ANEXO G: CULTURAL VALUES AND TECHNOLOGY ADOPTION: A MODEL COMPARISON WITH UNIVERSITY TEACHERS FROM CHINA AND SPAIN

Cultural values and technology adoption: A model comparison with university teachers from China and Spain

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ABSTRACT

In this study, we investigated how certain cultural values influenced Chinese and Spanish university teachers' intentions to use technology. Four hundred and twenty-six Chinese university teachers and 404 Spanish university teachers participated in the study. The participants completed self-designed questionnaires based on Hofstede's cultural dimensions (individualism-collectivism, power distance, uncertainty avoidance and indulgence-constraint) and other variables widely used in the research on technology acceptance (e.g., subjective norms and behavioural intention). We found consistent and significant relationships between subjective norms and behavioural intention in both the Spanish and Chinese samples. In addition, we found that the teachers' perceived cultural preferences influenced their subjective norms and intentions to use technology in both the Chinese and Spanish samples. However, the relationships between these variables were different in the Spanish and Chinese samples. In addition, we compared three models to determine the model that best fitted the data. This study contributes to our understanding of how culture influences teachers' intentions to use technology in the contexts of Spain and China.

Keywords

Culture; intention to use technology; Spain; China

1. Introduction

Originating from the information sciences (IS), the technology acceptance research initially focused on the acceptance of information technologies designed for work environments (Davis, 1989). To explain the attitudes and intentions of individuals towards using technology to perform certain tasks, researchers used different combinations of psychological and IS theories (e.g., self-efficacy, motivation and perceived usefulness) to examine the potential factors that may influence users' behavioural intentions to use technology (Teo, 2014). Theories that have been widely used in the technology acceptance literature include psychological constructs such as work motivation (Locke & Latham, 1990), intrinsic and extrinsic motivation (Ryan & Deci, 2000), self-efficacy (Bandura, 1977), hedonic motivation (Van der Heijden, 2004), reasoned action (Fishbein & Ajzen, 1975) and planned behaviour (Ajzen, 1991) and IS based models such as technology acceptance (Davis, 1989) and diffusion of innovation (Rogers, 2010). In the literature, scholars usually combine theories from psychology and IS to contextualise their research in diverse fields and focus on individual user's intentions to use technology in settings such as education (Teo, 2009; Teo, Huang, & Hoi, 2018), business (Pavlou, 2003; Venkatesh & Davis, 2000; Wu & Wang, 2005) and management (Lin, Fofanah, & Liang, 2011).

1.1. Problem statement

In the literature, the combinations of psychological and information sciences (IS) theories used to examine the factors that influence technology acceptance have almost reached a theoretical saturation point. This can be seen from the inclusiveness of the technology acceptance model 3 (TAM 3), which contains 17 variables (Venkatesh & Bala, 2008). However, TAM 3 did not reveal a high level of variance in the behavioural intentions of technology users – specifically, only 40-53% of variance was observed across the different periods (Venkatesh & Bala, 2008). In addition, studies have found inconsistent findings when contextualising technology acceptance theories and models in different cultures and settings. For example, in a study on Chinese university teachers, Teo et al. (2018) found that the perceived ease of use (PEU), a key variable in TAM, did not have a significant influence on users' attitudes to technology because the teachers were conscientious and focused on how the use of technology enhanced their teaching effectiveness and efficiency. Teo et al. (2018) examined how attitude influenced behavioural intention (BI) from a contextual and cultural perspective. Specifically, different from business and industrial settings, schools do not guarantee teachers any rewards for using technology. Moreover, in the Chinese collectivist culture, teachers have a strong 'we' consciousness and value the doctrine of the mean performance, and thus prefer to conform to expectations instead of making decisions based on personal likes or dislikes (Teo et al., 2018). In summary, these studies have encouraged researchers to take cultural influences into consideration when examining technology acceptance.

In a cross-cultural study, Srite (2006) also found major differences between Chinese and American students in terms of the influence of subjective norms (SN) on behavioural intention (BI). This relationship was only significant in the Chinese sample due to the Chinese preference for collectivist cultural values, which led the Chinese students to strongly value the salience of others' ideas. Srite (2006) also found another major difference in the relationship between perceived ease of use (PEU) and BI. In this case, the relationship was only significant in the US sample. Srite (2006) explained that if a technology requires less effort it might be more widely used because people may feel comfortable working with it and less frustrated. Moreover, the American preference for employment security, a friendly atmosphere and an environment in which work is less central and pressured may help explain the relationship between perceived ease of use and behavioural intention among US students. Finally, the relationship between perceived usefulness (PU) and behavioural intention was significant for the American students but not for their Chinese counterparts. This result was the opposite to Srite's assumption that the stronger masculinity of the Chinese students would mean that they placed higher value on work goals, achievement and success than their US counterparts. According to Srite (2006), it is possible that some unmeasured constructs influenced this relationship, and that PU and PEU are less important in a collectivistic culture.

In a study on technology acceptance among Lebanese and British university students, Tarhini, Scott, Sharma, and Abbasi (2015) found that the relationship between PU and PEU was only significant for the British sample. Although they did not measure cultural value preference, Tarhini et al. (2015) postulated that researchers should test the influence of culture on technology acceptance by empirically showing that TAM is biased in cross-cultural contexts (see also McCoy, Galleta, & King, 2005).

Considering the inconsistencies found in the above studies, researchers have highlighted the importance of taking cultural influence into consideration when researching technology acceptance (e.g., McCoy, et al., 2005; Straub, Keil, & Brenner, 1997; Srite, 2006). Culture teaches us what the important rules, rituals, norms, and procedures are within our society; culture also cultivates and reinforces our believes and values (Liu, Volcic, & Gallois, 2014). Thus, when considering technology acceptance and adoption, culture influences individual's thinking and attitudes, level of innovativeness and willingness to accept uncertainties, and also determines what norms are (how one should act in a situation in his or her organization) which indicates subjective norm. Considering such a big influence culture has on the way people think, it would be a logical assumption that culture may influence how people perceive technology. Given that the essential core of culture consists of traditional ideas (historically derived and shared) and their attached values (Kroeber & Kluckhohn, 1952), cultural factors can be considered to influence how people think and behave (Hofstede, 2001).

