Design of an Extended Educational Technology Acceptance Model (EETAM)

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Contents

Abstract

Educational technologies provide students with opportunities to learn remotely or on campus, to access learning materials, engage with interactive learning activities and to interact and communicate with the class. Student use may vary depending on several different factors, and technology acceptance models are well-suited to investigate these factors and how they may influence student behaviour. Because of their popularity and utility, many different models exist and there is no apparent pattern in terms of structure and included factors, and only a minority include factors relevant to education and learning.

The primary aim of this research was to form a robust and comprehensive technology acceptance model specifically suited to educational technologies and test it in the field. This was achieved using exploratory and confirmatory factor analysis, thematic analysis, and structural equation modelling.

The results demonstrated that the final proposed model was statistically sound and measured the majority of the variance of student behavioural intent. It also demonstrated the potential impact that student comfort and well-being may have on formation of student intentions. There was confirmation that the cognitive engagement construct improved the power of the proposed model, which suggested that students think that a technology is useful if it is also engaging. There were further indications that instructor attributes, feedback, and class interaction and communication are also influential, though further confirmation is required in more controlled settings.

A final extended educational technology acceptance model is presented here with strong theoretical and statistical justification in response to the perceived heterogeneity and lack of specificity to education in contemporary technology acceptance research.

Declaration

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint award of this degree.

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23 June 2023

Andrew C Kemp

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My heartfelt thanks and deep appreciation go to my principal supervisor, Associate Professor Edward Palmer, who has always welcomed my ideas and fostered my growth both as an academic and individual. Edward has that rare ability to quickly see the heart of the issue and offer a few words of advice that invariably provide the best way forward and through. It was one of those pieces of advice that led to this thesis after all, and during the middle when I thought I'd had enough, he gave me space and gently nurtured and encouraged me back on the horse.

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beach in Brazil those many years ago. My loving parents and step-parents, Sylvia and Gus, and Keith and Louie, have always encouraged me no matter what I get up to, who might also wonder when I might stop and smell life's roses – I can assure them that time might be drawing nearer with completion of this project.

Finally, I thank deeply the University of Adelaide for its quality of teaching and learning experience. I have been fortunate to have first studied here and received my Bachelor of Science in 1995 where I came of age, and throughout this doctoral project I have gained many skills in practical research, ideation, interpretation, and academic writing. This has enriched me and fed my soul.

Dedication

To those who start out,

those who complete,

and those who take the long road.

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CHAPTER 1 – INTRODUCTION

1.1 Background

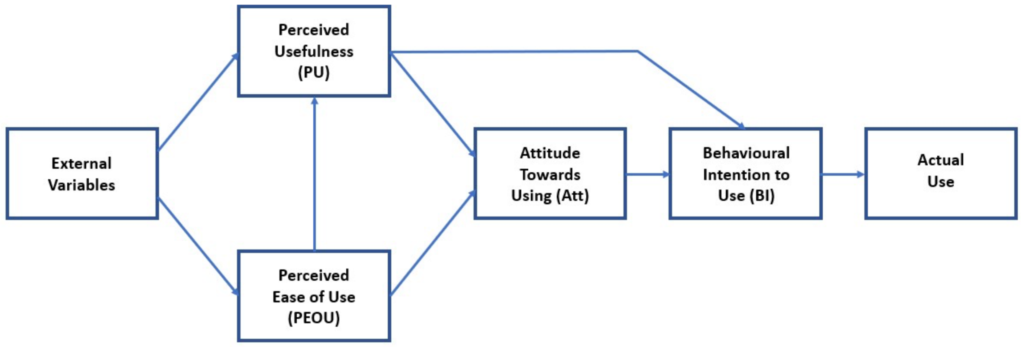
Technology acceptance models (TAMs) are used to measure the impact of user attitudes toward use of technology. They have their basis in behavioural psychology and employ quantitative multivariate methods to evaluate relations between factors. Fred Davis (1986) formulated the seminal 'Technology Acceptance Model' (TAM) which focused on peoples' attitudes towards business machines, and both his model and concept have since gained widespread support with demonstrated validity in many technological contexts. Other models have been proposed by either including more factors to Davis' original model (see Venkatesh & Davis, 2000), or by using different architectures altogether (see Martinez-Torres et al., 2008; Venkatesh et al., 2003). Technology acceptance models have been adopted by education researchers to investigate user attitudes towards many kinds of educational technologies (see Abdullah & Ward, 2016), resulting in many models that can be chosen to respond to a research question, and which are more fully explored in Chapter 2 Literature Review.

When educational technologies have been evaluated using such models, there has been little attention as to whether the model is sufficiently complete and measures everything that should be measured, and globally a variety of factors are included in the various models which vary from study to study. This heterogeneity shows that while a model may be successfully used in a setting, it doesn't indicate whether other factors or model architectures could be successful in the same setting. The question 'does this model include all identifiable influential factors?' has rarely been asked, although Venkatesh et al. (2003) and Abdullah and Ward (2016) have undertaken research towards this in their respective fields. Most of the empirical research has thus been internally valid within its stated confines but cannot be said to answer the complete picture, nor be used to compare technologies across settings. Using the models developed by Davis (1986) and Venkatesh et al. (2003) as examples, if an institution were to measure student attitudes towards a technology, they would gain different appreciations depending on the model they used because the models are different (see Figure 1.1 below).

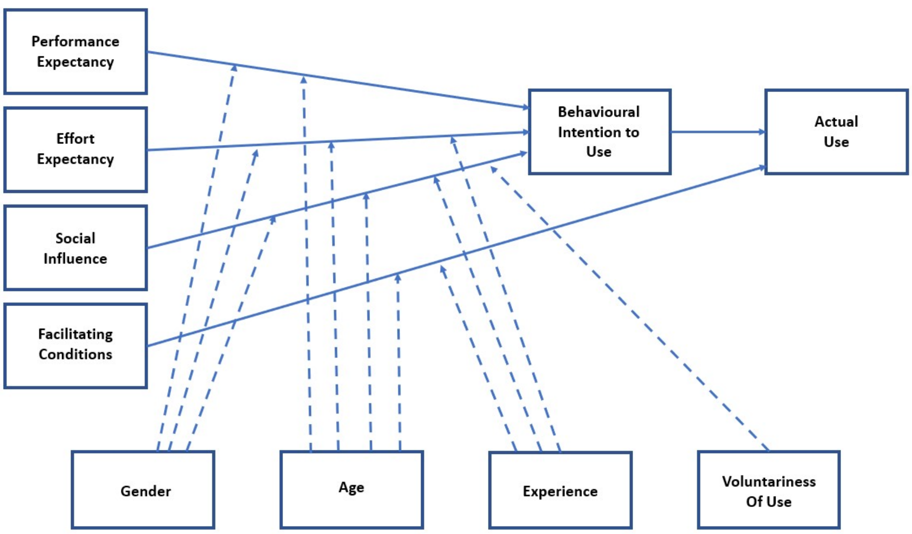
Figure 1.1

Comparison of the (a) Technology Acceptance Model (Davis, 1986) and the (b) Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003)

(a)



(b)



As can be seen in Figure 1.1, the models are very different so choice of model requires careful thought and deliberate choice. The variability of both model architecture and inclusions in contemporary practice and research thus presents two problems: one of comprehensiveness, which is due to selectivity of model factors, and secondly the variability in model architectures used across different settings. For example, if a wiki is evaluated in two institutions using two different models, the results are unlikely to be usefully compared. It would be of value to be able to measure the use of technologies within and across institutions using the same comprehensive measurement instrument, which would allow firstly a more complete evaluation to be conducted and secondly institutional differences to be compared. This information can inform what is important for users and what institutional factors impact user attitudes, and so it is practically useful to be able to perform such comparisons.

Key to forming a reliable and versatile model is to include a consistent set of factors that are thought to encompass the necessary aspects of educational technologies to be measured when it comes to educational technologies. A lot of empirical research incorporates factors that have been used in prior studies pertaining to general technologies, without including anything that pedagogical theory indicates might be important for learning technologies, such as feedback (Boud & Molloy, 2012) or instructional design attributes (Sadler, 1989). This leads to possibilities that models may be insufficient when it comes to appraising attitudes towards technologies used for learning. Granic (2022) also highlights the existence of less-explored factors that may influence attitude or intention, such as playfulness, conformity behaviour, and self-esteem, and this implies that popular models may be further developed.

Since generalist technology acceptance models may not be measuring what they could or should when it comes to educational technologies, and the various model inconsistencies prevent cross-institution comparisons and external validity of results, this research project addresses this problem by constructing a comprehensive model that could be consistently applied to a variety of educational technologies in a variety of educational settings. It is anticipated that combining the relevant factors in such a way would provide greater surety that all important factors are being measured.

This project broadly follows the approach suggested by Whetten (1989) who described what constitutes a sound theoretical contribution: identify the 'factors' (the 'what'), describe how they relate to each other (the 'how'), and explain the significance of such a contribution (the 'why'). By incorporating these aspects, this project produces an extended technology acceptance model suited to educational technologies and deploys it in the field to evaluate its performance.

1.2 Research Aims

The overall research aim was to develop a comprehensive and effective technology acceptance model suited to appraise a range of educational technologies, and to test its utility in a real-world test case. This involved gaining an appreciation of the range of factors that are currently known to affect user attitudes and intentions towards general and educational technologies, bringing them together into a reliable measurement model. Specifically, the primary aims of this research project were:

1. To identify the types, characterisations and scope of factors affecting attitudes and intentions towards use of educational technologies.
2. To construct a comprehensive technology acceptance model suited to education, and investigate:
    a. Whether its education-specific constructs improve its power when applied to educational technologies, and
    b. If it can explain the majority of variance of intent to use such technologies.

1.3 Scope and Research Objectives

Technology acceptance models are common instruments to measure attitudes and intentions towards general technologies and have been applied to educational technologies. However, researchers often modify or extend them to their circumstance by adding specific measurement constructs. Many educational studies do not include factors specific to education but rely on measurement constructs that were developed for technology in general. Thus, measurement models vary enough for empirical studies to be relevant only to their situation and context, and not necessarily measuring everything that may be important in educational settings.

Whereas Davis' (1986, 1989) TAM was developed to explain usage of computers in a business setting, educational use of technology is nested within a teaching and learning environment that is arguably more complex. For example, while an office employee might use a program to perform a specific function (such as payroll), a student would use a technology as part of a broader learning effort with less-defined boundaries. An LMS could be used in lectures, tutorials, and practicals and for different purposes in each. Furthermore, design of learning varies from teacher to teacher and between subjects but consideration of aspects of the learning setting outside of technology use is beyond the remit of a technology acceptance model. Moreover, appraisal of technology acceptance is only part of consideration of the broader student experience but must nonetheless be performed satisfactorily. As a result, the scope of this thesis is solely on development of a model to appraise the educational technologies employed in the broader learning setting, which can then be conducted with other research into the general student experience.

It is important to note that published (TAM) studies vary in the choice of dependent variables, with some only including intention, while others also include actual use. This thesis will limit itself to intention for two reasons: firstly, intention is pre-requisite to action, and secondly that the question of what links intention to action is a broader problem. For example, Venkatesh et al. (2003) included facilitating conditions as a moderating factor in the progression from intention to actual use and is brought to bear after intention has been formed. Thus, it is important to firstly realise what drives intention, as without it, factors that act downstream of this will have nothing to act upon. Intention is therefore the core issue to address.

The focus of this research was to bring order to a disorganised field by identifying, structuring, operationalising, and deploying a set of measurement constructs that could be said to reliably measure attitudes towards educational technologies. Specifically, the research objectives were:

1. To search for the latent factors related to educational technology use that have been shown to affect user attitudes and intentions.
2. To form a comprehensive, yet parsimonious, structural model that researchers can use to measure attitudes and intentions in a wide variety of educational settings.
3. To test this model in a real-world educational setting.

This model is being developed and tested within higher educational settings because the foundational behavioural theories that these models are based on describe adult behaviour. Child psychology and its effects on behaviour are beyond the scope of this work, and so the model developed pertains to adult learning situations. Further, in the interests of excluding confounders, the scope of research has been limited to learning in higher education institutions, not training in professional (non-educational) settings where technology acceptance models originated in the 1980s.

1.4 Hypotheses

It is hypothesised that:

1. A suitably constructed and relevant model will explain a majority of the variation of intention to use an educational technology (> 60%) (see Peterson, 2000).
2. The inclusion of factors specific to learning and pedagogy will increase the variance explained by the model when applied to an educational technology.

1.5 List of Scientific Papers by Author

Elements of this thesis have been published or submitted for publication in peer reviewed journals as shown in Tables 1.1 to 1.4.

Table 1.1

Details for Paper 1

Paper Number	1
Title	A taxonomy of factors affecting attitudes towards educational technologies for use with technology acceptance models.
Authors	**Andrew Kemp**, Edward Palmer, Peter Strelan
Publication status	**Published**
Citation	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

Paper 1 explored current research and collated the various constructs that were incorporated within their TAMs. Themes emerged which allowed the formation of taxonomic groups at the primary, secondary, and tertiary levels. This constituted the basis for further research and a grounding of the situation at the time.

Table 1.2

Details for Paper 2

Paper Number	2
Title	Exploring the specification of educational compatibility of virtual reality within a technology acceptance model.
Authors	**Andrew Kemp**, Edward Palmer, Peter Strelan, Helen Thompson
Publication status	**Published**
Citation	Kemp, A., Palmer, E., Strelan, P., & Thompson, H. (2022). 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

Paper 2 concerned the question of whether a construct that measures attitude should be included within a TAM since there is evidence for and against its inclusion. Additionally, this paper investigated the nature of educational compatibility which was a seldom-used construct, but which was deemed relevant to educational TAMs. This study was performed to inform the structure of the final model vis-à-vis attitude and educational compatibility.

Table 1.3

Details for Paper 3

Paper Number	3
Title	Key factors for student learning via Zoom: a thematic analysis of technology acceptance.
Authors	**Andrew Kemp**, Sarah Dart, Edward Palmer, Peter Strelan, Helen Thompson
Publication status	**Submitted** to Internet and Higher Education
Citation	-

Paper 3 investigated student attitudes to using Zoom for learning during the COVID-19 pandemic because it was firstly reasoned that it may have affected certain attitudes, and secondly because it was important to explore student views to appraise the completeness of the taxonomy produced in Paper 1. The results from this study informed whether any further constructs should be added to the final model over and above what the taxonomy suggested.

Table 1.4

Details for Paper 4

Paper Number	4
Title	Testing a novel extended educational technology acceptance model using student attitudes towards virtual classrooms
Authors	**Andrew Kemp**, Edward Palmer, Peter Strelan, Helen Thompson
Publication status	**Submitted** to British Journal of Educational Technology
Citation	-

Papers 1, 2 and 3 collectively informed the inclusions and structure of the final model. Paper 4 deployed this model in the field to test its utility and robustness.

1.6 Linkage of Scientific Papers to Research Objectives and Hypotheses

Table 1.5

Linkage of Scientific Papers to Research Objectives and Hypotheses

	Scientific Paper			
	1	2	3	4
Research Objectives				
1. To search for the latent constructs related to educational technology use that have been shown to affect user attitudes and intentions.	Y		Y	
2. To form a sufficient, but still parsimonious, structural model that researchers can use to measure attitudes and intentions in a wide variety of educational settings.		Y		Y
3. To test this model in a real-world educational setting.				Y
Hypotheses				
1. A suitably constructed and relevant model will explain a majority of the variation of intention to use an educational technology (> 60%).				Y
2. The inclusion of factors specific to learning and pedagogy will increase the variance explained by the model when applied to an educational technology.				Y

CHAPTER 2 – LITERATURE REVIEW

2.1 Introduction

This thesis is rooted in theories and research on behavioural intentions, which investigates the factors that influence why people take certain actions and how those factors relate to each other. There have been several models theorised, developed, and tested to explain behaviour in settings such as consumer, general technology use and educational technology use. The general pattern of all behavioural intention theories is belief → attitude → intention →action (P. C. Lin et al., 2013). Underpinning this research are the Theory of Reasoned Action (Fishbein & Ajzen, 1975), Theory of Planned Behaviour (Ajzen, 1985, 1991), and the Technology Acceptance Model (TAM) (Davis, 1986; Davis et al., 1989), which was based on the Theory of Reasoned Action. These theories and model are germane because the main objective of this research is to produce and test a technology acceptance model suited to educational technologies. After Davis' TAM, researchers have either extended it, or developed models with different architectures to explain technology use. Subsequently, researchers have applied it to technology use in education. In this literature review, the early seminal behavioural intention models are described followed by an exploration of the various technology acceptance models that have been developed for educational research, and their application.

2.2 Systematic Review of Literature

Several technology acceptance models have been developed and utilised for research since Davis' original TAM was formulated in 1986. A systematic review was conducted to identify the main TAMs and their derivatives, which are described here, grouped by characteristics and application.

2.2.1 Process for finding papers

A systematic review process (Page et al., 2021) was followed to identify relevant models. The search string [“TAM” OR “technology acceptance model”] was applied to the EBSCO, ERIC, A+ Education and APA PsychInfo databases, filtered for dates between January 1986 and March 2022. Returns were imported into Mendeley reference manager, where duplicates were removed first by Mendeley, then manually by the author. Titles and abstracts were reviewed to shortlist the papers for more in-depth review, which involved full-text review to exclude articles outside of the eligibility parameters or where a full text could not be obtained. The remainder of papers were coded according to the model used, the incorporated constructs and the target technology.

The process and associated numbers are provided in figure 2.1, and inclusion and exclusion criteria are provided in table 2.1.

