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Do Science and Social Science Differ? Multi-Group Analysis (MGA) of the Willingness to Continue Online Learning

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Abstract
Without proper preparation by higher institutions, the COVID-19 pandemic has forced the world to rely on online learning. Even students of social science and science are looking for different knowledge and skills. Currently, both groups rely on the same method to gather knowledge for future undertakings. Given the uncertainty regarding the resolution of COVID-19, which has driven students to continue using online learning, the current study aims to identify the factors of willingness to continue online learning among social science and pure science students by extending the use of expectation-confirmation theory. Applying a purposive sampling method, 2,215 questionnaires were collected among undergraduate students from Universiti Malaysia Terengganu (UMT) using an online survey. Current study found that expectation and confirmation positively affect satisfaction. Attitude, satisfaction and readiness were found to have a positive relationship with willingness to continue online learning. Meanwhile, self-efficacy was found unsupported hypothesis for the direct effect. For multigroup analysis, readiness was found to have a significant difference between students of social science and pure science. The findings of this research enrich the literature about online learning, especially in the COVID-19 setting. Moreover, this work is useful for higher education institutions seeking to design a better strategy that allows students to return to campus.

Keywords Online learning during COVID-19 · Expectation-confirmation theory · Multigroup analysis · Social science · Science

1 Introduction

The COVID-19 pandemic is the biggest challenge to all sectors of the world today. Hence, each sector should mitigate and adapt rapidly to the COVID-19 pandemic to overcome all the related issues and unforeseen issues. Education is one of the world's critical sectors, and numerous learning providers, educators, researchers, and students are struggling to adapt

Extended author information available on the last page of the article to the challenges caused by the pandemic. Universities' management teams should have new strategies that rely on technological advancement to ensure their education system and teaching and learning activities are implemented smoothly.

Online learning or e-learning systems can help educators engage their students and track the teaching and learning process. Although this approach is not new to all learners, online learning's successful usage relies on students' willingness and understanding of the adoption factors and the primary challenges faced by the current online learning systems (Almaiah and Alismaiel 2019; Garba Shawai and Amin Almaiah 2018). Furthermore, Almaiah et al. (2020) pointed out the lack of agreement on the critical challenges and factors that shape the successful use of e-learning systems during the COVID-19 pandemic. Hence, a clear gap has been identified in the knowledge on the critical challenges and factors of e-learning usage during this pandemic.

1.1 Science and Social Science

In Malaysia, students are categorised into the pure science and social science streams. Science is any system of knowledge that is concerned with the physical world and its phenomena and that entails unbiased observations and systematic experimentation. In general, science involves a pursuit of knowledge covering general truths or the operations of fundamental laws (Gregersen 2020). Social science can be defined as a group of academic disciplines dedicated to examining society. This branch of science studies how people interact with one another, behave, develop as a culture and influence the world (Liberto 2020). According to Bastow et al. (2014), social science focuses on the study of contemporary human societies, economies, organisations and cultures and their development. They look for 'laws' of social development and patterns of association and causation that make sense theoretically and can be evaluated by empirical investigation.

In terms of learning characteristics, science students are involved in laboratory-based practical work, assessment tools and methods (Jamil et al. 2013). Moreover, their assessment is based on performance-based tasks. In contrast, social science students are involved more in observations, presentations, conversations, discussions, interviews and transcript analysis techniques (Jamil et al. 2013), which lead to paper and pencil-based examinations (Lantz 2004). According to Noora (2008), a standard learning approach cannot be implemented in various disciplines, as different majors evaluate distinct skills and teaching methods.

For the study, 19 programs from four faculties were considered as science programs due to the students are involved in laboratory-based and practical work. Meanwhile, 8 programs from two faculties were classified as social science which not related in laboratory activities. The students in these programs are involved in understanding and applying theoretical concepts in the study. Appendix 1 illustrates the science and social science programs offered by Universiti Malaysia Terengganu (UMT).

The laboratory method, which provides students with the opportunity for active experimentation and hands-on testing of empirical variables, carries excellent value in terms of education. Laboratory applications are the complementary part and the focus point of science education (Serin 2002). The face-to-face practical laboratory or traditional laboratory provides students with the experience and opportunity for hands-on manipulation of teaching materials, procedures and equipment to learn the required techniques (psychomotor skills) for acquiring and manipulating data (Gamage et al. 2020). The face-to-face laboratory provides students with scientific communication skills and real experiences to explore experimental designs, understand the flow chart experimental steps, conduct experimental data analysis, generate experiment conclusions and make recommendations related to the theory. Alternative laboratory experiences have been used as a supplement in conjunction with face-to-face laboratories (Makransky et al. 2016). Studies of online laboratories used mainly as supplemental instruction have resulted in increasing test scores, improving students' attitudes and preparedness for the hands-on laboratory and strengthening conceptual knowledge (Dalgarno et al. 2009). Alternatively, in face-to-face laboratory experiences, the delivery of a remote or distance-based laboratory component has several advantages, including practically unlimited access and the ability to repeat the experiments (Conway-Klaassen et al. 2012).

A number of studies in various disciplines have reported results suggesting that an online laboratory can be comparable to the traditional laboratory in terms of learning outcomes (Feig 2010; Merchant et al. 2012) proved that an online laboratory enhances students' skills, spatial ability and self-efficacy and positively impacts achievement.

Brinson (2015) demonstrated that student learning outcome achievement is equal or higher in an online laboratory than in face-to-face or traditional laboratories across all learning outcome categories (knowledge and understanding, inquiry skills, practical skills, perception, analytical skills and social and scientific communication). Furthermore, Rowe et al. (2017) found that students feel that their online laboratory experience is the same as or better than their prior experiences in the traditional face-to-face laboratory setting.