Overall, there are two main trends in the research on the influence of culture on technology acceptance. Specifically, studies have compared participants from two different cultural groups (e.g., Srite, 2006; Tarhini et al., 2015) and used culture as a variable to test its potential moderating effects. However, an obvious problem in the technology acceptance studies that have used culture as a variable is that they do not examine the direct influence that culture has on the key technology acceptance variables such as subjective norm and behavioural intention. In addition, the majority of these studies only use students as participants, hence the findings may not hold for other educational users, such as teachers. To the best of our knowledge, no studies have examined how culture influences teachers' technology acceptance. Given that teachers are the key change agents in the use of technology in education (Teo, 2009), it is imperative to understand how their BI to use technology is affected by cultural influences.

1.2. The aim and context of this study

This study aimed to investigate the influence of the perceived culture of teachers on their intentions to use technology. We examined the widely-used cultural value dimensions proposed by Hofstede (2011), namely, power distance, individualism-collectivism, uncertainty avoidance and indulgence-constraint. Accordingly, the results of this study have the potential to enhance our understanding of the role of technology acceptance in education, with a particular emphasis on how culture moderates the intention to use technology among educational users such as teachers.

The study was guided by the research question: To what extent does culture influence the behavioural intentions of educational users? Because few studies have examined the link between culture and technology acceptance (Srite, 2006; Tarhini et al., 2015), it remains unclear how culture influences technology acceptance (Tarhini, Hong, Liu, & Tarhini, 2017). Therefore, we proposed to test several models to explore how culture influences technology acceptance.

2. Literature review and model development

2.1. Behavioural intention to use technology

Behavioural intention was initially proposed as a key variable that directly reflects an individual's actual behaviour (Venkatesh & Davis, 2000) in the theories of reasoned action (TRA) (Fishbein & Ajzen, 1975) and planned behaviour (TPB) (Ajzen, 1991). Davis (1989) included BI as an endogenous variable in the TAM to explain the technology acceptance among users in the IS field. In the TAM, BI is directly explained by perceived usefulness and attitude, and indirectly explained by perceived ease of use. Although TAM has been well recognized for its validity and reliability in explaining users' behavioral intentions to use technology, researchers have been criticizing TAM lacks consideration of external variables that would influence the key constructs of TAM (e.g., Venkatesh & Bala, 2008), particularly, researchers have claimed the necessity to consider cultural influence when examining individual's technology acceptance given that culture influences people's thinking and behavior as mentioned above (e.g., Teo et al, 2018; Teo & Huang, 2018). Thus, some technology acceptance researchers subsequently extended the TAM by specifying antecedents to its core variables, such as perceived usefulness (e.g., with subjective norm) and perceived ease of use (e.g., with computer self-efficacy) (Venkatesh & Bala, 2008). Behavioural intention is used as an endogenous variable in TAM 2 (Venkatesh & Davis, 2000), the unified theory of acceptance and use of technology (UTAUT) (Venkatesh, Morris, Davis, and Davis, 2003) and TAM 3 (Venkatesh & Bala, 2008), and has been examined in numerous studies on technology acceptance in educational settings (e.g., Teo, 2009, Teo et al., 2018, Tarhini et al., 2017). Others have been devoted in studying to what extent cultural values (e.g., individualism, power distance) influences individual's technology acceptance by treating cultural values as moderators and examining their moderating roles on certain relationships (e.g., Tarhini et al., 2017). In these studies, BI is operationalised as the degree to which a user is willing to use technology (e.g., Davis, 1989). On this basis, we used BI as an endogenous variable in this study.

As mentioned earlier in the introduction section, current culture-related technology acceptance studies are mainly focused on either cross-cultural comparisons (e.g., Tarhini et al., 2015) or treating culture as moderators for certain relationships (e.g., Tarhini et al., 2017), studies examining the direct influence that culture has on behavioral intentions are barely seen (see Teo & Huang 2018 as an exception). Furthermore, studies using teachers as study samples are even less, however, inviting teachers as participates are important to technology acceptance studies in educational context considering teachers as adults are usually more mature than students and their thinking and perceptions are comparatively stable. Thus, we believe it is very crucial and meaningful to test culture influence on behavioral intentions among teachers. In doing so, the study will address the research gaps and provide people with further understanding of how or to what extent culture influences people's intentions to use technology. The following sections further introduced the rationales of included variables in this study.

2.2. Subjective norms

The rationale for including subjective norm in the current research to examine teachers' intentions to use technology is based on the theory of reasoned action (Fishbein & Ajzen, 1975) and the theory of planned behavior (Ajzen, 1991). Both theories have indicated the importance of taking individual's psychological feature into consideration when examining his or her behavior.

Reflecting normative beliefs, subjective norm measures a 'person's perception that most people who are important to him or her think he or she should or should not perform the behaviour in question' (Fishbein & Ajzen, 1975, p. 302). As a manifestation of social influence, SN was included as a variable in the theory of reasoned action (TRA) (Fishbein & Ajzen, 1975) and later in the theory of planed behaviour (TPB) (Ajzen, 1991) to explain an individual's intention to perform a certain act. Although the original TAM did not include SN, Davis (1989) acknowledged the need for further research on the conditions and mechanisms through which social factors influence usage behaviour (Davis, 1989).

Following David (1989), studies have found that subjective norm has significant effects on BI (see, for example, Taylor & Todd, 1995). Venkatesh and Davis (2000) found a similar relationship between SN and behavioural intention in TAM 2 and TAM 3 (Venkatesh & Bala, 2008). They proposed that the direct relationship between SN and BI was predicated on the weight that technology users place on the views of those they perceive to be important to them in the workplace.

