Exploring the specification of educational compatibility of virtual reality within a technology acceptance model

Andrew Kemp
University of Adelaide; Queensland University of Technology

Edward Palmer, Peter Strelan
University of Adelaide

Helen Thompson
Queensland University of Technology

This study investigated the specification of educational compatibility within a technology acceptance model (TAM) suited to engaging educational technologies. Attitudes towards virtual reality (VR) for learning was used to test the experimental model. One hundred and seventy-nine valid survey responses were collected from 517 potential participants with the majority from first-year university students. The independent variables were educational compatibility, cognitive engagement, social influence, system attributes, perceived anxiety and facilitating conditions. Exploratory factor analysis showed that educational compatibility and attitude were collinear, and therefore were combined into one construct. Confirmatory factor analysis indicated that the combined educational compatibility-attitude construct and perceived usefulness were not discriminant. Two structural models were therefore compared: one where educational compatibility-attitude items were incorporated within perceived usefulness, and another where educational compatibility-attitude items were excluded entirely. The results showed that incorporating educational compatibility-attitude items within perceived usefulness affected the influence of cognitive engagement and system attributes on perceived usefulness, though overall model power was unchanged. The results suggested that (a) educational compatibility and attitude could be redundant, and (b) incorporating educational compatibility into perceived usefulness may help specify educationally focused TAMs.

Implications for practice or policy:

- Researchers may regard educational compatibility and attitude to be redundant and exclude them from TAMs as separate constructs.
- Researchers could consider tailoring the perceived usefulness construct to make it more specific to the educational context, for example by including one or more educational compatibility items.

Keywords: educational compatibility, attitude, perceived usefulness, virtual reality, technology acceptance model

Introduction

Compatibility was initially described by Rogers (1983), explored further by Moore and Benbasat (1991) as part of studies into adoption of innovation and defined as “the degree to which an innovation is perceived as being consistent with the existing values, needs, and past experiences of potential adopters” (Rogers, 1983, p. 250). Hardgrave et al. (2003) hypothesised that compatibility is positively related to intention, which Liao & Lu (2008) confirmed in an educational context. Chen (2011) further defined educational compatibility (EC) as “the degree to which an e-learning system is perceived as being congruent with a student’s learning expectancy” (Chen, 2011, p. 1504), and showed that EC has positive influence on intention to adopt and continue to use an educational system. These studies collectively offer evidence of EC’s ability to influence intention to use an educational technology, supporting its incorporation into technology acceptance models.

EC can also affect attitude (Kai-ming Au & Enderwick, 2000) and perceived usefulness (Lai, 2013; Lai et al., 2012). Moreover, EC and attitude can be highly correlated (Lai, 2013) and if so it is possible that EC acts as a proxy for attitude. Because of the demonstrated associations between EC, perceived usefulness, attitude, and intention, it is important to explore the associations between these constructs to specify EC appropriately within a technology acceptance model. In this study we appraised attitudes towards VR for learning to assist with this task using a novel technology acceptance model (TAM) suited to engaging educational technologies.

Virtual reality (VR) is a technology that provides a technological representation of an environment and is applied in settings such as education, entertainment, healthcare, and marketing (Radianti et al., 2020). While most VR deployments in higher education institutions have used high-end head mounted displays (Radianti et al., 2020), even desktop VR can deliver superior learning compared to lecture based instruction (Dubovi et al., 2017). The immersive nature of VR (Makransky & Lilleholt, 2018) gives a sense of presence (Steuer, 1992) and a positive user experience through affectual factors such as motivation (Radianti et al., 2020), interest and engagement (Parong & Mayer, 2018), and cognitive processes by enhancing 3D visualisation (Merchant et al., 2012). Such affectual factors positively affect learning and transfer (Makransky & Lilleholt, 2018), perceived learning effectiveness, outcomes, engagement and attitude (Janssen et al., 2016; Suh & Prophet, 2018) and perceived usefulness (Huang & Liaw, 2018) leading to intention to use the technology in question for learning. While these studies show learning benefits in certain situations, widespread deployment of VR is still uncommon (Radianti et al., 2020) and so in this study we investigated general student attitudes towards using VR to discover how to support and expand its use on campus.

This study therefore had two aims: to determine an appropriate specification of educational compatibility within a technology acceptance model suited to engaging educational technologies, and to use that to measure attitudes towards use of virtual reality for learning with a view to supporting its increased use on campus. Ethical approval was granted by the Low Risk Human Research Ethics Review Group (Faculty of Arts and Professions, University of Adelaide) for this research study (H-2017-144).

Theoretical background and research model

The technology acceptance model

The TAM (Davis, 1986, 1989) is a popular model to appraise acceptance and behavioural intent to use a technology (Eraslan Yalcin & Kutlu, 2019; Sánchez-Prieto et al., 2019; Šumak et al., 2011; Ursavaş et al., 2019), and has been recently assessed to "represent a credible model for facilitating assessment of diverse learning technologies" (Granić & Marangunić, 2019, p. 2572). The TAM is also noted to be current and versatile (King & He, 2006), effective across gender and user types (Teo et al., 2019) and can be easily extended to balance parsimony with specificity to suit a given research objective. While other technology acceptance models exist (see Abdullah & Ward, 2016; Venkatesh et al., 2003), Davis' TAM was chosen in this study because its core is well-validated and easily extended.

A previous review resulted in the construction of a comprehensive taxonomy of factors affecting attitudes towards educational technologies (Kemp et al., 2019) which was used to inform the expansion of Davis' TAM with appropriate factors for this study. The original TAM (TAM-O) consists of perceived usefulness (PU), perceived ease of use (PEOU), attitude (ATT) and behavioural intent (BI) (Davis, 1986). Attitude was removed in a revised TAM (TAM-R) (Davis, 1989) because it had no additional power when preceded by perceived usefulness and perceived ease of use, a finding replicated in other studies (Teo, 2009; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). Attitude has been shown to be nonetheless influential in some circumstances (López-Bonilla & López-Bonilla, 2011, 2017; Teo et al., 2017; Yang & Su, 2017), and due to its possible relationship with EC, a focus of this research, it was necessary to retain the attitude construct and adopt the TAM-O as the core model for this study. Accordingly, the following hypotheses were adopted:

- H1 ATT has a positive influence on BI
- H2 PU has a positive influence on ATT
- H3 PEOU has a positive influence on ATT
- H4 PEOU has a positive influence on PU

Educational compatibility (EC)

In addition to influencing behavioural intent, compatibility has been shown to directly influence attitude and perceived usefulness, central constructs of TAM-O. Kai-ming Au and Enderwick (2000) concluded that compatibility influences adoption attitudes ($\beta = 0.48$, $p < 0.05$). Lai et al. (2012) showed that EC also has direct effect on attitude to use ($\beta = 0.64$, $p < 0.001$) and perceived usefulness ($\beta = 0.47$, $p < 0.001$). Lai (2013) demonstrated links between EC and usefulness ($\beta = 0.20$, $p < 0.01$) and reported a high correlation between EC and attitude ($r = 0.82$, $p < 0.001$); attitude was subsequently dropped from Lai's model as it was deemed collinear. Other options available in situations of collinearity include reassigning items or aggregating the latent variables (Kock & Lynn, 2012).

Definitions of attitude (Ajzen & Fishbein, 1980) and educational compatibility (Chen, 2011) appear semantically similar. It could be surmised that they measure the same thing if highly correlated: While to a theoretician they may represent different nuanced ideas, a respondent to an acceptance survey may not appreciate the difference.

The studies above show that EC can influence the central TAM constructs of intent, attitude, and perceived usefulness, and also that EC and attitude can possibly be redundant. To determine the structure of this part of the model an exploratory factor analysis of items measuring perceived usefulness, EC and attitude was a necessary step to avoid potential collinearities and specify the model appropriately. A suitable hypothesis was that EC has positive influence on behavioural intention to use the technology either directly, indirectly via perceived usefulness or attitude, or even as a proxy for attitude itself.