However, with the extensive adoption of online education during the COVID-19 pandemic, the effectiveness of laboratory practical sessions in enhancing student scientific skills through online learning should be prepared and analysed comprehensively. Online laboratory sessions should be designed to provide equivalent laboratory experiences and skills to students. Furthermore, an online laboratory's student assessment should be covered correctly to meet the course's learning outcomes. Effective online laboratory sessions can be achieved with proper design and planning. The successful usage of online learning for science learners during the COVID-19 pandemic will depend on a good online or virtual laboratory that will lead to the achievement of the course's learning outcomes and to the associated student satisfaction. The online system's facilities, the educator's role and the learner's willingness to be involved in online learning also play important roles in the success of an online learning system during the COVID-19 pandemic.

The literature has shown that a higher willingness to accomplish tasks will produce better results than forcing students to perform. However, given the COVID-19 pandemic, online learning is not an option to maintain or enhance the student's performance. Hence, understanding the factors influencing a student's willingness to continue using online learning is crucial. In addition, science and social science students understandably look at different skills and knowledge in their learning process. Therefore, this research explores the factors that affect the willingness to continue online learning among science and social science students at UMT, the leading university in Malaysia's maritime and oceanic studies. The study only focuses on a single university because each university in Malaysia uses different platforms and programs. Given that this work examines the same environment and setting but focuses on science and social science students, examining participants within the same environment eliminates issues in comparing students across various settings (Vargas 2015).

Numerous studies have been conducted regarding online learning either during a regular or a new normal situation. Most of the studies have explored the science, technology, engineering and medicine (STEM) fields (Gamage et al. 2020; Jaber et al. 2018). However, a dearth of literature has attempted to compare experiences between science and social science students. Hence, to fill the gaps in the literature, the current study explores and compares the willingness to continue online learning among science and social science students attending UMT during the COVID-19 pandemic and associated social distancing restrictions. Considering this setting and the intention to prolong online teaching, revisiting and extending prior knowledge on online learning behaviour seems timely and warranted. By extending expectation-confirmatory theory (ECT) and by using smart partial least squares (Smart PLS) to run multigroup analysis (MGA), the current study aims to contribute to understanding student willingness further to continue online learning among both groups of students. The findings are crucial for university management and the Ministry of Higher Education to craft a better policy in preserving the quality of graduates during the COVID-19 pandemic, especially if the ministry decides to allow a limited number of students to return to campus in the near future.

2 Literature Review

2.1 Expectation-confirmation Theory

Expectation confirmation theory was proposed by Oliver (1980) and has been extensively used in consumer behaviour studies. The theory consists of expectation, perceived performance, confirmation, satisfaction and repurchase intention as primary constructs. According to Oliver (1980), the process of determining reuse intention includes five stages or steps. Firstly, a consumer begins to form an initial expectation of a product or service before making a purchase. Secondly, the product or service is purchased, and the consumer starts to use it. After a period of consumption, the consumer forms perceptions of its performance. Thirdly, the consumer compares the performance of the product or service with his or her initial expectation and decides to what extent the expectation is confirmed. Fourthly, on the basis of the degree to which the confirmation of expectations is met, the consumer forms an emotion of satisfaction. Finally, the satisfied consumer will reuse the product or service, whereas the dissatisfied customer will discontinue subsequent use. Therefore, this cognitive comparison suggests that all constructs in ECT are important in explaining repurchasing behaviour (Dai et al. 2020; Bhattacherjee 2001) adapted ECT into an information system context and formulated a model called the expectation confirmation model (ECM).

As a popular model for predicting consumer behaviour, the robustness of ECT and ECM has been confirmed in various research contexts, including the academic context (Alraimi et al. 2015; Cheng, 2020; Joo et al. 2018). The current study is based on the context provided by the relevant literature and its variable use of ECM.

2.2 Expectation

Expectation is defined as an individual's evaluation of a product based on the information given to the consumer before making a purchase (Zeithaml et al., 1988). Similarly, it can be defined as what a customer expects to obtain from a product or service (Hsieh and Yuan 2019). Expectation has two proposed levels, namely, desired expectation and adequate expectation (Parasuraman et al. 1991). The desired level is what a customer hopes to receive, while the adequate level is a lower level of service that a customer can accept. Hsieh and Yuan (2019) explained that between desired expectation and adequate expectation exists the zone of tolerance. Customer satisfaction can be achieved when customer expectation falls within the zone of tolerance. As customer expectation is an indicator of personal preferences and potential satisfaction level (Wang 2017), managing expectation to achieve a high level of satisfaction is important (Hsieh et al. 2011). In this study context, if students' expectations regarding online learning are met, expectation will influence their satisfaction towards the learning system.

Expectation has been found to influence satisfaction positively. In academic settings, expectation positively influences students' satisfaction in using digital textbooks (Joo et al. 2018). Therefore, on the basis of the literature provided, we develop our first hypothesis:

H1: Expectation has a positive influence on satisfaction in online learning.

2.3 Confirmation

According to ECM, confirmation is defined as the realisation of the expected benefit of a system (Bhattacherjee 2001). It can also be defined as the extent to which lived experience confirms an individual's initial expectation (Oghuma et al. 2016). When the initial expectation of a product or service is confirmed or even exceeded, confirmation occurs and leads to user satisfaction. In this study, when the students' expectations about online learning is confirmed by lived experience, then students will be satisfied with the use of the online learning system.

