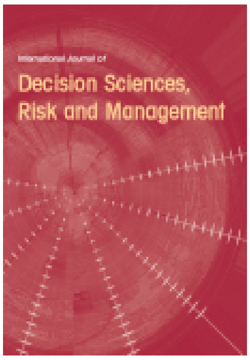

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Doctors' attitudes toward social media use amid the COVID-19 pandemic using an extended technology acceptance model

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Abstract: Social media have revolutionised communication, exchange of information, interaction, and collaboration. Research reported herein focuses on doctors' attitudes (ATT) towards the actual use (AU) of the social media Facebook and Twitter during the COVID-19 pandemic. The conceptual framework was driven by the technology acceptance model (TAM) and involves five factors: ATT, behavioural intention (BI), perceived ease of use (PEoU), perceived usefulness (PU), and AU. Structural equation modelling (SEM) was used on a random sample of 328 doctors from Greek public hospitals. For Facebook, the ATT towards AU of social networks through the mediating factors PU, PEoU, and BI. For Twitter, the ATT towards AU of the social networks. Doctors reported using social networks during the pandemic to read research outputs uploaded by other medical colleagues and researchers.

Results demonstrate that despite reliability issues, social networks may significantly contribute to the dissemination of medical knowledge and communication between health professionals.

Keywords: public hospitals; social networks; technology acceptance model; COVID-19; structural equation modelling; exploratory factor analysis; health professionals; health sector; correlations; differences; attitudes.

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1 Introduction

The development of the internet has led to the emergence of social networks, greatly facilitating the communication of individuals, businesses, and organisations, as well as the dissemination of information and knowledge. Social media encompasses online applications and programs that allow users to share varied content and thus network over assorted topics. The expansion of this media form has revolutionised how people share their knowledge and communicate and collaborate while engaging in timely conversations in the workplace (Ahmed et al., 2019). Social media is deemed among the most powerful communication tools of the 21st century (Farsi, 2021). The ascending societal use of social media has encouraged health professionals to use it in their professional activities (Hennessy et al., 2019). Chan and Leung (2018) reported that social networks ameliorated communication, information sharing, and professional collaboration among healthcare professionals. Hazzam and Lahrech (2018) in their research found that 53.6% of doctors used social media platforms for the exchange of peer medical information, and 53.2% used social media several times during the day to improve their interpersonal communication with colleagues (Hazzam and Lahrech, 2018). Public health professionals share a positive attitude toward using online media to inform health change behaviour (Franco et al., 2016). In addition, health professionals exhibit a positive attitude toward participation in social media platforms (Melkers et al., 2017). In their research, Hazzam and Lahrech (2018) found that attitude is one of the main factors in health professionals' use of social media.

The COVID-19 pandemic had a significant effect on the way people communicated worldwide. Due to social distancing and lockdowns, the use of social networks increased during the pandemic by 27% (New York Times, 2020). A study in Germany found that over 70% of citizen respondents representing the adult population reported increased use of digital media during the pandemic (Lemenager et al., 2021). Despite the reliability issues, it is worth noting that social networks were used by several professional groups, such as health professionals, to access information and share research outcomes. For instance, Murri et al. (2020) found that 70% of the participating doctors reported using social media to seek medical information during the COVID-19 pandemic. Isomursu et al. (2022) found that doctors' use of social media increased between 2018 and 2021 and continued to rise during the COVID-19 epidemic. Similarly, doctors' attitudes toward online education became more positive during the COVID-19 period compared to pre-COVID-19 attitudes. Pharmaceutical companies and other product and service providers used online education and social media during COVID-19 pandemic as marketing services to educate doctors about their products (Isomursu et al., 2022). Studies have shown that social networks can help understand public knowledge, fears, attitudes, and behaviour during a crisis (Jordan et al., 2018; Shah et al., 2019; Shah and Dunn, 2019).

Davis (1989) and Davis et al. (1989) introduced the technology acceptance model (TAM), which predicts behavioural intentions (BIs) toward technology use. Attitudes are significant in determining how people will behave when using a given technology or service (Ajzen and Fishbein, 1980) and are essential for understanding and anticipating how people will behave (Ajzen, 1991).

The primary objective of this research is to evaluate physicians' attitudes toward the use of social networks Facebook, and Twitter, during the COVID-19 pandemic using an extended TAM. A random sample of 328 physicians working in public hospitals in Greece between January 18, 2021, and June 21, 2021, was used to achieve this goal.

2 Theoretical background

TAM, introduced by Davis et al. (1986), is the most extensively utilised framework concerning the attitudes and adoption of technology and represents a validated endeavour encompassing standardised concepts and measures. TAM is a powerful indicator through which users can predict behaviour toward modern technologies before implementation (Abdelkawi and Salama, 2022). Davis (1989) supported that perceived usefulness (PU) and ease of use are two determinants of using new technologies. The model includes four constructs: perceived ease of use (PEoU), PU, attitude concerning the use, and actual system use.

PU measures an individual's belief that using a system will help them perform their job better (Corkindale et al., 2018), while PEoU measures an individual's belief that using a system will be free from effort. TAM focuses on technology use, where PEOU and PU are two factors or antecedents that influence user acceptance behaviour (Shrestha and Vassileva, 2019). Shin and Bianco (2020) verified that due to PEoU and convenience, usage improves; dependence is created, and trust increases. Although PEoU is not the only determinant of trust, it contributes substantially to creating trust (Liu and Ye, 2021).