H5 EC has a positive influence on BI either directly or indirectly

Cognitive engagement (CE)

VR can be a sensorially rich user experience (Kennedy et al., 2013), having an effect in terms of perceived fun, interest (Makransky & Lilleholt, 2018), losing track of time (flow) and augmented focus (Saade & Bahli, 2005). Together, these account for a cognitive engagement that results in the immersive presence felt by users of virtual reality. These features have been shown to lead to improved learning outcomes (Makransky & Lilleholt, 2018).

H6 CE has a positive influence on PU

Social influence (SI)

Social influence (SI) has been confirmed as an influencer of attitudes towards technology use (Abbad et al., 2009; Al-Ammary et al., 2014; Al-Gahtani, 2014). Taylor and Todd (1995) delineated it into peer influence and superiors' influence, while Thompson et al.(1991) also demonstrated the influence of the organisation as a whole. Accordingly, peer, superior and organisational influence were included in a single construct to test their influence on attitudes towards use of VR.

H7 SI has a positive influence on PU
H8 SI has a positive influence on PEOU

System attributes (SA)

System attributes was "a proposed primary taxonomic group related to how the system itself performs as a separate consideration to the learning it produces" (Kemp et al., 2019, p. 2407) and has been shown to influence attitudes towards the technology in question (Chen et al., 2007, 2013; Lin et al., 2010). Design quality has been shown to have some effect (Lee et al., 2009), as have user control (Martinez-Torres et al., 2008) and system functionality (Chen, 2011; Cho et al., 2009). In addition to function, aspects such as quality and accessibility have also been shown to have some effect (Martinez-Torres et al., 2008). We include these considerations in a system attributes construct to measure any effect on user attitudes.

H9 SA has a positive influence on PU
H10 SA has a positive influence on PEOU

Perceived anxiety (PA)

A user's own perceived abilities have been shown to affect attitudes towards technology in terms of self-efficacy (Abbad et al., 2009; Al-Gahtani, 2014; Chen et al., 2007; Cheng, 2011; Lee, 2006; Motaghian et al., 2013; Shen & Eder, 2009; Yang & Lin, 2011), internet experience (Abbad et al., 2009), and computer anxiety (Al-Gahtani, 2014). Whereas self-efficacy is "a person's judgement of what one can do with whatever skills one possesses" (Bandura, 1986, p. 391), and internet experience is an objective measure related to one's usage history, user anxieties are related to the affective axis and more about how the user feels. Venkatesh (2000) argues that anxieties negatively influence perceived ease of use of a technology, and are mediated by cognitive factors, measured by perceived ease of use in this study, and so we have placed perceived anxiety upstream of perceived ease of use.

H11 PA has a positive influence on PEOU

Facilitating conditions (FC)

Facilitating conditions (FC) has been characterised as an external control construct (Venkatesh, 2000). External factors can include context of opportunity (Sarver, 1983) trialability (Rogers, 1983), and organisational and technical support infrastructure (Venkatesh et al., 2003). Venkatesh (2000) relates that users in organisations have formed ideas about the help and support that their organisation provides, which in turn influence perceived abilities and effort expectancy. That is, there is acknowledgement that facilitating conditions can sit upstream of considerations of ability and ease of use. This suggested to us that awareness of facilitating conditions could very well affect anxiety levels related to ease of use. Because we wished to test whether facilitating conditions acted at this early stage, we placed facilitating conditions upstream of perceived anxiety in this study.

H12 FC has a positive influence on PA

Taking into consideration the above hypotheses we formed a starting model (Figure 1).

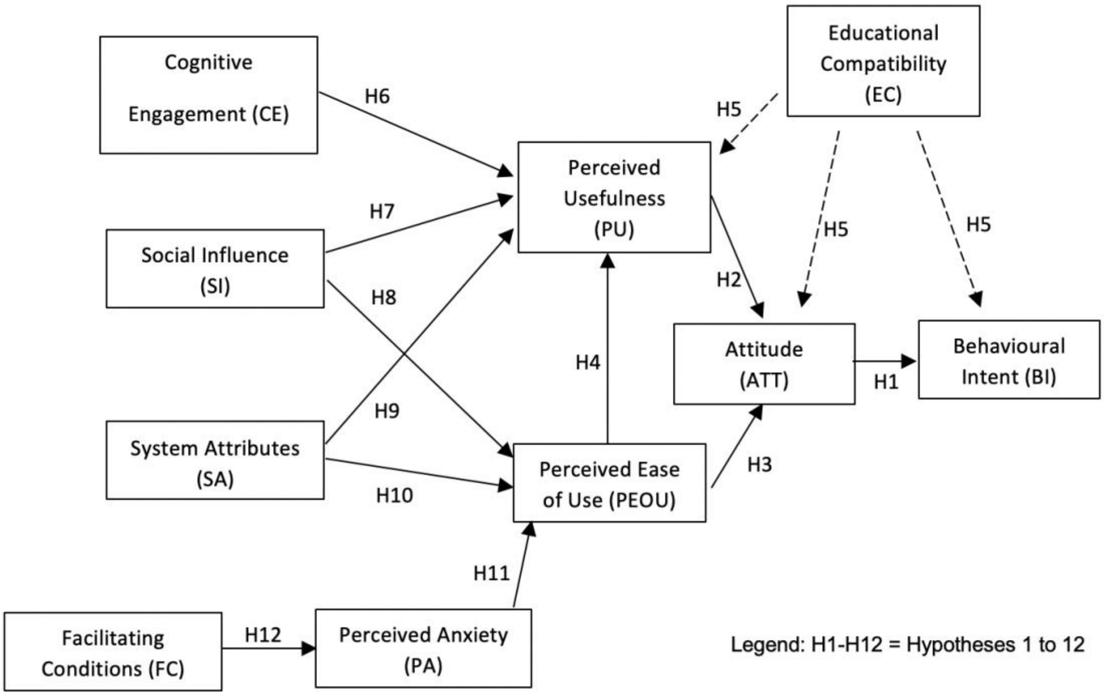

Figure 1. Starting model

Methods

Construct operationalisation

Previous research provided validated questionnaire items for the model constructs: perceived usefulness and perceived ease of use (Davis, 1989; Dečman, 2015), social influence (Taylor & Todd, 1995; Thompson et al., 1991), facilitating conditions (Dečman, 2015; Taylor & Todd, 1995), perceived anxiety (Venkatesh et al., 2003), attitude (Taylor & Todd, 1995; Thompson et al., 1991), educational compatibility (Chen, 2011), cognitive engagement (Saade & Bahli, 2005; Thompson et al., 1991), system attributes (Martinez-Torres et al., 2008; Venkatesh & Bala, 2008). The nine general constructs were operationalised to create pre- and post-use questionnaires (Appendix A), allowing the survey to examine attitudes of those who had used virtual reality as well as those who had not yet used it. A 7-point ordinal scale was used for the exogenous items with *Strongly Disagree* and *Strongly Agree* used as anchors. A 4-point ordinal scale was used for behavioural intent (Dečman, 2015) with an item added to capture no intention to use virtual reality in the future.

Demographic data of respondents

A total of 182 responses were received, with 179 being valid. Two missing response items were imputed with the item median. Table 1 shows the gender and age group breakdown of respondents, and Table 2 shows role and discipline.

Table 1
Personal demographics of the sampled cohort

Age group	Male	Female	Unknown	Totals
16-25	40	92	1	133
26-50	15	15	-	30
50+	5	11	-	16
Totals	60	118	1	179

Table 2
Educational demographics of the sampled cohort

Role	Comp. Sci / IT	Education	Medicine	Nursing	Psychology	Totals
Academic	1	2	6	9	1	19
Student	-	-	1	-	144	145
IT services	15	-	-	-	-	15
Totals	16	2	7	9	145	179

Analysis approach

We specified the measurement model before proceeding to path analysis of the structural model (Anderson & Gerbing, 1988), in three stages: (1) specification of educational compatibility, attitude and perceived usefulness using exploratory factor analysis, (2) confirmatory factor analysis of the measurement model and (3) path analysis of the structural model. The analyses were conducted using the 'psych' (version 1.8.12) (Revelle, 2019), 'lavaan' (version 0.6.4) (Rossel, 2012) and 'polycor' (version 0.7-10) (Fox, 2019) packages available in R version 3.6.0 (R Core Team, 2013) and RStudio version 1.2.1335 (RStudio Team, 2015). Diagonally weighted least squares (DWLS) was used to measure the polychoric correlations between the ordinal items and latent factors because Pearson's correlation based estimates (such as maximum likelihood) distort results when used on non-normal and ordinal data (Holgado-Tello et al., 2010; Li, 2016; Özdemir et al., 2019; Xia & Yang, 2019).