Previous studies have found that confirmation positively influences satisfaction. In the context of academic studies, Alraimi et al. (2015) found that confirmation while using massive open online courses (MOOC) has a positive effect on satisfaction. Other example of works that have explored this relationship are those by Joo and Choi (2015) regarding online library resources and by Daǧhan and Akkoyunlu (2016) regarding online learning environment. Based on previous literature, the second hypothesis is:

H2: Confirmation has a positive influence on satisfaction in online learning.

2.4 Readiness

Readiness in online learning is defined by three aspects: (1) students' preferences for the form of delivery as opposed to face-to-face classroom instruction, (2) student confidence in using electronic communication for learning and (3) the ability to engage in autonomous learning (Warner et al. 1998). In addition, readiness is the ability of an individual to use online learning resources and multimedia technologies to improve the quality of learning (Kaur and Abas 2004). According to Demir (2015), online learning readiness is an important indicator in completing online classes successfully. In this study, students' ability to use the available resources during online classes influences their continuance intention. Readiness could be formed by several factors.

Learning style also has a large influence on the student's readiness. Science students learn using the psychomotor domain and obtain better understanding and knowledge with the hands-on approach, which they require when running experiments in the laboratory. Thus, relying on the online and video explanation, students face a huge task of absorbing knowledge without touching real objects, which could affect their understanding and consequently their readiness to continue using online learning.

In contrast to students learning physical sciences, social science students have fewer challenges using online learning because their learning content is more about understanding and applying theoretical concepts using ideas as data, which therefore focuses more on cognitive tasks and not kinaesthetic or psychomotor tasks. Numerous higher education providers offer online courses and online distance learning (ODL) programs for social science students for this reason of ease. The effectiveness of the online mode of instruction for social science courses and the program is not an issue for social sciences as it may be for the physical sciences. Thus, studying online or offline should not be as severe for social science students as for science students.

A positive relationship between online learning readiness has been confirmed in various contexts, such as in open online course (Gupta and Maurya 2020), self-service technology (Lin and Chang 2011; Tuyet and Tuan 2020) and internet banking (Alghamdi et al. 2018). Hence, the third hypothesis is:

H3: Readiness has a positive influence on continuance intention in online learning.

2.5 Attitude

Attitude, or attitude towards behaviour, is the degree to which a person has a favourable or unfavourable appraisal of the behaviour in question (Ajzen 1991). Attitudes represent a psychological evaluation in attribute dimensions, such as good-bad, likeable-unlikeable and pleasant-unpleasant (Ajzen 2001). Additionally, students' attitude was proved to be a predictor for actual behaviour of using digital learning (He et al. 2020). This study posits that students with high attitude towards online learning will have a higher continuance intention.

Attitude has been confirmed to have a positive effect on continuance intention in academic settings. Participants' attitude towards using MOOCs has been found to have a positive effect on the intention to continue using them (Dai et al. 2020; Wu and Chen 2017). Attitude has also been established to have a positive effect on continuance intention in blended learning approach (Sabah 2020). Hence, the study proposes:

H4: Attitude has a positive influence on continuance intention in online learning.

2.6 Satisfaction

Satisfaction is an affect in which being satisfied is a positive feeling whereas being dissatisfied is a negative feeling (Bhattacherjee 2001) explained that satisfaction with prior experience influences an individual's intention to continue the usage of a system or service. In education contexts, satisfaction is the students' perceptions about the learning experience and how the learning environment aids their academic success (Lo 2010). In the context of this study, students' satisfaction with prior experience influences their continuance intention.

Past literature has found that satisfaction has a positive influence on continuance intention. In an academic setting, the relationship between satisfaction and continuance intention of online learning was confirmed by Joo et al. (2018) regarding Korean Cheng and Yuen

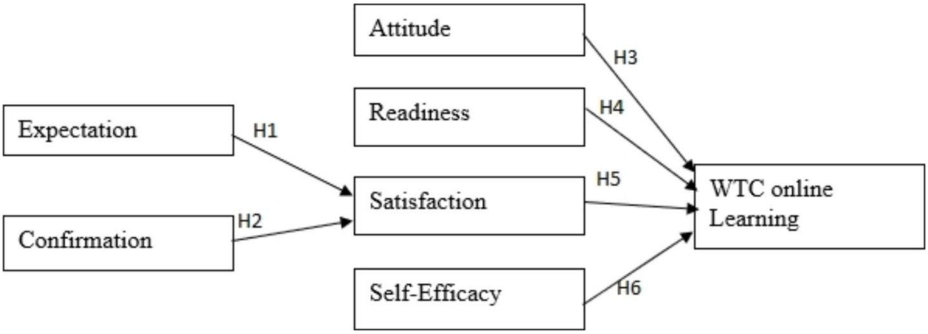

Fig. 1 Research Framework

(2020) regarding secondary students' and Cheng (2020) regarding cloud-based e-learning systems. Hence, the fifth hypothesis is:

H5: Satisfaction has a positive influence on continuance intention in online learning.

2.7 Self-efficacy

Self-efficacy is a judgement in personal ability to perform an intended behaviour (Bhattacherjee et al. 2008). According to Jan (2015), the previous literature has demonstrated that both computer self-efficacy and academic self-efficacy have been significant determinants in online learning studies. However, Shen et al. (2013) explained that students' self-assessment about their capabilities to complete online learning classes are more important. The literature has indicated that long-term exposure to technologies and applications has the potential to enhance a person's technological self-efficacy level (Menon et al. 2020). Therefore, in the context of this study, self-efficacy can be defined as the students' capability of using an online learning system.

In an academic setting, self-efficacy has been found to influence the continuance intention of using an online learning system positively. Research by Lwoga and Komba (2015) and Wang et al. (2019) demonstrated that self-efficacy has a positive relationship with continued intention on e-learning system usage and cloud e-learning applications, respectively. To have a clearer view, Fig. 1 illustrates the research framework of the study. Thus, the sixth hypothesis is:

H6: Self-efficacy has a positive influence on continuance intention in online learning.