TAM extends the theory of reasoned action (TRA) framework. TRA and the theory of planned behaviour (TPB) (Fishbein and Ajzen, 1975; Ajzen, 1991) were used to evaluate technology adoption. TRA demonstrates that a particular behaviour of an individual is critically determined by their attitudes and intentions (Fishbein, 1979; Madden et al., 1992; Sheppard et al., 1988). In TRA, attitude is defined as an individual's feeling regarding exhibiting a specific behaviour, whereas attitude is primarily determined by an individual's beliefs or evaluations (Davis, 1989; Davis et al., 1989). TRA theory states that a user's actual behaviour has four constructs: beliefs, attitudes, normative beliefs, and subjective norms that positively influence BI. TPB theory states that attitude toward behaviour, subjective norm, and perceived behavioural control determine BI and behaviour. Furthermore, individuals' attitudes largely determine their BI to use a particular technology or service (Ajzen and Fishbein, 1980) and are crucial to interpreting and predicting human actions (Ajzen, 1991).

In the literature, there are several modified versions of TAM that attempt to explain the BI to use technology, such as TAM 2 (Venkatesh and Davis, 2000), technology readiness and acceptance model (TRAM) (Parasuraman 2000), TAM 3 (Venkatesh and Bala, 2008), Technology Acceptance and Use Theory (UTAUT, Venkatesh et al., 2003, Melas et al., 2011; Rahman et al., 2019; Dwivedi et al., 2019; Wang et al., 2022) and UTAUT 2 (Venkatesh et al., 2012). TRAM measures optimism, novelty, discomfort, and insecurity to explain how people use new technologies at home and work (Parasuraman, 2000). UTAUT was derived from eight models of technology acceptance (Venkatesh et al. 2003), and its purpose is to evaluate the likelihood of new technology adoption. In the models mentioned above, many external variables have been used, such as social influence, performance expectancy, effort expectancy, the voluntariness of use, experience, age, subjective norm, image, task relevance, production quality, computer self-efficacy, computer playfulness, hedonic motivation, habit, etc. Nevertheless, TAM is the most widely cited technology acceptance framework and is gradually expanding (Taherdoost, 2022).

3 Study goals and research hypothesis

The primary objective of this research is to evaluate physicians' attitudes toward the use of social networks Facebook, and Twitter, during the COVID-19 pandemic using an extended TAM. Facebook and Twitter were selected due to their popularity (Pew Research Center, 2018; Statista, 2019). A random sample of 328 physicians working in public hospitals in Greece between January 18, 2021, and June 21, 2021, was used to achieve these goals. We modified the basic TAM model by adding the factor BI (Holden and Karsh, 2008; Melas et al., 2011). Thus, the extended TAM model consists of five factors (Figure 1). AU represents the dependent variable, and ATT is the independent variable. We examined a total of seven hypotheses driven from the literature.

3.1 Attitudes toward PU, PEoU, and BI of social media during the COVID-19 pandemic

Fetscherin and Lattemann (2008) found that the ability to interact in a 3D environment combined with voice-over IP serves a key role in user acceptance and adoption of virtual world technology. They hypothesised that ATT positively and directly influence PU. Their hypothesis was confirmed. They further found that ATT influences TAM related to user acceptance. Holden and Karsh (2008) studied the effects of TAM on different forms of TAM. In several tests, the correlation between ATT and BI was found to be significant. Lee et al. (2003) explained using TAM in the past, present, and future. The survey results revealed a significant relationship between PEoU and the dependent variables of TAM, thereby indicating that PEoU is an unstable measure in the prediction of BI. ATT, which reflects how much a person likes or dislikes an object, was an external variable with which PEoU had a substantial correlation (Chau, 2001). Motivated by the findings reported by Fetscherin and Lattemann (2008), Lee et al. (2003), Chau (2001), and Holden and Karsh (2008), we formulated the first, second, and third research hypotheses as follows:

H1 ATT has a significant impact on users' PU.

H2 ATT has a significant impact on users' PEoU.

H3 ATT has a significant impact on users' BI.

3.2 BI toward PEoU of social media during the COVID-19 pandemic

Muljo et al. (2020) investigated the factors influencing understanding the intention of using a mobile-based cancer early detection learning application and concluded a positive correlation between the BI and PEoU. In addition, Shahbaz and Gao (2020), in their survey concerning moderating effects of gender and resistance to change on adopting big data analytics in healthcare, found a positive, strong correlation between the BI and PEoU. Motivated by these findings reported by Muljo et al. (2020) and Shahbaz and Gao (2020), we formulated the fourth research hypothesis as follows:

H4 BI has a significant impact on users' PEoU.

3.3 PEoU toward PU of social media during the COVID-19 pandemic

Raza et al. (2017) investigated the variables affecting the intention of individuals to continue using mobile banking in Pakistan and suggested that PU was directly related to PEoU. Walczak et al. (2021) examined the use of telemedicine by general practitioners during the COVID-19 pandemic in Poland and found a positive correlation between PU and PEoU. Motivated by the findings reported by Raza et al. (2017) and Walczak et al. (2021), we formulated the fifth research hypothesis as follows:

H5 PEoU has a significant impact on users' PU.

3.4 PEoU and PU toward the actual use of social media during the COVID-19 pandemic

Alshibly (2011) studied the acceptance of electronic cheque-clearing systems at Jordanian commercial banks and suggested a positive correlation between PU and AU and PEoU and AU. Furthermore, Abdool et al. (2021), in their survey concerning the factors affecting the acceptance levels of and attitudes towards telemedicine among users in the United Arab Emirates (UAE) concluded a positive correlation between PU and AU and PEoU and AU. Motivated by the findings reported by Alshibly (2011) and Abdool et al. (2021) we formulated the sixth and seventh research hypotheses as follows:

H6 PEoU has a significant impact on users' AU.

