance	AU1	0.770	0.770	0.787	0.866	0.683
	AU2	0.859				
	AU3	0.848				
Users' Satisfaction	US1	0.835	0.776	0.794	0.763	0.537
	US2	0.772				
	US3	0.791				
Perceived Ease of Use	PEOU1	0.850	0.788	0.793	0.876	0.702
	PEOU2	0.834				
	PEOU3	0.812				
Perceived Usefulness	PU1	0.801	0.851	0.859	0.894	0.628
	PU2	0.868				
	PU3	0.844				
	PU4	0.806				
	PU5	0.838				
Content Richness	REL1	0.814	0.876	0.896	0.899	0.602
	REL2	0.853				
	REL3	0.704				
	TIM1	0.841				
	TIM2	0.814				
	TIM3	0.857				
	SUF1	0.808				
	SUF2	0.805				
	SUF3	0.800				
Personal Innovativeness	PI1	0.876	0.740	0.710	0.800	0.579
	PI2	0.836				
	PI3	0.872				
Flow State	FLO1	0.790	0.778	0.778	0.871	0.692
	FLO2	0.844				
	FLO3	0.879				

Table 6
Fornell-Larcker Scale

	AU	US	PEOU	PU	CR	PI	FLO
AU	**0.827**						
US	0.620	**0.809**					
PEOU	0.682	0.579	**0.832**				
PU	0.606	0.521	0.414	**0.838**			
CR	0.685	0.661	0.653	0.551	**0.892**		
PI	0.626	0.636	0.680	0.668	0.608	**0.961**	
FLO	0.529	0.658	0.589	0.680	0.538	0.656	**0.833**

Note: AU, YouTube, and TikTok acceptance; US, Users' Satisfaction; PEOU, Perceived Ease of Use; PU, Perceived Usefulness; CR, Content Richness; PI, Personal Innovativeness; FLO, Flow Experience.

Table 7
Heterotrait-Monotrait Ratio (HTMT)

	AU	US	PEOU	PU	CR	PI	FLO
AU							
US	0.727						
PEOU	0.663	0.513					
PU	0.761	0.730	0.311				
CR	0.731	0.755	0.520	0.514			
PI	0.655	0.591	0.528	0.697	0.369		
FLO	0.409	0.809	0.556	0.563	0.584	0.461	

Note AU, YouTube, and TikTok acceptance; US, Users' Satisfaction; PEOU, Perceived Ease of Use; PU, Perceived Usefulness; CR, Content Richness; PI, Personal Innovativeness; FLO, Flow Experience.
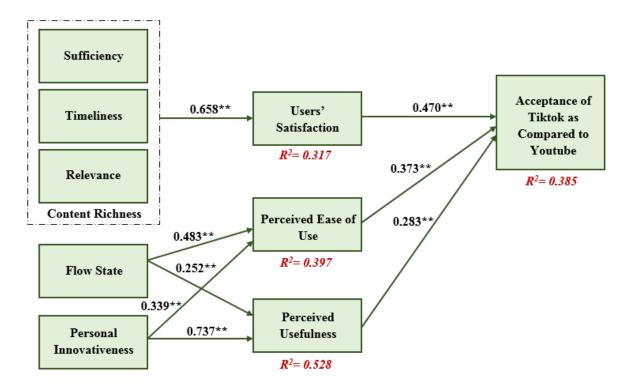
5.4 Model fit

SmartPLS offer the following fit measures: The model fit in PLS-SEM is represented by the exact fit criteria, standard root mean square residual (SRMR), d_G, d_ULS, NFI, Chi-Square, and RMS_theta (Trial, n.d.). The difference between model implied correlation matrix and observed correlations are inferred by the SRMR (Hair, et al., 2016), and researchers assume that values in good model fit are below 0.08 (Hair et al., 2016). A good model fit is depicted by the NFI values above 0.90 (Hu & Bentler, 1998). The proposed model's ratio of Chi2 value to the benchmark model or null model is called the NFI (Lohmöller, 1989). The NFI becomes higher due to larger parameters. Therefore, researchers do not suggest the NPI as a model fit indicator (Hair et al., 2016). Two metrics providing discrepancies between the covariance matrix and the empirical covariance matrix inferred by the composite factor model are the geodesic distance d_G and the squared Euclidean distance d_ULS (Dijkstra & Henseler, 2015; Hair et al., 2016). The RMS theta evaluates the degree of outer model residuals correlation, and it is only pertinent to the reflective models (Lohmöller, 1989). The PLS-SEM model will give better output if the RMS theta value gets closer to zero and the values below 0.12 are taken as a good fit, and the undesirable values indicate a lack of good fit (Henseler et al., 2014). As per (Hair et al., 2016), the saturated model's correlation among all constructs is evaluated, while the estimated model reflects the model structure and total effects.