3 Methodology

3.1 Instrument Development

The instrument was developed on the basis of latent constructs mentioned in the research model. All the construct items were taken from previous research. Items of expectation were adopted from Daɫhan and Akkoyunlu (2016). Items of confirmation and continuance intention were adopted from Bhattacherjee (2001). Meanwhile, items of student readiness were obtained from Mirabolghasemi et al. (2019), whereas items of attitude were from Salloum et al. (2019). Finally, the items of online learning service quality were taken from Wu et al. (2011). All independent variables were measured with a five-point Likert scale, whereas the dependent variable was measured with a seven-point Likert scale. Given the independent and dependent variables being collected from a single source, two different Likert scales were used to reduce common method variance (CMV) (Ngah et al. 2020).

3.2 Sampling and Data Collection

Given that the study is focused on comparing between science and social science students, the study was limited to the students in the same university. Results would not be comparable if the samples came from different populations, as they will have different settings. The study focused on UMT's students because this university offers both science and social science programs. Furthermore, UMT has required all lecturers to use online learning during the COVID-19 pandemic. Hence, a purposive sampling method was applied. In addition, a convenience sampling approach was acceptable according to Hulland et al. (2017); Ngah et al. (2019a, b) because the purpose of the current study was to concentrate on the theoretical effect on the variables within the research framework. Only degree students who studied in online learning sessions were eligible to be respondents in the study. Hence, students from diploma and postgraduates were excluded from the research. The data were distributed through an online survey using Google Forms. The survey was administered online via UMT's official Facebook page and the Centre for Academic Management and Quality's official Facebook page. The survey was conducted from 15 to 2020 to 11 August 2020, which was over the period of one month.

Sample size is crucial for quantitative studies. As proposed in the Smart PLS literature, sample size is determined by the model complexity and is calculated on the basis of the power of analysis (Ngah, Thurasamy et al., 2019). As proposed by Gefen et al. (2011), with a power of 80%, medium effect size and $p=0.05$, according to the table developed by Green (1991), the minimum sample size of the study was 85. A total of 2,215 completed questionnaires were returned. Hence, the sample size was not an issue in our study.

Table 1 indicates the demographic profile of the respondents. Most of the respondents were female students (79.3%), whereas only 20.7% were males. A total of 60.9% students majored in science, while students majoring in social science were 39.1%. Regarding electronic device usage, 78.8% of the respondents had more than one electronic device, while laptop, smartphone, desktop and tablet ownerships were 5.3%, 0.8% and 0.1%, respectively. In addition, 83.2% of the respondents had home internet access whereas 16.8% using mobile data.

4 Data Analysis

The nature of the study emphasises exploratory and predictive purposes (Hair et al. 2019) and therefore uses SEM with Smart PLS (Ringle et al. 2015), which is a co-variance-based SEM, to test the study's hypotheses. Prior to proceeding with the main analysis, a preliminary analysis, such as normality and common method bias, was addressed.

Table 1 Respondent Profile

Variable	Frequency (N=2215)	Percentage (%)
Gender		
Male	459	20.7
Female	1756	79.3
Field of Study		
Science	1349	60.9
Social Science	866	39.1
Electronic Device		
Laptop	334	15.1
Desktop/PC	17	0.8
Tablet	1	0.0
Smartphone	118	5.3
More than 1 device	1745	78.8
Internet Access at Home		
Yes	1843	83.2
No	372	16.8

4.1 Common Method Bias

Common method bias (CMB) is a serious issue of the study due to the method through which the data were collected. If the data were collected from a single source where the independent and dependent variables were answered by the same person, CMB should be addressed before continuing to test the hypotheses (MacKenzie and Podsakoff 2012; Ngah et al. 2020). The findings of the study could be contaminated, while an unsupported hypothesis could be supported due to the nature of CMB. Following the guidelines proposed by MacKenzie and Podsakoff (2012) and Ngah et al. (2020), the study used the procedural method. Furthermore, the procedural method is better than the statistical method, as the methodological part was done prior to the data collection process (Nisha et al. 2015). Hence, for the procedural method, the study used different anchor scales to measure the independent variables (1–5) and dependent variables (1–7).

4.2 Measurement Model

As mentioned in (Hair et al. 2019), the measurement model must be established prior to the structural model analysis. A measurement model can be established if the convergent validity and discriminant validity has been confirmed. The loading and composite reliability (CR) must be ≥0.7, and the average variance extracted (AVE) must be ≥0.5 to establish the convergent validity (Hair et al. 2019). Table 2 illustrates the results of the convergent validity test for the science and social science programs. Given that all the loading, AVE and CR were higher than the threshold values, convergent validity for both groups was not a problem for the study.

4.3 Discriminant Validity

Discriminant validity is a test to ensure that a construct empirically differs from other constructs within a research framework. Discriminant validity is confirmed if the values of the

Table 2 Convergent Validity

Construct	Science Item Loading CR AVE				Social Science Loading CR AVE		
Attitude	ATT1	0.914	0.930	0.815	0.914	0.932	0.820
	ATT2	0.910			0.903		
	ATT3	0.885			0.899		
Confirmation	CONF1	0.902	0.921	0.795	0.905	0.921	0.796
	CONF2	0.881			0.884		
	CONF3	0.893			0.888		
Expectation	EXP1	0.885	0.925	0.754	0.883	0.921	0.746
	EXP2	0.849			0.864		
	EXP3	0.847			0.822		
	EXP4	0.893			0.884		
Readiness	RE1	0.923	0.945	0.812	0.914	0.945	0.812
	RE2	0.892			0.886		
	RE3	0.871			0.878		
	RE4	0.917			0.926		
Satisfaction	S1	0.953	0.968	0.910	0.946	0.967	0.908
	S2	0.952			0.959		
	S3	0.957			0.954		
Self-Efficacy	SE1	0.942	0.961	0.893	0.944	0.960	0.890
	SE2	0.950			0.953		
	SE3	0.942			0.933		
Willingness to Continue	WC1	0.961	0.973	0.922	0.962	0.974	0.925
	WC2	0.961			0.965		
	WC3	0.959			0.959		