Figure 2.1

PRISMA Flow Diagram of Studies' Screening and Selection

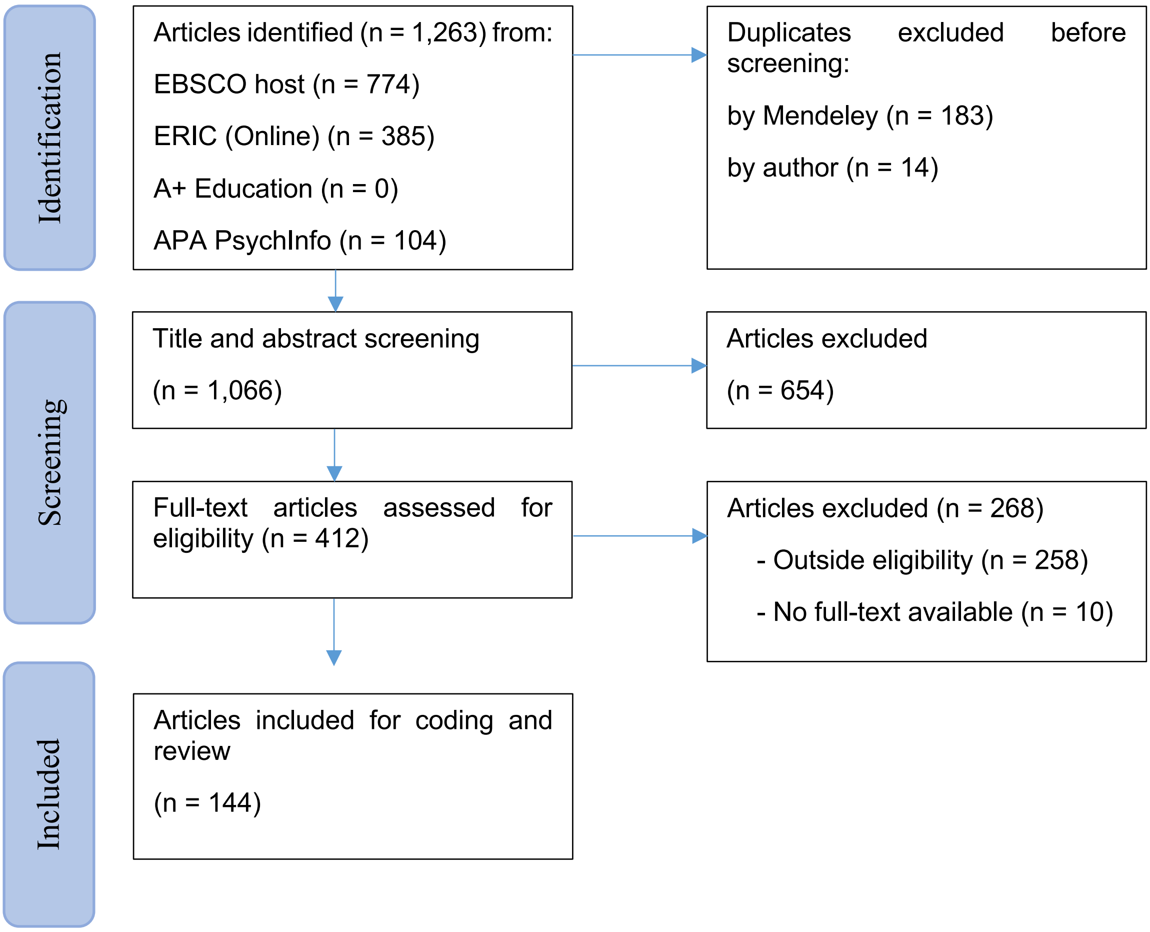


Table 2.1

Inclusion and Exclusion Criteria for Studies to Include in the Literature Review

Inclusion criteria	Exclusion criteria
Higher education context	Primary, secondary school, industry, business, medicine, nursing, MOOCs.
Educational technology target, LMS's, mobile learning, tablet PCs	General e-technology acceptance or attitudes.

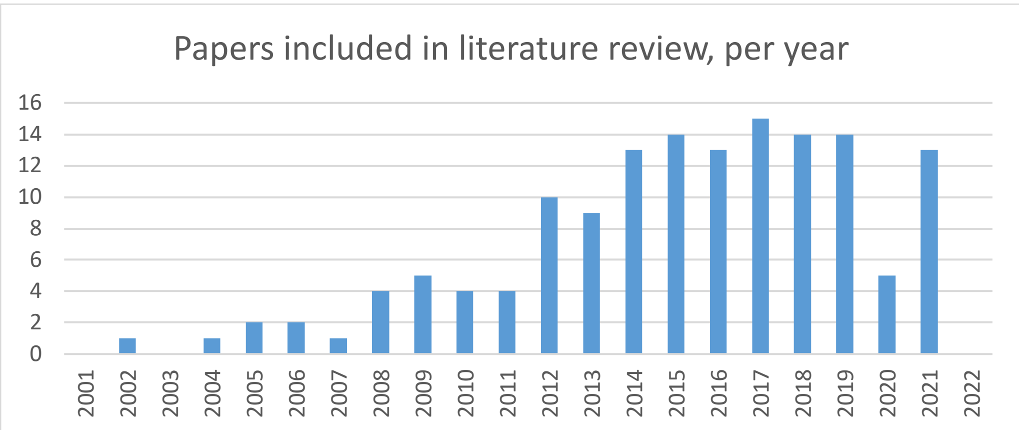
Instructional setting, adopting technology for teaching and/or learning.	Use for analytics, library systems, general cloud computing, exam systems, communications, social media, or other non-instructional uses.
TAM measures behavioural intention or use	TAM measures other constructs, such as satisfaction.
Articles report path regressions in a structural equation model	TAMs used as framing or context, or simple regressions
Students or instructors as subjects	Pre-service teachers as subjects

2.2.2 Results of systematic review

As reported by Figure 2.1, the systematic review returned 144 papers for coding and detailed consideration. The spread of publication date showed a steady increase from 2012 to 2021, with a noticeable dip during 2020, as shown in Figure 2.2.

Figure 2.2

Number of Review Papers by Year



The papers were published in fifty-four journals as listed in Table 2.2.

Table 2.2

List of Journals that Published the Returned Papers in This Review

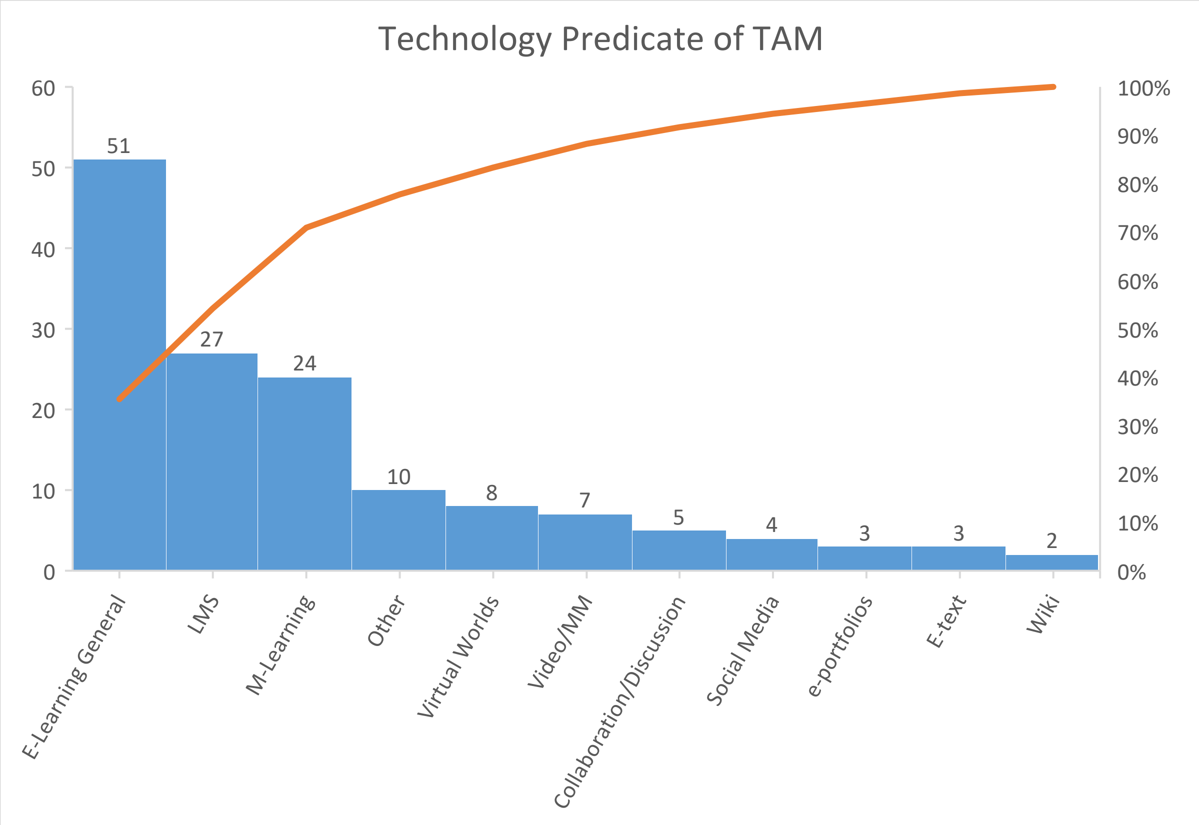
Journal Name	Frequency
American Journal of Business Education	1
Asia-Pacific Education Researcher	2
Australasian Journal of Educational Technology	7
Behaviour & Information Technology	2
British Journal of Educational Technology	11
Campus-Wide Information Systems	1
Communication Education	1
Computer Assisted Language Learning	1
Computers & Education	14
Computers in Human Behavior	4
Contemporary Educational Technology	1
Decision Sciences Journal of Innovative Education	1
Decision Sciences	1
Education and Information Technologies	5
Educational Studies	1
Educational Technology Research & Development	5
Electronic Journal of E-Learning	1
English Language Teaching	1
EURASIA Journal of Mathematics, Science & Technology Education	1
Group Decision and Negotiation	1
Information Technology for Development	1
Innovations in Education & Teaching International	3
Interactive Learning Environments	2
Interactive Technology and Smart Education	3
Interdisciplinary Journal of E-Learning & Learning Objects	2
International Education Studies	2
International Journal of Education & Development Using Information & Communication Technology	2
International Journal of Education and Literacy Studies	1
International Journal of Education Research	1
International Journal of Educational Technology in Higher Education	3
International Journal of Emerging Technologies in Learning	6
International Journal of Information and Communication Technology Education	1

International Journal of Information and Learning Technology	1
International Journal of Instruction	2
International Journal of Web-Based Learning and Teaching Technologies	2
International Review of Research in Open & Distance Learning	10
Journal of Computer Assisted Learning	1
Journal of Computing in Higher Education	5
Journal of Education for Business	1
Journal of Educational Computing Research	4
Journal of Educational Multimedia and Hypermedia	1
Journal of Educational Technology & Society	2
Journal of Educational Technology Development & Exchange	2
Journal of Educational Technology Systems	3
Journal of E-Learning & Knowledge Society	1
Journal of Information Systems Education	2
Journal of Information Technology Education	5
Journal of Online Learning & Teaching	1
KEDI Journal of Educational Policy	1
SAGE Open	1
South African Journal of Higher Education	1
The International Review of Research in Open and Distributed Learning	1
Turkish Online Journal of Distance Education	4
Turkish Online Journal of Educational Technology	4
Total	144

Figure 2.3 shows that most studies investigated e-learning in general, or online learning not further defined (n = 51), with learning management systems (n = 27) and mobile learning (n = 24) representing second and third place respectively. The ‘other’ category contained any technology not represented specifically in figure 2.3, for example, chatbots, automated writing systems, webinars, tablet PCs, cloud computing, statistical software, QR codes and clickers and email.

Figure 2.3

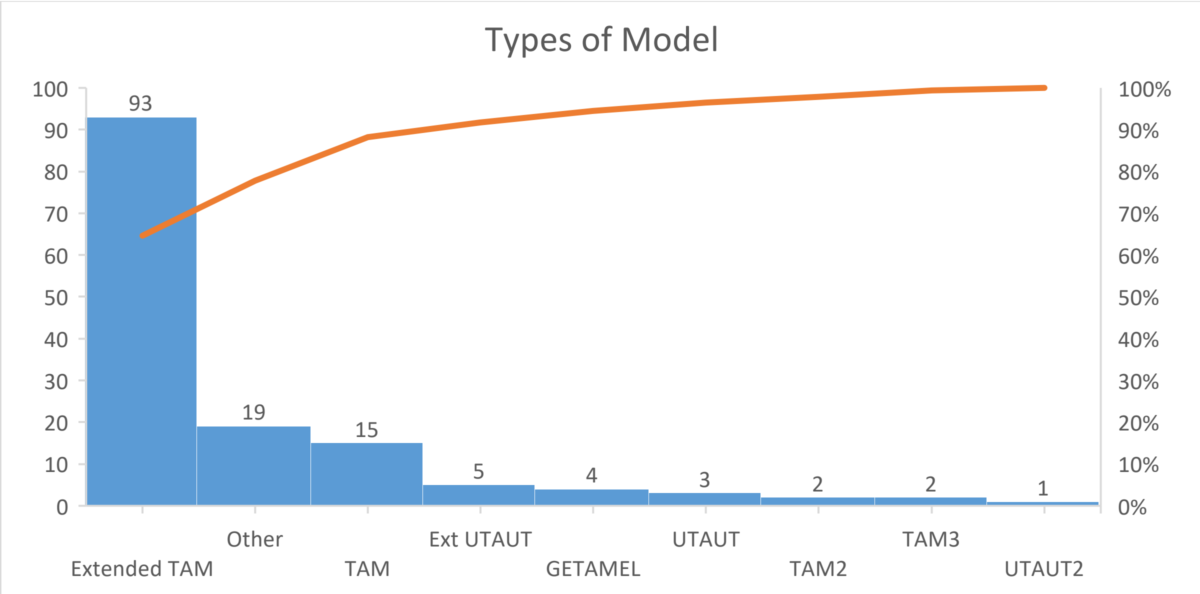
Frequency of Various Technologies Represented by the Review Papers



While there was some variation in the choice of model used, the vast majority (*n* = 93) employed an extended technology acceptance model type, where Davis' TAM was extended by one or more constructs generally upstream of perceived usefulness and perceived ease of use (see Figure 1.1). Thereafter, there were nineteen models that were departures from the recognised TAMs, for example aggregates of two or more models, constructs being connected in ways not specified by the seminal models, or other unique architectures. The pure TAM itself, consisting of only perceived usefulness, perceived ease of use, behavioural intent, was the third largest group (*n* = 15); this group included some variation in inclusion of attitude and actual use. Of note, the other often cited models (for example GETAMEL, UTAUT and their extended versions) were only featured in small numbers, as seen in figure 2.4.

Figure 2.4

Types of Models Featured in the Review Papers



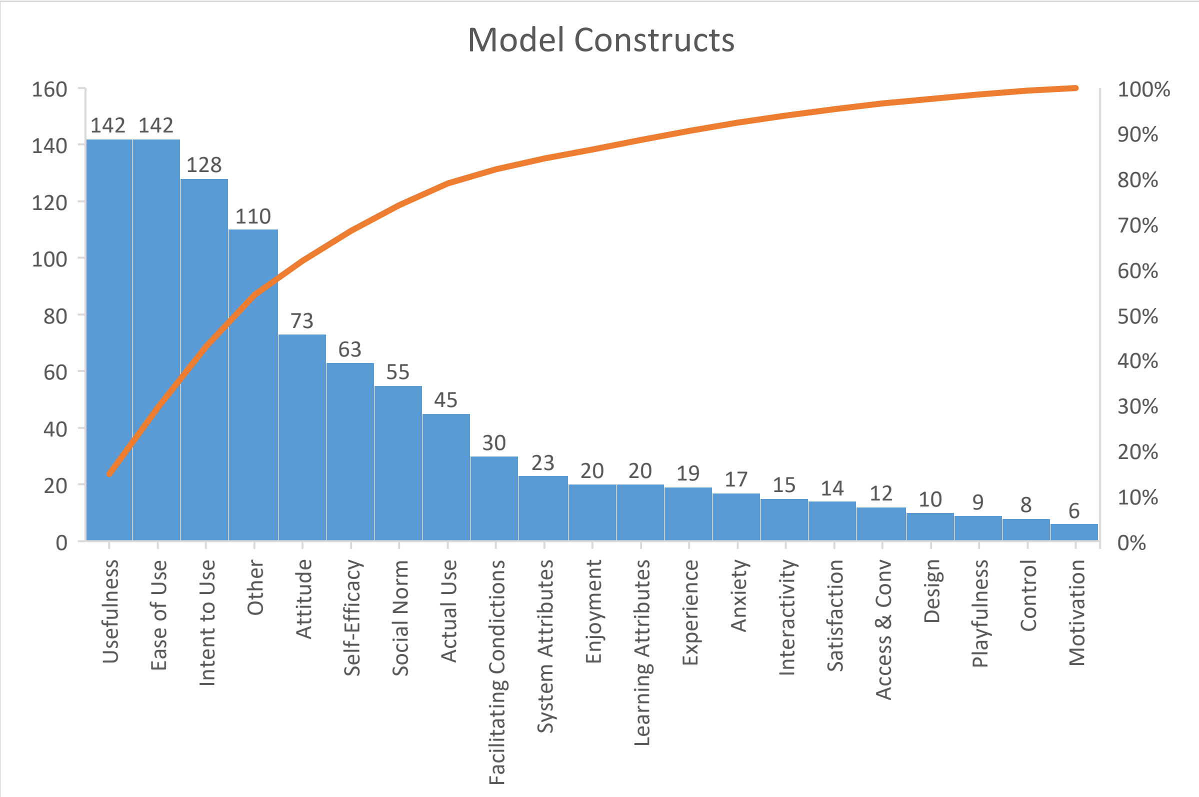
Note. TAM = Technology Acceptance Model, UTAUT = Unified Theory of Acceptance and Use of Technology, Ext UTAUT = Extended Unified Theory of Acceptance and Use of Technology, GETAMEL = General extended Technology Acceptance Model for E-Learning, TAM2, TAM3 and UTAUT2 are extensions of the core TAM and UTAUT models respectively.