As per Table 8, the value of RMS_theta was equal to 0.052, which reveals the appropriateness of the goodness-of-fit for the PLS-SEM model to demonstrate the global PLS model validity.

Table 8
Model fit indicators

	Complete Model	
	Saturated Model	**Estimated Mod**
SRMR	0.031	0.032
d_ULS	0.760	1.228
d_G	0.552	0.554
Chi-Square	449.530	449.530
NFI	0.808	0.808
Rms Theta	0.052	

5.5 Hypotheses testing using PLS-SEM

To discover the interdependence of several theoretical constructs of the structural model, the researchers utilized the structural equation model together with Smart PLS having maximum likelihood estimation (Al-Emran, Arpaci, & Salloum, 2020; Rana Saeed Al-Maroof, Alhumaid, Alhamad, Aburayya, & Salloum, 2021; Alshurideh et al., 2021; Salloum et al., 2021; Salloum, Alhamad, Al-Emran, Monem, & Shaalan, 2019; Shah, Alshurideh, Kurdi, & Salloum, 2021). Hence, they analyzed the proposed hypotheses. Figure 2 and Table 9 indicate that the model possessed a moderate predictive power (Chin, 1998), i.e., the R^2 values for Acceptance of TikTok as Compared to YouTube, Users' Satisfaction, Perceived Ease of Use, and Perceived Usefulness were found to be between 0.33 and 0.67; and hence, the predictive power of these constructs is considered as moderate.

For each of the developed hypotheses, the beta (β) values, t-values, and p-values were described in Table10, attributed to the generated results via the PLS-SEM technique. All the researchers have supported all hypotheses. The empirical data supported the hypotheses H1, H2, H3, H4, H5, H6, H7, and H8 based on the data analysis.

The relationships between Content Richness (CR) and Users' Satisfaction (US) (β= 0.658, P<0.001) was found to be statistically significant, and thus, the hypothesis H1 is generally supported. The results showed that Perceived Ease of Use (PEOU) significantly influenced Flow Experience (FLO) (β= 0.483, P<0.001) and Personal Innovativeness (PI) (β= 0.339, P<0.001), supporting hypothesis H2 and H4 respectively. Furthermore, the effect of Perceived Usefulness (PU) has a positive impact on Flow Experience (FLO) (β= 0.252; P<0.001), and Personal Innovativeness (PI) (β= 0.737; P<0.001), respectively, were found to be not significant; hence, H3 and H5 is supported. Users' Satisfaction (US), Perceived Ease of Use (PEOU), and Perceived Usefulness (PU) have significant effects on YouTube and TikTok acceptance (AU) (β= 0.470, P<0.001), (β= 0.373, and (β= 0.283, P<0.001) respectively; hence H6, H7, and H8 are supported.

Table 9

R² of the endogenous latent variables.

Constructs	R²	Results
AU	0.385	Moderate
US	0.317	Moderate
PEOU	0.397	Moderate
PU	0.528	Moderate

Note AU, YouTube and TikTok acceptance; US, Users' Satisfaction; PEOU, Perceived Ease of Use; PU, Perceived Usefulness.

Table 10

Hypotheses-testing of the research model (significant at p** < = 0.01, p* < 0.05)

H	Relationship	Path	t-value	p-value	Direction	Decision
H1	CR→US	0.658	28.537	0.000	Positive	Supported**
H2	FLO→PEOU	0.483	11.510	0.000	Positive	Supported**
H3	FLO→PU	0.252	10.595	0.000	Positive	Supported**
H4	PI→PEOU	0.339	8.398	0.001	Positive	Supported**
H5	PI→PU	0.737	5.123	0.002	Positive	Supported**
H6	US→AU	0.470	7.540	0.000	Positive	Supported**
H7	PEOU→AU	0.373	35.590	0.000	Positive	Supported**
H8	PU→AU	0.283	8.656	0.000	Positive	Supported**

Note AU, YouTube and TikTok acceptance; US, Users' Satisfaction; PEOU, Perceived Ease of Use; PU, Perceived Usefulness; CR, Content Richness; PI, Personal Innovativeness; FLO, Flow Experience.

Fig. 2. Path coefficient of the model (significant at p** < = 0.01, p* < 0.05).

