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Revisiting the Technology Acceptance Model: E-Learning Acceptance Under the Influence of Emotional Stress and Anxiety

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ABSTRACT

The use of e-learning methods in higher education is rapidly increasing worldwide. However, the relationship between students' acceptance of e-learning methods and their psychological adaptation remains uncertain. Events such as a global pandemic have brought significant changes to higher education while accelerating the popularity of e-learning. This sudden shift, nevertheless, may drive a fundamental and structural change in tertiary education, given the high levels of anxiety and stress caused by events such as a global pandemic and the impact of accompanying measures and restrictions on students' learning status. This paper examines students' willingness and acceptance of online learning processes in the context of health emergencies. The Technology Acceptance Model (TAM) is revised. Research findings suggest that emotional well-being plays an important role as an extension of the TAM model, which highlights the positive effects of anxiety and the negative effects of stress on enjoyment and perceived usefulness.

Keywords: Global pandemic, TAM, e-learning, stress, anxiety, PLS-SEM

INTRODUCTION

The term e-learning summarises and reflects web-based education, digital learning, and interactive learning, as well as learning facilitated by computers and the Internet (Lara et al., 2020; Yengin et al., 2011). Its benefits, including low cost and no geographic restrictions led to a rapid increase in its adoption in education systems (Maatuk et al., 2022). Besides the increasingly recognized potential of e-learning in the world education system, the global pandemic COVID-19 has no doubt speeded up its adoption (Choi, Song, & Zaman, 2020; Mseleku, 2020). Many universities had to develop online teaching mechanisms and promote e-learning during the COVID-19 lockdown (Ratten, 2020; Achmad Syam, & Achmad, 2022). Extensive research has focused on what challenges of e-learning were brought up by the COVID-19 pandemic, including requirements for online resources (Crawford et al., 2020), poor networking connections (Aboagye et al., 2020), and barriers of technological usability (Almaiah et al. 2020). More complex issues include how to enhance students' independent learning ability via e-learning (Rannastu-Avalos & Siiman 2020), comprehending the facility requirements for e-learning in higher education institutions (Mouchantaf, 2020), and the possible opportunities that COVID-19 has brought to e-learning and its development, post the global pandemic (Adedoyin & Soykan, 2020; Maatuk et al., 2022). The impact of COVID-19 on education has been profound and long-lasting. The theme of studying the impact of the epidemic on education is not outdated, but requires continued attention and research. (UN, 2023;2024)

In many countries and regions, COVID-19 and its derivative quarantine measures exacerbated psychological problems among college students, including anxiety and stress, and even depression (Fawaz & Samaha, 2021). Concerns about the impact on daily life due to the pandemic, delays in school, and a desire for social contact were the main causes of anxiety and stress (Debowska et al., 2020; Zurlo et al., 2020). Arribathi et al. (2021) reported that both regular and non-regular students showed higher than 70% learning anxiety in online learning environments during pandemic. The immediate application of the e-learning approach also increased stress among students, although eventually many adapted to the changes in this new learning process (Wahyu & Simanullang, 2020). Attarabeen, Gresham-Dolby & Brodel-Zaugg (2021) noted that perhaps students had the ability to do online distance learning, and thus there was no significant increase in perceived stress during online distance learning associated with the COVID-19 pandemic. Regardless, the impact of anxiety and stress (and even depression) on e-learning adoption needs to be carefully studied (Hu *et al.*, 2022). It is reasonable to assume that emotions may play a much more crucial role along with the COVID-19 pandemic affecting the adoption of e-learning. However, the distinction between the depression, anxiety, and stress generated by e-learning, and those effects of emotions influenced by COVID-19 have not yet been explored. The questions remain unanswered whether students' emotional responses from the global pandemic will affect e-learning in the global education system and the relation between students' emotional changes and future intentions towards e-learning. To bridge these research gaps, we address two research questions in line to explore the future of e-learning development:

RQ1: Does the TAM model apply in a pandemic (e.g., COVID) reality?
RQ2: Do stress and anxiety (largely derived from the pandemic and social situation) have any effects on students' adoption of e-learning?

LITERATURE REVIEW

E-learning under the impact of the COVID-19 outbreak

The COVID-19 pandemic accelerated the application and development of e-learning in education systems (Mseleku, 2020). Gurukkal (2020) argued that a major pandemic will not incur significant changes to higher education, however, it was also argued that the pandemic lockdown is likely to bring reforms to the education system, particularly in terms of teaching and assessment models (Lei & So, 2021). Limited literature has focused on the emotional changes caused by the pandemic, particularly in the context of the accelerated spread of technological applications.

At the beginning of the COVID-19 outbreak, e-learning mediated the effects of affective factors related to psychological stress (Gutiérrez-Aguilar et al., 2023). However, during the COVID-19 outbreak, the psycho-emotional state of university students was strongly influenced by factors such as economic status, disruption of daily activities and delays in academic activities, which largely contributed to depression, fatigue, loneliness, stress, or anger (Cao et al., 2020; Zolotov et al., 2020). Saha, Dutta & Sifat (2021) further demonstrated that the adoption of emergency e-learning at the undergraduate level derived from the COVID-19 pandemic had a significant psychological impact on students. Therefore, this study attempts to contribute to the acceptance of e-learning in the post-COVID-19 era context by exploring the relationship between emotional factors and e-learning adoption intention.