Table 3 Discriminant Validity (HTMT)

Construct (Science)	ATT	CONF	WTC	EXP	Readiness	SE	Satisfaction
ATT							
CONF	0.800						
Continue	0.815	0.712					
EXP	0.847	0.828	0.760				
Readiness	0.848	0.774	0.823	0.783			
SE	0.695	0.633	0.655	0.635	0.764		
Satisfaction	0.895	0.785	0.846	0.812	0.852	0.696	
Construct (Social Science)	ATT	CONF	WTC	EXP	Readiness	SE	Satisfaction
ATT							
CONF	0.804						
Continue	0.798	0.738					
EXP	0.821	0.825	0.766				
Readiness	0.851	0.764	0.849	0.778			
SE	0.713	0.647	0.680	0.671	0.756		
Satisfaction	0.892	0.812	0.828	0.813	0.858	0.745	

hetrotrait-monotrait (HTMT) ratio are lower than 0.9 (Franke and Sarstedt 2019). Table 3 illustrates the results of the HTMT, which shows that all the values were lower than 0.9, thus indicating that discriminant validity was confirmed for the study.

4.4 Measurement of the Invariance

Prior to running MGA, measurement invariance must be established to confirm which type of MGA could be performed. The measurement invariance of composite (MICOM) method in Smart PLS was developed by Henseler et al. (2016) to accommodate the previous technique commonly used in co-variance-based SEM, which is not suitable for Smart PLS. The steps in MICOM are configural invariance, compositional invariance assessment and equal means and variances. If only the first and second tests were passed, the partial measurement variance was established. Hence, the study could only compare the results between groups. If all the three steps were met, the full measurement variance would be established, and the study could compare between groups and for the overall group.

The first test is the configural invariance, which is easily met, as the data must have an identical indicator, identical data treatment and identical algorithm setting. The study already passed this stage because the data had been recorded and treated identically for both groups. For steps two and three, the MICOM analysis was conducted, and the results are shown in Table 4. For step two, which entailed assessing compositional invariance to establish the partial measurement invariance, the result demonstrated that compositional invariance was established because all the permutation P-values were higher than 0.05. This outcome indicated the original correlation for each variable did not significantly differ from 1. For the third step, the study failed to achieve the full measurement invariance, as the permutation P-value for the confirmation construct was less than 0.05, thus indicating significant differences between group 1 (science) and group 2 (social science). Hence, the study only achieved partial invariance, and the comparison between these two groups without the overall group could be reported.

4.5 Structural Model

Before proceeding to the hypothesis testing stage, the study needed to ensure that multicollinearity was not problematic. According to Hair et al. (2017), the variance inflated factor (VIF) must be ≤ 5 to ensure that a study is free from the multi-collinearity issue. Given that all the VIF values were lower than the maximum value set-up by Hair et al. (2017), multi-collinearity was not severe for the study. Table 5 illustrates the results of the hypothesis testing, variance explained (R^2), effect size (f^2) and multi-collinearity of the study. A hypothesis will be claimed as supported if the direction of beta is aligned with the direction of hypothesis, t-value is ≥ 1.645, p-value is ≤ 0.05 and no value of zero exists between the lower level (LL) and upper level (UL) of the confidence interval. On the basis of the results in Tables 5 and 10 out of the 12 hypotheses were supported by the data.

For the satisfaction variable, R^2 was 0.622 for science and 0.642 for social science, thus indicating that the expectation and confirmation explained 62.2% and 64.2% of variance for satisfaction for both groups. In addition, 70.7% and 70.8% variances of WTC the online learning were explained by attitude, readiness, self-efficacy and satisfaction among science and social science students, respectively. The effect size (f^2) indicates how big the influence of independent variables is towards the independent variable. For the f^2, Cohen (1992) classified 0.02 as small, 0.15 as medium and 0.35 as large effect sizes. According to Table 5, the relationship between expectation and confirmation on satisfaction had a medium effect size for both groups. For the relationship towards the WTC online learning, all supported

Table 4 Measurement Invariance assessment MICOM

Composite	C Value=1	5.0%	Permutation p-Values	Partial Measurement Invariance	Difference Composite Mean value (=0)	Confidence Interval	Permutation p-Values	Full Measurement Invariance
ATT	1.000	1.000	0.523	YES	0.036	(-0.087;0.079)	0.413	YES
CONF	1.000	1.000	0.397	YES	0.103	(-0.089;0.080)	0.018	No
Continue	1.000	1.000	0.807	YES	-0.010	(-0.086;0.079)	0.785	YES
EXP	1.000	1.000	0.780	YES	0.044	(-0.085;0.080)	0.306	YES
Readiness	1.000	1.000	0.988	YES	-0.007	(-0.085;0.077)	0.877	YES
SE	1.000	1.000	0.169	YES	0.074	(-0.087;0.079)	0.088	YES
Satisfaction	1.000	1.000	0.377	YES	0.004	(-0.084;0.079)	0.943	YES