Of the constructs that were incorporated (see Figure 2.5), perceived usefulness and perceived ease of use were the most used, appearing in 142 out of 144 studies; the two studies that did not incorporate these constructs employed unorthodox models (Adetimirin, 2015; Al-Adwan et al., 2018). Of note is that ‘perceived usefulness’ also incorporates ‘performance expectancy’ and ‘perceived ease of use’ incorporates ‘effort expectancy’, which are synonymous terms. As can be seen in Figure 2.5, attitude, intent to use and actual use were used variably as part of the core technology acceptance models. Beyond these three, other popular constructs such as self-efficacy, social norms and facilitating conditions, are shown in decreasing numbers, further demonstrating model variability.

Constructs relating to a user's experience (e.g., enjoyment, experience, anxiety, satisfaction, motivation) as well as some constructs relating to education or learning (e.g., learning attributes, interactivity, and design) are present in yet smaller numbers and are the least used by the surveyed models.

Figure 2.5

Constructs Included in the Review Papers



The papers provided by the systematic review process, in addition to other papers referred to by the author, provide a basis for the literature review where the main characteristics and findings of various published models are discussed in the next sections. Before delving further into the original technology acceptance model and its extensions or alternative versions, it is prudent to precis the epistemological roots of these models.

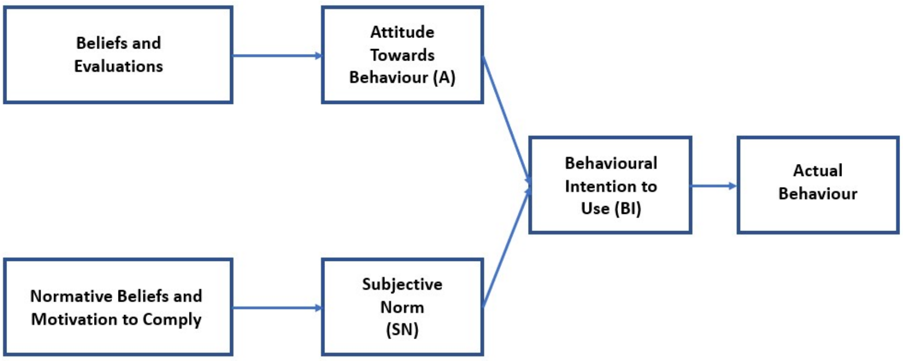
2.3 Epistemological Roots of the Technology Acceptance Model

2.3.1 Theory of Reasoned Action (TRA)

The TRA (Fishbein & Ajzen, 1975) (Figure 2.6) was developed to model behavioural intention towards a voluntary act, and theorises that a person's attitude towards a behaviour and subjective norm determine intention to engage in a behaviour. Attitude includes a person's beliefs about the behaviour and an estimation of the outcomes of performing the behaviour, while subjective norm is a product of normative beliefs about the behaviour and a person's motivation to comply with those norms (Nam et al., 2014). The TRA has been summarised as "human behavioural intentions are predicted by their attitude toward the given behaviour and the social pressures associated with it" (Lai et al. 2012, p.570).

Figure 2.6

Theory of Reasoned Action



Note. Adapted from Davis (1989).

The TRA has been applied to a broad variety of situations, such as consumer behaviour, voting, healthcare, work-related behaviours, dining and drinking, amongst others, and demonstrated to predict intentions and behaviour at varying levels (B. H. Sheppard et al., 1988). Meta-analyses of the TRA's ability to predict behaviour have determined strengths of associations between attitude and intention, subjective norm and intention, and intention and behaviour to be moderate to high (Cooke & French, 2008; Nam et al., 2014).

Burak (2004) used the TRA to examine and predict college students' reading intentions and found that the model explained 35-38% of the variance intention, with attitude being the strongest influence on intent to read. Park (1998) examined TRA's ability to predict college students' intention to study for exams and found moderate associations between attitude and subjective norm and intent to study, however a low explained variance for intention to study ($R^2 = 0.11$), which indicates that the TRA was not a sufficient model to explain student intention.

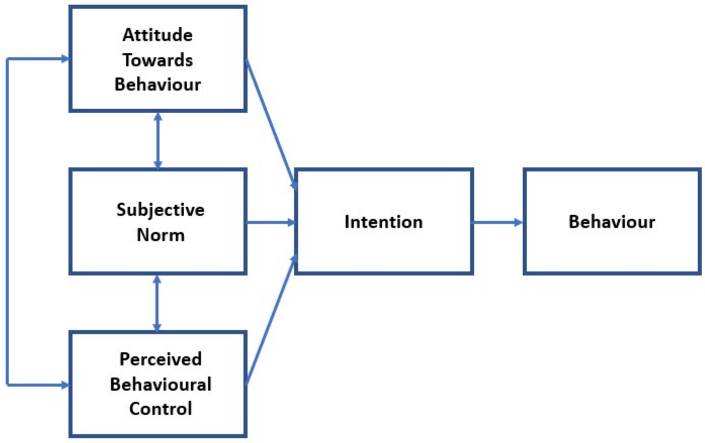
A limitation of the TRA is that behavioural intention alone does not lead to actual behaviour (Ajzen et al., 2018; B. H. Sheppard et al., 1988), and so the TRA can only be seen as a part of a more complete technology acceptance model. Its value lies in its establishment that a person's attitudes to a behaviour and social norms are drivers of behavioural intention for voluntary acts. In terms of educational technology, the fact that the TRA can apply to any behaviour limits its specificity and indicates that a model with greater specificity to educational technology would likely be more useful. It was for this reason that Davis formulated his Technology Acceptance Model, discussed in Section 2.4 below.

2.3.2 Theory of Planned Behaviour

The Theory of Planned Behaviour (TPB) (Ajzen, 1985, 1991) (Figure 2.7) was a response to a limitation of the Theory of Reasoned Action (TRA), which did not account for situations where an individual did not have complete voluntary control over their actions. Whereas the TRA is concerned with attitudes from self and others, the TPB is additionally concerned with the ability to perform vis-à-vis a user's perceived skills, resources and opportunities alongside perceived availability of support (Lai et al., 2012). While the TPB was not an epistemological root of Davis' TAM, the TPB and TAM were formed contemporaneously.

Figure 2.7

Theory of Planned Behaviour



Note. Adapted from Ajzen (1991)

The TPB retains the central structure of belief → intention → behaviour, but it adds perceived behavioural control to account for influences that either enable or inhibit a person's perceived ability to act. The nature of perception is important in the TPB, since Ajzen theorises that perceived behavioural control is context dependent and also moderates the link between intention and behaviour (Ajzen, 2011). Ajzen's perceived behavioural control differs from Rotter's (1966) locus of control, which is more central to a person: "a person may believe that, in general, her outcomes are determined by her own behaviour (internal locus of control), yet at the same time she may also believe that her chances of becoming a commercial airplane pilot are very slim (low perceived behavioural control)" (Ajzen, 1991, p. 183). Thus, Ajzen includes aspects of external opportunity (Sarver, 1983) as well as individual's assessment of their own abilities.

Armitage and Connor's (2001) meta-analysis of 185 studies showed that the TPB explained 27% of the variance of intention, and 39% variance of behaviour, with the perceived behavioural control component accounting for a substantial proportion of behaviour independent of attitude and subjective norm. Godin and Kok's (1996) meta-analysis of the TPB in a health context calculated correlations between 0.34 and 0.41 between intention and behaviour. Cooke and French's (2008) meta-analysis showed a high correlation between attitude and intent, and moderate correlation between subjective norm and intent, and perceived behavioural control and intent. Another study (McEachan et al., 2011) showed that the TPB explained only a modest amount of variance of intention and behaviour, and predictive power varied according to type of behaviour, age, and prior experience. Eren and Gould (2022) showed that adding other constructs to the TPB increased explained variance in a study exploring drivers' use of smartphones, albeit only by a small amount. In doing so Eren and Gould showed that extension of the TPB was justified in order to answer a research question in their context.

The picture that has emerged is that while the Theory of Reasoned Action and Theory of Planned Behaviour are satisfactory for explaining behaviour in general settings, they do not account for most of the intention or behaviour. This indicates that there are likely other factors that influence intention and behaviour that are not included in these models. With this background, Davis set out to formulate a model that was more effectively able to explain intention and behaviour vis-à-vis use of business machines in the mid 1980s.

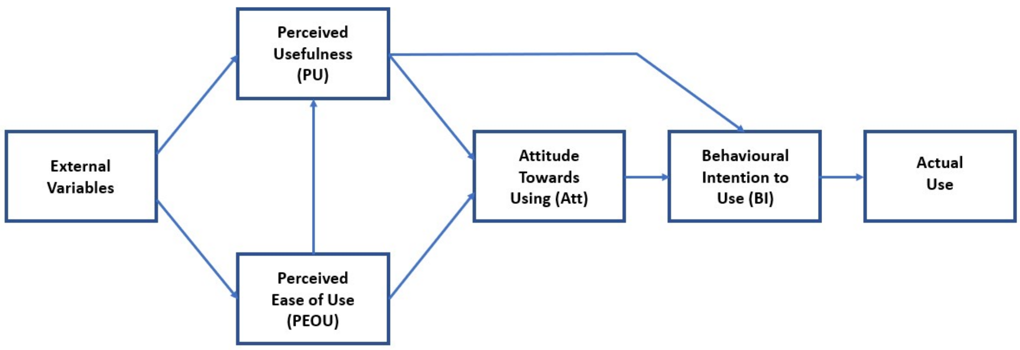
2.4 Davis' Original Technology Acceptance Model

In this section, Davis' seminal TAM is first presented and discussed, including a brief discussion of the question of attitude within the model, followed by exploration of how the TAM has been used in the literature.

The original Technology Acceptance Model (TAM) (Figure 2.8) was developed by Davis (1986) in part to “provide the theoretical basis for a practical ‘user acceptance testing’ methodology that would enable system designers and implementers to evaluate proposed new systems prior to their implementation” (Davis et al., 1989, p. 2), and is a popular choice to evaluate e-learning technology acceptance (Šumak et al., 2011).

Figure 2.8

The Technology Acceptance Model (Original)

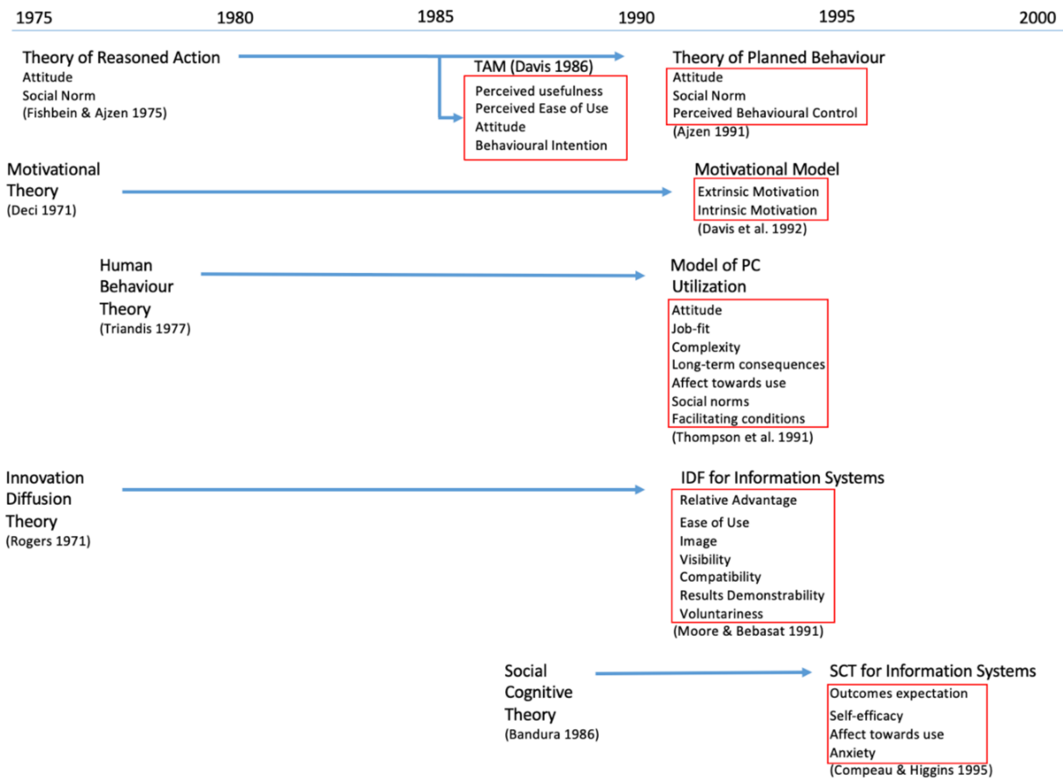


Note. Adapted from Davis et al. (1989).

Davis based the TAM on the Theory of Reasoned Action because the TRA provided a solid basis between external stimuli and resulting behaviour (Davis, 1986). Other theories contemporaneous with the TRA, such as motivation (Deci, 1971), human behaviour (Triandis, 1977, 1980), and innovation diffusion (Rogers & Shoemaker, 1971), did not necessarily provide sufficient clarity around the conditions under which attitude mediated the link between beliefs and intention (Davis et al., 1989). Figure 2.9 shows the TAM’s context in relation to other behavioural intention theories and models that relate to technology usage.

Figure 2.9

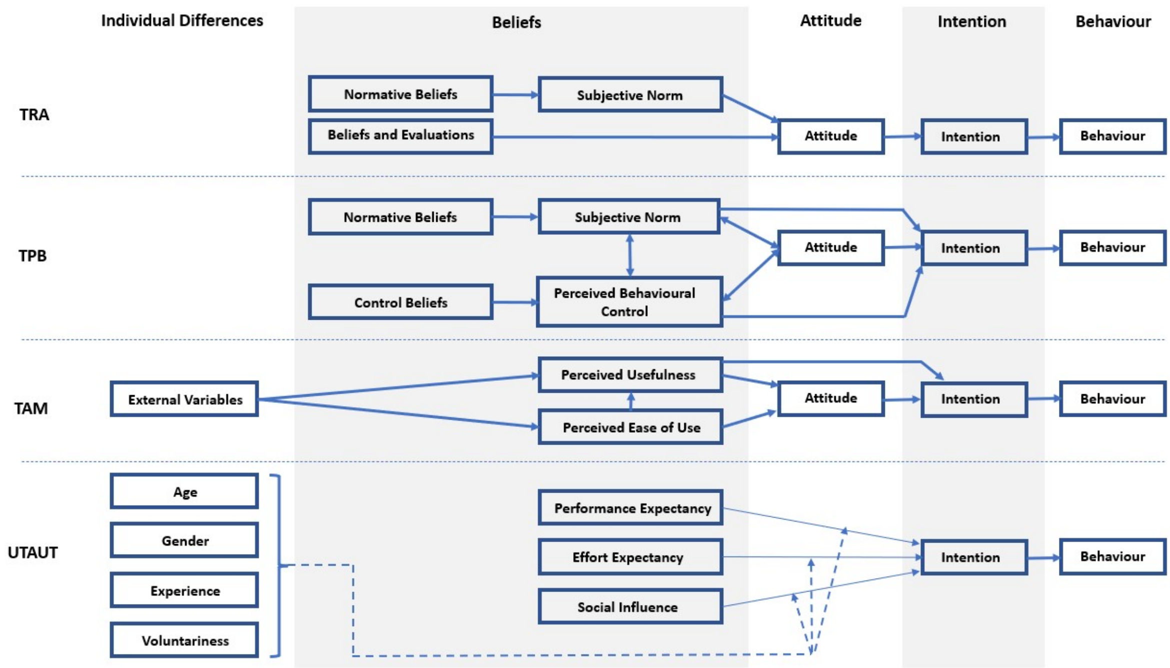
Development of Davis' TAM in Context



The TAM posits that perceived usefulness (PU) and perceived ease of use (PEOU) are personal beliefs that influence attitudes towards use of a technology and mediate the influence of other external variables. It further hypothesises that perceived ease of use influences a user's perception of usefulness "since, all else being equal, a system which is easier to use will result in increased job performance (i.e., greater usefulness) for the user" (Davis, 1986, p. 26). The TAM adopts the central idea from the Theory of Reasoned Action that attitude influences behavioural intent to use a technology or information system, which in-turn influences actual system use. Like the Theory of Reasoned Action, Davis' TAM does not address the gap between behavioural intention to use (BI) and actual system use (B. H. Sheppard et al., 1988), and so while the TAM may predict a high behavioural intention for a given context, it does not necessarily mean that actual use will occur (Ajzen et al., 2018). So long as this limitation is understood, the TAM is noted to be "reliable and may be used in a variety of contexts" (King & He, 2006, p. 751), but the size of causal effects may be influenced by moderating variables, type of user and type of technology (Šumak et al., 2011). Davis' TAM sits amongst other behavioural theories and is broadly aligned with them, where each model has its own nuances. A general framework is offered by Punnoose (2012) and shown in Figure 2.10.

Figure 2.10

Alignment of the Main Behavioural Theories



Note. TRA = Theory of reasoned Action, TPB = Theory of Planned Behaviour, TAM = Technology Acceptance Model, UTAUT = Unified Theory of Acceptance and Use of Technology. Adapted from Punnoose (2012).

Why did Davis limit determinant beliefs to just perceived usefulness and perceived ease of use? Davis was influenced by Fishbein and Ajzen's assertion that individuals are capable of only processing five to nine items of information concurrently, and that since individual beliefs vary, it is best to take the beliefs of the population in aggregate, especially since only a small number of beliefs actually determine behaviour. These concepts were at the heart of Davis' model limiting itself to only perceived usefulness and perceived ease of use as belief determinants of attitude.

In a departure from the Theory of Reasoned Action, Davis' TAM excluded the social norm pathway of the Theory of Reasoned Action because Davis reasoned that users who have not seen a technology in use would be unable to be influenced by others' use of it (Davis, 1986). Davis limited the context of user acceptance testing to situations where there were no avenues for a user to be aware of others' beliefs or wishes with respect to use of that system. This view arose because the process for normative beliefs in Fishbein's model were direct and did not include guessing, and Davis followed that line of reasoning, speculating that guessing what others might think would perturb results (Davis, 1986).