In an educational setting, Ballone and Czerniak (2001) found that students' positive opinions of technology led to an increased use of computers by teachers in the classroom. Moreover, because teachers may also consider school administrators, leaders and peers to be 'important people' (Marcinkiewicz & Regstad, 1996; Teo, Lee, & Chai, 2008), their perceptions can have a significant impact on teachers' intentions to use technology (Teo, 2009). In other words, teachers may use technology in the classroom if they believe their significant others or important referents think they should. We formulated the relationship between SN and BI examined in this study based on the above discussion.

2.3. Culture

Culture is reflected in the social behaviours and norms found in specific societies. As one of the central concepts in anthropology, culture encompasses a range of phenomena that are transmitted through social learning. Although culture has been widely studied in the fields of anthropology and management (Srite, 2006), it has received little attention in technology acceptance studies (Teo & Huang, 2018). Correa, Perry, Sims, Miller, and Fang (2008) provided evidence to suggest that the espoused cultural values of teachers may influence their approaches in designing and implementing coursework.

To test cultural influence on teachers' intentions to use technology, we used Hofstede's cultural dimension theory which established a major research tradition in cross-cultural psychology and has also been drawn upon by researchers and consultants in many fields such as business, management, and education (e.g., Srite, 2006; Tarhini et al., 2015), and continues to be a major resource in cross-cultural fields. Although some scholars (e.g., McSweeney, 2002) indicated Hofstede's cultural dimensions are limited due to the questionable validity and reliability to test different culture, more recent studies suggested Hofstede's cultural dimensions are useful and valid in exploring cultural influence on individual's technology acceptance (e.g., Tarhini et al., 2017; Teo & Huang, 2018). Therefore, in the current study we used the cultural dimensions proposed by Hofstede (2001) to measure the cultural influences on teachers' behavioural intentions to use technology, because these dimensions have been widely used in studies on measuring culture (Tarhini et al., 2017). The cultural dimensions are power distance, individualism-collectivism, uncertainty avoidance and indulgence-constraint. In the current study, we have examined Chinese and Spanish teachers' perceptions of these cultural dimensions and explored their influence on teachers' intentions to use technology in teaching, given that cultural influences people's thinking as mentioned earlier, in addition, Chinese and Spanish are suggested to perceive very differently in these cultural dimensions (Hofstede, 2001). For example, according to the most updated information provided by *Hofstede Insights,* an openly accessed website which provides cultural comparison information for people who are interested in culture, Chinese and Spanish score differently in dimensions of power distance ($PD_{Chinese} = 80$, $PD_{Spanish}=57$), individualism-collectivism ($IC_{Chinese} = 20$, $IC_{Spanish} = 51$), uncertainty avoidance ($UA_{Chinese} = 30$, $UA_{Spanish} = 86$), and indulgence -constraint ($IN_{Chinese} = 24$, $IN_{Spanish} = 44$).

Power distance (PD) measures the extent to which an individual expects and accepts that people possess different degrees of power (Hofstede, 2011). The rationale of PD is that teachers who score highly in PD tend not to disagree with their supervisors (faculty leaders, principles). Instead, the teachers perceive the views of their supervisors to be important and feel pressured to comply with them (Lin, 2014). Tarhini et al. (2017) found that PD influenced the relationship between subjective norm and behavioural intention among university students and that the relationship between SN and BI was stronger among students with a higher PD.

Individualism-collectivism (IC) refers to the extent to which individuals prioritise their self-interest over the group's interest (Hofstede, 2001). People who rank low on individualism (high on collectivism) tend to have a strong sense of belonging as members of a group and believe that it is important to follow group decisions (Hofstede, 1980). In contrast, people who rank high on individualism (low on collectivism) are self-oriented in their thinking and behaviour, and are encouraged to take initiative and make individual decisions (Hofstede, 2001).

Uncertainty avoidance (UA) refers to the extent to which an individual tolerates ambiguity and uncertainty (Hofstede, 2011). People who score high on UA usually attempt to reject all deviant and uncertain ideas and behaviours and seek ways to reduce uncertainty (Hofstede, 2001). In a study on language education, Lai, Wang, Li, and Hu (2016) found that UA plays an important role in influencing students' adoption of technology beyond the classroom.

Indulgence-constraint (IN) refers to the extent to which people try to control their desires and impulses (Hofstede, 2011). Relatively weak impulse control is called indulgence and people in indulgent cultures tend to focus more on individual happiness, well-being, leisure time, freedom and personal control. In contrast, people in restrained cultures (relatively strong impulse control) prefer not to freely express their positive emotions and happiness, and do not consider freedom and leisure to be important.

2.4. Model Development

Culture influences people in diverse ways and can directly influence people's beliefs and behaviour (Hofstede, 2001). However, because culture can be learned and shared by group members, culture may influence behavioural intention through subjective norm, given that SN is considered to have a strong influence on group members, especially the important people in an organisation. Therefore, we propose three models to explain the direct relationships between the four cultural dimensions and behavioural intentions (Figures 1 to 3)

Model 1 includes the following hypotheses: H1, Culture significantly influences subjective norm and H2a, SN significantly influences BI.

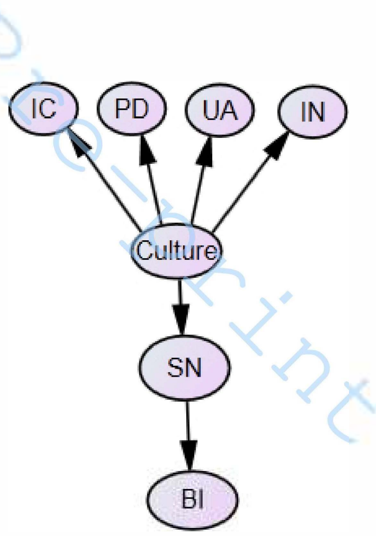

Figure 1. Research model 1.

Note. IN = indulgence-constraint index; UA = uncertainty avoidance index; PD = power distance index; IC = individualism-collectivism index; SN = subjective norm; and BI = behavioural intention.