Technology Acceptance Model (TAM) and e-learning

Technology Acceptance Model (TAM) is a powerful and influential model to study new technology adoption, while in a simple and easy-to-use form (McFarland & Hamilton, 2006). The TAM was developed by Davis (1989). Davis, Bagozzi & Warshaw (1989) established an extended TAM model that behavioural intention to use the technology precedes actual use, while several variables including attitude, perceived usefulness (PU) and perceived ease of use (PEOU) have direct and indirect impacts on both behavioural intentions and actual behaviours.

Many studies have extended and tested the original TAM to measure acceptance of using different techniques (Park et al., 2014). There are three main directions in the revision of TAM (Marangunić and Granić, 2015), including the addition of social factors such as subjective norms and perceived user behaviour (Ibrahim et al., 2017); diffusion of innovations theories that support the replication of TAM into e-learning (Mailizar, Almanthari & Maulina 2021); incorporating technology-related factors and further extending to users' affective responses such as perceived pleasure and playfulness of computers and technology (Castiblanco Jimenez et al., 2020; Salloum et al., 2019). Limited investigations have been conducted on the impact of feelings and emotions in the process of technology acceptance (Lee, Rhee, & Dunham, 2009). It is necessary to study psychological factors, including emotions, habits, personality differences, as well as exogenous factors such as technological and environmental changes (Marangunić & Granić, 2015; Rosli, *et al.*, 2022).

Emotional Factors

Social cognitive theory provides the basis for the inclusion of emotional variables in the TAM (Perlusz, 2004; McFarland & Hamilton, 2006), with stress and anxiety being two frequently cited psychological factors related to emotions. Anxiety and stress are often described as an individual feeling apprehensive about certain difficult scenario, along with frustration, apprehension, and fear (Gelbrich & Sattler, 2014; Park et al., 2014). Since the COVID-19 outbreak, anxiety and stress have been reported as common psychological consequences of the COVID-19 pandemic which undoubtedly had a huge impact on the public's psychology and behavior (Rajkumar, 2020). However, not much has been explored in the literature regarding the impact of psychological and emotional changes in users on e-learning acceptance.

CONCEPTUAL MODEL AND HYPOTHESES

This study extends the TAM model by introducing emotional factors that are associated with students' e-learning process under the context of the COVID-19 pandemic. The model is expanded by adding predictor variables, namely anxiety and stress.

Revisiting the classical TAM model

PU and PEOU are the two essential drivers affecting technology adoption in classical TAM models (Fathema, Shannon, & Ross, 2015). Davis (1989) emphasized that PEOU influences how much one accepts and adopts a particular technology (such as, information technology, computer technology, service, software) and refers to how much users find the system easy to make sense of and utilize (Han & Sa, 2021). PU, on the other hand, refers to the extent to which one finds the adoption of the technology useful to assist in improving job efficiency and performance (Masrom, 2007). Previous literature further argued that PEOU is directly leading to PU (Marangunić & Granić, 2015).

Behavioral intention in the TAM models refers to the probability of how one will produce certain upcoming behaviors (Fishbein & Ajzen, 1977), which determines the acceptance of technology and the propensity for continued future behavior (Alharbi & Drew, 2014). Thus, behavioral intention, a major determinant of user behavior, is cultivated by how much usefulness one sees from the technology, namely PU of the technology (Davis et al., 1989; Taat & Francis, 2019). Experimental results by Terzis & Economides (2011) demonstrated that both PU and perceived playfulness are antecedents of behavioral intentions, with direct impacts. Indirect influencers of behavioral intentions, on the other hand, include social factors, self-efficacy, content, facilitative conditions, and desired goals and objectives.

In line with the previous research on the classical TAM model, the following hypotheses are proposed:

H1: PU affects students' intention to use e-learning

H2: PEOU affects students' intention to use e-learning
H3: PEOU affects PU.

External Variables

Existing literature supports the inclusion of external variables such as subjective norms, self-efficacy, and emotional responses which have different effects on the two main beliefs PU and PEOU (Abdullah & Ward, 2016). Self-efficacy and enjoyment were found with significant impacts on students' intention to adopt e-learning, where high levels of self-efficacy and enjoyment led to better acceptance of e-learning (Alenezi, Abdul Karim, & Veloo, 2010; Abdullah, Ward, & Ahmed, 2016; Mun & Hwang, 2003).

Self-Efficacy

Self-efficacy refers to one's assessment in his/her capability to successfully organise and perform an action (Ajzen, 1991; Bandura, 1986; Fathema, Shannon, & Ross, 2015). Self-efficacy related to technology, concerns the concept of a person's ability to adopt a certain technology in fulfilling a specific task in job (Liao et al., 2018). Self-efficacy is critical in affecting students' perceptions and intentions to adopt e-learning mechanisms (Lee, Hsiao, & Purnomo, 2014). Self-efficacy often leads to perceived ease of use of the technology, as well as its usefulness (Fathema & Sutton, 2013, Ong & Lai, 2006; Park et. al., 2012). By contrast, if a person perceives him/herself to be less competent in using a system, then this person often evaluates the technology as "less easy to use" and "less useful" (Fathema, Shannon, & Ross, 2015). In the e-learning discipline, one's self-efficacy and technology acceptance are related to his/her e-learning performance (Chen, 2014). Zapata-Cuervo, et.al. (2022) r provide evidence to support the view that students' anxiety level and self-efficacy are two factors significantly influencing their engagement in e-learning, and further influencing their performances from e-learning.

In accordance with previous literature testing the relationships between relevant variables, this study proposes H4.1, H4.2, and H4.3:
H4.1: Self-efficacy affects PEOU.
H4.2: Self-efficacy affects PU.
H4.3: Self-efficacy affects students' intention to use e-learning.