When considering attitude and its relation to behavioural intention, Davis reported that where an intention has already been formed, it is more powerful than attitude, but where an intention has not yet been formed, attitude is more influential (Davis, 1986). Davis et al. (1989) conducted a follow-up longitudinal study comparing the Theory of Reasoned Action with the Technology Acceptance Model. This study revealed that attitude mediated the effect of belief on intention less than expected according to the Theory of Reasoned Action or Davis' TAM (Davis, 1989). This research resulted in the removal of attitude from the original TAM (TAM-O) to form the revised TAM (TAM-R). Teo (2009a) performed a study to specifically measure the effect of attitude within a TAM and found that attitude did not contribute to explained variance of the dependent variable, behavioural intent, thus claiming that it was an unnecessary construct within the TAM. This is despite a contemporaneous publication (Teo, 2009b) which showed that attitude did influence behavioural intent (but which did not investigate explained variance). Nistor and Heymann (2010) subsequently investigated Teo's findings and reported that while attitude had influence on behavioural intent to use the computer system, it did not contribute to behavioural intent's explained variance. These findings agreed with both of Teo's 2009 papers that showed that while attitude influences behavioural intent, it has no statistical power in the model overall. Nistor and Heyman explained that the effects of attitude were influential but that variables such as perceived usefulness and perceived ease of use subsumed attitude and carried its effect indirectly.

The question of removal of attitude was not, however, settled, since some studies were able to demonstrate that attitude still had a statistical effect. López-Bonilla and López-Bonilla (2011) showed that the methodology could influence results, where if covariance-based structural equation modelling was used, then TAM-R was the preferred model, however if partial least squares-based structural equation modelling was used then TAM-O was the preferred model. This demonstrated that different statistical methods could affect path coefficient strengths and the power of the model, as measured by the amount of variance measured of the dependent variable.

To help settle the question, Ursavaş (2013) compared the results of Teo (2009a), Nistor and Heymann (2010) and López-Bonilla and López Bonilla (2011) and confirmed that attitude did have an influence on behavioural intent to use the technology in question but did not explain any variance in actual usage. This result is congruent with Nistor and Heymann (2010), and Venkatesh et al. (2003). One can conclude from these findings that while attitude does indeed influence intention, it is contained by other constructs, and does not individually account for actual behaviour.

Whereas Davis' TAM specified that beliefs pertaining to perceived usefulness and perceived ease of use are central determinants of attitude, it posited the existence of upstream external variables that influence those beliefs about usefulness and ease of use. The external variables can be anything and context specific, but work through perceived usefulness and perceived ease of use. Accordingly, researchers would determine which external variables apply in each specific case (Davis, 1986).

There are many versions of Davis' TAM in use. They can be categorised as core models, where researchers have simply adopted Davis' model without any additions (though sometimes with deletions), and extended models, which add constructs. We now turn to an exploration of research that has used Davis' core TAM before turning our attention to extended versions of the model.

This systematic review identified fifteen studies that employed the TAM alone as the research framework, ranging from 2002 to 2021. Almarabeh (2014) applied the TAM to two computer science classes at the University of Jordan using Moodle and concluded that the TAM's five hypotheses were validated, as did Dastjerdi (2016) in a study of distance education students in Iran. This pattern of verifying the TAM relationships is also found in Gao (2005), Luan and Teo (2009), Shroff et al. (2011), Kwok and Yang (2017) and Robinson (2019). Sprenger and Schwaninger (2021) used an abridged TAM consisting of only perceived usefulness, perceived ease of use and behavioural intent to compare four technologies (classroom response system, classroom chat, e-lectures and mobile virtual reality) and confirmed the TAM's hypothesised relationships between the three variables. Learning management systems have also been technology targets of simple TAM models, for example Al-Maroof and Al-Emran (2018) used the core TAM to study student attitudes to Google classroom use in Oman, Landry et al. (2006) used a truncated TAM to study student attitudes to Blackboard in New Orleans, while Schoonenboom (2014) used a truncated TAM model to study instructors' attitudes towards using Blackboard at a Dutch university. Whereas Landry et al. used a model incorporating perceived usefulness, perceived ease of use, and actual use, Schoonenboom's model incorporated perceived usefulness, perceived ease of use, and intent to use. These studies serve to illustrate that deployment of an unextended TAM achieves little in terms of investigating how students or other users relate to educational technologies but have value in validating the model.

Collectively, most of these studies concluded that the TAM could predict student or instructor attitudes towards various technology targets but offered no implications for teaching or delivery. However, Dasgupta et al. (2002) investigated how prior use of a system affects intentions and found that experience strengthens the usefulness → actual use and ease of use → actual use relationships, intimating that support should be provided to new users, and Maziriri et al. (2020) concluded that perceived usefulness is stronger than ease of use, which can provide an educator a hint as to how to improve uptake of educational technologies.

2.5 General Extensions of the Technology Acceptance Model

Since the time of its introduction, a number of external factors that influence perceived ease of use and perceived usefulness have been studied by various researchers using the TAM, resulting in a proliferation of 'extended' TAMs (see Abdullah & Ward, 2016). This implies that the TAM can be applied to a variety of settings by simply choosing appropriate external variables that influence perceived usefulness and perceived ease of use. A perceived limitation of the TAM, however, is that behavioural intent is only estimated through the lenses of perceived usefulness and perceived ease of use, and while these two constructs are robust influencers of behavioural intent (Šumak et al., 2011) there may be other reasons for why someone may choose to use a technology. There is nothing to take into account other factors which may interfere with actual use given a high behavioural intent (for example prohibitive costs or absence of training), whereas other models do take such 'Facilitating Conditions' into account (Lai et al., 2012; Venkatesh et al., 2003).

An over-arching feature of the TAM is that all factors must filter through both perceived usefulness and perceived ease of use. A person might consider that a particular technology looks easy to use and is potentially useful, but these factors alone do not guarantee behavioural intent to use, because other influential factors may be involved that are not measured by the TAM. It is for this reason that extended TAMs have been theorised, resulting in nearly as many different models as there are pieces of research. Whereas the core of the TAM remains in all of them, the variety of constructs and structures presents one with difficulty in knowing which one to choose for a particular research question or setting.

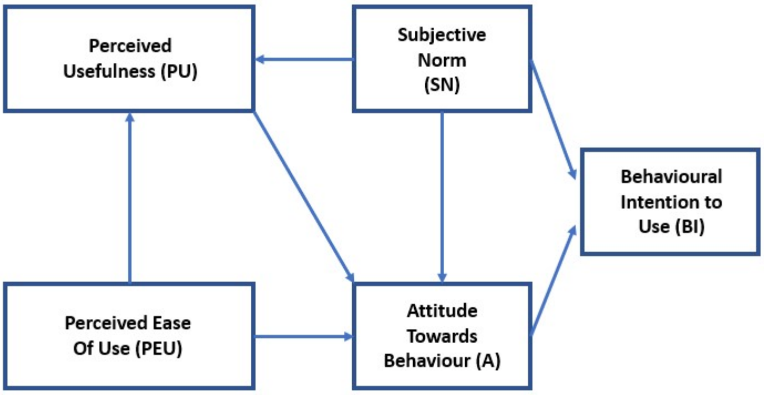
Context may determine such other influences due to various personal, social or institutional factors, for example a user's computer anxiety, prior experience, other's use (social influence), organizational support, task structure, system quality, and perceived usefulness, amongst others (McFarland & Hamilton, 2006). Thus, while the TAM has been reported to be internally robust, it is only a general model (Chow et al., 2012) and needs to be extended to account for specific settings or research questions. The implication is that even though the TAM has been applied in the educational setting, it is likely not sufficient to do so on its own. Relevant main varieties of TAM are presented in the next sections.

2.5.1 Combinations of the Technology Acceptance Model with other seminal theories

There have been occasions where the TAM has been combined with other behavioural intention theories. For example, Buabeng-Andoh (2018) combined the Technology Acceptance Model and Theory of Reasoned Action (Figure 2.11) to investigate mobile learning adoption in Ghana, because while the TRA was well-established to explain any kind of user behaviour, the TAM is suited to modelling technology usage. The resultant model has perceived usefulness, perceived ease of use, subjective norm, attitude, and intent as its variables, and despite it being the merger of two powerful models was only able to explain 23% of variance of behavioural intent. Buabeng-Andoh's model is an illustration of the sometimes-arbitrary nature of technology acceptance model construction in that the model dropped Davis' theorised connection between perceived usefulness and behavioural intent. Thus, while demonstrating that attitude was stronger than subjective norm, it is unclear if that would still be the case if perceived usefulness retained its connection to intent as per Davis' TAM.

Figure 2.11

Combined Technology Acceptance Model and Theory of Reasoned Action

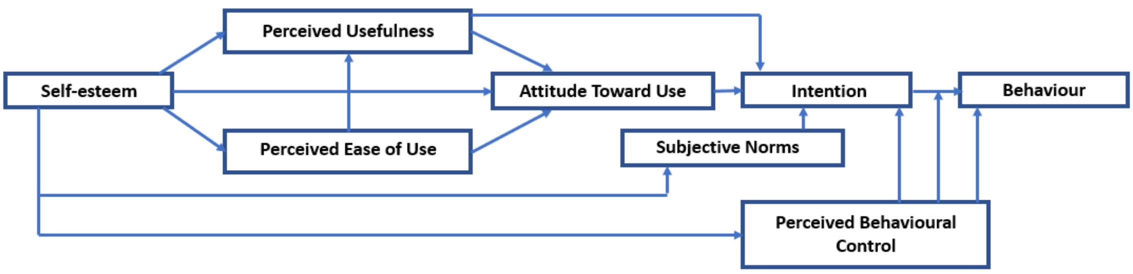


Note. Adapted from Buabeng-Andoh (2018)

Another example was provided by Cheng (2019), who conducted a study on student intentions to use a wiki for learning by comparing the TAM, Theory of Planned Behaviour (TPB) and a model integrating both, shown in Figure 2.12 below.

Figure 2.12

Cheng's Integrated TAM-TPB Model



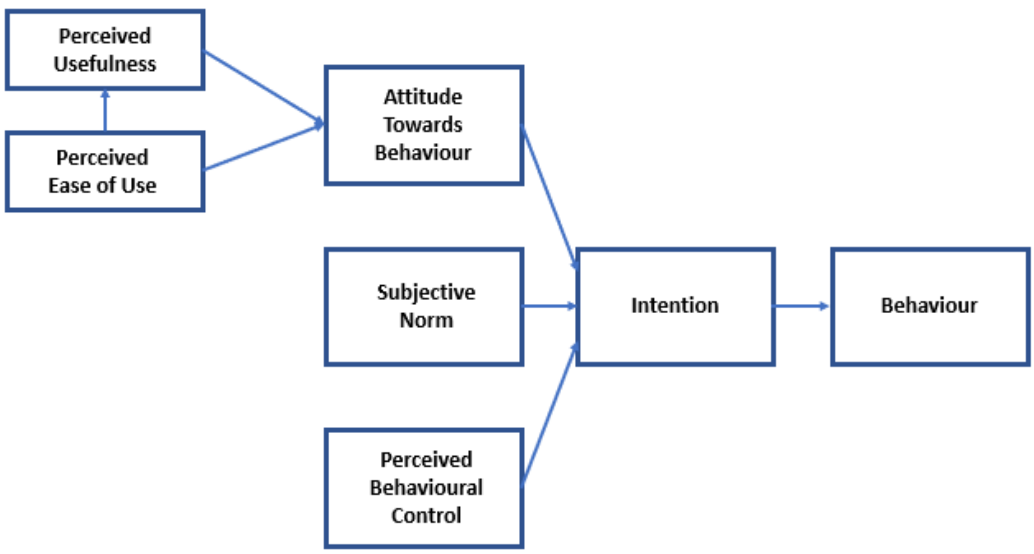
Note. Adapted from E. W. L. Cheng (2019)

E. W. L. Cheng showed that whereas attitude influenced intention in the TAM model, in the TPB and integrated model attitude became insignificant, with the influence on intention being carried instead by subjective norm and perceived behavioural control. This example demonstrated that blind trust in the abilities of the TAM can sometimes be misplaced, and that it is important to choose the model carefully. In Cheng's study, "the TPB, unlike the TAM, considers social influences on technology adoption and use, which should not be overlooked." (E. W. L. Cheng, 2019, p. 32). Cheng's observation that social influence is not included in the TAM carry weight when the TAM is used in situations where that is relevant.

Nadlifatin et al., (2020) (Figure 2.13) also combined the TAM and TPB in a study that is illustrative of both model variability and cohort effects. Their combined model differs slightly from E. W. L. Cheng's model above in that it does not include any external variables, so the TAM-TPB model can be assessed on its own.

Figure 2.13

Nadlifatin et al.'s TAM-TPB Model



Note. Adapted from Nadlifatin et al. (2020)

Nadlifatin et al. (2020) deployed their model to study student use of a blended learning system in Indonesia and Taiwan. The results show different path values and significances based on the cohort. This is an important finding and shows that behavioural intention model results are generally cohort and setting-dependent, and researchers must always bear this in mind. Thus, in E. W. L. Cheng's (2019) study it was concluded that subjective norm and perceived behavioural control supplanted the influence of attitude on intent, but Nadlifatin et al. demonstrated that these types of results are generally not concrete and can vary from cohort to cohort or setting to setting.

Other examples of TAM being combined with the TRA and/or TPB exist but the above examples serve to highlight three important points:

1. One model cannot measure all that affects intention to use a technology – model combinations and extensions can change results;
2. The same model applied in different settings will yield different results, and therefore, inform different practice implications; and
3. Researchers often form models according to their needs, and there is no one model that can satisfy everyone, even using the most parsimonious models such as TRA, TPB or TAM.

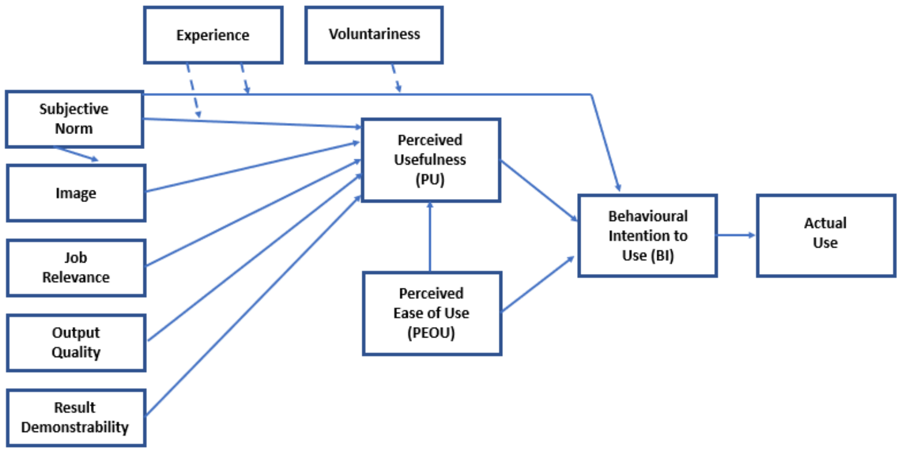
The next section reviews exemplars of extended technology acceptance models, which will serve to illustrate variability and breadth of external variables.

2.5.2 Technology Acceptance Models 2 (TAM2) and 3 (TAM3)

Venkatesh and Davis (2000) formulated a theoretical extension of Davis' original TAM called the TAM2, represented in figure 2.14, and tested the model in four different institutions using four different (business) systems across three time periods. The model was found to explain 40-60% of the variance of usage intention across voluntary and involuntary usage settings. A characteristic of the TAM2 is that it was formulated to measure both social and job relevance influences that sit upstream of perceived usefulness but did not introduce new constructs purported to influence perceived ease of use.

Figure 2.14

The Technology Acceptance Model 2 (TAM2)



Note. Adapted from Venkatesh & Davis (2000)

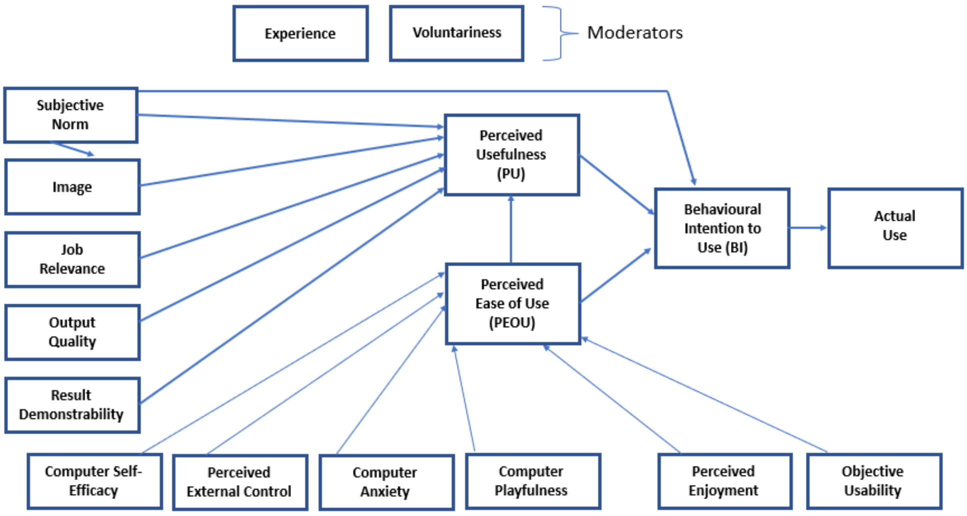
The TAM2 was notable in that it re-introduced subjective norm after Davis had excluded it from his original model. Venkatesh and Davis were influenced by Taylor and Todd's (1995) research, which found that social norms did influence intention, but only had a small effect on model power, and by other research suggesting that internalisation of another person's beliefs about a system's usefulness played a role in moderating a user's own perceptions of its usefulness. Venkatesh and Davis also hypothesised that social influence is stronger in mandatory-use situations compared to voluntary-use situations. As a result, Venkatesh and Davis re-introduced social norms into the TAM2 model, with voluntariness and experience as moderators, and found that subjective norm has a stronger effect when usage is mandated or a user is relatively naïve to the technology (Venkatesh & Davis, 2000).

Only one study using TAM2 as a model was returned in the systematic review. Venter et al. (2012) studied student attitudes towards a learning management system in a South African business college and found strong support for the core constructs of perceived usefulness and ease of use. In addition, the study found strong support for job relevance and facilitating conditions, however there was only weak support for TAM2's other constructs that extended the original TAM, including subjective norm.