Model 2 includes the following hypotheses: H2b, subjective norm significantly influences behavioural intention; H3a, indulgence-constraint index (IN) significantly influences SN; H4a, uncertainty avoidance index (UA) significantly influences SN; H5a, power distance index (PD) significantly influences SN and H6a, individualism-collectivism index (IC) significantly influences SN.

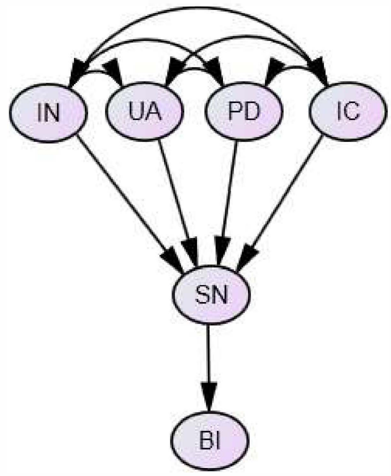

Figure 2. Research model 2

Note. IN = indulgence-constraint index; UA = uncertainty avoidance index; PD = power distance index; IC = individualism-collectivism index; SN = subjective norm; and BI = behavioural intention.

Given that culture consists of traditional ideas and their attached values and that these values influence how people think and behave (Hofstede, 2001; Kroeber & Kluckhohn, 1952), we believe that it is plausible to propose direct links between cultural values and behavioural intention. Therefore, model 3 includes the following hypotheses: H2c, subjective norm significantly influences BI; H3b, indulgence-constraint index significantly influences SN; H4b, uncertainty avoidance index significantly influences SN; H5b, power distance index significantly influences SN; H6b, individualism-collectivism index significantly influences SN; H7, IN significantly influences BI; H8, UA significantly influences BI; H9, PD significantly influences BI and H10, IC significantly influences BI.

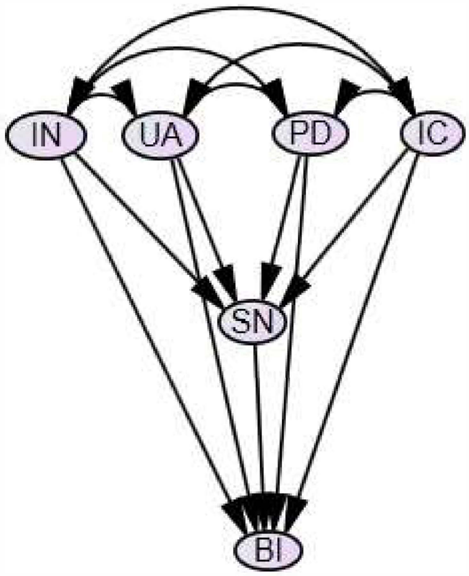

Figure 3. Research model 3

Note. IN = indulgence-constraint index; UA = uncertainty avoidance index; PD = power distance index; IC = individualism-collectivism index; SN = subjective norm; and BI = behavioural intention.

3. Method

3.1. Participants

The participants in this study were university teachers from Spain and China. As mentioned earlier, these two countries have nearly opposite cultural dimensions according to the Hofstede research reports (https://www.hofstede-insights.com/product/compare-countries/), in addition, teachers in the two countries have been encouraged to use technology in teaching while the actual usages are problematic (Sánchez-Prieto, Olmos-Migueláñez, & García-Peñalvo, 2016; Huang, Teo, & Zhou, 2017), we believe that it is appropriate to test whether the relationships between the cultural dimensions and technology acceptance variables vary between Spanish and Chinese teachers. Thus, the second aim of this study was to investigate whether the cultural dimensions have different effects on the Spanish and Chinese teachers' intentions to use technology. The third aim was to specify a model that can best explain the teachers' intentions to use technology in the two countries. Table 1 shows the most updated information on the perceptions of cultural dimensions among Spanish and Chinese.

Table 1. Cultural differences between Spain and China

	Power distance	Individualism	Uncertainty avoidance	Indulgence
Spain	57	51	86	44
China	80	20	30	24

Note. Values based on the Hofstede research website (https://www.hofstede-insights.com/product/compare-countries/)

3.2. Procedure

Data for both countries were collected using the convenient sampling technique by means of an online survey. Specifically, the Spanish teachers received emails that included a link to a questionnaire on Google Drive and the Chinese teachers were accessed through an online survey provided by WeChat, a popular free messaging and calling app in China. As a social media tool, the WeChat software allows researchers to get access to teachers from diverse universities.

In both cases the data collection was performed through a snowballing procedure. Consents were received from the Spanish and Chinese participants and they were informed of their rights to withdraw from the study at any time for any reason. Altogether, through online questionnaires, 830 questionnaires were collected; 404 from Spanish teachers from 43 Spanish universities and 426 from Chinese teachers from 93 Chinese universities. We believe the generalizability of samples from the two countries are satisfying for research aim although not perfect considering the large population of the two countries. The representation of males and females was relatively equivalent, at 52.4% and 47.6%, respectively. The mean age was 42.64 years (SD = 9.66). The participants were from diverse academic fields, including the sciences (20%), engineering (33.2%), social sciences and humanities (46.8%). On average, the participants had 12 years of teaching experience (SD = 8.00).

3.3. Instrument

The self-designed survey instruments comprised two parts. The first part collected the participants' demographic information, such as gender, age, teaching experience and the technologies they use in teaching. The second part comprised a set of items (measured by 7 point Likert Scale, 1 = strongly disagree, 7 = strongly agree) representing the underlying constructs of interest, namely, subjective norm (4 items) (adapted from Fishbein & Ajzen, 1975), behavioural intention (4 items) (adapted from Davis, 1989), the cultural dimensions of power distance index (3 items) (adapted from Hofstede, 2011), individualism-collectivism index (5 items) (adapted from Hofstede, 2011), uncertainty avoidance index (5 items) (adapted from Hofstede, 2011) and indulgence-constraint index (4 items) (adapted from Hofstede, 2011). The details of the items used in this study are provided in Appendix A.