6.   Discussion

The literature review has shed light on the importance of social media in the learning environment, considering the main factors that influence the acceptance of social media (Oum & Han, 2011; Ryu, Kim, & Lee, 2009). However, this study highlights the key determinants that show the differences in the acceptance of YouTube and TikTok. Accordingly, the present study attempted to expand the vision of TikTok and YouTube by creating a comparative atmosphere. Based on the obtained results, it seems that YouTube is more widely accepted among innovative medical users since it provides a more detailed and specialized type of information. In agreement with our proposed hypotheses, personal innovativeness plays a crucial role in increasing the chances of accepting YouTube and TikTok.Hence, YouTube is highly recognized by users in the medical field due to its detailed information. This result consists of previous literature where YouTube is classified as a learning community where users have the voice to contribute and have the right to gain and create knowledge (Al Suwaidi, Alshurideh, Al Kurdi, & Salloum, 2021; Almansoori A., AlShamsi M., Salloum S.A., 2021; Duffy, 2008; Mehrez, Alshurideh, Kurdi, & Salloum,

2021). Similarly, a recent study by (Wang, 2020) on TikTok has investigated the effects of short-form videos features on users' psychological and acceptance of TikTok. It is concluded that TikTok short videos immensely enhance its acceptance due to the wide-spread humour feature. However, the current results are not in agreement with the literature review. This stems from the fact that TikTok has more general information created by unspecialized users with only one main aim: passing the time. TikTok is created for the mere purpose of socialization and self-expression. TikTok designers and users aim to share funny and cheerful feelings and emotions where their main focus is on the pleasant and upbeat feelings, affecting users' mood only. No attention is paid to the type of offered content (Yang & Zilberg, 2020). Accordingly, YouTube has been evaluated as useful, motivated, intensely enjoyable and more satisfactory by users with a percentage of around 73%.

On the other hand, TikTok has been evaluated as useful, enjoyable and satisfactory by around 27%. Crucial justifications have to be made in this regard. First, content creators on TikTok seem to tackle general topics and ignore the more specialized type of content that is useful to users in the medical field. Second, the main goal of content creators in TikTok is to pass time which stands in contrast with the aim of those on YouTube with the more specified and directed type of content. Third, most TikTok video creators are not interested in educational and specialized issues. In contrast, YouTube has more variation to the type of creators, varying from uneducated people to professors and doctors. On the other hand, TikTok is described as a short video that inspires people and brings joy without referring to the specialized content. Being described as enjoyable and funny implies that its global-wide scope stems from factors related to creating a positive atmosphere. The previous perspective is strengthened by the fact that most influencers in TikTok are aged from 13 to 64; that is, most of them are teenagers, young or middle-aged adults (Yang & Zilberg, 2020).

The results obtained from the various conceptual model constructs have affected the acceptance of these two social websites. Regarding content richness, the hypotheses have made a direct relation between users' satisfaction and content richness. The current result seems to align with previous studies where content richness plays a crucial role in accepting YouTube and TikTok. Content richness affects users' eagerness to use social media continuously because richness in content urges governments and companies to develop better social media content to attract more users. In a study by (Boyinbode, Agbonifo, & Ogundare, 2017), content richness was one of the significant factors behind the acceptance of WhatsApp. The fact that WhatsApp can provide its users with recent information enables its users to accept this technology.

In terms of personal innovativeness, YouTube has proven to be an innovative and efficient learning medium. Its growing effect in educational settings has been highlighted in many studies where the motivational factors significantly affect the acceptance behaviour of users (Jaffar, 2012; Krauskopf, Zahn, & Hesse, 2012). The recent studies support the results obtained in previous literature. Personal innovativeness is a personal and psychological factor that has been supported positively in the current study. Personal readiness to accept new technology may lead to a significant impact on users' daily life. Recent studies on personal innovativeness have shown that users can be affected psychologically by their readiness to accept new technology. Users who are personally motivated to accept new technology have a higher willingness to accept new technology.

On the contrary, users who are hesitant to accept new changes are less motivated and will not be ready to accept new technology (Ciftci et al., 2021; Lu et al., 2005; Xu & Gupta, 2009). The widespread use of YouTube creates a social and digital community where users become more experienced due to the YouTube specialized topics. The popularity of YouTube urges more users to construct knowledge actively and search for more information (Oum & Han, 2011).

Flow theory has added a new dimension to the current conceptual model and the current results because it tackles the enjoyment factor that has both personal and psychological implications. In line with our hypotheses, the present results have confirmed that users who are intensely involved in technology are more willing to accept the technology due to the enjoyable experience they had in the past. Similarly, the present results are consistent with recent studies where flow theory significantly affects adoption or acceptance. Flow theory positively impacts the acceptance of technology because it integrates motivation, personality, and subjective experience. The integration of these factors lead to the fact that users will be psychologically and cognitively more engaged in the technology, hence, ready to accept it (Altalhi, 2021; Bölen, Calisir, & Özen, 2021; Hameed, Zaman, Waris, & Shafique, 2021).