In 2008, Venkatesh and Bala (2008) extended the TAM2 to produce the TAM3 (Figure 2.15) to further address how managerial interventions can influence IT adoption. A feature of TAM3 is the four anchor constructs that are purported to influence perceived ease of use: computer self-efficacy, perceptions of external control, computer anxiety and computer playfulness. Adetimirin (2015) used the anchors of TAM3 in a study of online discussion forum use by library and information systems students and found that the anchors were the predominant determinants of use even though there were other factors influencing intention.

Figure 2.15

The Technology Acceptance Model 3 (TAM3)



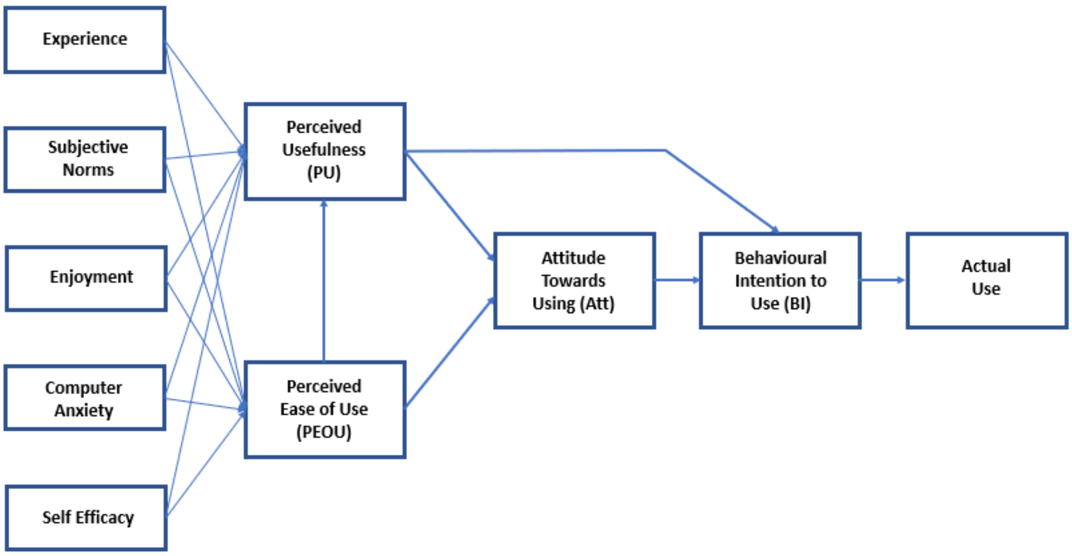
Note. Adapted from Venkatesh & Bala, (2008)

2.5.3 The General Extended Technology Acceptance Model for E-Learning (GETAMEL)

Abdullah and Ward (2016) performed a meta-analysis of 107 papers based on the use of Davis' TAM in educational settings and identified the five most commonly used external factors from those papers. They used those five factors as the basis of a General Extended Technology Acceptance Model for E-Learning (GETAMEL) (Figure 2.16). The five factors are: Enjoyment, Subjective Norm, Self-Efficacy, Experience and Computer Anxiety.

Figure 2.16

The General Extended Technology Acceptance Model for E-Learning (GETAMEL)



Note. Adapted from Abdullah & Ward (2016).

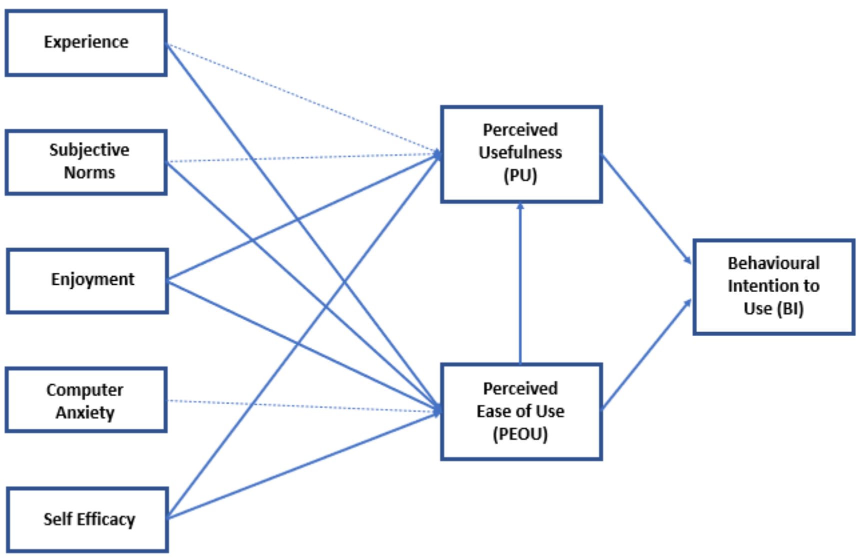
The five external variables influence students' perceived usefulness and perceived ease of use differently, with most exhibiting small to moderate mean path coefficients of β = 0.07 to 0.34. Enjoyment was the strongest influencer of perceived usefulness, with a mean path coefficient of $\beta = 0.45$ across all included studies. The effect sizes for 'students', 'teachers' and 'employees' indicate that user-type has a moderating effect on acceptance and attitude (see also Šumak et al. 2011).

These data also show that subjective norms greatly influence the perceived usefulness by 'teachers' of E-Learning, while computer anxiety greatly influences perceived ease of use, thus acceptance of the technology by peers served to bring down the perceived ease of use barrier somewhat. For employees, enjoyment was the most significant contributor to perceived usefulness, closely followed by experience with computers in general. Related to this, the high effect size of subjective norms and computer anxiety on perceived ease of use suggest that administrators will use an e-learning system if it is fun/easy to use, their peers are using it too, and they have experience with computers.

In a follow up study to test GETAMEL model, Abdullah et al. (2016) applied the model to 242 students' attitudes towards e-portfolios in the United Kingdom. As can be seen from figure 2.17, not all hypothesised paths were found to be significant for that study's context. Specifically, the paths from experience to perceived usefulness, subjective norm to perceived usefulness and computer anxiety to perceived ease of use were all non-significant.

Figure 2.17

GETAMEL Model Used to Assess Student Attitudes to e-Portfolios



Note. Adapted from Abdullah et al. (2016). Dashed lines are insignificant paths.

Chang et al. (2017) used the GETAMEL in their study of 714 higher education students' intentions to use e-learning in Azerbaijan, however their model was modified to include a direct influence of social norm to behavioural intent, using findings by Venkatesh and Davis (2000) as justification to adjust the model, and included technological innovativeness as a moderator. The study authors concluded that the GETAMEL model was validated.

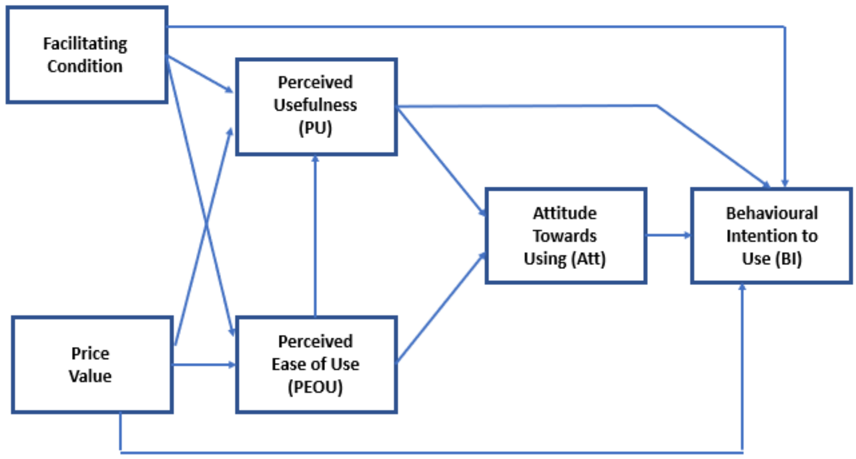
Matarirano, Panicker, et al. (2021) adopted the GETAMEL for their study of 125 South African university student attitudes towards the Blackboard learning management system and found that perceived usefulness was only influenced by subjective norm and enjoyment, and that perceived ease of use was only influenced by self-efficacy, enjoyment and anxiety. In a separate study, Matarirano, Jere, et al. (2021) used an extended GETAMEL model to study lecturer attitudes towards use of Blackboard learning management system. While the authors did not provide a reason for extending the model, they added job relevance, technical support and system accessibility to the original GETAMEL. They concluded that the "GETAMEL may not be the best model to measure adoption and acceptance of technology by lecturers, as shown by the number of external factors that were found to be insignificant." (Matarirano, Jere, et al., 2021, p. 73), and that another model that considers the characteristics of lecturers might need to be developed.

2.5.4 Miscellaneous examples

In addition to the examples of extended TAMs described above, research literature includes other examples that are not as neatly characterised. These serve to remind that different researchers, research questions and contexts can call for bespoke models. Three such models will be briefly described here to illustrate. Firstly, Fauzi et al. (2021) performed a study to investigate student acceptance of Google Classroom in West Sumatera, Indonesia. The model included facilitating conditions and price value, shown in Figure 2.18.

Figure 2.18

Model Used by Fauzi et al.



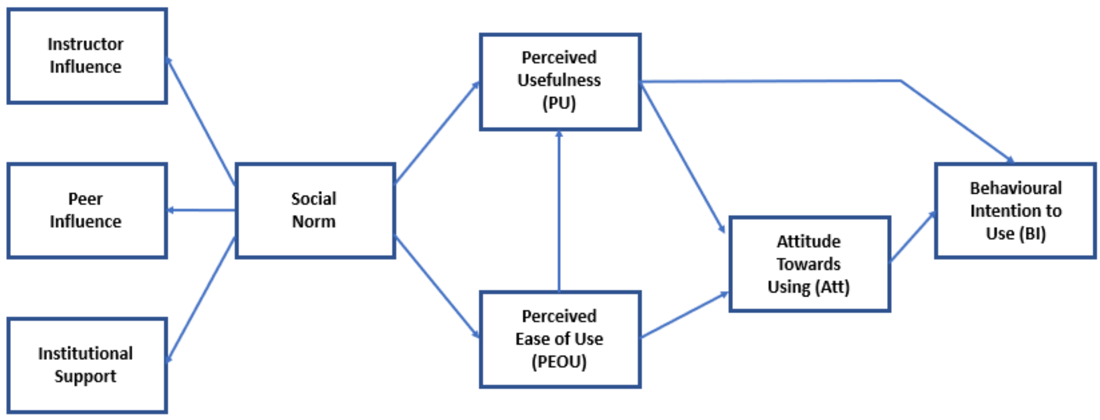
Note. Adapted from Fauzi et al. (2021).

While the study reported that usefulness and ease of use were important influencers of attitude, it did not explain why only facilitating conditions and price value were chosen . This study also did not report a percentage of variance explained in the dependent variables, and so a reader cannot be sure how powerful the model was in accounting for all factors that might have influenced students' attitudes.

F. Huang et al. (2020) studied student attitudes to internet-based technology across 16 universities in China. The study specifically investigated purported components of subjective norm, namely teacher influence, peer influence and institutional support. The model is an extended TAM incorporating subjective norm, so relates to the Theory of Reasoned Action. It differs from the TRA, though, by the position of subjective norm, shown in Figure 2.19.

Figure 2.19

Extended Technology Acceptance Model Including Subjective Norm



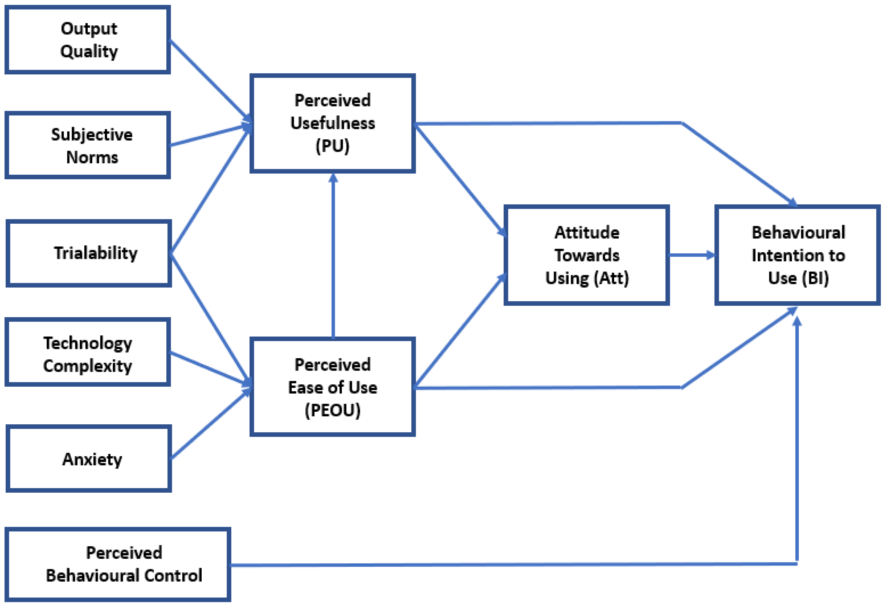
Note. Adapted from F. Huang et al. (2020).

F. Huang et al.'s study was better predicated than others in that it provided a justification for its model, namely that even though student perceptions of school factors (subjective norms) were known to be important, "very few studies have tested the influence of these variables by incorporating them into a general concept of school influence" (F. Huang et al., 2020, p. 277). For this reason, the model is parsimonious and is designed to gain a general appreciation of the value of subjective norms in Chinese higher education settings. The fact that subjective norm is theorised to influence both the TAM and TRA variables is tested, with the results showing that subjective norm influenced all the variables. Thus, this study is a strong example of how seminal models can be insufficient when exploring factors that influence belief, and that parsimony can often be unhelpful with these sorts of questions.

In a third example, Teo et al. (2019) studied the factors that influence student intention to use Moodle in universities in Macau. This study was interesting in that it combined the constructs from the Diffusion of Innovations Theory (DIT) (Rogers, 1995) with the TAM, which made the TAM more specific to aspects of the technology, shown in Figure 2.20 below.

Figure 2.20

Combined Diffusion of Innovations Theory – Technology Acceptance Model



Note. Adapted from Teo et al. (2019)

Teo et al.'s study demonstrated that the variables associated with Diffusion Innovation Theory were valid inclusions, with all hypothesised paths, bar anxiety to ease of use, being supported . Sixty six percent of the variance of behavioural intent was explained by the model. The study by Teo et al. differs from many by providing a sound justification for why these specific constructs were chosen, arguing that by extending the TAM with other known (evidence-based) relevant constructs from the Diffusion of Innovation Theory, the limitations of TAM parsimony can be overcome.

These three examples (Figures 2.18, 2.19, 2.20) demonstrate that research using TAM models differ not only in structure and inclusion, but also justification. Whereas Fauzi et al.'s (2021) study did not justify why the constructs were chosen, more justification is evident in F. Huang et al.'s (2020) model and further in Teo et al.' (2019)

model. By justifying included constructs, the research is more convincing that all required constructs have been included and there is less of a chance for anything to be missed. In doing so, they support the quest to find a complete model.

2.6 Alternative Architectures

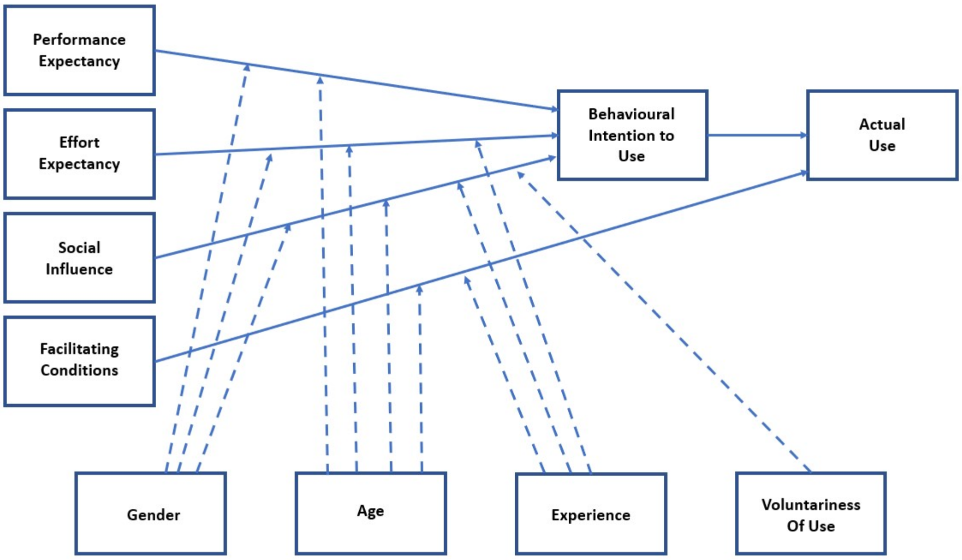
2.6.1 The Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT (Figure 2.21) was formulated in 2003 after the review of eight "key competing theoretical [acceptance] models" (Venkatesh et al. 2003, p.427), and has since been used to investigate *inter alia* intention to use webinars (Khechine et al., 2014), general e-learning systems (El-Masri & Tarhini, 2017; Sumak et al., 2010), mobile learning (Mtebe & Raisamo, 2014), and video platforms (Jung & Lee, 2015). The UTAUT was validated by its authors, who reported that it "outperform[ed] the eight individual models" (Venkatesh et al. 2003, p.425). In addition to the 32 constructs included in their review of the theoretical acceptance models, Venkatesh et al. (2003) included experience, voluntariness, gender and age as moderators of constructs' influence on behaviour.

Venkatesh et al. (2003) identified seven significant contributors to behavioural intent to use a general technology, though selected only four in the final UTAUT model: performance expectancy, effort expectancy, social influence and facilitating conditions. Attitude towards using technology, self-efficacy and anxiety were thought by the authors "to not be direct determinants of intention" (Venkatesh et al. 2003, p.447) after controlling for other mediating effects.