4. Results

4.1. Descriptive statistics

SPSS 22.0 was used to compute the descriptive statistics and test the univariate normality. After cleaning the data to delete questionnaires either involving a mass of incomplete information or unengaging answers (same answers for all items), the samples for Spain and China were reduced to 385 and 421, respectively. The values for the cultural dimensions reported by the Spanish and Chinese teachers varied from 3.55 to 5.82 and 4.51 to 5.79, respectively, and the SDs varied from .85 to 1.31 and .98 to 1.43, respectively. For SN and BI, the means were 5.57 (SD = 1.17) and 6.48 (SD = .74) for the Spanish teachers, and 5.73 (1.15) and 6.08 (1.09) for the Chinese teachers. The figures are shown in Table 2. For the Spanish sample, the skewness and kurtosis varied from -1.84 to .03 and from -.28 to 4.00, respectively. For the Chinese sample, the skewness and kurtosis varied from -1.35 to -.23 and from -.27 to 1.87, respectively. The results indicated that the Spanish and Chinese samples both achieved normal distributions based on the respective criteria of | 3 | and | 8 | for skewness and kurtosis (Kline, 2010).

Table 2. Descriptive results for the Spanish and Chinese teachers

	Power distance	Individualism	Uncertainty avoidance	Indulgence	Subjective norms	Behavioural intention
Spain	3.55	4.5	4.88	5.82	5.57	6.48
China	4.51	5.19	5.3	5.79	5.73	6.08

4.2. Test of the measurement model

We conducted confirmatory factor analysis (CFA) with maximum likelihood estimation in Amos 22.0 to verify the factor structure of the observed variables underlying the constructs and analyse the congeneric measurements with uncorrelated errors. We used Mardia's coefficient to test the multivariate normality of the observed variables. The Mardia's coefficients for the Chinese and Spanish samples were 325.297 and 263.852, respectively, much lower than the 650 calculated by the formula p (p+2), where p represents the number of observed variables. Therefore, the multivariate normalities of the Spanish and Chinese samples were confirmed (Raykov & Marcoulides, 2012).

We used the composite reliability (CR) and average variance extraction (AVE) to test the reliability and validity of the constructs used in this study, with values of .50 and above indicating adequate levels (Fornell & Larcker, 1981). Standardised estimates of the items were conducted, with values greater than .50 indicating that the items were significantly related to their underlying constructs (Hair, Black, Babin, & Aunderson, 2010). The results for the item loadings, CRs and AVEs for the Spanish, Chinese, and the whole sample were in the acceptable ranges (see Table 3), except for the AVEs for PD and indulgence for the Spanish sample. However, the CRs and standardised estimates of these two variables for the Spanish sample supported the reliabilities of their items.

Table 3. Results of the measurement model

			Spain			**China**			**Whole**	
Constructs	Items	SE	CR	AVE	SE	CR	AVE	SE	CR	AVE
IC	IC1	0.84	0.90	0.65	0.85	0.93	0.72	0.85	0.92	0.68
	IC2	0.80			0.87			0.85		
	IC3	0.94			0.88			0.90		
	IC4	0.84			0.86			0.83		
	IC5	0.56			0.80			0.68		
PD	PD1	0.74	0.71	0.45	0.80	0.84	0.64	0.80	0.81	0.60
	PD3	0.65			0.74			0.72		
	PD4	0.62			0.86			0.79		
IN	IN1	0.77	0.75	0.44	0.88	0.80	0.50	0.82	0.78	0.47
	IN2	0.81			0.74			0.76		
	IN3	0.51			0.66			0.61		
	IN4	0.50			0.51			0.51		
BI	BI1	0.88	0.94	0.79	0.91	0.96	0.84	0.90	0.95	0.83
	BI2	0.88			0.92			0.91		
	BI3	0.89			0.93			0.92		
	BI4	0.91			0.92			0.92		

UA	UA1	0.74	0.86	0.57	0.86	0.93	0.72	0.82	0.90	0.65
	UA2	0.90			0.93			0.91		
	UA3	0.91			0.89			0.89		
	UA4	0.58			0.77			0.68		
	UA5	0.56			0.79			0.69		
SN	SN1	0.87	0.95	0.83	0.86	0.94	0.79	0.86	0.95	0.81
	SN2	0.96			0.92			0.94		
	SN3	0.91			0.90			0.91		
	SN4	0.90			0.88			0.89		

Note. IN = indulgence-constraint index; UA = uncertainty avoidance index; PD = power distance index; IC = individualism-collectivism index; SN = subjective norm; BI = behavioural intention.
SE = standardised estimates.
CR = composite reliability.
AVE = average variance extracted.

The comparative fit index (CFI) and Tucker-Lewis index (TLI) were used to analyse the fit of the measurement model, with values greater than .90 indicating an acceptable fit. We also calculated the root mean square error of approximation (RMSEA) and standardised root mean square residual (SRMR), with values less than .08 indicating acceptable results (Hair et al., 2010). The model fit indices for the measurement models indicated they had acceptable fit to the data (Spanish, Chinese, and whole sample). The model fit indices were CFI = .915, TLI = .902, RMSEA = .074 [.068, .080], SRMR = .0660 for the Spanish sample; CFI = .927, TLI = .916, RMSEA = .079 [.073, .084], SRMR = .0519 for the Chinese sample and CFI = .931, TLI = .920, RMSEA = .072 [.068, .076], SRMR = .0557 for the whole sample.

4.3 Test of the structural models

After confirming the factor structure of the constructs (CFA), we then tested the structural models. We proposed three models to explore the potential influence of culture on the teachers' intentions to use technology, and the results for the relationships proposed in the three models are described in Table 5. Generally, although culture influenced the teachers' perceptions of technology use, the Spanish and Chinese teachers had different perceptions of the proposed relationships.