Specification of the measurement model using exploratory factor analysis (EFA)

A randomised subset was extracted ($n = 89$) to perform the EFA. The hetcor function of the polycor package was used to produce the matrix of polychoric correlations for the items relating to perceived usefulness, educational compatibility, and attitude (PU, EC, PB items). Parallel analysis was performed to suggest the number of factors to extract, which was performed applying a cut-off of 0.3 for loadings in the pattern matrix and the oblique promax rotation (allowing for the measurement of correlation between factors).

Confirmatory factor analysis (CFA) and structural equation modelling (SEM)

CFA and SEM were performed using the randomised dataset not used for the EFA (*n* = 90). Exogenous constructs were assessed for convergent and discriminant validity (Hair et al., 2010). Fit indices were chosen to report absolute (χ^2; RMSEA; SRMR), incremental (CFI, TLI) and parsimonious fit (χ^2/df) (Hooper et al., 2008; Kline, 2015) using cut-offs recommended by Hu and Bentler (1999). The structural equation modelling (Crockett, 2012) of the resultant measurement model was performed using R version 3.6.0 (R Core Team, 2013) and RStudio version 1.2.1335 (RStudio Team, 2015).

Results

Exploratory factor analysis (EFA)

Parallel analysis suggested a 2-factor solution and produced the following scree plot:

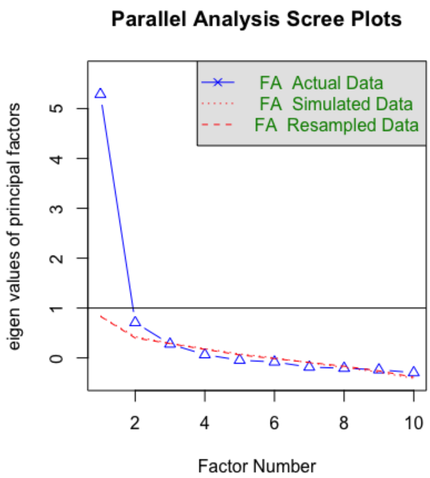

Figure 2. Parallel analysis scree plot of perceived usefulness, attitude, and educational compatibility items from R Studio

The pattern matrix for a 2-factor solution with promax rotation is shown in Table 3, and Table 4 shows a 0.68 correlation between the two factors.

Table 3
Pattern matrix for 2 factors

	Perceived usefulness (PU)	Educational compatibility-Attitude (EC-ATT)
Proportion of variance %	*0.33*	*0.29*
Cumulative variance %	*0.33*	*0.62*
PU1	0.900	
PU2	0.927	
PU3	0.861	
PU4	0.733	
rPB1		0.431
PB2		0.726
PB3		0.696
rPB4		0.558
EC1		0.931
EC2		0.565

Table 4
Correlation matrix for 2 factors

	PU	EC-ATT
Factor 1	1.00	
Factor 2	0.68	1.00

The attitude (PB items) and educational compatibility (EC items) items loaded cleanly onto one factor. This outcome indicated redundancy between EC and attitude (ATT) for our respondents. Perceived usefulness remained distinct from the combined ATT-EC factor with a 0.68 correlation. This finding is consistent with Lai (2013) who also showed a high correlation between EC and ATT (0.82). Based on the EFA result, EC and ATT items were aggregated as one factor in a revised model (Kock & Lynn, 2012).

Confirmatory factor analysis (CFA)

The attitudinal nature of the EC-ATT construct placed it within a revised structural model as depicted in Figure 3:

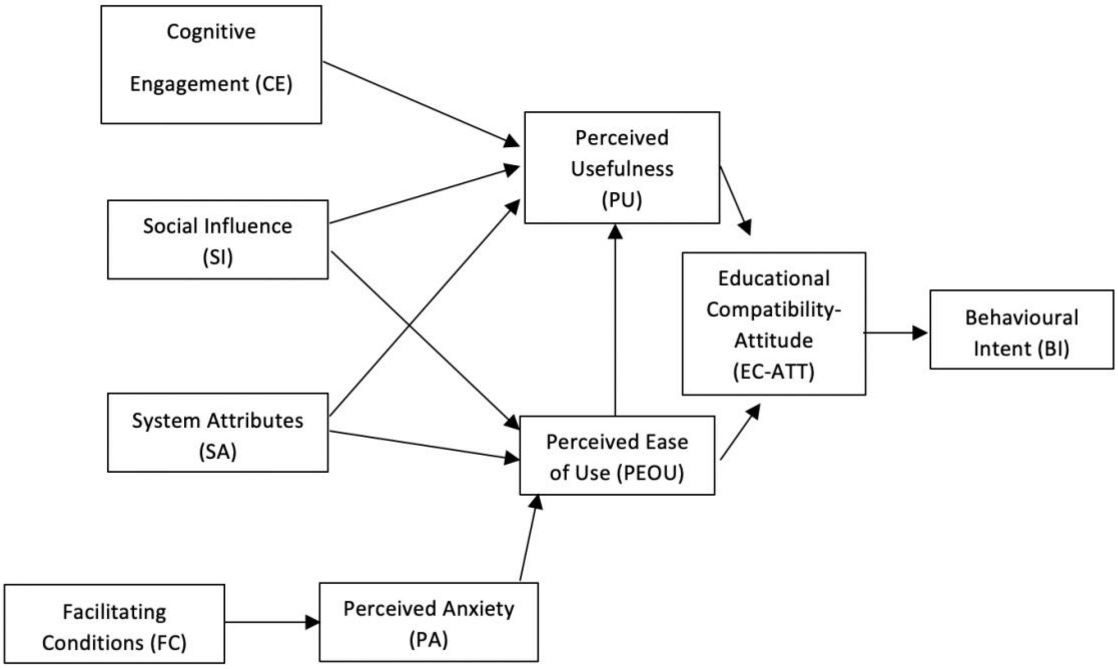

Figure 3. Revised model

The confirmatory factor analysis was run according to the revised model (Figure 3). Unidimensionality analysis resulted in the removal of one item from the educational compatibility-attitude (EC-ATT) construct and one from the facilitating conditions (FC) construct whose factor loadings were less than the 0.60 threshold. The CFA was re-run, with all remaining items reporting a significance level of $p < 0.001$. The average variance extracted (AVE) for each construct was > 0.50 indicating acceptable convergent validity, and composite reliability > 0.70 was used to confirm reliability of each construct (Hair et al., 2010). The convergent and discriminant validities are shown in Tables 5 and 6 respectively.