Figure 2.21

The Unified Theory of Acceptance and Use of Technology (UTAUT)



Note. Adapted from Venkatesh et al. (2003)

The researchers reported "strong empirical support for UTAUT, which posits three direct determinants of intention to use (performance expectancy, effort expectancy and social influence) and two direct determinants of usage behaviour (intention and facilitating conditions)." (Venkatesh et al. 2003, p.467)

While designed for general technologies, the UTAUT framework has nonetheless been used to measure acceptance of technology and behavioural intent in educational contexts (J. L. Chen, 2011; Dečman, 2015; Khechine et al., 2014; Sumak et al., 2010; Thomas et al., 2013; Yueh et al., 2015). Using this model, Dečman found that social influence and performance expectancy had significant influence on behavioural intent to use. Dečman also found that "young people…are ready to use it if only an increase in performance is expected" (Dečman, 2015, p. 272), and the UTAUT addresses this with its inclusion of Performance Expectancy as an independent variable and age as a moderator.

The addition of an attitude measure was found to improve the predictive nature of the UTAUT in an African educational context (Thomas et al., 2013), even though the creators of the UTAUT found that performance and effort expectancy superseded the need to measure attitude explicitly (Venkatesh et al., 2003). This discrepancy could have arisen because Thomas et al. specifically measured “attitude towards the use of the mobile technologies for learning” (Thomas et al., 2013, p. 84) and this was the only measure specifically aligned to learning in the model. The authors also theorized that different national or ethnic contexts may play a part in forming attitudes to educational technology, and so the inclusion of an attitude construct may be an important element that was excluded seemingly based on statistical evidence.

In contrast to Thomas, one study that applied the UTAUT to Moodle showed that attitude had little influence on behavioural intent (Sumak et al., 2010), and that social influence and facilitating conditions were the main drivers for actual use of the system. The limitation with this study, however, was that it did not measure attitudes to learning specifically, or perceived usefulness of Moodle in terms of learning, which J. L. Chen (2011), Lai (2012), and Thomas et al. (2013) have shown to be influential in their studies.

Jung and Lee (2015) used the UTAUT to investigate factors influencing YouTube acceptance by lecturers and students in a cross-cultural study involving the USA and Japan. They found that the UTAUT held up as a model that could explain acceptance, but that there were role and cultural differences. For example, social influence was a stronger influencer of behavioural intent for students than lecturers; the authors hypothesise that this was because younger students were less likely to exercise autonomy. In addition, the study revealed cultural differences in expectancy of effort to use YouTube, but that this heterogeneity did not translate into differences in influence of intent to use YouTube. The researchers explained that this was likely due to YouTube being easy to use, and that overrode any cultural differences in effort expectancy.

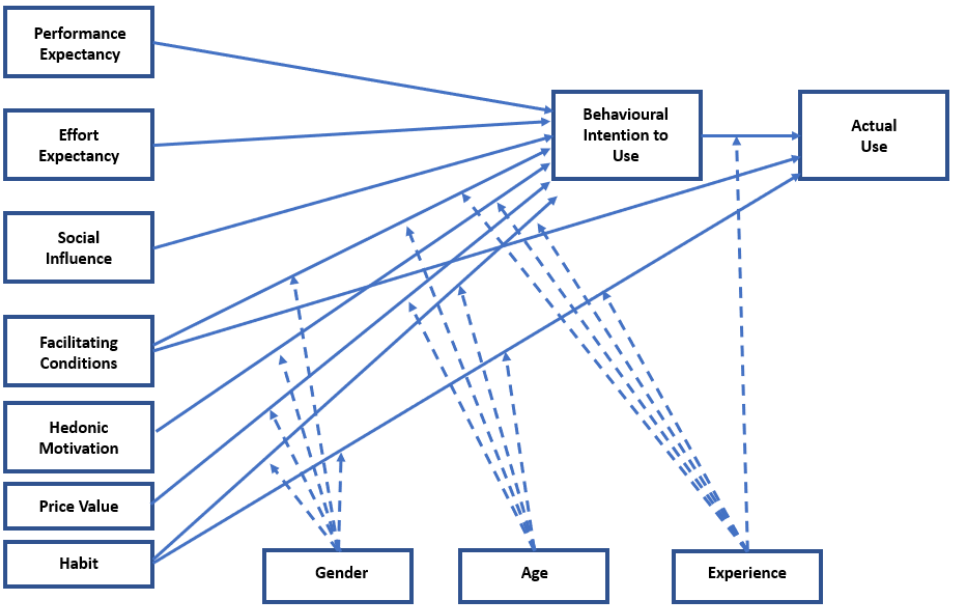
Khechine, et al. (2014) used the UTAUT to explore gender and age differences in intention to use webinars for learning, with 114 Canadian university students as study subjects. They found that performance expectancy, social influence and facilitating conditions influenced intention to use the webinar system, and that age moderated the strength of association between performance and intention and facilitating conditions and intention. Gender was not found to moderate any of the determinants of intention.

2.6.2 UTAUT2 and other extensions

The UTAUT2 (Figure 2.22) was developed by Venkatesh, Thong and Xu (2012) by adding hedonic motivation, price value and habit to the UTAUT. The aim of the research that led to the formation of the UTAUT2 was to adapt the UTAUT to the consumer technology context.

Figure 2.22

The UTAUT2 model

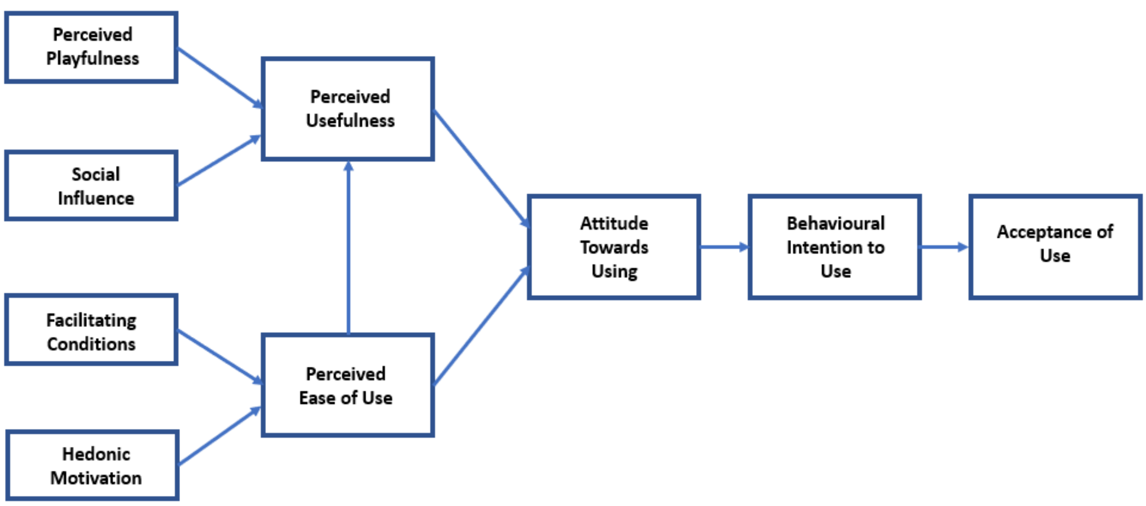


Note. Adapted from Venkatesh et al. (2012).

While the UTAUT2 was developed for consumer contexts, there are cases where it has been applied to the educational context. El-Masri and Tarhini (2017) added trust to the UTAUT2 and applied it to measure student attitudes to e-learning systems in both Qatar and the USA. Their research revealed that performance expectancy, hedonic motivation, habit, and trust were influential in student intent to use e-learning in both developing and developed settings. Abdul Rabu et al. (2019) adopted two of UTAUT2's constructs (social influence and hedonic motivation) and incorporated them into an extended TAM (with perceived playfulness and facilitating conditions as external variables) to measure student attitudes to QR codes in a large classroom. Their research found that perceived playfulness, facilitating conditions and hedonic motivation were influential in student intention to use QR codes in the classroom. Abdul Rabu et al.'s model is shown in figure 2.23 as an example of a blended TAM and UTAUT2 model.

Figure 2.23

Blended TAM and UTAUT model

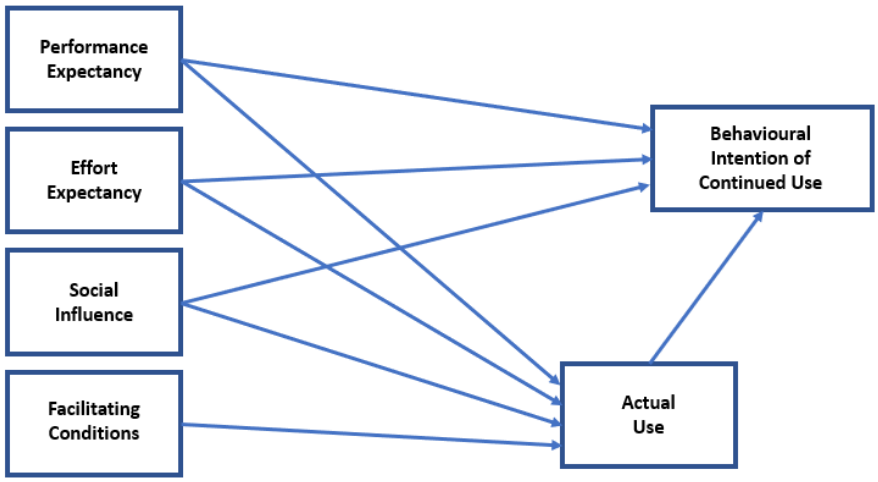


Note. Adapted from Abdul Rabu et al. (2019)

Yueh et al (2015) developed an extended UTAUT which omits 'Behavioural intention to use' and adds 'Behavioural intention of continued use' (Figure 2.24). This research showed that “students’ actual use of the [technology] influences their intention of future use” (Yueh et al., 2015, p. 16). Previous Use has also been found to moderate factors affecting Perceived Ease of Use, and also mitigate the negative effects of Perceived Ease of Use on Behavioural Intent and Perceived Usefulness (Venkatesh & Bala, 2008). Their results did not confirm the influence of performance expectancy or facilitating conditions.

Figure 2.24

An extended UTAUT with continued use



Note. Adapted from Yueh et al. (2015)

Finally, El-Gayar et al. (2011) used a modified UTAUT model to investigate 230 Midwestern USA college student attitudes to tablet PCs for learning. Their study was notable because it incorporated attitude where Venkatesh et al. (2003) had specifically excluded attitude from their original model. El-Gayar et al. (2011) found that attitude did have a statistical effect within the model and mediated the effect of performance and effort expectancy onto behavioural intention. This study helps to demonstrate that a model can perform differently in different situations.

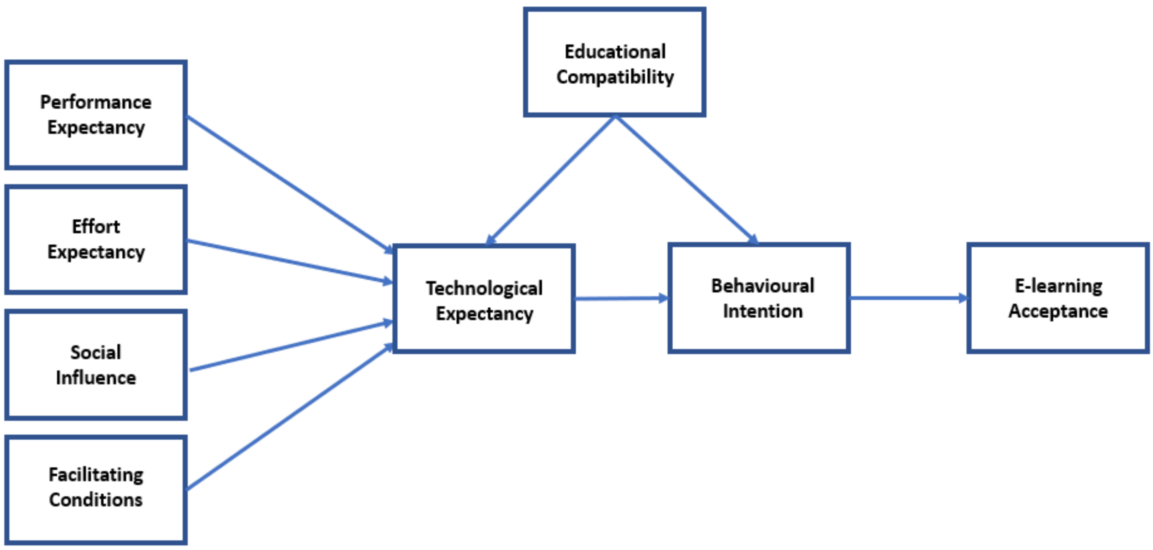
2.7 Technology Acceptance Modelling in Educational Contexts

2.7.1 E-learning in general

J. L. Chen (2011) applied the UTAUT in an educational context, and the findings support the explicit measurement of Educational Compatibility, and to this end a modified UTAUT was proposed to integrate this additional construct (Fig 2.25).

Figure 2.25

Addition of educational compatibility to the UTAUT



Note. Adapted from J. L. Chen (2011)

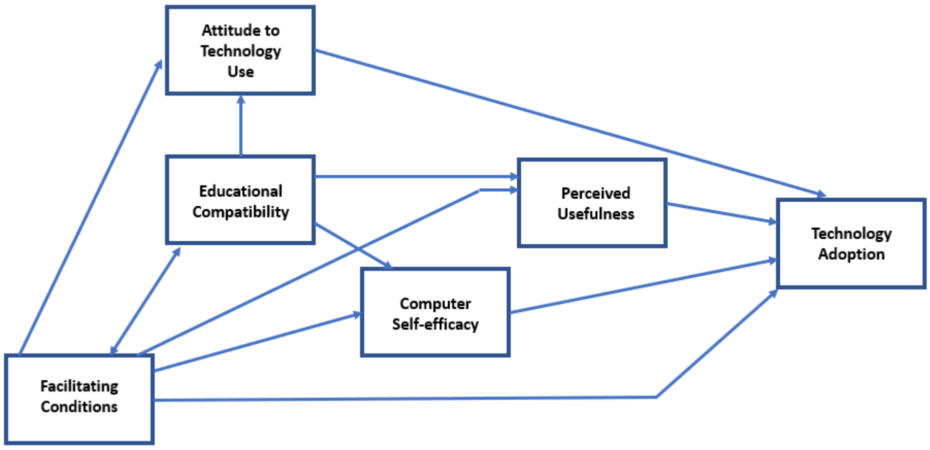
Chen defined educational compatibility as “a student’s perceptions of an e-learning system to fit with his or her learning expectancies” (J. L. Chen, 2011, p. 1503). Lai et al. (2012) also found educational compatibility to be important in educational settings. In J. L. Chen’s modified model, the whole UTAUT model was classified as ‘Technological Expectancy’, and it was reported that “that technological expectancy and educational compatibility were both important determinants of e-learning acceptance” (J. L. Chen, 2011, p. 1508) with educational compatibility being more critical.

It could be argued that educational compatibility comes under UTAUT's performance expectancy. Venkatesh et al. (2003) include perceived usefulness and outcome expectations in this measure, and it is conceivable that a learner perceives the only function of an educational technology to achieve learning. There is a subtle difference, though, between a technology's delivery of an outcome, and the manner in which it does so. For example, a learning management system may offer educational videos through its interface to students, but it may do so in a way that makes it difficult to locate or control. This important difference comes apparent when using immersive technologies for example, which have a variety of technical attributes that affect how the system performs, and which are designed to deliver a 3D immersive environment, but not necessarily learning. Whereas the UTAUT did not address pedagogical factors, it is deemed that 'Educational Compatibility' could accordingly address this by being added to the UTAUT (J. L. Chen, 2011; Lai et al., 2012).

Lai et al. (2012) also included educational compatibility in their model (Figure 2.26) but arrived at this position not from extending the UTAUT but using the TRA and TPB as a base. Lai et al. drew on the TRA and TPB frameworks to determine five important independent variables to include in an acceptance model for undergraduate students at a Hong Kong university: Perceived Usefulness, Attitude to Technology Use, Educational Compatibility, Facilitating Conditions and Computer Self-Efficacy.

Figure 2.26

Lai et al.'s incorporation of educational compatibility



Note. Adapted from Lai et al. (2012).

The model found that the three most influential independent variables (reported with their respective effect sizes) vis-à-vis student adoption of technology for learning were educational compatibility, facilitating conditions, and attitude towards technology use. In contrast to the TAM (Davis, 1986) and GETAMEL (Abdullah & Ward, 2016), perceived usefulness and computer self-efficacy had "less predictive power on [students'] technology use" (Lai et al. 2012, p.569). An explanation for the lower-than-expected influence of perceived usefulness is that it may be more influential in Western settings (ibid.). Lai et al. also highlighted an important relationship between educational compatibility and technology use in respect of students: "When the use of technology aligns with their beliefs in and approaches to learning and when students perceive the compatibility between technology use and their learning style and needs, students are most likely to adopt technology for learning." (Lai et al. 2012, p.576). This may be true of teachers and teaching as well, and so it should be tested for teachers, since to find a factor that aligns with both students and teachers would be powerful in considering new learning technologies for adoption.

2.7.2 Learning management systems

All together there were 26 studies returned from the PRISMA process with a learning management system as the technology target, six of which did not include any factors beyond Davis' model (Al-Maroof & Al-Emran, 2018; Amin & Mohammed, 2018; Juhary, 2014; Landry et al., 2006; Schoonenboom, 2014; Van De Bogart & Wichadee, 2015) and could only therefore confirm that model. Eight studies extended the model using factors such as self-efficacy, experience and facilitating conditions (Arpaci, 2017; Dai et al., 2021; Fathema et al., 2015; Fauzi et al., 2021; Ngai et al., 2007; Pan et al., 2005; Venter et al., 2012; Yeou, 2016), all of which concluded that experience, self-efficacy and facilitating conditions positively influenced perceived ease of use, attitude or intention to use the learning management system. Teo et al. (2019) extended that investigation further by including anxiety and technological complexity, finding that technological complexity influenced perceived ease of use (but anxiety did not).