Enjoyment

Enjoyment in the TAM model is considered as the reflection of associated pleasure that one receives from adopting a technology, and thus is another intrinsic motive driving technology adoption (Praveena & Thomas, 2014). The level of enjoyment of participating in computer activities is an antecedent of EU and behavioral intention, playing a vital role in TAM models (Davis et al., 1992). Enjoyment directly and positively affects PU of an e-learning system (Munabi, Aguti, & Nabushawo, 2020; Bhattarai & Maharjan, 2020). Besides, enjoyment is identified as an intrinsic motivation to help users build confidence in actions (Mun & Hwang, 2003).

This study proposes H5.1, H5.2, and H5.3 accordingly:
H5.1: enjoyment positively affects perceived self-efficacy.
H5.2: enjoyment positively affects PEOU.
H5.3: enjoyment positively affects PU.
H5.4: enjoyment positively affects students' intention to use e-learning.

Emotional Factors (General Anxiety and Stress)

Prior literature has an emphasis on linking beliefs, attitudes, as well as perceptions to technology adoption (Davis, Bagozzi, & Warshaw, 1992), and emotional effects on technology adoption (Perlusz, 2004). Anxiety and stress as psychological terms usually denote the mental activity of an individual. Many studies found computer self-efficacy and enjoyment associated with emotional changes.

Enjoyment reflects one's desire for emotional reliefs, the pleasant feeling of using a particular system reduces anxiety (Mun & Hwang, 2003; Holdack, Lurie-Stoyanov, & Fromme, 2020). Saadé, Kira & Nebebe (2013) stated that students participating in e-learning courses were found to have a considerable emotional response to usability issues. Studies exploring the impact of emotions on technology adoption have mostly investigated the anxiety and stress caused by the adoption of technology, restricting research on emotional responses to context (Dönmez-Turan & Kır, 2019). In other words, anxiety in the previous literature addresses those anxieties that arise from the use of technology, rather than those caused by the environment. Almaiah *et al.* (2022) found a positive indirect effect of social anxiety on intention to adopt new technology, in contrast with a widely reported negative relationship between technology anxiety and adoption. Keskin *et al.* (2023) tested a Social Anxiety Scale for e-Learning Environments (namely SASE) but did not examine the effect of social anxiety on the TAM model.

Stress indicates a psychological state that is on-going with over arousal, and easy to incur frustration (Oei et al., 2013). It is the stress response's by-product (Robinson, 1990).Stress often has negative effects on cognitive functioning and learning (Abdulghani *et al.*, 2011). It is therefore seen as a factor negatively leading to the effectiveness of adopting a new technology, that is, the adoption of e-Learning in the during- and post-COVID scenario. This does not imply any fundamental difference in terms of whether the stress is caused by adopting the technology or other contextual matters. Therefore, H6.1, H6.2, H6.3, and H6.4 are proposed:

H6.1: Stress negatively affects enjoyment.
H6.2: Stress negatively affects self-efficacy.
H6.3: Stress negatively affects PEOU.
H6.4: Stress negatively affects PU.

Anxiety derives from self-referent preoccupations that drive attention from tasks at hand to personal worries about perceived inefficacy (Sarason, 1978). It is a state with mixed distress, including feelings of irritability, impatience, agitation, and the feeling of not being able to relax from these worries (Oei *et al.*, 2013). It is an affective and cognitive response shaped by worries and apprehensions, which often derives from concerns of things going toward negative outcomes that is unavoidable (Schlenker & Leary, 1982).

Anxiety in developmental psychology and social psychology has been studied for its effects on individual performances and behavioural changes. Specifically, anxiety related to the tasks was found to be negatively related to the performance on these tasks in various studies (Seipp, 1991; Woodman & Hardy, 2003). However, general anxiety not directly derived from the task (for example, adoption of technology) tends to correlate positively with the performance on the task in general (Sarason, 1957). In a pandemic context e such as the COVID-19 scenario, adoption of e-learning is often seen as a proactive action against the spread of the virus, and therefore has the potential for reducing general anxiety caused by the pandemic and its relevant context.

Therefore, H7.1, H7.2, H7.3, and H7.4 are proposed:

H7.1: Anxiety positively affects enjoyment.

H7.2: Anxiety positively affects self-efficacy.
H7.3: Anxiety positively affects PEOU.
H7.4: Anxiety positively affects PU.

METHODOLOGY

The study employed an empirical data set involving students' acceptance of the e-learning method under the main structure of the TAM model, which enables PU and PEOU from students and their behavior intention, and identify self-efficiency under the e-learning environment. The research model illustrating the relationships between targeted variables is shown in Figure 1.