The results of model 1 indicated that the proposed paths, namely the culture→SN and SN→BI relationships, were consistent in the Spanish and Chinese samples. The results of model 2 indicated that the IN→SN and SN→BI relationships were significantly supported in both the Spanish and Chinese samples. The IC→SN and PD→SN relationships were only significantly supported in the Spanish sample, whereas the UA→SN relationship was only significantly supported in the Chinese sample. The results for model 3 indicated consistency of significance in the IN→SN and SN→BI relationships for the Spanish and Chinese samples; for the other relationships, inconsistencies were found for the two country groups. All three models achieved acceptable levels of fit. The results of the model fit are shown in Table 6 (Spanish and Chinese samples) and Table 7 (whole sample).

For the Chinese sample, the variances of SN and BI explained were 33% and 57% (model 1), 34% and 57% (model2) and 33% and 58% (model 3). For the Spanish sample, the variances of SN and BI explained were 18% and 20% (model 1), 13% and 20% (model 2) and 13% and 22% (model 3). Therefore, model 3 is the model that explains the higher percentage of the variance of the outcome variable (BI) in both samples.

Table 5. Results of the structural model.

		China		**Spain**		**Whole**	
	Hypotheses	Path coefficient	results	Path coefficient	results	Path coefficient	results
Model 1	Culture→SN	0.574***	-	0.421***	-	0.513***	-
	SN→BI	0.752***	-	0.443***	-	0.582***	-
	Culture→IC	0.842***	-	0.537***	-	0.729***	-
	Culture→PD	0.791***	-	0.647***	-	0.747***	-
	Culture→UA	0.769***	S	0.663***	S	0.743***	S
	Culture→IN	0.724***	S	0.32***	S	0.548***	S
Model 2	IC→SN	0.104	NS	0.129*	S	0.121*	S
	PD→SN	-0.047	NS	0.167*	S	0.074	NS
	UA→SN	0.307***	S	0.085	NS	0.189***	S
	IN→SN	0.3***	S	0.162**	S	0.237***	S

	SN→BI	0.753***	S	0.443***	S	0.583***	S
Model 3	IC→SN	0.094	NS	0.128*	S	0.117*	S
	PD→SN	-0.039	NS	0.168*	S	0.085	NS
	UA→SN	0.308***	S	0.082	NS	0.183***	S
	IN→SN	0.291***	S	0.161**	S	0.232***	S
	SN→BI	0.661***	S	0.396***	S	0.505***	S
	IC→BI	0.105	NS	0.06	NS	0.078	NS
	PD→BI	-0.081	NS	-0.072	NS	-0.208***	S
	UA→BI	0.005	NS	0.138*	S	0.122**	S
	IN→BI	0.134*	S	0.074	NS	0.176***	S

Note. IN = indulgence-constraint index; UA = uncertainty avoidance index; PD = power distance index; IC = individualism-collectivism index; SN = subjective norm; and BI = behavioural intention. SE = standardised estimates. CR = composite reliability. AVE = average variance extracted.
S = supported.
NS = not supported
*p<.05, **p<.01, ***p<.001

To select the model that best fitted the data, we compared a set of model fit indices using the whole sample dataset to identify the model that was closest to reality, as suggested by Burnham and Anderson (2004). In addition to the CFI, TLI, SRMR and RMSEA, we considered the expected cross-validation index (ECVI), the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). The ECVI ranks models based on their ability to cross-validate with other samples of equivalent size, with the model having the lowest ECVI being desired (Browne & Cudeck, 1989). The AIC estimates the quality of the model of interest relative to other models, and is a simple and versatile procedure for model selection (Akaike, 1973; Bozdogan, 1987). The BIC indicates the model parsimony with the lowest value preferred (Schwarz, 1978), and provides a criterion for selecting the optimal model among a finite set of models.

The results in Table 7 show that model 3 has the highest values for CFI (.931) and TLI (.920), and the lowest values for SRMR (.0557) and RMSEA (.072). In addition, model 3 has the lowest

ECVI (1.831) and AIC (1473.934) compared with model 2 and model 1. The BIC value for model 3 is not the lowest (lower than model 2 but higher than model 1), which suggests that model 3 does not have the best model parsimony. However, considering that the model selection is not determined by a single criterion (Bozdogan, 1987) and the CFI, TLI, RMSEA, SRMR, ECVI and AIC all satisfied the model selection criteria, we concluded that model 3 best fitted the data. In addition, because models 2 and 3 are nested, we conducted a chi-square difference test to examine whether the two models were significantly different. The results indicated that the two models were significantly different ($\Delta\chi2 = 50.775$, $\Delta df = 4$, $p = .000$). Thus, it is appropriate to conclude that model 3 is significantly better than model 2. No invariance tests were conducted for models 1 and 3 because they have different model structures. In conclusion, according to the abovementioned model fit indices, model 3 best explained how culture influenced the teachers' intentions to use technology.

The results of the structural model (model 3) using the whole sample indicated that the amount of variance explained for SN and BI was 23% and 39%, respectively. As an outcome variable, the variance explained for BI in model 3 was higher than that for model 2 (34%) and model 1 (34%).

Table 6. Model fit indices (Spain and China)

	CFI		TLI		RMSEA		SRMR	
	China	Spain	China	Spain	China	Spain	China	Spain
Model 1	0.919	0.913	0.909	0.903	.082 [.077, .087]	.074 [.068, .079]	0.0756	0.0765
Model 2	0.926	0.914	0.916	0.902	.079 [.074, .084]	.074 [.068, .080]	0.0591	0.0733
Model 3	0.927	0.915	0.916	0.902	.079 [.073, .084]	.074 [.068, .080]	0.0519	0.066

Note. CFI = comparative fit index, TLI = Tucker-Lewis index, RMSEA = the root mean square error of approximation and SRMR = standardised root mean square residual.