Addressing the affective axis, Matarirano, Jere et al. (2021) studied *inter alia* the effects of enjoyment on intention to use a learning management system, and found that it influenced perceived ease of use, whereas Matarirano, Panicker et al. (2021) found that it influences both perceived ease of use and perceived usefulness. This comparison serves to remind that not one study can serve to provide a maxim for what a factor influences and that this can also depend on context, technology, cohort, or other aspects of the study. Unal & Uzun (2021) also studied perceived enjoyment's influence of perceived ease of use and found a weak effect. Finally, Sanchez-Franco (2010) specifically investigated perceived affective quality, which was defined as 'the ability to cause a change in core affect' (Sanchez-Franco, 2010, p. 39). The results indicated that perceived affective quality directly affected intent to use the learning management system, and also acted as a moderator of other antecedents to intent. Together, these studies indicated that affective factors such as enjoyment or motivation play an influential role in how users respond to learning management systems.

Seven studies investigating learning management systems (30%) included factors that related to learning or pedagogy, such as interactivity, design and learning attributes. Alshammari (2020) measured the effect of instructional design on perceived usefulness and perceived ease of use (in addition to self-efficacy and technical support) of students using a LMS in Saudi Arabia and found a moderate positive influence (β = 0.22-0.23)[1]. Eraslan and Kutlu (2019) examined interface design along with social norm and computer self-efficacy and concluded that user-friendly interface design is important for perceptions of usefulness and ease of use. Ros et al. (2015) had similar results, finding that instructional design elements positively influenced perceived usefulness and interactivity, and that interface design positively influenced perceived ease of use. Binyamin et al. (2019) investigated several factors relating to learning and pedagogy, viz. feedback, interactivity, access, interface navigation, visual design, student support and content quality. Of these factors, access, navigation, and system interactivity were all influential on perceived ease of use, and interactivity, feedback, and content quality all influencers of perceived usefulness. Zain et al. (2019) also support the result that content quality is a positive influencer of perceived usefulness. Chung & Ackerman (2015) found that communication with classmates was a strong influencer of student satisfaction in a business school context, reminding that interaction with classmates is another form of interactivity. Lastly, Escobar-Rodriguez & Monge-Lozano (2012) have found that student perceptions of a learning management system's support of their professors' ability to teach,

[1] β is the standardised regression coefficient between two latent constructs within a technology acceptance model, and p is the level of statistical significance of that measurement. Interpretation: a value of β between constructs A and construct B says "if construct A is moved by one standard deviation, construct B will move by β of a standard deviation." β is thus a measure of strength of association between two constructs.

assess and interact with the class also affects their perceptions of its usefulness and their intent to use it.

This research concerning student perceptions of learning management systems follows a similar characteristic of research using other educational technologies, that only a minority of the models incorporate factors that are specific to learning, teaching or pedagogy. The ones that did all support the premise that content design, interface design, and interaction with the class are all influential in forming student attitudes towards use of a learning management system.

2.7.3 Mobile learning

24 studies ranging from 2012 to 2021 were identified by the systematic review that related to mobile learning, with 19 using an extended TAM model, three using the UTAUT or an extension, and two using a different architecture.

Six of the studies identified as relating to mobile learning did not include learning-specific constructs but used a general model. B. Chen et al. (2013) surveyed a class of students who used Blackboard Mobile Learn mobile app and found that perceived usefulness, ease of use and perceived resources (support and training resources) were reasonably strong influencers of attitude, intent and actual use. These findings are mirrored by Hao et al. (2017) in a Northern Chinese university, who also found that facilitating conditions was important. This is a salient aspect of mobile learning considering that Bao et al. (2013) found that females had a lower general computer self-efficacy than males in their study. Joo et al. (2016) surveyed students at a Korean online university and found that expectation confirmation (congruence between a user's expectations of a technology and its actual performance) strongly influenced satisfaction with mobile learning, and that perceived usefulness strongly influenced intent to use mobile learning. These studies describe the general situation that perceived usefulness, ease of use and facilitating conditions, such as support, are all influential in determining student acceptance of mobile learning technologies, but they offer nothing specific to learning.

A defining feature of mobile learning is its mobility, and five studies investigated this feature or its related factors such as learning flexibility and access. Park et al (2012) showed that accessibility was only a weak influence of behavioural intent to use mobile learning ($\beta = 0.21$, $p < 0.01$), overshadowed by subjective norm ($\beta = 0.28$, $p < 0.01$) and attitude ($\beta = 0.35$, $p < 0.05$). Yamakawa et al. (2013) found a similar result, with mobility of service exhibiting a mild to moderate influence ($\beta = 0.30$, $p < 0.001$) on behavioural intent and accounting for only 5% of its variance. Bere & Rambe (2016) investigated the influence of portability of a text messaging service for learning in a South African higher education context, and found that while portability's influence on usefulness ($\beta = 0.16$, $p < 0.01$) and attitude ($\beta = 0.23$, $p < 0.001$) were low, the ability to collaborate with other students had a substantial influence on both perceived usefulness ($\beta = 0.56$, $p < 0.01$) and attitude ($\beta = 0.53$, $p < 0.01$) towards the service. This result indicates that access in and of itself might be less important than the ability to communicate or collaborate with other students. Pramana (2018) investigated influencers of mobile learning adoption in an Indonesian context and found that perceived mobility had a strong influence on perceived usefulness ($\beta = 0.56$, $p < 0.001$) although the analysis was conducted as a principal components analysis and so the results may considered with that in mind (the reader is referred to section 3.4.2 Principal Components Analysis in Chapter 3 Methods for an explanation). Finally, Saroia & Gao (2019) investigated the value of perceived mobility value on perceived usefulness of a learning management system in Sweden, where perceived mobility allows users geographical and temporal access to information or services using a mobile device and found a moderate influence on perceived usefulness ($\beta = 0.29$, $p < 0.01$). Together, these studies revealed that perceived mobility generally has only a weak to moderate influence on perceived usefulness, attitude, or intent to use a mobile device for learning.

Chang et al. (2013) reported that playfulness, convenience, usefulness and ease of use all influenced Taiwanese students' continued usage of language learning on a mobile device, with usefulness outweighing playfulness. Al-Adwan et al. (2018) found that enjoyment had only a weak influence on Jordanian university students' intent to use mobile learning, with no moderation from age or gender. Similarly, Leong et al. (2018) found only a moderate influence from perceived enjoyment on Malaysian university students' intent to use mobile social network sites for learning, with similar influence from usefulness and task-technology fit. Aburub and Alnawas (2019) investigated the strength of influence of different forms of gratification on Jordanian university students' intention to use mobile learning and found that hedonic gratification (enjoyment and pleasurable experiences) was the weakest influencer ($\beta = 0.18$, $p < 0.05$), but that cognitive gratification (gratification of acquiring information and knowledge) was stronger ($\beta = 0.39$, $p < 0.001$), and social integrative gratification (users feel satisfied using technology to integrate with others) ($\beta = 0.27$, $p < 0.01$) were stronger. Together, these studies indicate that enjoyment and satisfaction at best only have a moderate influence on usefulness or intent to use a mobile technology for learning.

In summary, these studies on mobile learning reveal that the mobility and enjoyment factors are not as influential compared to the core factors such as usefulness, ease of use and support.

2.7.4 Virtual worlds and multimedia

Second Life was an early example of a virtual world where users could interact with spaces, objects, and people via avatars. Shen and Eder (2009) investigated intentions to use

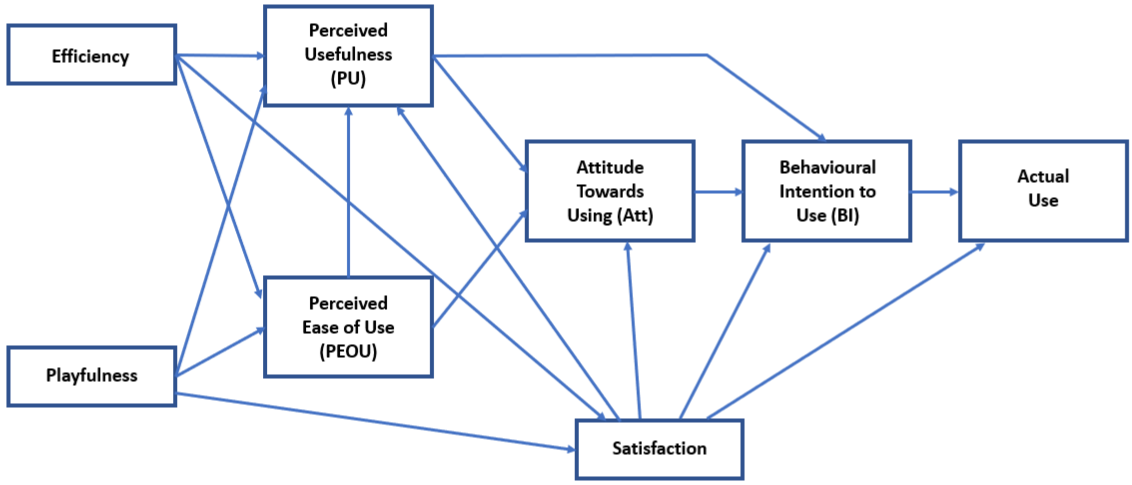
Second Life for education as a broad question, using a simple model that was limited to usefulness, ease of use, and three upstream influencers of ease of use, namely computer playfulness, computer self-efficacy and computer anxiety. They found that computer playfulness and self-efficacy influenced ease of use, which in-turn influenced perceived usefulness, which was a strong influencer of intent to use Second Life for learning. This suggested that the platform's perceived ease of use was key to perceived benefits of the platform, however, the study was limited in that it did not investigate any education-specific factors, or any factors that measured presence and immersion (such as cognitive absorption for example). Chow et al. (2012) had similar results and also found that computer self-efficacy influenced ease of use, which in-turn influenced perceived usefulness and intent to use the technology for learning rapid sequence induction. Just as with Shen & Eder, Chow et al. did not include any education-specific factors and concentrated solely on self-efficacy and ease of use as determinants, possibly because the technology was relatively new at the time of the studies.

Fagan et al. (2012) investigated nursing student attitudes to a virtual simulation in terms of personal innovativeness, which is concerned with how willing a user is to try new things, in this case, a new technology. The results showed that personal innovativeness was a strong driver of perceived ease of use of the virtual simulation technology, which aligned with Chow et al.'s findings of computer self-efficacy driving perceived ease of use. Thus, just as with Chow et al. and Shen & Eder, Fagan et al. did not include any education specific factors but concentrated only on a user's own self-efficacy and perceived ease of use.

Estriegana et al. (2019) ventured further than self-efficacy to investigate efficiency, playfulness and satisfaction of students using a virtual laboratory to learn electronic engineering and found that these factors influenced perceived ease of use, usefulness, attitude, and intention to use the virtual laboratory and actual use (see Figure 2.27).

Figure 2.27

Acceptance of use of virtual laboratories to learn electronic engineering



Note. Adapted from Estriegana et al. (2019)

This model demonstrated an 'everything to everyone' approach of forming relationships between many factors, making it more difficult to know which ones are important: A case could be made that statistical association could be found between factors given enough sample size or even coincidence, and so in this example it is not known if all these purported associations were confirming theory. Regardless, Estriegana et al.'s results demonstrated that affective factors, such as satisfaction, and cognitive factors, such as playfulness, can and do play a part in formation of intention to use virtual laboratories.

Huang and Liaw (2018) also investigated the affective and cognitive axes in their research of learner attitudes to virtual reality for learning. Specifically, they investigated the influence of learner motivation on perceived usefulness of virtual reality, and the influence of interaction within the virtual environment. Their findings indicated that motivation was an influencer of perceived usefulness, and that self-efficacy and interaction influenced ease of use, usefulness, and motivation. This study provided further evidence that cognitive and affective factors are influential, alongside perceptions of self-efficacy.

Shin et al. (2013) investigated how immersion and presence within a 3D virtual learning experience influenced a student's satisfaction and intention, finding that presence, flow and immersion all served to confirm a user's expectations of the 3D environment, which influenced their satisfaction of it as a learning tool. Sagnier et al. (2020) incorporated enjoyment into a model to investigate virtual reality because of its hedonic qualities. Their findings indicated that these hedonic qualities, and personal innovativeness, were influential upon perceived usefulness, and pragmatic useability influenced perceived ease of use. In addition, the effects of cybersickness and presence were shown to directly influence intention to use the system for learning.

Together, these studies showed how research at the beginning of viable virtual reality focussed on users' ease of use, innovativeness and perceptions of self-efficacy but later included cognitive factors such as presence, playfulness, and affectual factors such as satisfaction, and more recently, enjoyment. However, there appears to have been little focus on factors directly related to teaching, learning, or pedagogy, although the trend towards immersion and cognitive presence might be an indicator that this may be a natural evolution seeing as immersion and presence help to facilitate learning (Makransky & Lilleholt, 2018).

2.8 Criticisms and limitations of the Technology Acceptance Model

One claim of Davis' TAM is that perceived usefulness and perceived ease of use mediate external influences of attitude and intention. This supposition contrasts with the Unified Theory of Acceptance and Use of Technology and Unified Theory of Acceptance and Use of Technology 2 which draw direct relationships between external variables and behavioural intent. Burton-Jones and Hubona (2006) performed a study that showed direct effects can occur alongside the indirect effects postulated by the TAM. Their model's dependent variables were frequency and volume of use, and their findings showed that system experience had moderate direct influence on both dependent variables in addition to its mediation by perceived ease of use. The results of this study might be called into question however because the authors used principal components to estimate the factors, which is a technique not suited to the reflective variables used in factor analysis, as explained in section 3.4. The context is also in a government office setting instead of the education setting. Despite these possible criticisms, their research does suggest that TAM's supposition that external variables always act via perceived usefulness and perceived ease of use might be called into question.

Another claim of Davis' TAM is that perceived ease of use influences perceived usefulness. Sheppard and Vibert (2019) performed a study to investigate the relationship between task technology fit and perceived usefulness, and found that, contrary to Davis' TAM, perceived ease of use did not influence perceived usefulness directly. Their findings indicated instead that perceived ease of use moderated the influence of task technology fit onto perceived usefulness. This study is relevant in that it tested student attitudes to a multimedia delivery system in higher education. The authors concluded that the familiarity of users with modern technologies may have rendered Davis' perceived ease of use to perceived use link obsolete and in need of revisiting.

The studies included in this systematic review consistently demonstrated that the technology acceptance model alone is not sufficient to investigate attitudes towards educational technologies and that extending it is required to answer specific research questions. Whereas a majority extend it by including factors of a general nature, such as for example social norm, system attributes, self-efficacy and facilitating conditions, only a minority include factors relevant to learning, and even then, the field is sparse and inconsistent.

2.9 Rationale for research

The literature review shows that there has been no consistent approach to measuring technology acceptance in educational contexts, that many different models are used and that only a few of them include constructs that directly relate to learning and teaching. There are instances where learning and teaching constructs are included, such as class interaction and collaboration, feedback, student engagement with content and learning process, however this has been piecemeal and varied across different research, with a lack of a consistent approach across the breadth of studies. Thus, this project was conceived to support coherence and consistency within the field of educational technology acceptance research.

This doctoral project addresses these perceived shortcomings by constructing an extended technology acceptance model that suits the educational context by including constructs that are known to be important for learning achievement, while remaining parsimonious enough to be of practical use. Despite the limitations of the TAM architecture briefly described in section 2.8, the TAM is chosen as a core model because it can be easily extended in a way that suits the situation and will capture the effects of mediation by core factors such as perceived usefulness and perceived ease of use, which have been validated in many pieces of research.

As the many TAMs demonstrate, researchers adapt factors and structures to suit specific research questions. However, one flaw is that researchers conceivably start with a core model and decide what to add, which risks omitting factors that might be relevant. This thesis takes the opposite approach by constructing a model that research indicates is comprehensive, allowing for researchers to remove factors that are irrelevant. In this way, the model can be applied and adapted to a variety of situations and research questions and remain comprehensive. For example, if a technology doesn't support interaction or communication, then that factor can be omitted. Similarly with feedback, or instructor practice. Thus, while the model is intended to be comprehensive, it is envisaged that different practitioners will adapt it to suit their situation, while remaining reasonably confident that their resultant model would likely measure appropriate factors compared to building a model from scratch.

CHAPTER 3 – METHODOLOGY AND METHODS

3.1 Introduction

The main objective of this research project was to create and test a technology acceptance model suited to educational technologies. Exploratory factor analysis and thematic analysis were used to identify as-yet unknown underlying factors that needed to be included in the final model. Confirmatory factor analysis and structural equation modelling were used to confirm the factors and measure their associations. In this way, a technology acceptance model specifically suited to educational technologies was constructed and evaluated.

It was necessary to progress through three broad steps to achieve the research aims and objectives:

1. Gathering known constructs: conducting a review of the extant technology acceptance literature and collating the constructs into a manageable framework so that each could be easily identified.
2. Searching for new factors: undertaking qualitative research to identify and describe any missing or new factors that had not been investigated or included in prior technology acceptance research.
3. Building and deploying a model: constructing the model, including constructs suggested by previous research, and deploying it in a real-world setting to test its utility and effectiveness.

3.2 Methodology

Overall, this doctoral research project employed an abductive approach (J. Thompson, 2022) to investigate and derive a new theoretical model because while there were existing theoretical foundations they required further exploration to expand and include relevant new insights. Mixed methods including both qualitative and quantitative inquiry afforded the benefit of collecting different types of data, employing different analysis techniques, and asking different types of questions to explore what concepts are important and how they might fit together. In this way, the qualitative and quantitative research could be considered collectively to inform the final model. The mixed methods employed in this thesis included deductive and inductive qualitative inquiry, and exploratory and confirmatory multivariate analysis, in order to address the specific research aims and achieve the research objectives.

The objective of Paper 1 (Chapter 4) was to identify and collate all factors known to have influence in forming attitudes and intentions vis-à-vis educational technologies from previously published technology acceptance research. The process of formation of the taxonomy was initially inductive (Braun & Clarke, 2006) in that the core behavioural theories and semantics of included constructs informed the root of the taxonomy. From that point the root was expanded by incorporating other constructs from the extant literature, so was more deductive in nature.