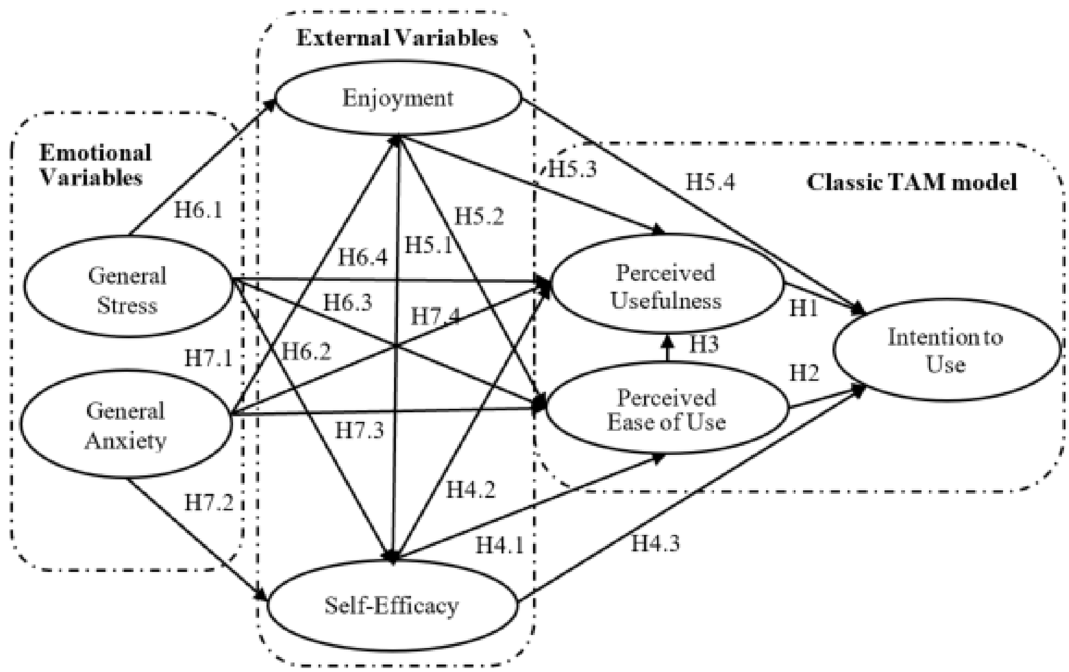

Figure 1: Proposed model and hypotheses

This study used a quantitative approach and hypothesis testing. Purposive sampling with snowballing technique was used, targeting full time undergraduate and postgraduate students from higher education institutions that have been taught via online platforms. A filtering question on whether the participant studied via online platform in a college setting for 4 months or longer was used at the beginning of the questionnaire, to make sure all included responses fell within the target sample. The survey was drafted in English based on existing validated measurement and scales, and then translated into Chinese by two bilinguals through back translation. A total of 406 valid responses were collected.

The questionnaire was presented in two parts. The first part was used for constructs including e-learning experiences during the COVID-19 pandemic, behavioral intentions, and emotional performance when conducting e-learning in the context of the outbreak. The second part focused on the collection of demographic information. This study also employed a pilot study with five students for validating the included items. These five students were further excluded from the main survey. According to the outcome of the pilot study, the scales included in the survey were reliable and valid.

Measurement

In measuring constructs in this proposed structural model, scales from previous literature were retrieved. All scales were statistically validated by various testing in previous studies, for example, via structural equation modeling. Each item was measured upon a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree). Scales of PE, PEOU, and behavioral intention were adopted from previously validated studies on TAM models, such as Davis (1989) and Findik-Coşkunçay et al. (2018). A five-item scale on self-efficacy, developed by Bandura (1986) was adopted, as well as a five-item scale on enjoyment developed by Venkatesh (2000). In measuring anxiety and stress, this research adopted the widely applied Depression Anxiety Stress Scale 21, DASS-21, (Oei et al., 2013), with eight items measuring general anxiety and six items measuring stress. DASS-21 is a well-developed scale widely applied in measuring anxiety and stress in various contexts, from clinical practice (Brown *et al.*, 1997) to non-clinical samples (Henry & Crawford, 2005). According to DASS-21, the anxiety scale is operated strictly to its definition on worries toward a potentially negative outcome, while the stress scale is operated to its captures of the state of constant over arousal, as well as easy incurrence of the feeling of frustration (Oei et al., 2013).

Data Analysis

This empirical study applies partial least square -based structural equation(PLS-SEM) modeling to test the structural model. The PLS-SEM approach is appropriate in this study for its robustness on data distribution and on testing relationships between latent variables on a relatively small sample size (Hair et al., 2021). This study applied SmartPLS version 3.3.9 in analysing the data, based on a standard PLS algorithm of 1,000 iterations. The stop criterion was set at 10^{-7}. Relative significance levels were estimated based on a bootstrapping of 5000 times (Hair et al., 2021). Descriptive statistics of the sample are illustrated in Table 1 below. Th sample mean of age is 20.99 with a standard deviation of 2.851. Average length of e-learning of the sample is 5.97 months, with a standard deviation of 5.802.

Table 1: *Descriptive Statistics* (n = 406)

	Count	%
Gender		
Male	186	45.8%
Female	220	54.2%
Current education		
High school or lower	3	0.7%
Polytech certificates	39	9.6%
Undergraduate degree	328	80.8%
Postgraduate and above	36	8.9%
Prior online class experience		
Yes	268	66.0%
No	138	34.0%

RESULTS

Reliability and Validity

In verifying reliability and validity, this study firstly conducted a confirmatory factor analysis, evaluating internal reliability via composite reliability (CR) and Cronbach's alpha (α). All Cronbach's alpha (α) and composite reliability values were above 0.9, higher than the acceptance value of 0.7 (Hair et al. 2021), indicating an acceptable measurement reliability. All standardized indicator loadings were significant and higher than 0.74, indicating an acceptable convergent validity (Chen & Dwyer, 2018; Hulland, 1999). Furthermore, all average variance extracted (AVE) are higher than 0.69, exceeding the minimum cap of 0.5 (Bagozzi & Yi, 1988). Table 2 illustrates item loadings, composite reliability, and Cronbach's alpha.