H7 PU has a significant impact on users' AU.

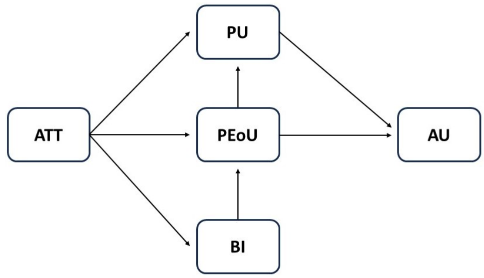
4 Methods

4.1 Conceptual model

The modified TAM is presented in Figure 1 and involves five constructs: ATT, BI, PEoU, PU, and AU. We modified the basic TAM model by adding the factor BI (Holden and Karsh, 2008; Melas et al., 2011). Thus, the extended TAM model consists of five factors (Figure 1). AU represents the dependent variable, and ATT is the independent variable.

1. (PU): represents the perception of the worthiness of a specific system or application when used in conjunction with the daily tasks of a medical doctor.
2. (PEoU): represents the perception of ease while using the system or application.
3. (ATT): represents the individual perception regarding the system or application; for example, 'Do I prefer using a specific application or system over an available alternative?'.
4. (BI): represents the likelihood of using a certain system or application.
5. (AU): represents the actual use, usually measured by the time or frequency of use of a particular application.

Figure 1 The modified TAM



Although AU represents the dependent variable (Figure 1), the dependencies between the constructs may be significant and, therefore, subject to further investigation. For example, as depicted in Figure 1, ATT may influence BI, PU, and PEoU. Moreover, PEoU may be envisaged as influencing PU and influenced by BI. Finally, AU may be envisaged as influencing PU and PEoU.

4.2 Measurement instrument

The instrument was based on the questionnaire of McGowan et al. (2012) (demographic questions and 16 factor questions). Because participants were Greek-speaking, two translators first translated the scale used into Greek and then compared their versions until they agreed on the most correct translation; the scale was then back-translated into English by a bilingual, native English-speaking translator, following the procedure recommended in the literature (Cha et al., 2007). The few discrepancies found between the original English version and the back-translated version resulted in adjustment of the Greek translation based on direct discussion between the translators.

To explore the variables of the extended model and the possible correlations among them, the researchers collaborated with three medical doctors and university professors, who proposed 34 additional questions (experts decided that additional questions should be added because of the pandemic). Thus, the questionnaire consisted of a total of 50 factor questions and demographic questions. After deleting the redundant items and the face validity procedures, 36 questions were finally added to the original model (the 14 deleted questions are marked with italic letters in Table 2).

4.3 Sampling method and participants

The survey was carried out via personal interviews after the human resources department of each hospital had first been informed by phone about the day and time of our arrival. Out of a total population of 350 public doctors were randomly selected from six public hospitals (General Hospital of Athens G. Gennimatas, General Hospital of Athens Evangelismos, General Hospital of Thessaloniki Papageorgiou, and University General Hospital of Thessaloniki AHEPA, and two hospitals from Thessaly) in Greece, 328 answered the questionnaire during their work, during the third wave of the COVID-19 pandemic in Greece (January 18, 2021, and June 21, 2021) (response rate 93.71%). During the pandemic, the Greek Government allowed only public hospitals to treat cases of COVID-19. The sample comprises 195 males (59.45%) and 133 females (40.54%).

The questionnaire was proposed only to doctors who answered they use either Facebook or Twitter. The average age of the participants was 40.98 years (SD = 11.61), ranging between 23 and 66 years. Furthermore, 58.6% of doctors held a bachelor's degree in medicine, 31.7% held an MSc degree, and 9.7% held a PhD degree.

In the sample, 55.5% of the doctors were pathologists, 29.9% were surgeons, and 14.6% were laboratory doctors. Furthermore, 100% of doctors used Facebook, and 62.8% used Twitter. 40.3% of the doctors reported being slightly active daily on social networks, 47.4% read research outputs uploaded by other researchers and medical doctors, and 38.3% exchanged messages using social networks (Table 1).

Table 1 Descriptive demographic data

		Frequency	*Percentage*
Gender	Male	195	59.45%
	Female	133	40.54%
Age	< 30	50	15.1%
	30–39	132	40.4%
	40–49	64	19.4%
	> 49	82	25.1%
Education	Medical diploma	192	58.6%
	MS	104	31.7%
	PhD	32	9.7%
Medical specialties	Pathology	182	55.5%
	Surgery	98	29.9%
	Clinical laboratory or laboratory medicine	48	14.6%
Social networks	Facebook	328	100%
	Twitter	206	62.8%
Frequency of use	Very active	33	10.1%
	A little bit every day	132	40.3%
	A few days a week	54	16.5%
	Seldom	95	29.1%
	Less than once a month	14	4.0%
Purpose of use	What others are posting	155	47.4%
	For exchanging messages	125	38.3%
	Comment on posts related to COVID-19	0	0%
	You are very active and frequently post articles/surveys, almost daily	0	0%
	All the above	22	6.3%
	None of the above	26	8%