The TAM model has contributed significantly to the acceptance of YouTube and TikTok. Inconsistent with the proposed hypotheses, perceived usefulness is considered an immediate predictor of behavioural intention to accept both YouTube and TikTok. In light of this finding, the obtained result has shown that the role of PEOU and PU to facilitate acceptance cannot be ignored. Whenever the technology is classified as free of effort and useful, it implies a higher level of acceptance. In previous studies, YouTube has been classified as a useful tool to activate extrinsic motivation in determining technology usage behaviour. In other words, the acceptance might be closely affected by the efforts of goal-oriented behaviour (Deci, 1985; Shang, Chen, & Shen, 2005), which is driven by the fact that YouTube is a significant tool that improves the understanding of how things are made and analyzed (D. Y. Lee & Lehto, 2013). Another study by Gefen & Straub (2000) and Bettayeb et al. (2020) highlighted that perceived usefulness directly impacts user acceptance in cases where performing an extrinsic task is a final goal. The obtained results align with an assumption proposed by both (Gefen & Straub, 2000; Lee & Lehto, 2013). TAM was extended in the present study to include users' satisfaction closely related to the users real and practical experience. Users' satisfaction is postulated as the more salient factor behind the intention to use technology. Therefore, users' satisfaction is related to long term usage and not initial acceptance. The main reason that urges researchers of the present study to add

user satisfaction is that it is a critical factor used to measure the level of satisfaction in the medical field where the effectiveness of the information affects motivation and commitment. Previous studies agree with the present results where a high level of satisfaction leads to continuous acceptance of technology (Shee & Wang, 2008; Wang, Wang, & Shee, 2007; Wu, Tennyson, & Hsia, 2010).

6.1 Theoretical and Practical implications

With the recent and rapid development of social media in information technology, YouTube and TikTok are currently the most common types of social networks that gain huge popularity among people worldwide. To put it differently, YouTube has been considered a promising channel for learning. It is the most common free of charge video-sharing website with its unique learning and teaching features. People can upload and download specialized and recent information. Similarly, TikTok is classified as the most enjoyable short video-sharing app. Shortness in time and content leads to millions of viewers (Lee & Lehto, 2013; Y. Wang, 2020).

Theoretically speaking, users in the medical field have experienced enjoyable and useful times when YouTube is used as a source of information. Therefore, there is a need to increase the chance to get more specialized and up-to-date videos that enhance doctors' knowledge and experience. TikTok has affected users in the medical field in a limited perspective due to its short videos, which add users' knowledge in a restricted manner. The only striking feature is the fact that it keeps in users' mind more enjoyable with funny experiences (Yang & Zilberg, 2020). Therefore, the content should be evaluated to guarantee richer, up-to-date and specialized information offered by the creators of TikTok.

The previous theoretical assumption may be transformed to more practical implications for website developers. Website developers should focus on creating features that help classify the short video to reach the targeted uses easily. In addition, the classification should offer users options to choose among different content easily by classifying them as educational and non-educational. The detailed classification will increase the chances to use TikTok in the long term continuously.
Previous studies on YouTube have focused on the fact that the availability of unique learning features enables users to obtain information and create and upload videos (Lee & Lehto, 2013). Similarly, a literature review on TikTok as a recent social media platform has shown that TikTok, with its mobile short video features, can enhance in a limited way the users' knowledge and experience due to its short video. Developers need to take the fact that too short videos may negatively affect the acceptance of TikTok and should add more features that can urge users in the medical field to continue using TikTok (Wang, 2020).

6.2   Managerial implications

The fact that YouTube and TikTok are sources of information to users in different fields implies that both are significant and widely spread platforms for knowledge sharing and acquisition. Though the Chinese government recently invented TikTok as a source of spreading knowledge throughout the COVID19 period, the short videos persuaded its users to adopt it. However, the adoption can be greater. The acceptance will be higher in the long term when managers and developers focus on upgrading more important features, focusing on uploaded videos' content, and extending the short form of video-sharing apps to understand and improve users' experience.

6.3   Limitations and Suggestions for Future Studies

The study has proposed certain limitations. Firstly, the study is limited to two types of social networks, which are YouTube and TikTok. Recently many other platforms have been initiated to have similar functions to the chosen one, such as Reels. Therefore, future studies can focus on these new platforms or app. by investigating their effectiveness and creating a comparative study in this respect. Secondly, the current study has focused on users in the medical field. The comparisons and the results have taken into consideration users' attitude and perception in the medical field; hence, future studies can focus on the effectiveness of YouTube and Tik Tok in other fields where the comparison may lead to completely different results due to the differences in the setting. Thirdly, the present study is an acceptance study of YouTube and TikTok. It deals with current users' conception and perception. Therefore, future studies can focus on the continuous intention to use these two platforms on the log-term acceptance.

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