Table 2: *Reliability and Validity test results* (n = 406)

Constructs	Mean	SD	t	Loading
Anxiety (α = 0.977, CR = 0.980, AVE = 0.863)				
Anxiety Item 1	2.14	1.108	18.946	0.896
Anxiety Item 2	2.03	1.064	22.550	0.945
Anxiety Item 3	2.31	1.210	22.754	0.866
Anxiety Item 4	2.04	1.078	23.722	0.953
Anxiety Item 5	2.12	1.106	28.521	0.944
Anxiety Item 6	2.08	1.122	26.168	0.952
Anxiety Item 7	2.00	1.058	24.490	0.955
Anxiety Item 8	2.15	1.131	27.255	0.916
Stress (α = 0.982, CR = 0.985, AVE = 0.918)				
Stress Item 1	2.10	1.097	47.737	0.941
Stress Item 2	2.13	1.153	53.731	0.952
Stress Item 3	2.09	1.106	41.557	0.960
Stress Item 4	2.12	1.139	51.501	0.961
Stress Item 5	2.15	1.154	60.427	0.969
Stress Item 6	2.15	1.147	56.647	0.964
Enjoyment (α = 0.957, CR = 0.967, AVE = 0.853)				
Enjoyment Item 1	3.66	1.001	66.634	0.921
Enjoyment Item 2	3.57	1.039	96.801	0.940
Enjoyment Item 3	3.56	1.061	73.766	0.929
Enjoyment Item 4	3.57	1.039	81.299	0.940
Enjoyment Item 5	3.55	1.038	45.094	0.887
Self-efficacy (α = 0.943, CR = 0.957, AVE = 0.816)				
Self-efficacy Item 1	3.59	0.999	40.160	0.872
Self-efficacy Item 2	3.65	1.023	62.699	0.915
Self-efficacy Item 3	3.73	0.957	79.829	0.932
Self-efficacy Item 4	3.69	0.996	88.376	0.937
Self-efficacy Item 5	3.52	1.000	37.836	0.858
Perceived ease of use (α = 0.911, CR = 0.931, AVE = 0.693)				
PEOU Item 1	3.43	1.083	22.099	0.740
PEOU Item 2	3.87	0.908	26.972	0.844
PEOU Item 3	3.87	0.944	28.188	0.844
PEOU Item 4	3.93	0.919	35.767	0.874
PEOU Item 5	3.85	1.021	31.985	0.845
PEOU Item 6	3.72	1.004	34.938	0.843
Perceived usefulness (α = 0.907, CR = 0.932, AVE = 0.734)				
PU Item 1	3.47	0.980	28.919	0.804
PU Item 2	3.74	0.972	62.628	0.909
PU Item 3	3.64	0.999	52.959	0.905
PU Item 4	3.62	0.986	60.336	0.905
PU Item 5	4.01	0.851	16.646	0.746
Behavioral intention (α = 0.922, CR = 0.941, AVE = 0.762)				
BI Item 1	3.66	0.998	38.122	0.852
BI Item 2	3.38	1.186	35.779	0.844
BI Item 3	3.56	1.001	53.916	0.878
BI Item 4	3.65	0.986	47.858	0.886
BI Item 5	3.52	1.027	58.586	0.902

The square root of AVE values was compared with latent variable correlations to test the discriminant validity. The square root of each construct is greater than the highest correlation with any other construct, as illustrated in Table 3, suggesting that the data passed the discriminant validity testing (Chen & Dwyer, 2018). The study further applied statistical remedies in addressing and controlling common method biases concerns raised by Podsakoff *et al.* (2003), for example, Harman's single-factor test and multiple method factors.

Table 3: *Discriminant validity testing* (n = 406)

	ANX	STR	ENJ	SE	PEOU	PU	BI
ANX	**0.929**						
STR	0.918	**0.958**					
ENJ	0.146	0.065	**0.924**				
SE	0.138	0.102	0.634	**0.904**			
PEOU	0.084	0.050	0.717	0.775	**0.833**		
PU	0.131	0.050	0.732	0.695	0.792	**0.857**	
BI	0.160	0.083	0.797	0.690	0.778	0.817	**0.873**

Notes: ANX = anxiety; BI = behavioral intention; ENJ = enjoyment; PEOU = perceived ease of use; PU = perceived usefulness; SE = self-efficacy; STR = stress.

Main Effects

PLS-SEM evaluates the structural model's predictive relevance, via calculating effect size, coefficient of determination (R^2), and path coefficients (Hair et al., 2021). Table 4 illustrates the path coefficients of the tested relationships, along with *t* value, significance level, and 95% bias-corrected confidence intervals, providing evidence in testing each hypothesis. The results support classical TAM model, while showing structural differences among external variables including the two main constructs reflecting well-being status. In the results on testing direct effects, anxiety positively influences enjoyment (β = 0.551, *p.* < 0.001) supporting H7.1, and PU of e-learning (β = 0.232, *p.* < 0.01) supporting H7.4. On the other hand, stress has negative impacts on these two variables (β = -0.441, *p.* < 0.001; β = -0.220, *p.* < 0.01), supporting H6.1 and H6.4. Enjoyment, as predicted in previous studies (Abdullah et al., 2016; Mun & Hwang, 2003), have significant direct impacts on self-efficacy (supporting H5.1), PEOU (supporting H5.2), and PU (supporting H5.3). Another direct effect from enjoyment to behavioural intention was also found (β = 0.350, *p.* < 0.001), supporting H5.4. Results of the effects of self-efficacy are also found consistent with the majority of previous research (Abdullah et al., 2016; Mun & Hwang, 2003), with significant effects on both PEOU (β = 0.536, *p.* < 0.001) supporting H4.1, and PU (β = 0.138, *p.* < 0.05) supporting H4.2, but not directly on behavioural intention. As for the relationships between PEOU, PU, and behavioural intention, both directly and indirectly, results are consistent with previous TAM studies, with H1, H2, and H3 all supported by the sample data.