Table 5
Reliabilities and convergent validity of the measurement model

Construct	Item	Factor loading (> 0.60)	Composite reliability (> 0.70)	Average variance extracted (> 0.50)
Perceived usefulness (PU)	PU1	0.941	0.94	0.78
	PU2	0.902		
	PU3	0.834		
	PU4	0.871		
Perceived ease of use (PEOU)	PE1	0.917	0.95	0.81
	PE2	0.932		
	PE3	0.915		
	PE4	0.833		
Educational compatibility (EC-ATT)	EC1	0.833	0.91	0.67
	EC2	0.766		
	rPB1	0.612		
	PB2	0.923		
	PB3	0.904		
Cognitive engagement (CE)	EU1	0.846	0.92	0.79
	EU2	0.960		
	EU4	0.862		
Social influence (SI)	SI1	0.926	0.87	0.77
	SI2	0.831		
Facilitating conditions (FC)	FC2	0.887	0.87	0.77
	FC3	0.867		
Perceived anxiety (PA)	rPA1	0.906	0.88	0.78
	rPA2	0.860		
System attributes (SA)	SA1	0.750	0.88	0.65
	SA2	0.844		
	SA3	0.769		
	SA4	0.847		

Table 6
Discriminant validities of the measurement model

	PU	PEOU	EC-ATT	CE	SI	FC	PA	SA
PU	**0.89**							
PEOU	0.68	**0.90**						
EC-ATT	0.93	0.74	**0.82**					
CE	0.83	0.64	0.79	**0.89**				
SI	0.65	0.60	0.63	0.46	**0.88**			
FC	0.51	0.54	0.51	0.41	0.53	**0.88**		
PA	0.20	0.33	0.22	0.16	0.21	0.39	**0.88**	
SA	0.85	0.77	0.83	0.86	0.61	0.62	0.24	**0.81**

Table 6 shows that educational compatibility-attitude (EC-ATT) was not discriminant from perceived usefulness (PU) or system attributes (SA). The high correlation between PU and EC-ATT was possibly a result of lateral collinearity (Kock & Lynn, 2012). On inspection of PU and EC-ATT item semantics (see Appendix A), we can surmise this is the case and these are not sufficiently separate in respondents' eyes. Remedies include survey item removal or reassignment, latent variable removal or latent variable aggregation (Kock & Lynn, 2012). A comparison of latent variable subtraction versus aggregation was chosen to explore the effect of the educational compatibility-attitude construct within the model. The aggregated model is shown in Tables 7 to 9 and Figure 4, whereas the subtracted model is shown in Tables 10 to 12 and Figure 5.

Table 7
Reliabilities and convergent validity of the aggregate measurement model

Construct	Item	Factor loading (> 0.60)	Composite reliability (> 0.70)	Average variance extracted (> 0.50)
Perceived usefulness + Educational compatibility + Attitude (PU-EC-ATT)	PU1	0.934	0.95	0.72
	PU2	0.892		
	PU3	0.823		
	PU4	0.861		
	EC1	0.815		
	EC2	0.752		
	rPB1	0.603		
	PB2	0.909		
	PB3	0.893		
Perceived ease of use (PEOU)	PE1	0.917	0.95	0.81
	PE2	0.933		
	PE3	0.917		
	PE4	0.834		
Cognitive engagement (CE)	EU1	0.847	0.92	0.79
	EU2	0.959		
	EU4	0.863		
Social influence (SI)	SI1	0.925	0.87	0.77
	SI2	0.831		
Facilitating conditions (FC)	FC2	0.887	0.87	0.77
	FC3	0.867		
Perceived anxiety (PA)	rPA1	0.904	0.88	0.78
	rPA2	0.861		
System attributes (SA)	SA1	0.753	0.88	0.65
	SA2	0.847		
	SA3	0.772		
	SA4	0.850		

Table 8
Discriminant validities of the aggregate measurement model

	PU-EC-ATT	PEOU	CE	SI	FC	PA	SA
PU-EC-ATT	**0.85**						
PEOU	0.71	**0.90**					
CE	0.83	0.63	**0.89**				
SI	0.65	0.61	0.45	**0.88**			
FC	0.52	0.54	0.41	0.54	**0.88**		
PA	0.21	0.33	0.16	0.21	0.39	**0.88**	
SA	0.85	0.76	0.85	0.61	0.62	0.24	**0.81**

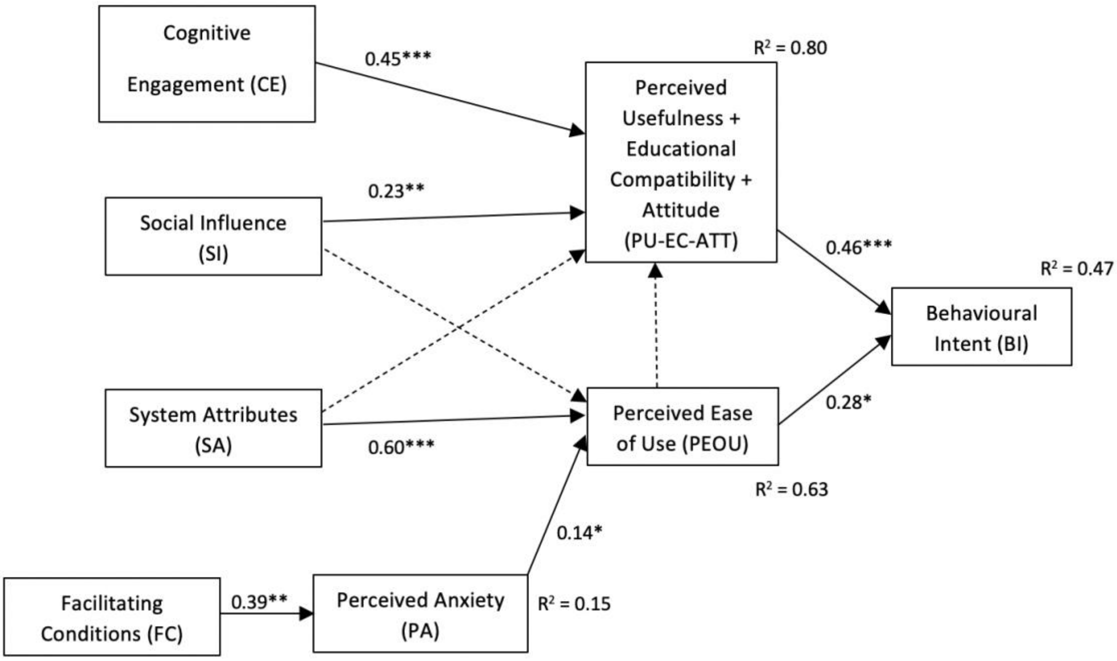

Figure 4. Structural aggregate model showing standardised path coefficients. Dashed lines indicate non-significant paths ($p < 0.001$ = ***, $p < 0.01$ = **, $p < 0.05$ = *).

Table 9
Structural aggregate model fit indices (Hooper et al., 2008; Hu & Bentler, 1999; Kline, 2015)

Fit category	Name of index	Level of acceptance	Value
Absolute fit	χ^2, df, p	$p > 0.005$	453.330, *df*=309, $p = 0.000$
	RMSEA	< 0.08	0.072 (0.058 – 0.086)
Incremental fit	CFI	> 0.9	0.976
	TLI	> 0.95	0.972
	SRMR	< 0.08	0.065
Parsimonious fit	χ^2/df	< 3	1.47

Table 10
Reliabilities and convergent validity of the subtracted measurement model

Construct	Item	Factor loading (> 0.60)	Composite reliability (> 0.70)	Average variance extracted (> 0.50)
Perceived usefulness (PU)	PU1	0.957	0.95	0.81
	PU2	0.912		
	PU3	0.836		
	PU4	0.896		
Perceived ease of use (PEOU)	PE1	0.918	0.95	0.81
	PE2	0.931		
	PE3	0.916		
	PE4	0.836		
Cognitive engagement (CE)	EU1	0.847	0.92	0.80
	EU2	0.943		
	EU4	0.883		
Social influence (SI)	SI1	0.923	0.87	0.77
	SI2	0.832		
Facilitating conditions (FC)	FC1	0.676	0.85	0.65
	FC2	0.885		
	FC3	0.845		
Perceived anxiety (PA)	rPA1	0.880	0.88	0.78
	rPA2	0.883		
System attributes (SA)	SA1	0.756	0.88	0.65
	SA2	0.844		
	SA3	0.767		
	SA4	0.843		

Table 11
Discriminant validities of the subtracted measurement model

	PU	PEOU	CE	SI	FC	PA	SA
PU	**0.90**						
PEOU	0.69	**0.90**					
CE	0.76	0.64	**0.89**				
SI	0.64	0.61	0.46	**0.88**			
FC	0.54	0.56	0.36	0.61	**0.81**		
PA	0.18	0.33	0.12	0.19	0.32	**0.88**	
SA	0.84	0.77	0.86	0.61	0.63	0.20	**0.80**