Table 5 Hypothesis testing

Hypothesis	Relationship	Beta	Se	T Value	P Value	LL	UL	R^2	f^2	VIF	Decision
H1a	**EXP -> Satisfaction**	0.485	0.030	16.371	0.001	0.435	0.532	0.622	0.287	2.165	Supported
H2a	**CONF -> Satisfaction**	0.361	0.030	12.123	0.001	0.312	0.411	-	0.159	2.165	Supported
H3a	**ATT -> Continue**	0.156	0.033	4.758	0.001	0.102	0.211	0.707	0.024	3.486	Supported
H4a	**Readiness -> Continue**	0.296	0.031	9.442	0.001	0.244	0.347	-	0.083	3.614	Supported
H5a	**SE -> Continue**	0.038	0.024	1.543	0.061	-0.002	0.079	-	-	2.142	Unsupported
H6a	**Satisfaction -> Continue**	0.417	0.032	13.060	0.001	0.364	0.469	-	0.149	3.982	Supported
H1b	**EXP -> Satisfaction**	0.443	0.035	12.508	0.001	0.383	0.500	0.642	0.257	2.129	Supported
H2b	**CONF -> Satisfaction**	0.419	0.037	11.357	0.001	0.358	0.480	-	0.231	2.129	Supported
H3b	**ATT -> Continue**	0.120	0.038	3.115	0.001	0.058	0.183	0.708	0.020	3.468	Supported
H4b	**Readiness -> Continue**	0.414	0.047	8.871	0.001	0.337	0.491	-	0.167	3.504	Supported
H5b	**SE -> Continue**	0.046	0.035	1.307	0.096	-0.012	0.105	-	-	2.235	Unsupported
H6b	**Satisfaction -> Continue**	0.326	0.047	7.000	0.001	0.248	0.400	-	0.087	4.179	Supported

hypotheses had a small effect size, except for readiness, where the study found that readiness and WTC online learning for social science students had a medium effect size. Thus, readiness was the most influential factor for the WTC online learning for social science students.

For hypothesis testing, no difference existed between the science students and the social students. The study found that for science students, the results for expectation were $\beta=0.485$ and $p<0.001$, and those for confirmation were $\beta=0.361$ and $p<0.001$. Meanwhile, for social science students, the values for expectation were $\beta=0.443$ and $p<0.001$, and those for confirmation were $\beta=0.419$ and $p<0.001$. These outcomes confirmed the positive effects of expectation and confirmation on students' satisfaction, thus supporting H1 and

Table 6 Multi-Group Analysis

Hypothesis	Relationship	PLS MGA Beta	P value	Welch-Satterthwaite T value	P Value	Decision
H1c	**EXP -> Satisfaction**	0.042	0.187	0.891	0.187	Unsupported
H2c	**CONF -> Satisfaction**	-0.058	0.114	1.207	0.114	Unsupported
H3c	**ATT -> Continue**	0.037	0.237	0.714	0.238	Unsupported
H4c	**Readiness -> Continue**	-0.117	0.020	2.087	0.019	Supported
H5c	**SE -> Continue**	-0.009	0.418	0.199	0.421	Unsupported
H6c	**Satisfaction -> Continue**	0.090	0.055	1.605	0.054	Unsupported

H2. The results for science show that attitude ($\beta=0.156$, $p<0.001$), readiness ($\beta=0.296$, $p<0.001$) and satisfaction ($\beta=0.417$, $p<0.001$) had a positive effect on the students' WTC online learning, thus supporting the H3a, H4a and H6a. Similar results for social science students were found in terms of attitude ($\beta=0.120$, $p<0.001$), readiness ($\beta=0.414$, $p<0.001$) and satisfaction ($\beta=0.326$, $p<0.001$), thus supporting H3b, H4b and H6b. Meanwhile, the results for self-efficacy ($\beta=0.038$, $p=0.061$) for science and ($\beta=0.0346$, $p=0.061$) for social science demonstrated that self-efficacy was an insignificant factor towards WTC to online learning. As such, H5a and H5b were not supported. Table 5 illustrates the results for the hypothesis testing.

4.6 Multigroup Analysis

Even on the basis of hypothesis testing, the results reflected no difference in the findings for both groups. However, the results for MGA showed a different story. PLS-MGA was conducted to explore differences by using MGA and the Welch-Satterthwait test (Sarstedt et al. 2011) on science and social science students' data sets. Differences in the path coefficients between the two data sets are shown in Table 5. Out of the six hypotheses for MGA, only one hypothesis was supported. The relationship between readiness and WTC online learning for science students was weaker than that for social science students. The results were $\beta = -0.117$ and $p<0.05$ for MGA and $t=2.087$ and $P=0.019$ for the Welch-Satterthwaite test, thus supporting H4c. For other hypotheses, MGA and the Welch-Satterthwaite test revealed that the differences were not statistically different. Hence H1c, H2c, H3c, H5c and H6c were unsupported. Differences in the path coefficients between the two data sets are shown in Table 6.

5 Discussion

Using the ECT model, the study explored the factors influencing the satisfaction and willingness to continue of students to use online learning to pursue their university education during the COVID-19 pandemic season. Extending the ECT model with attitude, readiness and self-efficacy, the study would also like to have a clearer view of the differences between science and social science students. Furthermore, the differences between these groups must be unearthed, as most universities offer both programs on their campus. The findings can support the universities' top management's efforts to plan further for their students' success. Considering these new norms due to the COVID-19 pandemic and the intention of higher education to prolong the use of online teaching, revisiting and extending prior knowledge on online learning behaviour seems timely and warranted.

The analysis has found that expectation has a positive effect on the attitude for both groups. The finding is in line with the previous study by Ashfaq et al. (2019). It shows that higher expectation produces higher satisfaction among the students for both groups. Hence, lecturers should set high expectations from the online session among the students. Sharing class previews or sharing what should be taught in future classes may create higher expectations among the students.