Table 7. Model fit indices (whole sample)

	CFI	TLI	RMSEA	SRMR	ECVI	AIC	BIC
Model 1	0.925	0.916	.074 [.070, .077]	0.0751	1.935	1557.632	1561.371
Model 2	0.928	0.918	.073 [.069, .077]	0.0651	1.884	1516.609	1802.826
Model 3	0.931	0.92	.072 [.068, .076]	0.0557	1.831	1473.834	1779.819

Note. CFI = comparative fit index, TLI = Tucker-Lewis index, RMSEA = the root mean square error of approximation, SRMR = standardised root mean square residual, ECVI = expected cross-validation index, AIC = Akaike information criterion and BIC = the Bayesian information criterion.

5. Discussion

Given the lack of research on the relationship between technology acceptance and culture (Srite, 2006), in this study, we examined how culture influenced teachers' intentions to use technology in the context of higher education institutions in Spain and China. Also, since it remains unclear how culture influences technology acceptance (Tarhini, Hong, Liu, & Tarhini, 2017), We tested three models based on related theories and literature, and we used a model selection approach to specify the model that best explained the teachers' perceptions of how culture influenced their intentions. We discuss the research findings based on results of proposed research models in the following sections.

5.1. Cultural influence on teachers' intentions to use technology: Results from model 1

The results of model 1 indicated that for both the Spanish and Chinese teachers, culture (as indicated by IC, PD, UA and IN) was significantly related to subjective norm, thus suggesting that culture was an important factor influencing the teachers' perceptions of SN. This is in line with research that suggests that culture should be taken into consideration when conducting technology acceptance research (McCoy et al., 2005; Teo & Huang, 2018). Moreover, consistent with previous studies (e.g., Huang et al., 2017; Venkatesh & Bala, 2008), the Spanish and Chinese teachers believed that the suggestions and opinions of important figures significantly influenced their intentions to use technology in teaching, as noted by the significant SN→BI relationship found in this study.

5.2 Cultural influence on teachers' intentions to use technology: Results from model 2

The Chinese and Spanish teachers indicated that there was a significant relationship between subjective norm and behavioural intention. This finding suggests that if teachers perceive that important figures (e.g., students) think they should use technology, the teachers will be very likely to use technology in the classroom. This finding is in line with previous studies (e.g., Huang et al., 2017). In addition, it is interesting to note that the SN and BI relationship was stronger for the Chinese teachers (.753) than for the Spanish teachers (.443). This finding is understandable because Chinese people tend to highly value group interests and are accustomed to acting in conformity with cultural norms (Hofstede, 2001; Teo & Huang, 2018).

With respect to the cultural dimensions proposed to influence subjective norm, consistency was only found in the indulgence-constraint (IN)→SN relationship, and the relationship was stronger in the Chinese sample (β = .3) than the Spanish sample (β = .162). In this study, we used indulgence-constraint index (IN) to measure the extent to which the teachers believed they had control over their desires and impulses by using items that inquired about the teachers' perceptions of happiness and wellbeing. The relationship between IN and SN suggested that the teachers who perceived themselves as happy and having a high level of wellbeing were more likely to be influenced by people who are important to the teachers.

It is interesting that a significant relationship between individualism-collectivism index and subjective norm was found in the Spanish sample, but not in the Chinese sample, which is opposite to what we assumed would be the case. The IC index measured the extent to which individual teachers were integrated into groups. In this study, the Spanish teachers showed a comparatively greater preference for individualism (although slightly collectivist (M = 4.5)) than the Chinese teachers (M = 5.19) who demonstrated a collectivist orientation. Nevertheless, the Spanish teachers indicated that they were more likely to perceive influence or even pressure from important figures. This result might be explained by Spain's inclusion in the Latin-European cluster (Gupta, Hanges, & Dorfman, 2002; Quinones, Rodriguez-Carvajal, Clarke, & Griffiths, 2016) because the countries in this cluster are characterised as possessing some collectivistic features within an individualistic system of values. From this perspective, the influence of IC on SN can be regarded as a manifestation of this peculiar form of collectivism. It is also worth noting that although the Chinese teachers' perceptions of subjective norm (SN) were consistent with studies indicating that the Chinese are highly collectivist-oriented (Hofstede, 2001; Triandis, 2018), their perceptions were not necessarily related to their preference for group interests; instead, SN was found to be significantly related to uncertainty avoidance index and indulgence-constraint index among Chinese teachers.

The power distance index measured the extent to which teachers expected and accepted that people possess different degrees of power (Hofstede, 2011). Example items are 'teachers should agree with the administrator or superior's decisions' and 'administrators should use authority and power when dealing with teachers'. PD was found to be significantly related to subjective norm (SN) in the Spanish sample, indicating that although Spanish teachers perceive others as having relatively equal status or power (M = 3.55), the PD increases their awareness of the social pressure to use ICT. Although the PD→SN relationship was surprisingly not supported in the Chinese sample, this is understandable considering that the participants in this study were university teachers who usually have a high degree of autonomy in making teaching-related decisions. Therefore, when we measure teachers' perceptions of the influence of their superiors or leaders on their decision making process, they may not think superiors or leaders play substantial roles, as it is the case when measuring students' perceptions of PD (e.g., Tarhini et al., 2017). The inconsistency of the PD→SN relationship in the Spanish and Chinese samples indicates that further research is needed in this area.

Although the relationship between uncertainty avoidance and subjective norm was not significantly supported in the Spanish sample, it was supported in the Chinese sample. This finding suggests that the Spanish teachers who avoided doing uncertain things (M = 4.88) and preferred to do tasks they were personally sure about, did not perceive others' opinions as important, and therefore, theses opinions would not influence their behavioural intentions to complete these tasks, for example, using technology in the classroom. However, the significant UA→SN relationship found in the Chinese sample indicates that Chinese teachers who tend to avoid doing uncertain or challenging tasks (M = 5.3) would be more inclined to perceive opinions from others as important, and furthermore, would be very likely to do these tasks.