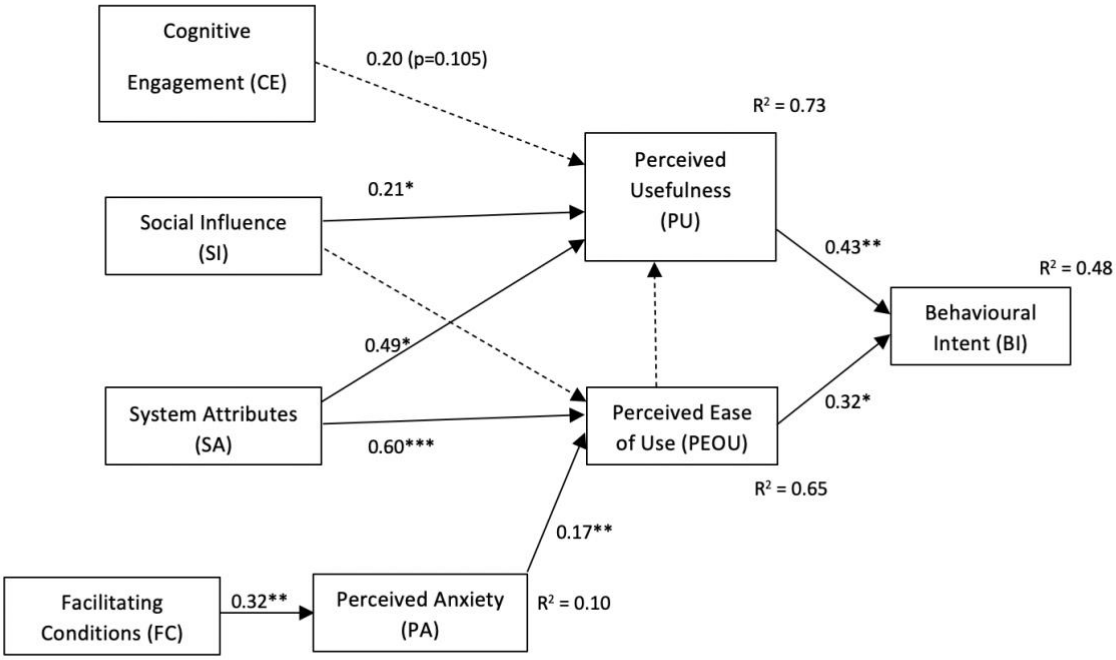

Figure 5. Subtracted structural model showing standardised path coefficients. Dashed lines indicate non-significant paths ($p < 0.001$ = ***, $p < 0.01$ = **, $p < 0.05$ = *).

Table 12
Structural model fit indices (Hooper et al., 2008; Hu & Bentler, 1999; Kline, 2015)

Fit category	Name of index	Level of acceptance	Value
Absolute fit	χ^2, df, p	$p > 0.005$	307.352, *df*=215, $p = 0.000$
	RMSEA	< 0.08	0.069 (0.051 – 0.086)
Incremental fit	CFI	> 0.9	0.981
	TLI	> 0.95	0.978
	SRMR	< 0.08	0.063
Parsimonious fit	χ^2/df	< 3	1.43

Comparison of the two models showed that there was no appreciable difference in model power (as measured by R^2 of behavioural intent, BI) nor fit. However, there were marked differences in two path coefficients. In the aggregate model, the path between cognitive engagement and perceived usefulness-compatibility-attitude was significant and moderate ($\beta = 0.45$, $p < 0.001$), and there was no significant path between system attributes and perceived usefulness-compatibility-attitude. In contrast, the subtracted model lost the significant path between cognitive engagement and perceived usefulness, and the influence of system attributes on perceived usefulness became significant ($\beta = 0.49$, $p < 0.05$). A comparison of the supported hypotheses between the two models is shown in Table 13.

Table 13
Hypothesis results

Hypotheses	Path	Aggregate model results	Subtracted model results
H1	ATT → BI	NA	NA
H2	PU → ATT	NA	NA
H3	PEOU → ATT	NA	NA
H4	PEOU → PU	Not supported	Not supported
H5	EC → BI	NA	NA
H6	CE → PU	Supported	Not supported
H7	SI → PU	Not supported	Not supported
H8	SI → PEOU	Supported	Supported
H9	SA → PU	Not supported	Supported
H10	SA → PEOU	Supported	Supported
H11	PA → PEOU	Supported	Supported
H12	FC → PA	Supported	Supported

Discussion

Exploratory factor analysis (EFA)

The exploratory factor analysis demonstrated that educational compatibility and attitude neatly aligned into one factor, supporting Lai's (2013) earlier findings of high correlation between these two constructs. It is not surprising therefore that educational compatibility has also been shown to directly influence attitude (Lai et al, 2012) and behavioural intention (Chen 2011, Liao & Lu, 2008). Compatibility has also had the same influences in non-educational settings (Au et al 2000; Hardgrave et al, 2003). While Lai (2013) showed that educational compatibility can influence usefulness, this study showed that it can also act as an indicator of attitude in educational settings. This suggests that educational compatibility could potentially supplant attitude in educational technology acceptance studies or act as a proxy for it when it is included.

Confirmatory factor analysis (CFA) and structural equation modelling (SEM)

The unidimensionality, composite reliability, and convergent validities of the revised measurement model were within acceptable limits, however the discrimination model showed a high correlation between the attitude-educational compatibility construct and perceived usefulness (r = 0.93), and also with system attributes (r = 0.83). While we note that the perceived usefulness construct has been well-validated and used since Davis (1986), the results of the confirmatory factor analysis indicate that the correlation be considered closely. Lateral collinearity can cause such high correlations, and one solution is to re-specify the model (Kock & Lynn, 2012). Chen (2011) demonstrated an influence from educational compatibility onto technological expectancy (which included perceived usefulness), and Lai (2013) also showed that educational compatibility can directly influence perceived usefulness. Looking more deeply at the semantics of the constructs themselves hints at possible equivalence: if a technology is thought to be suitable for adoption (compatibility) then it can also be thought to be useful (usefulness) and vice versa. Whereas Chen and Lai measured educational compatibility and usefulness separately, this study showed a possible confluence.

With the EFA showing confluence between educational compatibility and attitude, and the CFA showing a confluence between educational compatibility-attitude and perceived usefulness, it is possible that these three constructs measure different aspects of the same idea for respondents in educational contexts. The resultant construct in the aggregate model was a merging of usefulness, educational compatibility and general attitude, showing a standardised path coefficient of 0.46 (p <0.001) onto behavioural intent. This result indicates that respondents who had a general attitude of compatibility and usefulness of virtual reality as a learning technology would have a moderate intention to use it for learning.

Cognitive engagement showed a moderate influence onto perceived usefulness (β = 0.45, p <0.001) for the aggregate model but not for the subtracted model. This result suggests that cognitive engagement was associated with the educational compatibility-attitude items, suggesting they helped to measure the engaging qualities of VR in this context. Cognitive engagement captured the ideas of virtual reality being fun, making learning interesting and supporting stronger focus on the learning activity. Given the links between the affectual and cognitive aspects of VR and improved learning outcomes (Janssen et al., 2016;

Makransky & Lilleholt, 2018; Merchant et al., 2012; Suh & Prophet, 2018), it is not surprising to find that respondents linked cognitive engagement to the educational compatibility items within the modified perceived usefulness construct within this study. There are two broader implications that may stem from this result: firstly, that educational compatibility items should possibly be included within an expanded perceived usefulness construct when studying educational technologies, and secondly that educational technologies are perceived to be more useful if they are also engaging.

In contrast, system attributes (SA) had a significant association with perceived usefulness (PU) only when educational compatibility-attitude items were excluded from PU ($\beta = 0.49$, $p < 0.05$). SA items included the quality of the virtual reality experience, control of learning rhythm, security and reliability. These seemed to associate with general usefulness items and not so much with educational compatibility-attitude. This possibly indicates that though such system attributes influence general usefulness, they are not a strong influencer of educational compatibility nor relevant when the PU construct is flavoured towards educational usefulness.