4.4 Content reliability and validity

We used exploratory factor analysis and varimax rotation to check the underlying dimensions of the scale. The internal reliability was checked using Cronbach's alpha coefficient (Aletras et al., 2016). All Cronbach's alpha values were found above 0.70, i.e., 0.76–0.98, which indicates good reliability (Jackson and Ferguson, 1941; Cronbach, 1951; Novick and Lewis, 1967). The Kolmogorov-Smirnov test was used to analyse the suitability of the data for parametric tests. Correlations indicate the degree of influence of one variable on another. A negative correlation means that when one variable increases, the other variable decreases. The independent samples t-test (Student, 1908) was used for differences between genders and analysis of variance (Fisher, 1921) with the Bonferroni (1936) criterion applied for differences based on age, education, and specialty. Furthermore, SEM tests the correlations between latent factors and measurement variables. SEM was used to test our measurement models convergent and discriminant validity and the presence of common method bias in our data, as well as the causal-effect relations among latent constructs, which are the effects of ATT on AU through BI, PEoU, and PU. All criteria were acceptable. Statistical analysis was conducted using the open-source software Statistical Processing PSPP v.1.4.1 (PSPP 1.4.1., 2020). SEM data analysis was performed using Jamovi software version 2.3.26.

5 Results

5.1 Exploratory factor analysis for the entire sample

The first criterion applied was the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy to examine the degree of homogeneity of the variables (0 to 1 scale) (Klein and Dabney, 2013). The sample appeared to be adequate for all the factors with KMO > 0.60. The second criterion applied was Bartlett's sample test of sphericity, which examines whether a relationship exists between the variables (Bartlett, 1937). For all factors, p = 0.000; therefore, the null hypothesis $p < 0.05$) was rejected (Table 3). All initial exports were > 0.50, which indicated a good contribution by each sentence to the final model (Tucker and MacCallum, 1993). All questionnaires were valid except for Facebook attitudes, which had low validity (52.3% < 65%).

All cumulative loadings per TAM factor were > 65%, except for the ATT, which had a cumulative loading of 52.3% < 65%. Therefore, the questionnaire was considered valid for Facebook and Twitter, except for the ATT factor.

In the component matrix stage, the PEoU factor had two variables (variable 6 for Facebook, and variable 10 for Twitter) which had loadings on both factors (variable 6 for the social network Facebook in factor 1 had a value of 0.59 and in factor 2 it had a value of 0.48. For the social network Twitter variable 10 in factor 1 had a value of 0.68 and for factor 2 it had a value of 0.65. For this reason, the above variables were included in the factor that had the highest loading in absolute value (Jollife, 2002). From the rotated component matrix (Table 2) all sentences are in one factor. One factor emerged for Facebook variables ATT, BI, and AU, and two factors for the variables PU and PEoU. Accordingly, one factor emerged for Twitter variables PU, BI, ATT, and AU, and two factors for the variable PEoU; however, a single-factor approach was used in the analysis. In addition, all variable values were > 0.40. The values and ranking of the variables by factor are presented in Table 2.

Table 2 Factor analysis with the principal components in a correlation matrix with varimax rotation

	Items in the questionnaire	*Facebook*		*Twitter*	
PEoU		*Fact 1*	*Fact 2*	*Fact 1*	*Fact 2*
1	Using social networks has made or is making my patient care more effective		0.73		0.81
2	I promote healthy behaviours and healthcare outcomes		0.72		0.85
3	I am in direct contact with my colleagues	0.80		0.88	
4	I discuss current scientific topics in groups	0.78		0.74	
5	I communicate with hospital management easily and quickly		0.91		0.86
6	It is easy to discuss health care and related policy issues	0.71			0.86
7	I engage in education and interaction with colleagues or patients	0.89		0.89	
8	I engage in interaction with the general public	0.83		0.77	
9	I publish the latest valid surveys	0.79		0.83	
10	I am informed about the social dimensions of the issue such that patient treatment can be decided	0.77		0.82	
11	Social media helps facilitate my work		0.81		0.89
12	I avoid fake news		0.82		0.87
	Social network use negatively impacts my working time, social media helps me quickly share business ideas and information, social media has lots of false information that prevents people from finding valid information				
PU		*Fact 1*	*Fact 2*	*Fact 1*	
1	Social networks allow me to solve health problems fast		0.91	0.89	
2	Social network improves my performance in critical health matters		0.91	0.80	
3	Social networks increase my productivity in dealing with health-related issues		0.84	0.93	
4	Social networks increase my effectiveness in dealing with health-related issues		0.87	0.94	
5	Social networks help me work better, e.g., by improving communication	0.85		0.89	
6	Social networks are effective in handling the health issues that I manage	0.77		0.92	
7	Working without social networks would be difficult	0.61		0.83	
8	I should spend more time on issues that are currently being resolved immediately	0.61		0.80	

Note: Italic items represent deleted items after face validity procedures.

Table 2 Factor analysis with the principal components in a correlation matrix with varimax rotation (continued)