In particular, the results from PLS-SEM analysis support various mediating effects, in testing the indirect effects of anxiety, stress, enjoyment, and self-efficacy on various dependent variables. For instance, the indirect effects of both anxiety and stress on self-efficacy, PEOU, PU, and behavioral intention were found significant, but with opposite directions (positive for anxiety while negative for stress). Enjoyment, again, is found its significant influences on each construct in the TAM model, so as self-efficacy, consistent with previous studies. As for total effects, neither anxiety nor stress was found significant on self-efficacy or PEOU, suggesting both self-efficacy and PEOU independent from such emotional statuses.

Table 4: *Hypothesis testing results*

Hypothesis		*β*	*t*	*p.*	95% BC CI 2.50%	97.50%	Hypothesis testing
Direct							
ANX → ENJ	H7.1	0.551***	3.747	0.000	0.242	0.807	supported
ANX → SE	H7.2	-0.068	0.502	0.616	-0.347	0.182	n.s.
ANX → PEOU	H7.3	-0.125	1.441	0.150	-0.305	0.033	n.s.
ANX → PU	H7.4	0.232**	2.870	0.004	0.077	0.399	supported
ANX → BI		0.081	1.243	0.214	-0.042	0.212	n.s.
STR → ENJ	H6.1	-0.441**	2.926	0.003	-0.720	-0.125	supported
STR → SE	H6.2	0.123	0.819	0.413	-0.153	0.430	n.s.
STR → PEOU	H6.3	0.085	0.947	0.343	-0.080	0.268	n.s.
STR → PU	H6.4	-0.220**	2.656	0.008	-0.396	-0.068	supported
STR → BI		-0.048	0.723	0.469	-0.181	0.077	n.s.
ENJ → SE	H5.1	0.636***	11.474	0.000	0.524	0.734	supported
ENJ → PEOU	H5.2	0.389***	9.631	0.000	0.310	0.468	supported
ENJ → PU	H5.3	0.287***	6.254	0.000	0.200	0.380	supported
ENJ → BI	H5.4	0.350***	7.253	0.000	0.255	0.446	supported
SE → PEOU	H4.1	0.536***	12.888	0.000	0.455	0.617	supported
SE → PU	H4.2	0.138*	2.544	0.011	0.035	0.249	supported
SE → BI	H4.3	0.071	1.526	0.127	-0.021	0.159	n.s.
PEOU → PU	H3	0.471***	8.552	0.000	0.359	0.577	supported
PEOU → BI	H2	0.185***	3.810	0.000	0.085	0.278	supported
PU → BI	H1	0.357***	6.680	0.000	0.255	0.462	supported
Indirect							
ANX → SE		0.350***	3.491	0.000	0.162	0.551	supported
ANX → PEOU		0.366**	3.149	0.002	0.121	0.582	supported
ANX → PU		0.311**	2.677	0.007	0.042	0.505	supported
ANX → BI		0.451***	3.591	0.000	0.173	0.668	supported
STR → SE		-0.280**	2.997	0.003	-0.465	-0.094	supported
STR → PEOU		-0.256*	2.245	0.025	-0.467	-0.021	supported
STR → PU		-0.229	1.956	0.050	-0.436	0.017	n.s.
STR → BI		-0.357**	2.781	0.005	-0.588	-0.082	supported
ENJ → PEOU		0.341***	8.192	0.000	0.264	0.425	supported
ENJ → PU		0.432***	8.724	0.000	0.341	0.535	supported
ENJ → BI		0.437***	10.321	0.000	0.361	0.529	supported
SE → PU		0.253***	6.979	0.000	0.185	0.326	supported
SE → BI		0.239***	7.019	0.000	0.177	0.310	supported
PEOU → BI		0.168***	4.996	0.000	0.110	0.241	supported
Total							
ANX → SE		0.282	1.936	0.053	-0.041	0.551	n.s.
ANX → PEOU		0.241	1.678	0.093	-0.101	0.484	n.s.
ANX → PU		0.543***	3.770	0.000	0.249	0.803	supported
ANX → BI		0.532***	3.801	0.000	0.216	0.768	supported
STR → SE		-0.157	1.041	0.298	-0.452	0.137	n.s.
STR → PEOU		-0.171	1.140	0.254	-0.452	0.127	n.s.
STR → PU		-0.449**	2.993	0.003	-0.737	-0.145	supported
STR → BI		-0.406**	2.895	0.004	-0.650	-0.101	supported
ENJ → PEOU		0.730***	16.189	0.000	0.641	0.810	supported
ENJ → PU		0.719***	16.622	0.000	0.633	0.797	supported
ENJ → BI		0.787***	25.290	0.000	0.722	0.843	supported
SE → PU		0.391***	7.882	0.000	0.292	0.484	supported
SE → BI		0.310***	6.683	0.000	0.220	0.402	supported
PEOU → BI		0.353***	8.137	0.000	0.269	0.437	supported

Notes: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$; ANX = anxiety; BI = behavioral intention; ENJ = enjoyment; PEOU = perceived ease of use; PU = perceived usefulness; SE = self-efficacy; STR = stress; BC CI= bias-corrected confidence interval.

The structural model testing shows strong predictive capability on the proposed dependent variables especially those in the classical TAM models. In calculating the adjusted R^2 values for all the mediators and dependent variables, the variance of self-efficacy is explained 40.2% in the structural model. The three constructs in the classical TAM models, namely PEOU (adjusted R^2 = 68.5%), PU (adjusted R^2 = 69.5%), and behavioral intention (adjusted R^2 = 76.9%) are well explained by the model in their variances. However, the variance of enjoyment is only interpreted at 4.7% in this structural model, implying an exogenous variable nature with very limited impact by the emotional status.