The study has also found that confirmation has a positive relationship for both groups of students. The findings corroborate other findings from previous studies by Alraimi et al. (2015) and Daılhan and Akkoyunlu (2016). They indicate that once students attain what they expected from the online session, they will be satisfied with online learning. Thus, once the lecturers promise to deliver certain topics, they must ensure that they deliver these topics effectively to fulfil the students' expectations. Once expectations are met or confirmed, the students will be satisfied with the online learning session.

Readiness has been found to have a positive relationship with willingness to continue an online learning program for both groups of students. The findings are similar with that of Gupta and Maurya (2020) and Alghamdi et al. (2018). The results indicate the fundamental nature of the readiness factor to influence students' willingness to continue to use online learning. Readiness can be formed by numerous factors, such as technology, network and human readiness. Hence, if universities still insist on continuing teaching and learning via online platforms rather than in classrooms, the readiness factor must be of utmost concern. Once students are ready, they are more willing to pursue online learning sessions smoothly. Introducing financial assistance to ease the burden of networking costs is a wise idea to sustain, as the study reveals that a majority of the students do not have a fixed Internet connection at home.

Attitudes have also been confirmed to have a positive relationship with willingness to continue online learning for both social science and science students. The results were aligned with Dai et al. (2020) and Wu and Chen (2017) in their studies on students' intention to continue MOOCs. This outcome confirms that by having a positive attitude, students' willingness to continue online learning increases. The parties involved in the online learning could create a positive attitude among the students. A good understanding on the current situation of the COVID-19 pandemic enables students to understand and have a positive attitude on why the lesson should be continued online. Lecturers should also fulfil their significant role especially well when they have several students from Internet-disadvantaged areas. By recording the sessions and uploading them to the cloud storage, lecturers can share the links via chatting applications. This setup may form a positive attitude among the students.

The study has also revealed that satisfaction has a positive effect on the willingness to continue online learning for both groups of students. The finding strengthens the previous study by Cheng and Yuen (2020) and Cheng (2020), who found similar results. Thus, we have clear information that if the university is planning to continue the use of online sessions, students having a positive experience from the previous semester is crucial. Once they are satisfied, they will have no issue in continuing to use online learning either for social science or for science programs.

Interestingly, for the last direct hypothesis, the study has found that self-efficacy is not a significant factor towards students' willingness to continue to use online sessions to pursue their study. The unsupported hypothesis is not only for social science students but also for science students. The findings are similar to those of San-Martín et al. (2020), who found that self-efficacy is not a significant factor for the teachers' continuance intention to commit to online learning. The logical reasoning why the hypotheses are not supported is that the university students in question are categorised as Gen Z. As mentioned extensively in the literature, Gen Z are bound to use the Internet because they have always had access it. Thus, the issue on online platforms is not a big change for them. Self-efficacy does not affect their willingness to continue the online session because these students were born in an era when online-based activities are commonplace.

The results for the individual group show that no difference exists between social science and science students. However, given that the existing literature confirms that learning approaches are dissimilar between these two groups, the study continues the analysis with MGA. Using MGA and the Welch-Satterthwaite tests, the study has found that out of six hypotheses tested for MGA, five hypotheses are not supported. Thus, no difference is observed between the groups for H1, H2, H3, H5 and H6. However, the only supporting hypothesis for the MGA test is for readiness. A significant difference exists in the readiness to continue to use online learning between the two groups. The analysis shows that social science students are more prepared for such setup compared with science students. This difference in readiness is understandable, as science students learn using the psychomotor domain with greater emphasis on practical and hands-on sessions found in laboratories. Even if the lecturers provide them with videos, which they can review more than once, the feeling of handling the actual experiment is irreplaceable. As mentioned by Azlan et al. (2020), experiments in laboratories cannot be replaced by videos. All other hypotheses show that no differences exist between science students and social science students.

The study has also revealed no significant difference between science and social science students or between expectation and satisfaction. This outcome indicates that both groups of students are satisfied if they receive what they expect from the online session.

In addition, no significant differences have been observed for the relationship between confirmation and satisfaction for both groups of students. Thus, confirmations are similar in both groups. Moreover, some of the science students also learn similarly to social science students except for the subjects or learning tasks which require a laboratory or field visit to perform certain practical tests involving touching objects. Thus, students in the two groups still have the same confirmation from the online learning.

Furthermore, no significant difference exists between the two groups in terms of the relationship between attitude and willingness to continue online learning. This lack of difference is due to both groups of students having the same understanding that no option is available apart from using online learning platforms during the COVID-19 pandemic. Hence, the lack of alternatives explains why they have a similar attitude towards willingness to continue online learning during this period.

Given that both groups belong to the same generation, their self-efficacy is also similar towards online learning. This aspect confirms the findings that both groups have an identical capability to handle online learning. Lastly, the study has also found no statistical difference in the relationship between satisfaction and willingness to continue online learning. Once the students are satisfied, both groups are willing to continue to use online learning to gain knowledge from their respective lecturers.

6 Conclusions

The study compared the willingness to continue online learning between science students and social science students from UMT. Understanding that both groups were dissimilar in terms of subjects and style of learning, the study revealed meaningful information to several parties to decide what was best for the students, university, industry and country in the long run. Besides claiming these groups were different, the analysis showed that most of the factors had a similar effect towards students' willingness to continue using online learning, except for readiness. The findings showed that social science students were more prepared to use online learning than science students. As science students required more hands-on sessions in the laboratory or field, they had lower readiness and willingness to continue to use online learning. Other than that aspect, both groups had no difference.