Social networks distract me from my work, social networks facilitate the resolution of patient's health problems, social networks are important to use for my work, social networks help me manage multiple situations/issues quickly, I use social media too much during working hours				
PU		*Fact 1*	*Fact 2*	*Fact 1*
9	Social networks improve the quality of my work (e.g., via the exchange of views)	0.90		0.86
10	Social networks help me focus on important issues	0.82		0.93
11	Overall, I find social networks useful for solving health problems	0.72		0.93
ATT		*Fact 1*		*Fact 1*
1	Social media makes decision-making difficult	0.64		0.83
2	The quality of shared information is low compared to the quantity	0.78		0.54
3	Social media use presents a possibility of conflict (conflict of interest) in topics of discussion	0.78		0.94
4	Social media has a non-transparent method for peer review and comments	0.76		0.88
5	I am anxious while using social networks	0.65		0.90
I feel that there is insufficient security of private data/discussions on important topics, social networks help improve the quality of care for my patients, social media facilitates direct communication, social media use presents a risk of leaking professional information, social media increases personal awareness by discovering medical news, social media helps me relax while working				
BI		*Fact 1*		*Fact 1*
1	I prefer to use social networks every day during my work	0.97		0.95
2	I plan to use social networks every day at my work	0.98		0.99
3	I would use social networks every day at my work	0.99		0.98
AU		*Fact 1*		*Fact 1*
1	I have the skills to use social networks every day during my work	0.84		0.78
2	I have the skills to use social networks effectively for my work	0.89		0.94
3	I have the knowledge to use social networks for my work	0.88		0.87
4	If I need help or face an issue, I know where to go to use social networks properly	0.80		0.75
5	I have used social networks effectively in the past many times for my work	0.83		0.73

Note: Italic items represent deleted items after face validity procedures.

5.2 Correlations among model factors

In Table 3, the correlations between the model factors are presented. For Facebook, a strong positive correlation was found between AU and PEoU (r = 0.66), AU and BI (r = 0.64), and AU and PU (r = 0.57). For Twitter, a strong positive correlation was found between AU and PEoU (r = 0.70), and AU and PU (r = 0.77) and a strong negative correlation was found between AU and ATT (r = 0.64). Finally, ATT (Facebook and Twitter) had negative correlations with PEoU.

Table 3 TAM factors statistically significant correlations: $^{**}p < 0.05$

Factors		*Facebook*			
		PEoU	*ATT*	*PU*	*BI*
Facebook	ATT	–0.15**			
	AU	0.66**		0.57**	0.64**
Factors		*Twitter*			
		PEoU	*ATT*	*PU*	*BI*
Twitter	ATT	–0.54**			
	AU	0.70**	–0.64**	0.77**	0.46**

5.3 Differences between model factors and gender

In Table 4, a statistically significant difference (t = 3.220, $p < 0.01$) was found in Facebook ATT towards between males and females. Females (3.12 ± 0.82) have a significantly different attitude compared to males (2.85 ± 0.68). In addition, the difference in Twitter ATT between genders is not statistically significant. No statistically significant difference in Facebook AU was found between genders. Finally, the Twitter AU shows no statistically significant difference between males and females.

Table 4 TAM factors – demographic statistically significant differences

		Gender		
Factors		*Female* n_F *= 133 Mean-S.D*	*Male* n_F *= 190 Mean-S.D*	t
Facebook	ATT	3.12 ± 0.82	2.85 ± 0.68	3.220**
	AU	3.49 ± 0.94	3.42 ± 0.73	0.746
		Gender		
Factors		*Female* n_T *= 94 Mean-S.D*	*Male* n_T *= 112 Mean-S.D*	t
Twitter	ATT	3.04 ± 0.83	2.88 ± 0.80	1.395
	AU	2.81 ± 0.81	2.94 ± 0.99	–1.027

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, t-test for gender.

5.4 Differences between model factors and age

In Table 5, statistically significant differences were found for Facebook ATT and Twitter ATT across age groups. The Facebook ATT varies significantly across different age groups ($F = 22.461$, $p < 0.01$). Participants under 30 have a significantly different mean attitude compared to those aged 30–39, 40–49, and over 49, with positive mean differences. Participants aged 40–49 have a significantly different mean attitude compared to those aged 30–39, and over 49, with positive mean differences. Furthermore, Twitter ATT differs significantly across age groups ($F = 27.878$, $p < 0.01$). Participants under 30 have a significantly different mean attitude compared to those aged 30–39, 40–49, and over 49, with positive mean differences. Participants aged 40–49 have a significantly different mean attitude compared to those aged 30–39 with positive mean differences. In addition, there is no significant difference in the Facebook AU among different age groups. The Twitter AU shows a significant difference across age groups ($F = 25.034$, $p < 0.01$). Participants under 30 have a significantly different mean actual use compared to those aged 30–39, 40–49, and over 49, with positive mean differences. Participants aged 40–49 have a significantly different mean actual use compared to those aged 30–39, and over 49, with positive mean differences.

Table 5 TAM factors – demographic statistically significant differences

		Age				
Factors		*< 30*	*30–39*	*40–49*	*> 49*	*F*
		$n_F = 50$	$n_F = 132$	$n_F = 64$	$n_F = 68$	
		Mean-S.D	*Mean-S.D*	*Mean-S.D*	*Mean-S.D*	
Facebook	ATT	3.54 ± 0.82	2.70 ± 0.64	3.20 ± 0.82	2.82 ± 0.52	22.461**
	AU	3.31 ± 0.90	3.58 ± 0.62	3.40 ± 0.63	3.34 ± 1.20	2.267
		Age				
Factors		*< 30*	*30–39*	*40–49*	*> 49*	*F*
		$n_T = 36$	$n_T = 86$	$n_T = 47$	$n_T = 37$	
		Mean-S.D	*Mean-S.D*	*Mean-S.D*	*Mean-S.D*	
Twitter	ATT	3.71 ± 0.53	2.53 ± 0.57	3.23 ± 0.74	2.86 ± 0.96	27.878**
	AU	3.63 ± 0.60	2.60 ± 0.71	3.27 ± 0.79	2.30 ± 1.08	25.034**

Notes: *$p < 0.05$, **$p < 0.01$. Analysis of variance for age (< 30, 30–39, 40–49, > 49).