PLS-SEM calculates by evaluating the relevant impact of certain exogenous variables examining the variation in the R^2 (Hair *et al.*, 2021). Benchmarks of evaluating effect size are determined in previous research at 0.02, 0.15, and 0.35 (Chen & Dwyer, 2018; Chin, 1998; Cohen. 1992; Hair *et al.*. 2021; Xu *et al.*, 2021). Accordingly, anxiety has weak effects on enjoyment ($f^2_{ANX \to ENJ}$ = 0.050) and PU ($f^2_{ANX \to PEOU}$ = 0.027), similar to stress ($f^2_{STR \to ENJ}$ = 0.032; $f^2_{STR \to PEOU}$ = 0.024). Enjoyment has moderate effects on both PEOU ($f^2_{ENJ \to PEOU}$ = 0.280) and behavioral intention ($f^2_{ENJ \to BI}$ = 0.216), while a strong effect on self-efficacy ($f^2_{ENJ \to SE}$ = 0.645) and a weak effect on PU ($f^2_{ENJ \to PU}$ = 0.123). Self-efficacy has a relatively weak effect on PU ($f^2_{SE \to PU}$ = 0.024) but a strong effect on PEOU ($f^2_{SE \to PEOU}$ = 0.548). PEOU has a weak effect on behavioral intention ($f^2_{PE \to BI}$ = 0.038) and a moderate effect on PU ($f^2_{PE \to PU}$ = 0.230). PU has a moderate impact on intention to adopt e-learning ($f^2_{PU \to BI}$ = 0.038), similar to that reflected in the path coefficient.

Q^2 values in PLS-SEM, calculated in a blindfolding procedure, reveal the quality of the path model as model testing indices (Geisser, 1974; Stone, 1974). In the calculation, all Q^2 values of various endogenous latent variables are positive, suggesting sufficient predictive relevance (Chin, 1998; Reinartz et al., 2009). The only noticeable aspect is that the predictive relevance of enjoyment is relatively low (Q^2 = 0.043), similar to that revealed in the predictive capability calculation based on adjusted R^2. Figure 2 illustrates the variations in the relationship testing.

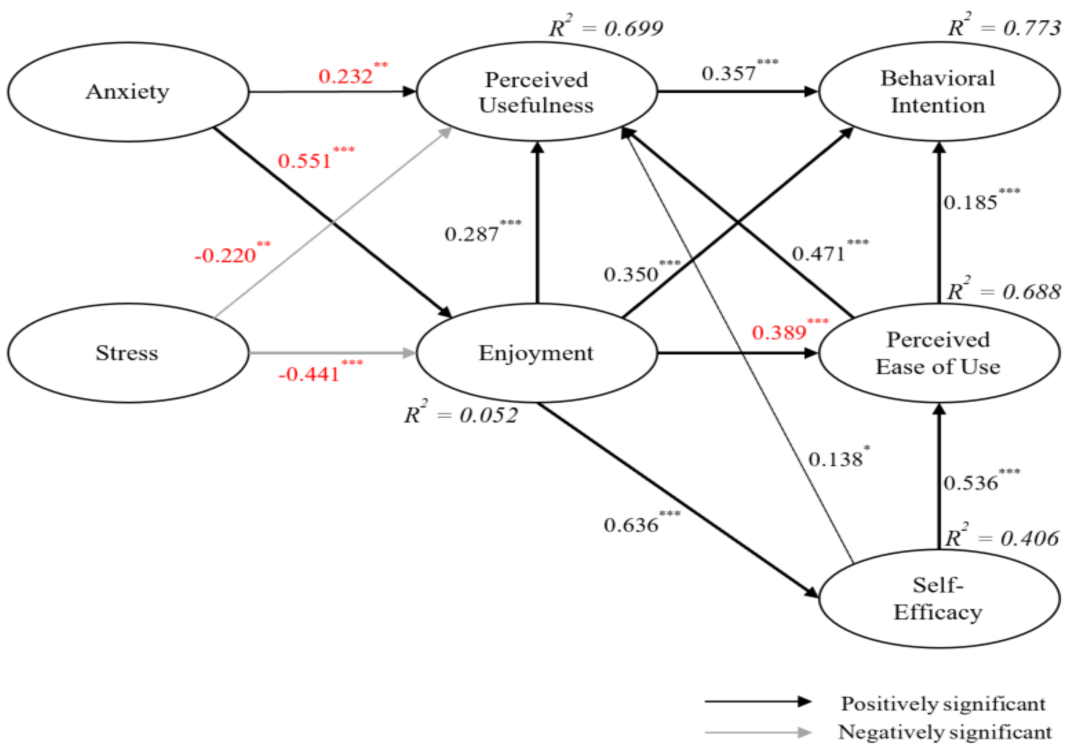

Figure 2: Results of Structural Model Testing

DISCUSSION

This empirical study firstly revalidates the usefulness of the TAM model in a pandemic context, like findings by Hu *et al*. (2022) and Prasetyo *et al*. (2021). Different from previous research on technology anxiety and stress (such as, Dönmez-Turan & Kir, 2019; Gutiérrez-Aguilar *et al.*, 2023; Rosli *et al.*, 2022; Sugandini *et al.*, 2022), this study focused on general anxiety and stress mainly derived from the context such as the COVID-19 pandemic and found distinctive effects by anxiety and stress on various variables in the full TAM model. What is worthy of theoretical discussion and further investigation, is the positive impact of general anxiety on other variables in the TAM models consistent with similar studies (such, Almaiah *et al.*, 2022), in contrast with the widely reported negative relation between technology anxiety and adoption (Dönmez-Turan & Kır, 2019).