5.3. Cultural influences on teachers' intentions to use technology: Results from model 3

Among the nine relationships proposed in model 3, two relationships (IN→SN, SN→BI) were consistently supported in both the Spanish and Chinese samples and two relationships (IC→BI, PD→BI) were not significantly supported in the two samples. For the SN→BI relationship, Chinese teachers perceived that subjective norm had a greater influence on behavioural intention than their Spanish counterparts. This finding may be attributable to the Chinese tradition of valuing harmony among group members and pursuing conformity in behaviour (Hofstede, 2001). The IN→SN relationship was also significantly supported in both the Spanish and Chinese samples, suggesting that teachers who perceive themselves as having free choices in life are happier and more inclined to follow the suggestions of significant figures.

Consistent with the findings from model 2, the IC→SN and PD→SN relationships were only supported in the Spanish sample. Considering that the IC→BI and PD→BI relationships were not significantly supported in the Spanish sample, the cultural influences of individualism-collectivism and power distance on the Spanish teachers' intentions to use technology may have been mediated by subjective norm. In the Chinese sample, the teachers' perceptions of important figures were not significantly influenced by IC and PD. Moreover, the influence of uncertainty avoidance on BI was mediated by SN in the Chinese sample, given the supported UA→SN relationship and unsupported UA→BI relationship. Different from the Chinese teachers, in the

Spanish sample, the UA→SN relationship was not significantly supported while the UA→BI relationship was. As Kilinc et al. (2016) noted, when teachers use technology in teaching, they tend to not only consider the pedagogical benefits but also weigh the risks related to technology use. The results for the Spanish sample suggest that the teachers who perceived themselves as avoiding doing tasks they were not used to or considered risky, did not consider the suggestions of important figures, but were still very inclined to use technology in the classroom. In addition, the IN→BI relationship was significantly supported in the Chinese sample, which suggests that teachers who perceive themselves as having free choices and as happy are more inclined to use technology in the classroom. In the Spanish sample, the influence of IN on BI may have been mediated by SN, because the IN→SN relationship was significantly supported in this sample.

5.4 Contributions, limitations and further research

In this study, we investigated how culture influenced Spanish and Chinese university teachers' intentions to use technology in the classroom. The results of this study contribute to the technology acceptance literature by providing empirical evidence on how culture influences teachers' intentions to use technology and the differences between Spanish and Chinese teachers. Our findings provide further evidence that culture influences people's perceptions and decision-making and suggest that researchers should consider cultural factors when conducting studies on technology acceptance and interpreting the results.

This study has a number of limitations. First, we used the convenient sampling technique to collect data in Spain and China, which may have influenced the generalisability of the results to the target sample (Bornstein, Jager, & Putnick, 2013). Thus, the results of this study may not be representative of university teachers' perceptions as a whole. Future research should include teachers from a number of different countries to achieve better generalisability. Second, although acceptable, the loadings for some of the items underlying the indulgence index for the Spanish sample were not very satisfying, which may have influenced the model fit and results of the structural model (Schumacker & Lomax, 2004). Future technology acceptance studies should consider the appropriateness of the items underlying the cultural dimensions when they are contextualised in the study setting. Third, because cross-sectional quantitative studies have limited capacity to uncover rich insights, further qualitative studies are needed to gain deeper insights on the views of teachers and thus enrich our understanding of how culture influences teachers' technology acceptance.

Last but not least, our study is limited in terms of variance explained by the proposed models, especially for Spanish sample. The research on the factors that explain Spanish teachers' technology adoption is still in an exploratory stage of development, however there are some studies that indicate that subjective norm may not be the strongest predictor of behavioural intention (Gonzalez & Gonzalez Ruiz, 2017; Martín García, García del Dujo, Muñoz Rodríguez, 2014). Future studies are encouraged to include more related variables to further explore factors that influence Spanish teachers' intentions to use technology.

6. Conclusion

In this study, we investigated how culture influences intention to use technology among teachers in Spanish and Chinese higher education institutions. Research results suggested culture influenced teachers' intentions to use technologies in both Spain and China. The current study contributed to people's understanding of existing technology acceptance literature by providing empirical results from the two culturally different countries.

In addition to investigating how culture influences technology acceptance, we compared three models based on the model fit indices. The results of this study add to the theory of technology acceptance by providing empirical evidence on how culture influences people's decision making.

Appendix A.

Behavioural Intention (adapted from Davis, 1989).

1: I will use technologies in teaching in the future.

2: I plan to use technologies in teaching often.

3: I expect that I will use technologies in teaching in the future.

4: I will continue using technologies in teaching.

Subjective Norms (adapted from Fishbein & Ajzen, 1975; Taylor & Todd, 1995).

1: People whose opinion I value think that I should use technologies in teaching.

2: People who are important to me think that I should use technologies in teaching.

3: People who influence my behaviour think that I should use technologies in teaching.

4: People who I admire think that I should use technologies in teaching.

Individualism-Collectivism index (adapted from Hofstede, 2011)

1. Individuals should sacrifice their self-interest for the interest of the groups they belong to.

2. Individuals should stick with the group even when facing difficulties.

3. Group interest/welfare is more important than individual interest.

4. Group success is more important than individual success.

5. Being accepted as a member of a group is more important than having autonomy and independence.

Power Distance index (adapted from Hofstede, 2011)

1: Teachers should make most of their decisions by consulting/discussing with administrators/superiors.

2: Administrators/superiors should use authority and power when dealing with teachers.

3: Teachers should agree with administrators/superiors' decisions.

Uncertainty Avoidance index (adapted from Hofstede, 2011)

1: Specific rules or regulations are important to me.

2: Detailed requirements are important to me.

3: Detailed instructions are important to me.

4. Standardised operating procedures help me follow suit.

5: The best option is to closely follow requirements, instructions and procedures.

Indulgence-constraint index (adapted from Hofstede, 2011)

1. Overall I consider myself to be a very happy person.

2. I have complete free choice over my life.

3. Leisure time is a very important part in my life.

4. Wellbeing is very important to me.

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