5.5 Differences between model factors and education levels

In Table 6, a statistically significant difference was found in Facebook ATT among different education levels ($F = 9.096$, $p < 0.01$). Participants with a medical diploma have a significantly different mean attitude compared to those with a Master's degree and to those with a Ph.D., with positive mean differences. Twitter ATT also varies significantly based on education levels ($F = 7.491$, $p < 0.01$). Participants with a medical diploma have a significantly different mean attitude compared to those with a Master's, with a positive mean difference. In addition, the Facebook AU is significantly different among doctors with different educational backgrounds ($F = 3.301$, $p < 0.05$). Participants with a medical diploma have a significantly different mean actual use compared to those with a Master's degree, with a negative mean difference. Finally, the Twitter AU also shows a significant difference based on education levels ($F = 3.490$, $p < 0.05$). Participants with a medical diploma have a significantly different mean actual use compared to those with a Master's degree and those with a PhD, with positive mean differences.

Table 6 TAM factors – demographic statistically significant differences

		Education levels			
		Medical diploma	*MS*	*PhD*	
Factors		$n_F = 191$	$n_F = 104$	$n_F = 29$	*F*
		Mean-S.D	*Mean-S.D*	*Mean-S.D*	
Facebook	ATT	3.09 ± 0.76	2.86 ± 0.68	2.52 ± 0.79	9.096**
	AU	3.36 ± 0.88	3.61 ± 0.68	3.43 ± 0.88	3.301*
		Education levels			
		Medical diploma	*MS*	*PhD*	
Factors		$n_T = 129$	$n_T = 69$	$n_T = 8$	*F*
		Mean-S.D	*Mean-S.D*	*Mean-S.D*	
Twitter	ATT	3.11 ± 0.83	2.66 ± 0.64	2.95 ± 1.17	7.491**
	AU	3.00 ± 0.95	2.65 ± 0.79	2.75 ± 0.98	3.490*

Notes: *$p < 0.05$, **$p < 0.01$. Analysis of variance for education (medical diploma, Master, PhD).

5.6 Differences between model factors and medical specialties

In Table 7, a statistically significant difference in ATT Facebook among different medical specialties ($F = 5.878$, $p < 0.01$). Clinical laboratory or laboratory medicine doctors have a significantly higher mean attitude compared to pathologists and surgeons. ATT Twitter varies significantly based on specialty ($F = 21.390$, $p < 0.001$). Surgeons have a significantly lower mean attitude compared to pathologists, and clinical laboratory or laboratory medicine doctors. Furthermore, the AU Facebook is significantly different among doctors with different specialties ($F = 6.112$, $p < 0.01$). In addition, clinical laboratory or laboratory medicine doctors have a significantly higher mean actual use compared to pathologists and surgeons. AU Twitter shows a significant difference based on specialty ($F = 23.814$, $p < 0.001$). Surgeons have a significantly lower mean actual use compared to pathologists and clinical laboratory or laboratory medicine doctors.

5.7 Structural equation modelling (SEM)

SEM data analysis was performed using Jamovi software version 2.3.26. ATTs were recorded to show high scores for positive ATTs.

Weighted path values ($P < 0.05$) of the model for both social networks (Facebook and Twitter) showed that all paths were statistically significant $p \leq 0.001$ in all cases (Table 8). Furthermore, a statistically significant correlation was observed between AU and PU for the Twitter model.

Overall, the models showed excellent acceptance indices CFI, TLI, RNI, GFI > 0.93 (acceptable), RMSEA = 0.069 (Facebook)/0.079 (Twitter) (acceptable), SRMR = 0.017

(Facebook)/0.025 (Twitter) (acceptable). In addition, the model comparison indices Facebook (AIC = 2,734, BIC = 2,791) and Twitter (AIC = 1,659, BIC = 1,709) (Bollen and Bauldry, 2011; Kyndt and Onghena, 2014). Overall, the models considering Facebook and Twitter presented good model acceptance indices, respectively (Table 9).

Table 7 TAM factors – demographic statistically significant differences

Factors		*Education levels*			*F*
		Pathologists	*Surgeons*	*Clinical laboratory or laboratory medicine*	
		n_F = 182	*n_F = 95*	*n_F = 48*	
		Mean-S.D	*Mean-S.D*	*Mean-S.D*	
Facebook	ATT	2.89 ± 0.75	2.93 ± 0.74	2.29 ± 0.73	5.878**
	AU	3.46 ± 0.75	3.27 ± 0.94	3.77 ± 0.80	6.112**
Factors		*Education levels*			*F*
		Pathologists	*Surgeons*	*Clinical laboratory or laboratory medicine*	
		n_T = 98	*n_T = 70*	*n_T = 38*	
		Mean-S.D	*Mean-S.D*	*Mean-S.D*	
Twitter	ATT	3.20 ± 0.76	2.48 ± 0.81	3.18 ± 0.56	21.390***
	AU	3.23 ± 0.84	2.34 ± 0.75	2.97 ± 0.92	23.814***

Notes: **p* < 0.05, ***p* < 0.01, ****p* < 0.001. Analysis of variance for medical specialties (pathologists, surgeons, clinical laboratory or laboratory medicine.

ATTs had no statistically significant contribution toward AU and BI. In addition, ATTs positively influenced PU 33% and negatively influenced PEoU 9%. PU strongly positively influenced PEoU 77%. PEoU strongly positively influenced BI 95%. PEoU positively influenced AU 42%. Finally, BI positively influenced AU 23%. All relationships were statistically significant for the Facebook model (Figure 2).