Distance education or distance learning using the online system is not new to science students and social science students. Normally, distance learning education is preferable due to the impossibility of physically attending a classroom, lack of time or distance of residence or even unwillingness to be in the classroom regularly (Oliveira et al. 2018). ODL academic programs are not new to both programs. Numerous universities around the world offer ODL programs to provide learners from other countries the opportunity to connect or engage with the university without being physically at the university. Normally, ODL programs for pure and applied science embed a virtual laboratory in their courses. Furthermore, to achieve the higher level of psychomotor domain that is stated in the course learning outcomes, some adjustment in terms of course design and delivery have been implemented. In addition, ODLs require effective curriculum design and techniques to assess the students' psychomotor achievement and align them with the requirements of quality assurance standards, professional bodies and industry.

If universities or higher education institutions continue relying on online learning, proper modification in their curriculum should be made to ensure that the quality of graduates is unquestionable. Furthermore, the current curriculum was based on normal situations. In online platforms, the learning situations are totally different, especially in the evaluation of the assessments for each subject. Social science and pure science are measured differently. Thus, different approaches should be taken by the universities' top management to counter this issue for the benefit of students, universities and industries that reflect our needs and welfare, business, economic and environmental sustainability in the future.

6.1 Theoretical Contribution

The current study enriches the literature on online learning, especially during the COVID-19 pandemic, which most universities have been forced to use. Besides looking at the intention or reuse intention, the study has focused on how to enhance the students' willingness to continue online learning. Furthermore, scant literature has used ECT theory in education studies, especially for online learning. Our study effectively extends ECT theory with the attitude and readiness to enhance the research model's explanatory power. Despite confirming prior findings, the study contributes to the literature by comparing social science and science students on their willingness to use online learning at UMT.

6.2 Managerial Implication

The findings reveal the importance of expectation, confirmation, readiness, attitude and satisfaction towards the willingness to continue online learning. The management at universities and government could seriously consider these factors if they decide to continue requiring online learning. If any option or any clause allows a limited number of students to return to universities, science students should be prioritised. Authentic experience in the laboratory is a necessary experience and provides better explanations for particular scenarios for science students. The quality of students has a crucial impact on their future employability and career path. Given that social science students are more willing to continue to use online learning than science students, science students should be given priority if the universities are willing to allow their students to return to campus.

As noted, Malaysia still has an issue with Internet coverage. In addition, students from remote areas who have Internet accessibility or connectivity problems and still use prepaid lines for Internet access have suffered from this kind of limited data plan. They could be considered a priority for returning to campus. Universities and the government should not let these students lose their competitiveness from the lack of online data access. Although this situation is not their fault, authorities should aid in alleviating and supporting students' learning process, as they will be the future leaders of the nation.

6.3 Limitation and Recommendation for Future Studies

Each university has its social science and science programs. This study is limited by categorising students from the Faculty of Science and Maritime Environment (six programs), the Faculty of Fisheries and Food Science (seven programs), the Faculty of Ocean Engineering and Technology Informatics (eight programs) and the Faculty of Maritime Management (one program) to represent science programs. In contrast, students from the Faculty of Business, Economy and Social Development (six programs) and the Faculty of Maritime Management (one program) represent social science programs. Furthermore, all students are from UMT, thus limited the findings to be generalized to all universities in Malaysia or the whole world. Thus, future study should collect the data from different university in Malaysia, or from another country which offer both program science and social science for a better generalizability. Further studies should emphasise the effectiveness of online learning to deliver deep knowledge and understanding of the high level of the psychomotor domain for real-life applications. In addition, the variable of 'grit' proposed by Duckworth et al. (2007) should be included in future studies for better understanding on student behaviours. Research on other programs to represent the sciences, especially for medical and engineering fields that are highly dependent on psychomotor skills and assessment, is recommended. On top of that, other methods, models or theories on learning behaviour could be applied to provide other perspectives on the willingness to continue using online learning among pure science and social science students.

7 Appendix 1: Programs of Study

Faculty	Science Programs	Social Science Programs
Faculty of Business, Economics & Social Development		Bachelor of Economics (Natural Resources)
		Bachelor of Counselling
		Bachelor of Management (Marketing)
		Bachelor of Management (Policy Studies)
		Bachelor of Management Tourism
		Bachelor of Accounting
Faculty of Maritime Studies		Bachelor of Management (Maritime)
	Bachelor of Science (Nautical and Maritime Transportation)	
Faculty of Science and Maritime Environment	Bachelor of Science (Marine Biology)	
	Bachelor of Science (Marine Geoscience)	
	Bachelor of Science (Analytical and Environmental Chemistry)	
	Bachelor of Science (Biological Science)	
	Bachelor of Science (Chemical Science)	
	Bachelor of Science (Marine Science)	
Faculty of Fisheries and Food Science	Bachelor of Science in Agrotechnology (Aquaculture)	
	Bachelor of Science Agrotechnology (Crop Science)	
	Bachelor of Science Agrotechnology (Postharvest Technology)	
	Bachelor of Applied Science (Biodiversity Conservation and Management)	
	Bachelor of Applied Science (Fisheries)	
	Bachelor of Food Science (Food Service and Nutrition)	
	Bachelor of Food Science (Food Technology)	
Faculty of Ocean Engineering Technology & Informatics	Bachelor of Applied Science (Electronic and Instrumentation)	
	Bachelor of Applied Science (Maritime Technology)	
	Bachelor of Computer Science with Maritime Informatics	
	Bachelor of Science (Applied Mathematics)	
	Bachelor of Science (Financial Mathematics)	
	Bachelor of Science (Software engineering)	
	Bachelor of Science (Mobile Computing)	
	Bachelor of Technology (Environment)	

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Code Availability Not applicable.

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