Social influence (SI) moderately influenced virtual reality's perceived usefulness (PU) ($\beta = 0.23$, $p = 0.01$ and $\beta = 0.21$, $p = 0.05$ for the aggregate and subtracted models respectively) though had no significant influence on perceived ease of use for either model. Notwithstanding that items SI3 and SI4 failed the unidimensionality test, peer and instructor influence did still have a general effect on ideas of usefulness and compatibility of virtual reality use for learning.

Both the aggregate and subtracted model did indeed show that facilitating conditions influenced respondents' anxiety vis-à-vis use virtual reality as hypothesised, although the low R^2 of the perceived anxiety construct ($R^2 = 0.15$ and $R^2 = 0.10$ for the aggregate and subtracted models respectively) indicates that facilitating conditions is only a minor influencer of a user's perceived anxiety. This result indicates that FC can probably be excluded from this position in future models and that FC may act more broadly than just on anxiety.

In a departure from Davis' TAM model (Davis, 1986) there was no significant link between perceived ease of use and perceived usefulness for either the aggregate (Figure 4) or subtracted model (Figure 5). Thus, this study showed that the mediation of perceived ease of use by perceived usefulness may not be universal. It is possible that respondents' computer self-efficacy has advanced to such a degree compared to 1986 when Davis first developed the TAM that perceived ease of use's association with perceived usefulness may be less influential, or that this cohort thinks that virtual reality 'just works' and has no bearing on its usefulness in a university setting where technical staff and academics set learning environments up for students.

Speaking to the first aim of this study, the importance of inclusion of educational compatibility and attitude must be carefully considered. The EC-ATT construct had no real bearing on model power ($R^2 = 0.47$ vs $R^2 = 0.48$ for the aggregate and subtracted models respectively), nor fit, and on these grounds can be safely excluded. This is in agreement with those who have shown that attitude is redundant (Davis, 1989; Teo, 2009; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). However, inclusion of attitude and educational compatibility items within the perceived usefulness construct appeared to provide a path linking cognitive engagement, usefulness and intention. While acknowledging the many studies validating the standard perceived usefulness construct, these results may support adding educational compatibility items to perceived usefulness when applying technology acceptance models to educational technologies, especially ones that have features relevant to learning (for example engagement). Further research to investigate this effect would be very insightful.

In terms of the second aim, measurement of attitudes towards virtual reality for learning, the overall picture painted by this structural model was one where students saw virtual reality as positive for learning because of its perceived abilities to improve cognitive focus on the learning task, be fun and make learning more interesting and enjoyable. Thus, by concentrating on activating cognitive interest through 3D visualisation (Merchant et al., 2012), incorporating a strong sense of environmental presence (Steuer, 1992) and active engagement with virtual objects and worlds (Parong & Mayer, 2018), educators who design and deploy virtual reality are likely to attract and engage more students and help improve learning outcomes (Makransky & Lilleholt, 2018). This implies that virtual reality for learning needs to be designed with these characteristics to heighten student satisfaction with it as a learning technology; this is a signpost for those institutions thinking about introducing virtual reality as a learning technology. Designing for cognitive engagement may also go some way to closing the pedagogical gap that Radianti et al. identified (2020). In contrast to the importance that respondents placed on cognitive engagement, we saw less influence of ease of use, and as long as virtual reality setups remain easy to use this will not be a large barrier for student acceptance. In addition to concentrating on engagement, the results also showed that educators should be mindful of the quality of the virtual reality experience and the ability for learners to control their own rhythm of learning within a virtual environment. This also suggests that immediate technical support for the use of VR in classes might be required as academic staff are rarely experts in the implementation of technology and its interactions with local systems and servers.

Conclusion

This study had two aims: (1) to explore the specification of educational compatibility in an educationally focused technology acceptance model, and (2) to appraise general attitudes towards virtual reality for learning in an institution exploring its introduction and use.

This study showed that educational compatibility and attitude appear redundant and non-influential on the power and fit of the model in the presence of perceived usefulness, confirming prior research. However, we showed that inclusion of educational compatibility-attitude items within perceived usefulness moderated the nature of the perceived usefulness construct to appear more specific to learning. This finding may support including educational compatibility items as part of perceived usefulness in educationally focused technology acceptance models instead of excluding it entirely. Using this model, this study also indicated that cognitively engaging affective virtual reality learning environments are seen as educationally compatible and therefore more likely to support student intention to use them.

Limitations and future research

The results of this study are limited in the ability to generalise owing to a dominant concentration of first year psychology students and a sample size on the lower end for a factor analysis study, and so these results can be seen as indicative but need further research to confirm findings. Further, this study examined attitudes on imagined future use and not on a defined didactic experience. Future research may wish to look more closely at the possible redundancy of educational compatibility with attitude and the inclusion of educational compatibility items within the perceived usefulness construct.

Acknowledgement

The authors wish to acknowledge the kind assistance of PhD student Patricia Gilholm of the Queensland University of Technology School of Mathematical Sciences for her assistance with the R environment and commands, and interpretation of output.

References

Abbad, M. M., Morris, D., & de Nahlik, C. (2009). Looking under the bonnet: factors affecting student adoption of E-learning systems in Jordan. *International Review of Research in Open and Distance Learning*, *10*(2), 1–25. https://doi.org/10.19173/irrodl.v10i2.596

Abdullah, F., & Ward, R. (2016). Developing a General Extended Technology Acceptance Model for E-Learning (GETAMEL) by analysing commonly used external factors. *Computers in Human Behavior*, *56*, 238–256. https://doi.org/10.1016/j.chb.2015.11.036

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. Prentice Hall. https://pdfs.semanticscholar.org/0e84/1ed289a3cf9b9a799da4b344bd9397542c2e.pdf

Al-Ammary, J. H., Al-Sherooqi, A. K., & Al-Sherooqi, H. K. (2014). The Acceptance of social networking as a learning tools at University of Bahrain. *International Journal of Information and Education Technology*, *4*(2), 208–214. https://doi.org/10.7763/IJIET.2014.V4.400

Al-Gahtani, S. S. (2014). Empirical investigation of e-learning acceptance and assimilation: A structural equation model. *Applied Computing and Informatics*, *12*(1), 27–50. https://doi.org/10.1016/j.aci.2014.09.001

Anderson, J. C. J., & Gerbing, D. D. W. (1988). Structural equation modeling in practice: A review and