ATTs had no statistically significant contribution toward PEoU and BI. ATTs strongly positively influenced PU 86% and AU 57%. In addition, PU strongly positively influenced PEoU 88%. Furthermore, the contribution of PEoU on AU was not statistically significant. PEoU strongly positively influenced BI 73%. BI positively influenced AU 30%. All relationships were statistically significant for the Twitter model (Figure 3).

R-Square (R2) is a statistical measure in a regression model that determines the proportion of variance in the dependent variable that can be explained by the independent variable (Chicco et al., 2021). In Table 10, based on the value of R2 (Facebook) is known that variable AU has R-Square of 0.505 which means PEoU, and BI are able to explain the variable AU of 0.505 or 50.5%. Furthermore, variable PU has R-Square of 0.076 which means ATT is able to explain the variable of 0.076, or 7.6%. In addition, the variable PEoU has R-Square of 0.698 which means ATT and PU are able to explain the variable PEoU of 0.698 or 69.8%. Finally, variable BI has R-Square of 0.455 which means PEoU is able to explain the variable BI of 0.455 or 45.5%. Based on the value of R2 (Twitter) is known that variable AU has R-Square of 0.419 which means ATT, and BI are able to explain the variable AU of 0.419 or 41.9%. Furthermore, variable PU has R-Square of 0.429 which means ATT is able to explain the variable of 0.429, or 42.9%.

In addition, the variable PEoU has R-Square of 0.743 which means PU is able to explain the variable PEoU of 0.743 or 74.3%. Finally, variable BI has R-Square of 0.537 which means PEoU is able to explain the variable BI of 0.537 or 53.7%.

Table 8 Weighted path values of the two models (path values/standard. SEM values)

	Lhs	*Op*	*Rhs*	*Est. std.*	*Se*	*Z*	*P value*	*ci. lower*	*ci. upper*
SEM model considering Facebook									
1	Facebook PU	~	Facebook ATT	0.333	0.067	4.93	< 0.001	0.201	0.466
2	Facebook PEoU	~	Facebook PU	0.765	0.031	24.03	< 0.001	0.704	0.827
3	Facebook PEoU	~	Facebook ATT	–0.090	0.029	–3.07	0.002	–0.146	–0.032
4	Facebook BI	~	Facebook PEoU	0.954	0.064	14.86	< 0.001	0.828	1.080
5	Facebook AU	~	Facebook PEoU	0.425	0.063	6.71	< 0.001	0.301	0.549
6	Facebook AU	~	Facebook BI	0.230	0.048	4.78	< 0.001	0.136	0.325
SEM model considering Twitter									
	Lhs	*Op*	*Rhs*	*Est. std.*	*Se*	*Z*	*P value*	*ci. lower*	*ci. upper*
1	Twitter PU	~	Twitter ATT	0.865	0.088	9.80	< 0.001	0.692	1.037
2	Twitter PEoU	~	Twitter PU	0.880	0.036	24.15	< 0.001	0.808	0.951
3	Twitter BI	~	Twitter PEoU	0.727	0.055	13.15	< 0.001	0.619	0.836
4	Twitter AU	~	Twitter ATT	0.307	0.054	5.72	< 0.001	0.202	0.412
5	Twitter AU	~	Twitter BI	0.777	0.109	7.12	< 0.001	0.563	0.991

Figure 2 Structural model of the acceptance of the use of Facebook by doctors during the COVID-19 pandemic

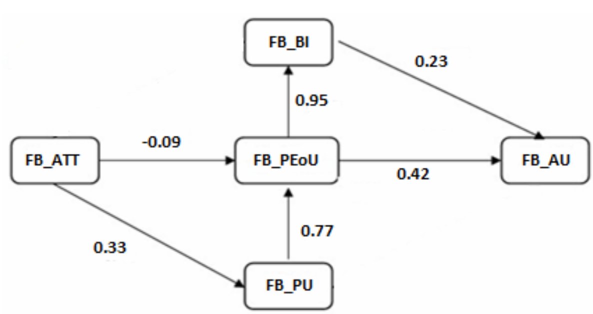


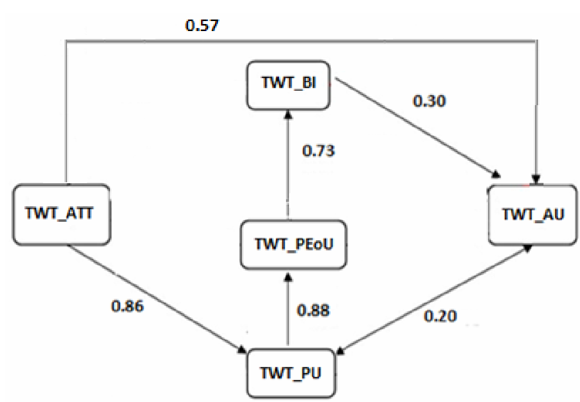
Table 9 Model acceptance indices (fit indices)

	SEM model considering Facebook	*SEM model considering Twitter*
n_obs	328	206
chisq	7.67	6.85
df	3	3
chisq/df	2.56	2.28
p-value	0.053	0.077
cfi	0.99	0.99
tli	0.98	0.98
rni	0.99	0.99
gfi	0.99	0.99
rmsea	0.069	0.079
srmr	0.017	0.025
pgfi	0.150	0.150
bic	2,791	1,709
aic	2,734	1,659

Table 10 R-Square

	SEM model Facebook	*SEM model Twitter*
AU	0.505	0.419
PU	0.076	0.429
PEoU	0.698	0.743
BI	0.455	0.537

Figure 3 Structural model of the acceptance of the use of Twitter by doctors during the COVID-19 pandemic



6 Discussion

In the present study, half of the doctors participating in the research reported being slightly active daily on social networks. They used social networks during the COVID-19 pandemic to read research outputs uploaded by other researchers and medical doctors (Table 2). In their research, Hazzam and Lahrech (2018) found that doctors used social media several times during the day and used social platforms to exchange peer medical information. In our sample, ATT had a negative correlation with the rest of the factors of TAM (Table 3), although Abdool et al. (2021), in their research, found positive correlations between ATT and the rest of the factors. We found a strong positive correlation between AU and PEoU of Facebook and Twitter, which is confirmed by Liang et al. (2003) in their research.