This findings of this study adds further understanding of the role of emotional factors in the TAM model and its impact on the adoption of e-learning in the post-COVID-19 era. Research findings support the classical TAM model, showing both structural differences between external and emotional variables, including the two main constructs reflecting emotional well-being status. Firstly, in terms of the relationship between the variables in the classical TAM model, PEOU has a positive impact on PU that is statistically significant, and PEOU (along with PU) have direct effects on students' intention to use e-learning. These are fundamentally consistent with previous TAM research (Almaiah *et al.*, 2022; Gutiérrez-Aguilar *et al.*, 2023; Kiraz & Ozdemir, 2006; Rosli *et al.*, 2022). A high level of ease of use as well as usefulness of the e-learning system has a strong impact on the intention to choose online education (Ibrahim, et.al., 2017). In other words, students' learning experiences (even during the global pandemic) have a positive effect on their future intention to pursue online learning. Improving how easily the technology can be used, interface of e-learning, the quality of the e-learning system, information, as well as content in the online teaching platform, combined with guiding students to accept the platform and teaching methods, can generate positive attitudes towards online learning (Prasetyo *et.al.*, 2021). Furthermore, in previous research, self-efficacy and enjoyment reflected students' assessment of their ability to use e-learning functions, intrinsic motivation and the associated pleasure and enjoyment they derive from e-learning (Rosli *et al.*, 2022; Fathema, Shannon & Ross, 2015; Praveena & Thomas, 2014). Results of the effects of self-efficacy and enjoyment were found to be consistent with the majority of previous research (Abdullah et al., 2016; Mun & Hwang, 2003), with significant effects on both perceived ease of use, and perceived usefulness but not directly on behavioural intention. Therefore, improving students' ability to use and enjoy online learning systems that effectively increase the usefulness and ease of use of e-learning, indirectly enhance their intention to choose e-learning as an educational platform in the future.

As anxiety and stress were common among students during the pandemic (Fawaz & Samaha, 2021), this study further explored the impact of emotions on students' adoption of the e-learning process under the circumstances of COVID-19 from an emotional perspective. General anxiety was found to significantly and positively influence both enjoyment and perceived usefulness. Its impact on perceived usefulness is consistent with previous research, positively associating negative emotions and TAM constructs (Chien, 2012; Bates, & Khasawneh, 2007). However, anxiety was found to be positively linked with enjoyment, different from standpoints in previous research (Almaiah *et al.*, 2022; Holdack, Lurie-Stoyanov, & Fromme, 2020; Saadé, et al., 2013; Mun & Hwang, 2003), suggesting a positive role for anxiety specifically as potentially a healthy emotion driving positive outcomes. Maintaining a healthy level of anxiety encourages students to seek enjoyment and further adopt e-learning practice. In contrast, stress as another negative emotion illustrates entirely opposite effects, with negative impacts on both enjoyment and perceived usefulness. These findings provide evidence to revalidate previous research on examining negative emotions overall (Holdack, Lurie-Stoyanov, & Fromme, 2020; Saadé, et al., 2013; Mun & Hwang, 2003), while stress does not show any positive impact on driving acceptance or adoption of new technology in the e-learning scenario. However, considering that the variance of enjoyment is only

4.7% in this structural model, the effects of either anxiety or stress are relatively weak. Furthermore, neither anxiety nor stress was found significant on self-efficacy or perceived ease of use, suggesting that both self-efficacy and perceived ease of use are independent of emotional state in the e-learning scenario.

In testing the overall effects, anxiety was found again with positive overall effects on both perceived usefulness and behavioral intention, suggesting its potential as a motive driving the acceptance and adoption of e-learning. As for the constructs in classical TAM models, all relationships tested were again in line with previous research, suggesting the appropriateness of TAM under circumstances such as the COVID-19 pandemic.

In summary, the findings from this extended TAM model suggest the potential of two negative emotions of anxiety and stress in driving tertiary students' adoption of e-learning, and further distinguish these two emotions in their respective effects (positive for anxiety and negative for stress). This further revalidates Saadé et al.'s (2013) standpoint on balancing the challenges and motivations of e-learning, enhancing students' confidence in the online environment to accommodate different needs. To reduce the potential negative impact of stress on TAM, flexible schedules and environments may play a positive role when studying online (Lazarevic & Bentz, 2021).

CONCLUSION

This study contributes to the literature on TAM by revalidating its usefulness and appropriateness under a pandemic scenario, and further by expanding the model with inclusion of two emotional variables of anxiety and stress as extraneous affecting factors. It provides evidence to support the application of TAM in future complex scenarios considering technology acceptance and adoption. By distinguishing the positive effect of anxiety on TAM and the negative effect of stress, this study points out a direction for future research, in further exploring and studying in-depth, the various emotions and their roles in technology acceptance. It suggests that human psychology and emotions are complex in driving behaviors and the impact of various emotions must not be simplified or assumed to be the same.

From a practical sense, this study provides implications for tertiary education practitioners on encouraging acceptance and adoption of e-learning. Firstly, educators and course coordinators and content developers should acknowledge the potentially positive role of general anxiety as a healthy motive driving behavioral change and e-learning adoption, while pursuing reduction of students' stress and anxiety due to technology itself (as suggested by previous research) via procedures such as flexible schedules and environments. In designing e-learning components, a focus on students' enjoyment and perceived fun is important to increasing students' acceptance rate. Practitioners should also pay attention to other traditional TAM constructs such as perceived ease of use, perceived usefulness, and self-efficacy in e-learning design and development.

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