recommended two-step approach. *Psychological Bulletin*, *103*(3), 411–423. https://doi.org/10.1037/0033-2909.103.3.411
Bandura, A. (1986). *Social foundations of thought and action - a social cognitive theory*. Prentice Hall.
Chen, J. L. (2011). The effects of education compatibility and technological expectancy on e-learning acceptance. *Computers and Education*, *57*(2), 1501–1511. https://doi.org/10.1016/j.compedu.2011.02.009
Chen, Y. C., Chen, C. Y., Lin, Y. C., & Yeh, R. C. (2007). Predicting college student use of e-learning systems: an attempt to extend technology acceptance model. *Proceedings of Pacific Asia Conference on Information Systems 2007, 121*, (pp.172–183). https://aisel.aisnet.org/pacis2007/121
Chen, Y. C., Lin, Y. C., Yeh, R. C., & Lou, S. J. (2013). Examining factors affecting college students' intention to use web-based instruction systems: towards an integrated model. *Turkish Online Journal of Educational Technology*, *12*(2), 111–121. http://tojet.net/articles/v12i2/12211.pdf
Cheng, Y. M. (2011). Antecedents and consequences of e-learning acceptance. *Information Systems Journal*, *21*(3), 269–299. https://doi.org/10.1111/j.1365-2575.2010.00356.x
Cho, V., Cheng, T. C. E., & Lai, W. M. J. (2009). The role of perceived user-interface design in continued usage intention of self-paced e-learning tools. *Computers and Education*, *53*(2), 216–227. https://doi.org/10.1016/j.compedu.2009.01.014
Crockett, S. A. (2012). A five-step guide to conducting SEM analysis in counseling research. *Counseling Outcome Research and Evaluation*, *3*(1), 30–47. https://doi.org/10.1177/2150137811434142
Davis, F. D. (1986). *A technology acceptance model for empirically testing new end-user information systems: Theory and result* [Doctoral dissertation, Massachusetts Institute of Technology]. http://dspace.mit.edu/handle/1721.1/15192
Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008
Dečman, M. (2015). Modeling the acceptance of e-learning in mandatory environments of higher education: The influence of previous education and gender. *Computers in Human Behavior*, *49*, 272–281. https://doi.org/10.1016/j.chb.2015.03.022
Dubovi, I., Levy, S. T., & Dagan, E. (2017). Now I know how! The learning process of medication administration among nursing students with non-immersive desktop virtual reality simulation. *Computers and Education*, *113*, 16–27. https://doi.org/10.1016/j.compedu.2017.05.009
Eraslan Yalcin, M., & Kutlu, B. (2019). Examination of students' acceptance of and intention to use learning management systems using extended TAM. *British Journal of Educational Technology*, *50*(5), 2414–2432. https://doi.org/10.1111/bjet.12798
Fox, J. (2019). *polycor: Polychoric and Polyserial Correlations. R package version* (0.7-10). https://cran.r-project.org/package=polycor
Granić, A., & Marangunić, N. (2019). Technology acceptance model in educational context: A systematic literature review. *British Journal of Educational Technology*, *50*(5), 2572–2593. https://doi.org/10.1111/bjet.12864
Hair, J., Black, W., Babin, B., & Anderson, R. (2010). *Multivariate Data Analysis*. (7th ed.). Pearson Prentice Hall.
Hardgrave, B. C., Davis, F. D., & Riemenschneider, C. K. (2003). Investigating determinants of software developers' intentions to follow methodologies. *Journal of Management Information Systems*, *20*(1), 123–151. https://doi.org/10.1080/07421222.2003.11045751
Holgado–Tello, F. P., Chacón–Moscoso, S., Barbero–García, I., & Vila–Abad, E. (2010). Polychoric versus Pearson correlations in exploratory and confirmatory factor analysis of ordinal variables. *Quality and Quantity*, *44*(1), 153–166. https://doi.org/10.1007/s11135-008-9190-y
Hooper, D., Coughlan, J., & Mullen, M. R. (2008). Structural equation modelling : guidelines for determining model fit. *The Electronic Journal of Business Research Methods*, *6*(1), 53–60. http://mural.maynoothuniversity.ie/6596/
Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118
Huang, H. M., & Liaw, S. S. (2018). An analysis of learners' intentions toward virtual reality learning based on constructivist and technology acceptance approaches. *International Review of Research in Open and Distance Learning*, *19*(1), 91–115. https://doi.org/10.19173/irrodl.v19i1.2503
Janssen, D., Tummel, C., Richert, A., & Isenhardt, I. (2016). Virtual environments in higher education – immersion as a key construct for learning. *International Journal of Advanced Corporate Learning*, *9*(2), 20–27. https://doi.org/10.3991/ijac.v9i2.6000

Kai-ming Au, A., & Enderwick, P. (2000). A cognitive model on attitude towards technology adoption. *Journal of Managerial Psychology*, *15*(4), 266–282. https://doi.org/10.1108/02683940010330957

Kemp, A., Palmer, E., & Strelan, P. (2019). A taxonomy of factors affecting attitudes towards educational technologies for use with technology acceptance models. *British Journal of Educational Technology*, *50*(5), 2394–2413. https://doi.org/10.1111/bjet.12833

Kennedy, G., Ioannou, I., Zhou, Y., Bailey, J., & O'Leary, S. (2013). Mining interactions in immersive learning environments for real-time student feedback. *Australasian Journal of Educational Technology*, *29*(2), 172–183. https://doi.org/http://dx.doi.org/10.14742/ajet.700

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information and Management*, *43*(6), 740–755. https://doi.org/10.1016/j.im.2006.05.003

Kline, R. B. (2015). *Principles and Practice of Structural Equation Modeling, Fourth Edition* (4th ed.). Guilford Publications. http://ebookcentral.proquest.com/lib/adelaide/detail.action?docID=4000663

Kock, N., & Lynn, G. S. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. *Journal of the Association for Information Systems*, *13*(7), 546–580. https://doi.org/10.17705/1jais.00302

Lai, C. (2013). A framework for developing self-directed technology use for language learning. *Language Learning and Technology*, *17*(2), 100–122. https://doi.org/10125/44326

Lai, C., Wang, Q., & Lei, J. (2012). What factors predict undergraduate students' use of technology for learning? A case from Hong Kong. *Computers & Education*, *59*(2), 569–579. https://doi.org/10.1016/j.compedu.2012.03.006

Lee, B. C., Yoon, J. O., & Lee, I. (2009). Learners' acceptance of e-learning in South Korea: Theories and results. *Computers and Education*, *53*(4), 1320–1329. https://doi.org/10.1016/j.compedu.2009.06.014

Lee, Y. (2006). An empirical investigation into factors influencing the adoption of an e-learning system. *Online Information Review*, *30*(5), 517–541. https://doi.org/10.1108/IJBM-07-2013-0069

Li, C. (2016). Confirmatory factor analysis with ordinal data : Comparing robust maximum likelihood and diagonally weighted least squares. *Behavior Research Methods*, *48*(3), 936–949. https://doi.org/10.3758/s13428-015-0619-7

Liao, H. L., & Lu, H. P. (2008). The role of experience and innovation characteristics in the adoption and continued use of e-learning websites. *Computers and Education*, *51*(4), 1405–1416. https://doi.org/10.1016/j.compedu.2007.11.006

Lin, Y. C., Chen, Y. C., & Yeh, R. C. (2010). Understanding college students' continuing intentions to use multimedia e-learning systems. *World Transactions on Engineering and Technology Education*, *8*(4), 488–493. http://www.wiete.com.au/journals/WTE&TE/Pages/Vol.8, No.4 (2010)/14-20-Lin-Y-C.pdf

López-Bonilla, L. M., & López-Bonilla, J. M. (2011). The role of attitudes in the TAM: A theoretically unnecessary construct? *British Journal of Educational Technology*, *42*(6), 2005–2008. https://doi.org/10.1111/j.1467-8535.2011.01232.x

López-Bonilla, L. M., & López-Bonilla, J. M. (2017). Explaining the discrepancy in the mediating role of attitude in the TAM. *British Journal of Educational Technology*, *48*(4), 940–949. https://doi.org/10.1111/bjet.12465

Makransky, G., & Lilleholt, L. (2018). A structural equation modeling investigation of the emotional value of immersive virtual reality in education. *Educational Technology Research and Development*, *66*(5), 1141–1164. https://doi.org/10.1007/s11423-018-9581-2

Martinez-Torres, M. R., Toral Marin, S. L., Barrero Garcia, F., Gallardo Vazquez, S., Arias Oliva, M., & Torres, T. (2008). A technological acceptance of e-learning tools used in practical and laboratory teaching, according to the European higher education area. *Behaviour & Information Technology*, *27*(6), 495–505. https://doi.org/10.1080/01449290600958965

Merchant, Z., Goetz, E. T., Keeney-Kennicutt, W., Kwok, O. M., Cifuentes, L., & Davis, T. J. (2012). The learner characteristics, features of desktop 3D virtual reality environments.; College chemistry instruction: A structural equation modeling analysis. *Computers and Education*, *59*(2), 551–568. https://doi.org/10.1016/j.compedu.2012.02.004

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, *2*(3), 192–222. https://doi.org/10.1287/isre.2.3.192

Motaghian, H., Hassanzadeh, A., & Moghadam, D. K. (2013). Factors affecting university instructors' adoption of web-based learning systems: Case study of Iran. *Computers & Education*, *61*. https://doi.org/10.1016/j.compedu.2012.09.016