We found a statistically significant difference in Facebook ATT between males and females. Females had a significantly different posture compared to males and larger mean, although Florek and Lewicki (2021) found that males have a significantly different posture compared to females and larger means. The difference in Facebook AU, Twitter ATT, and Twitter AU between genders was not statistically significant which is in line with Priyadarshini et al. (2022). Also, we found a statistically significant difference in Facebook ATT, and Twitter ATT compared to age. Participants under 30 had a significantly different mean attitude compared to the other age groups, with positive mean differences which is in line with Florek and Lewicki (2021). We found a statistically significant difference in Twitter AU compared to age. Participants under 30 had a significantly different mean actual use compared to the other age groups, with positive mean differences which is in line with Faturohman et al. (2021). There was no significant difference in Facebook AU between different age groups. Furthermore, we found a statistically significant difference in Facebook ATT, Twitter AU, and Twitter ATT between different levels of education. Participants with a medical degree had a significantly different mean Facebook ATT and Twitter AU compared to those with a Master's degree and to those with a PhD degree, with positive mean differences which is in line with Florek and Lewicki (2021) while participants with a medical degree had a significantly different mean Twitter ATT compared to those with a master's degree, with positive mean difference. Furthermore, we found a statistically significant difference in Facebook AU between different levels of education. Participants with a Master's degree have a significantly different mean Facebook AU compared to those with a Master's degree, with a negative mean difference, although Faturohman et. al. (2021) found that there is no significant difference between the education levels with the factors of the TAM. Makeover, we found a statistically significant difference in ATT Facebook among different medical specialties. Clinical laboratory or laboratory medicine doctors have a significantly higher mean attitude compared to pathologists and surgeons. ATT Twitter varies significantly based on specialty surgeons have a significantly lower mean attitude compared to pathologists, and clinical laboratory or laboratory medicine doctors. Ulvenes et al. (2009) found significant differences between medical specialties and found that laboratory specialties had lower attitudes compared with surgeons, and pathologists.

According to the SEM results, for both social networks (Facebook, and Twitter), ATT positively influenced PU (Hypotheses H1), although Sternad Zabukovsek et al. (2022) found that PU positively influenced ATT. Furthermore, PU positively influenced PEoU, although Almaiah et al. (2022) found that PEoU positively influenced PU. We found that

PEoU had a positive influence on BI, which is in line with Saeed and Al-Emran (2018). In addition, BI positively influenced AU, which is in line with Almaiah et al. (2022).

ATT negatively influenced PEoU (Hypotheses H2), although Alyoussef (2021) found that PEoU positively influenced ATT. In addition, PEoU positively influenced AU (Hypothesis H6), which is in line with Alyoussef (2021), for Facebook.

ATT positively influenced AU, which is in line with Teran-Guerrero (2019), for Twitter.

Hypotheses H2 (Twitter), H3, H4, H5, H6 (Twitter), and H7 were not confirmed.

ATT towards AU of social networks through the mediating factors PU, PEoU, and BI. ATTs had no statistically significant contribution toward AU and BI for Facebook (Figure 2).

ATT towards AU of the social networks. ATTs had no statistically significant contribution toward statistically significant contribution PEoU and BI, for Twitter (Figure 3). Classification of correlations was annotated according to Evans (1996).

7 Limitations and recommendations for future research

Although the sampling method was random, respondents participated in the survey while at work and only after confirming that they use Facebook or Twitter. This may raise some bias issues. In addition, the generalisation of the results should be considered with caution due to the sample size. Our research relied on a sample from public Greek hospitals, thus results may reflect a bias since doctors from other counties were not incorporated. Future research could be extended to other health professionals and social networks using a larger sample. It would also be interesting to explore the attitudes of doctors across the different specialties. Finally, as the pandemic changed how people communicate, it would be interesting to investigate whether this effect remained in the field of scientific information after the end of the pandemic.

8 Conclusions

The COVID-19 pandemic has affected people's lives in every country on Earth. The present research was conducted during the third wave of the pandemic COVID-19 when the consequences of lockdowns and social distancing were already embedded in society forcing people to adopt new behaviours. The medical community followed the trend and used alternative ways of communicating and sharing medical information. The research showed doctors used social networks during the COVID-19 pandemic as a communication tool. Social networks can contribute to such high requirements despite the possible reliability issues.

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Ethics approval

This research was carried out according to The Code of Ethics of the World Medical Association (Declaration of Helsinki) for experiments involving humans.

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Notes

1 ATT: attitudes, AU: actual use, BI: behavioural intention to use, EFA: exploratory factor analysis, PEoU: perceived ease of use, PU: perceived usefulness, SEM: structural equation modelling, TAM: acceptance model, TRA: theory of reasoned action, TPB: theory of planned behaviour.