Özdemir, H. F., Toraman, Ç., & Kutlu, Ö. (2019). The use of polychoric and Pearson correlation matrices in the determination of construct validity of Likert type scales. *Turkish Journal of Education*, *8*(3), 180–195. https://doi.org/10.19128/turje.519235
Parong, J., & Mayer, R. (2018). Learning science in immersive virtual reality. *Journal of Educational Psychology*, *110*(6), 785–797. https://doi.org/10.1037/edu0000241
R Core Team (2013). *R: A Language and Environment for Statistical Computing* (3.6.0). https://www.r-project.org
Radianti, J., Majchrzak, T. A., Fromm, J., & Wohlgenannt, I. (2020). A systematic review of immersive virtual reality applications for higher education: Design elements, lessons learned, and research agenda. *Computers and Education*, *147*, Article 103778. https://doi.org/https://doi.org/10.1016/j.compedu.2019.103778
Revelle, W. (2019). *psych: procedures for psychological, psychometric, and personality research*. Northwestern University, Evanston, Illinois. R Package Version 1.9.12. https://cran.r-project.org/package=psych
Rogers, E. M. (1983). *Diffusion of Innovations* (3rd Ed.). The Free Press.
Rossel, Y. (2012). lavaan: An R package for structural equation modelling. *Journal of Statistical Software*, *48*(2), 1–36. http://www.jstatsoft.org/v48/i02/
RStudio Team (2015). *RStudio: Integrated Development for R* (1.2.1335). RStudio, Inc. http://www.rstudio.com/
Saade, R., & Bahli, B. (2005). The impact of cognitive absorption on perceived usefulness and perceived ease of use in on-line learning: An extension of the technology acceptance model. *Information and Management*, *42*(2), 317–327. https://doi.org/10.1016/j.im.2003.12.013
Sánchez-Prieto, J. C., Huang, F., Olmos-Migueláñez, S., García-Peñalvo, F. J., & Teo, T. (2019). Exploring the unknown: The effect of resistance to change and attachment on mobile adoption among secondary pre-service teachers. *British Journal of Educational Technology*, *50*(5), 2433–2449. https://doi.org/10.1111/bjet.12822
Sarver, V. T. (1983). Ajzen and Fishbein's "Theory of Reasoned Action": A Critical Assessment. *Journal for the Theory of Social Behaviour*, *13*(2), 155–164. https://doi.org/10.1111/j.1468-5914.1983.tb00469.x
Shen, J., & Eder, L. (2009). Intentions to use virtual worlds for education. *Journal of Information Systems Education*, *20*(2), 225–234. http://jise.org/volume20/n2/JISEv20n2p225.html
Steuer, J. (1992). Defining virtual reality: dimensions determining telepresence. *Journal of Communication*, *42*(4), 73–93. https://doi.org/10.1111/j.1460-2466.1992.tb00812.x
Suh, A., & Prophet, J. (2018). The state of immersive technology research: A literature analysis. *Computers in Human Behavior*, *86*, 77–90. https://doi.org/10.1016/j.chb.2018.04.019
Šumak, B., Heričko, M., & Pušnik, M. (2011). A meta-analysis of e-learning technology acceptance: The role of user types and e-learning technology types. *Computers in Human Behavior*, *27*(6), 2067–2077. https://doi.org/10.1016/j.chb.2011.08.005
Taylor, S., & Todd, P. A. (1995). Understanding information technology usage : a test of competing models. *Information Systems Research*, *6*(2), 144–176. https://doi.org/10.1287/isre.6.2.144
Teo, T. (2009). Is there an attitude problem? Reconsidering the role of attitude in the TAM: Colloquium. *British Journal of Educational Technology*, *40*(6), 1139–1141. https://doi.org/10.1111/j.1467-8535.2008.00913.x
Teo, T., Milutinović, V., Zhou, M., & Banković, D. (2017). Traditional vs. innovative uses of computers among mathematics pre-service teachers in Serbia. *Interactive Learning Environments*, *25*(7), 811–827. https://doi.org/10.1080/10494820.2016.1189943
Teo, T., Zhou, M., Fan, A. C. W., & Huang, F. (2019). Factors that influence university students' intention to use Moodle: a study in Macau. *Educational Technology Research and Development*, *67*(3), 749–766. https://doi.org/10.1007/s11423-019-09650-x
Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal computing: Toward a conceptual model of utilization. *MIS Quarterly*, *15*(1), 124–143. https://doi.org/10.2307/249443
Ursavaş, Ö. F., Yalçın, Y., & Bakır, E. (2019). The effect of subjective norms on preservice and in-service teachers' behavioural intentions to use technology: A multigroup multimodel study. *British Journal of Educational Technology*, *50*(5), 2501–2519. https://doi.org/10.1111/bjet.12834
Venkatesh, V. (2000). Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model. *Information Systems Research*, *11*(4), 342–365. https://doi.org/10.1287/isre.11.4.342.11872
Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on

interventions. *Decision Sciences*, *39*(2), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x
Venkatesh, V., & Davis, F. D. (2000). Theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. *Management Science*, *46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926
Venkatesh, V., Morris, M. G. ., Davis, G. B. ., & Davis, F. D. . (2003). User acceptance of information technology: toward a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540
Xia, Y., & Yang, Y. (2019). RMSEA, CFI, and TLI in structural equation modeling with ordered categorical data: The story they tell depends on the estimation methods. *Behavior Research Methods*, *51*(1), 409–428. https://doi.org/10.3758/s13428-018-1055-2
Yang, H.-H., & Su, C.-H. (2017). Learner Behaviour in a MOOC Practice-Oriented Course: In Empirical Study Integrating TAM and TPB. *International Review of Research in Open and Distributed Learning*, *18*(5), 35–63. https://doi.org/10.19173/irrodl.v18i5.2991
Yang, S., & Lin, C. (2011). Factors affecting the intention to use Facebook to support problem-based learning among employees in a Taiwanese manufacturing company. *African Journal of Business Management*, *5*(22), 9014–9022. https://doi.org/10.5897/AJBM11.1191

Corresponding author: Andrew Kemp, andrew.c.kemp@adelaide.edu.au

Please cite as: Kemp, A., Palmer, E., Strelan, P. & Thompson, H. (2021). Exploring the specification of educational compatibility of virtual reality within a technology acceptance model. *Australasian Journal of Educational Technology, 38*(2), 15-34. https://doi.org/10.14742/ajet.7388

Appendix A
Survey Instrument

Item code	Item text
PU1	VR helps/will help students learn more quickly
PU2	VR enables/will enable the achievement of learning goals
PU3	VR makes/will make learning easier
PU4	VR was/will be useful for learning
PE1	I think it is/will be easy to use VR technology
PE2	I think it is/will be easy to learn how to use VR
PE3	I think using VR is/will be clear and understandable
PE4	I think it is/will be easy to become skilful at using VR
SI1	Students I know think it should be used in teaching
SI2	Lecturers I know think it should be used in teaching
SI3	Please rate the amount of your peers you know who are using or have used VR
SI4	My university supports the use of VR in teaching
FC1	I had/have the resources I need to use VR
FC2	Instruction concerning the use of VR was/will be available to me
FC3	Help was/will be available for technological difficulties
PA1	I felt/feel apprehensive about using VR
PA2	VR was/is somewhat intimidating for me
PB1	VR is OK for some learning but not the learning that I want
PB2	I think that using VR is a good idea
PB3	I like the idea of using VR
PB4	I don't have time to look into using VR
EC1	I think VR fits well with how students like to learn
EC2	VR as a technology is compatible with my university's learning/teaching aims
EU1	Using VR was/would be fun
EU2	Using VR made/would make learning more interesting
EU3	Learners lost/would lose track of time using VR
EU4	VR allowed/would allow learners to focus more intensely on a learning task
SA1	The quality of the VR experience was/will be high
SA2	VR allowed/will allow the learner to control the rhythm of learning
SA3	I trust VR with respect to the security of a learner's details
SA4	I think VR is a reliable technology