The objective of Paper 2 (Chapter 5) was to determine the value of the attitude and educational compatibility construct to determine whether to include them in the final model. This was achieved using exploratory and confirmatory factor analysis and structural equation modelling.

The objective of Paper 3 (Chapter 6) was to identify any new or emergent constructs that needed to be included in an educational technology acceptance model, that weren't initially identified as being part of the taxonomy. This process required analysis of student comments for themes that could be compared to the taxonomy from Paper 1, and so this process was deductive in nature.

The objective of Paper 4 (Chapter 7) was to test the final model in a real-world setting to determine if it worked as a model. This was done using exploratory and confirmatory factor analysis and structural equation modelling, which produced fit indices and explanation of variance of dependent variables which could be used to ascertain model performance.

Chapter 8 and Appendix A employed confirmatory factor analysis and structural equation modelling to investigate certain aspects of the models from the main body of work.

3.3 Factor Analysis and Structural Equation Modelling

Factor analysis and structural equation modelling are complementary techniques that together allow for the measurement of associations between inherently unmeasurable factors (latent constructs). An unmeasurable factor is one whose values cannot be directly measured, for example, a person's intention or attitude. In social research it is sometimes valuable to measure how peoples' attitudes affect their intentions, as is the case with this research project. Factor analysis provides a way to understand the relationship between observed variables and the latent factors they reflect. Once that has been achieved then structural equation modelling is used to demonstrate how the factors associate and influence each other to produce an outcome. This project measures and models factors affecting the attitudes of users to educational technologies and how those factors influence user intention. The purpose is to identify which factors are more influential on a user's behaviour, and by how much. This is valuable because it allows educators to manage those factors to then support users' intentions to use an educational technology, and ultimately improve uptake and ongoing use of the technology.

There are two kinds of factor analysis: exploratory and confirmatory. Exploratory factor analysis (EFA) is used to discover what relevant factors emerge from a sample, whereas confirmatory factor analysis (CFA) is used to confirm that previously determined factors are valid for analysis in structural equation modelling (SEM). A factor itself is measured by observed variables which act as proxies for that inherently unmeasurable factor. These observed variables are, in practice, the items of a questionnaire, commonly using Likert scales. EFA then is the process that shows which questionnaire items measure which factors and is used when one does not have previously confirmed factors with their associated questionnaire items, or when such associations are uncertain. The questions answered by EFA are ‘what latent factors are present?’ and ‘which questionnaire items are associated with each of the latent factors?’ In contrast, CFA is used when one is analysing already established factors that have been demonstrated to be measured by an associated set of questionnaire items. The measurement of these known factors varies from sample to sample, and so CFA is used to confirm that the factors are in fact reliable for the sample in question. The question answered by CFA is ‘do my questionnaire items reliably measure the latent factors?’. Because of this, the model analysed by a CFA is sometimes known as the ‘measurement model’.

Once a CFA has verified that the factors are valid and reliable, the factors can then be subject to structural equation modelling (SEM) to measure the associations between them. The hypothesised relationship between factors is known as the ‘structural model’ and the analysis produces standardised regression values between each factor, and measures of how much variance of each factor is measured by the model.

Each type of analysis used during this project will now be explored in more detail.

3.4 Exploratory Factor Analysis (EFA)

In discussing EFA, it is necessary to incorporate a description of the difference between exploratory factor analysis and principal components analysis because they are often confused, and the discussion serves to highlight the difference between reflective and formative variables.

3.4.1 Exploratory Factor Analysis and Shared Variance

Exploratory factor analysis (EFA) is a technique that identifies the unknown latent factors that explain the correlations among observed variables exhibited by a dataset (Holgado–Tello et al., 2010) and is used when one wishes to identify which factors emerge naturally from collected data. In practice, a survey is deployed containing questions thought to reflect a variety of latent factors which are themselves unmeasurable directly. The process of EFA consists of analysing the variances of each of the question items (observed variables) and grouping those items whose variances behave in similar ways, the assumption being that question items that measure the same latent factor will behave similarly and this is seen in patterns of shared variance. Once observed variables are associated with latent factors, the factors themselves can then be indirectly measured through the observed variables and modelled.

The total variance of each of the observed variables consists of three components: shared, unique, and error. Shared variance is the variance that is shared with other variables because they measure the same latent variable, those that do share enough variance are grouped and are said to *reflect* a common latent factor. Unique variance is variance in each item that is not due to the latent factor it reflects but due to other influences specific to each item (which may be part of the model or not). Error variance is the variance attributable to measurement or random error and rests on the assumption that no measurement is perfect. This may be due to respondents being distracted, not being sure, or other random reasons that perturb true responses at the time of the survey.

In factor analysis, only the shared variance of the observed variables is used in the calculation of weightings between these variables and the putative latent factors. The extent of the shared variance of these observed variables allows them to be collated into groups which collectively allow the quantitative measurement of the different factors. The assumption is that if a group of observed variables measures a latent factor, then they will exhibit shared variance with each other above certain thresholds, and less so with other observed variables, and this is reflected in the weightings between the variables and factors.

The prime philosophical basis of factor analysis is that latent factors can be *measured by* observed variables; this implies that the latent factors influence the value of the observed variables. This is represented by the general algebraic form as shown in Equation 3.1.

Equation 3.1

Algebraic Form of Factor Analysis

$$X_1 = v_{1(1)}CF_{(1)} + v_{1(2)}CF_{(2)} + \cdots + v_{1(m)}CF_{(m)} + e_1$$

$$X_2 = v_{2(1)}CF_{(1)} + v_{2(2)}CF_{(2)} + \cdots + v_{2(m)}CF_{(m)} + e_2$$

$$\vdots$$

$$X_p = v_{p(1)}CF_{(1)} + v_{p(2)}CF_{(2)} + \cdots + v_{p(m)}CF_{(m)} + e_p$$

Note: The value of each observed variable, X_i, depends on its association with the latent factors in the model (called 'common factors' (CF)). $v_{j(i)}$ is the weight of the *i*th common factor associated with the *j*th measured variable. Adapted from H. S. Park et al. (2002)

3.4.2 Principal Components Analysis

In social science research, Principal Components Analysis (PCA) can be confused with EFA. PCA has a different objective to EFA, which is to simply reduce the number of variables to work with by organising them into dimensions which act as mathematical aggregates of the component question items. Whereas in EFA the three types of variance are recognised in the observed variables, in PCA they are not, and calculations are based on total variance, not shared variance. Thus, PCA does not recognise the concept of shared variance and so does not organise variables or calculate weightings based on it. The extracted dimensions identified this way are called components as opposed to factors. Extracted components from PCA have a mathematical form that is opposite to that of factor analysis (Equation 3.2).

Equation 3.2

Algebraic Form of Principal Components Analysis

$$PC_{(1)} = w_{(1)1}X_1 + w_{(1)2}X_2 + \cdots + w_{(1)p}X_p$$

$$PC_{(2)} = w_{(2)1}X_1 + w_{(2)2}X_2 + \cdots + w_{(2)p}X_p$$

$$\vdots$$

$$PC_{(m)} = w_{(m)1}X_1 + w_{(m)2}X_2 + \cdots + w_{(m)p}X_p$$

Note. Mathematical description of components calculated in PCA. PC = principal component, m = the number of principal components, p = the number of measured variables, X = each observed variable,, $w_{i(j)}$ = the weight chosen for the *j*th measured variable to maximise the ratio of variance of the variance of PC(i) to the total variation. Adapted from H. S. Park et al. (2002)

Figure 3.2 clearly shows that principal components are a function of the measured variables (H. S. Park et al., 2002) whereas Figure 3.1 shows that in EFA the measured variables are a function of the latent factors (H. S. Park et al., 2002). This says that whereas PCA produces components that are mathematical reductions of several variables that are not related by shared variance, in EFA factors are identified based on the shared behaviour of observed variables. The major implication is that EFA produces factors that are thematically distinct, whereas PCA produces components which are not.

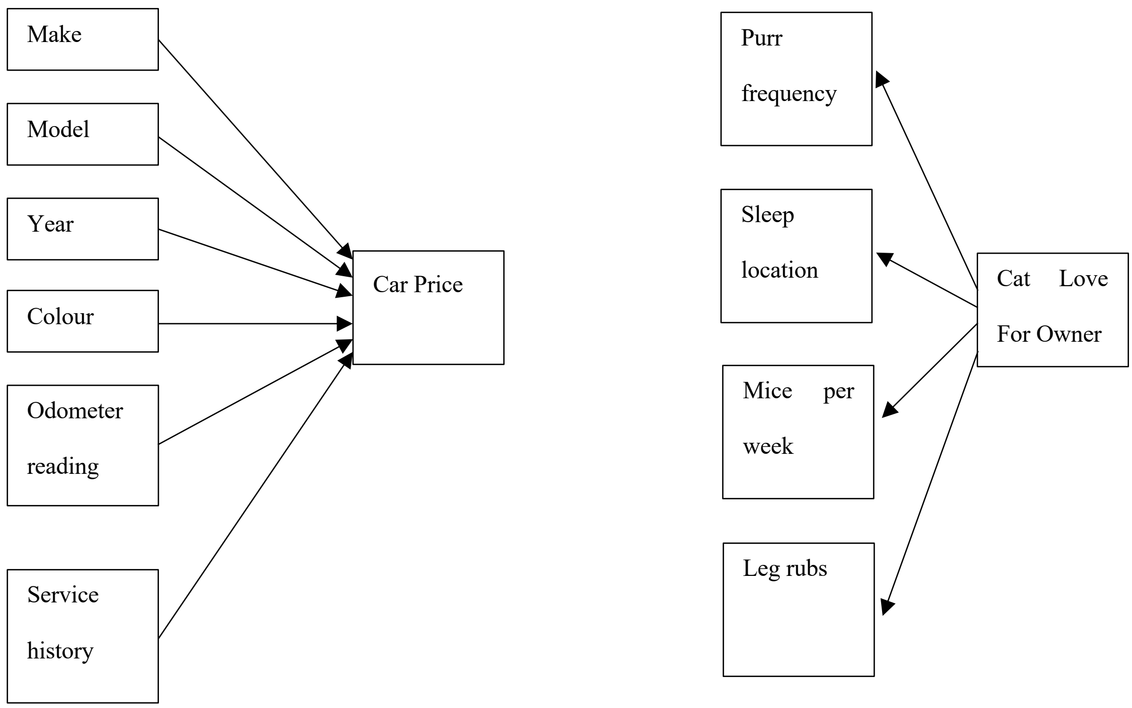
3.4.3 Reflective vs Formative Variables

In sections 3.4.1 and 3.4.2 it was stated that in EFA, latent factors produce ('load onto') the observed variables whereas in PCA the observed variables produce the components. This leads to an important consideration of the types of variables used in the models in this project. In factor analysis the observed variables reflect the latent factor and so are called 'reflective variables'; in PCA the observed variables form the component and so are said to be 'formative variables'. Factor analysis presumes common factors, measured by observed variables that exhibit random error variance, measure-specific variance, and shared variance (see Anderson & Gerbing, 1988). This shared variance is able to be measured among the observed variables and is a result of the influence of the latent factors, which is the basis of factor analysis. In contrast, in principal components observed variables are not grouped by shared variance, but total variance: components are simply a linear combination of the observed variables, which load on to all components (see Anderson & Gerbing, 1988, p. 412). Because PCA does not calculate factors based on shared variance only, the results do not accurately convey the influence of a factor on a collection of observed variables.

A practical example serves to illustrate the difference between formative and reflective variables. The price a person is willing to pay for a car is based on observed variables such as make, model, year, colour, odometer reading, service history, and so the observed variables influence the car price. These observed variables do not reflect underlying themes but are instead individual and often unrelated data points. The car price can also have a defined value and is made up of observed variables, which are therefore described as 'formative' because they form the value of the dependent variable. In contrast, how much a cat loves its owner does not have a defined value, but it can be measured by indicators, such as *inter alia* how many times it purrs in the presence of its owner, where it sleeps, how many dead mice it brings home. These observed variables don't determine the amount that the cat loves its owner but are reflective of it. In this case, the factor is 'how much the cat loves its owner'. These relationships are illustrated in Figure 3.1.

Figure 3.1

Comparison of Formative and Reflective Variables



Note: Formative variables of principal components analysis (left) and reflective variables of factor analysis (right).

The distinctions made here between formative and reflective variables are important to consider for a few reasons. First among them is so that the correct model characterisation and analysis technique is chosen for the given research objective. If one is aiming to perform a factor analysis then models need to be specified using reflective variables. Secondly, given that the research aim is to perform a factor analysis, it is theoretically incorrect to use principal components analysis as the extraction method to identify the factors, for example if performing an EFA using principal components extraction, then the extracted factors cannot be relied upon because they were estimated using total variance, not shared variance.

3.5 Confirmatory Factor Analysis (CFA)

Sections 3.4.1, 3.4.2 and 3.4.3 have established that if the research question seeks to model the relationships between latent factors, then factor analysis using reflective variables is the correct approach.

In contrast to EFA, Confirmatory Factor Analysis (CFA) begins with a known set of latent factors and tests how well a dataset reflects that *a priori* structure. Thus, while EFA is data driven, CFA is model driven. It is called confirmatory because research employing this technique has a proposed model that is being evaluated (confirmed) by collected data. The proposed model consists of several latent factors that are measured by sets of associated observed variables. The latent factors together with their associated observed variables are collectively called a measurement model (Anderson & Gerbing, 1988). Confirmatory factor analysis then is a technique for quantitatively evaluating the robustness of an entire measurement model; its central question is 'how well are the latent factors measured by the observed variables?'

The two main principles of CFA are convergent and discriminant validity:

- Convergent validity: Because the measurement items are not 100% reliable, it is necessary to include several observed measurement items for each latent factor, and it is expected that each factor's measurement items will share variance because they are reflecting the same latent construct albeit slightly differently. Each measurement item should load onto its latent factor, and although an item may also demonstrate some loading onto another latent factor, this cross-loading should be minimal. A latent factor's items loading predominantly onto it is known as convergent validity and shows that the items do in fact measure the construct reliably and collectively represent a high percentage of the construct's variance. Measures of convergence and their acceptable thresholds are provided by Hair et al. (2010): average variance extracted (>0.50), individual factor loadings (>0.60), and composite reliability (>0.70).

- Discriminant validity: A robust model will have its different latent factors representing different dimensions of a problem and so it is expected that they do not share too much variance. When a set of latent factors share little variance, then they can be said to measure different dimensions of a phenomenon. During analysis, discrimination is shown by comparing the average variance extracted by a factor's items to the variance that factor shares with other factors. As a rule of thumb, a factor's average variance extracted must be greater than the variance it shares with other factors – this is known as discriminant validity. Thus, discriminant validity concerns measuring the covariance of the latent factors themselves and demonstrating that the different constructs are sufficiently separate from each other. Statistically, this is demonstrated by the square root of the average variance extracted (equivalent to correlation) of a factor being greater than its correlation the other factors (Hair et al., 2010).

A successful measurement model will therefore show both convergent and discriminant validity at or beyond acceptable levels, and both measures depend on measurement of variance matrices of the model. Depending on the types of data , measurement models can be estimated by such software as Microsoft Excel, SPSS, SPSS AMOS, LISREL, MPlus or by R packages. In this project, Microsoft Excel was used for data preparation and R version 3.6.0 (R Core Team, 2013) and R Studio version 1.2.1335 (RStudio Team, 2015) was used for data analysis because it allows for a broader range of analysis techniques and is free open-source software with solid community support.

CFA is a quantitative technique, and so the answer to the question of how well a theoretical model is reflected in a dataset is provided quantitatively in the form of fit statistics. Collectively, the fit statistics answer the question of how well the model reproduces the dataset. If the model represents the population, then the dataset represents a sample, and one would expect similar datasets to be produced by the model if it did reflect the population.

Mathematically, the fit statistics for CFA measure the difference between a covariance matrix implied by the model and the covariance matrix of the dataset. If the two covariance matrices closely match, then the model closely represents that dataset. Thus, it has become convention that the model can be confirmed to the extent that its fit statistics fall within conventionally used thresholds or limits.

Some seminal and oft-cited studies have used artificial models and/or data to recommend fit statistics and produce recommended thresholds to determine model acceptability. Hooper et al. (2008) and R. B. Kline (2015) recommend absolute fit ($\chi 2$; root mean square error of approximation (RMSEA < 0.06); standardised root mean residual (SRMR < 0.08)), incremental fit (comparative fit index (CFI >0.9), Tucker-Lewis index (TLI > 0.9)), and parsimonious fit ($\chi 2/df < 3$) using thresholds recommended by Hu and Bentler (1999) and Hooper et al. (2008), and these thresholds are commonly used to support or discard measurement models in CFA. However, there is also controversy, since the value of fit statistics can depend on the factor estimation method (Xia & Yang, 2019) or other influences such as sample size and model specification (Hu & Bentler, 1999). In practice, problems have been identified in using fit statistics as gold standard measures (Marsh et al., 2004), and so the assumption that fit thresholds apply as stated in all models has been called into question (Curran et al., 1996). While this controversy exists, a sensible approach to assess overall model suitability remains grounded in its theoretical sense, with judicial use of fit estimates used as one element in the overall assessment of measurement model.

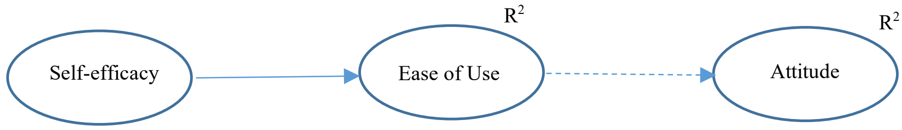
The scope of this research is not to address the appropriateness of commonly used fit statistics or thresholds, and so while noting that some discussion still occurs in this area, CFA used in this project will report model fit in terms of the accepted and common limits while discussing fit results in context with theory and other measures of model suitability.

3.6 Structural Equation Modelling

Once the measurement model was deemed reliable by CFA, the constructs within it were structurally arranged to show how they theoretically related to each other. Some acted as independent variables (whose value was not dependent on other variable(s)), others dependent variables (whose value depended on other variable(s)), while others were intermediary (whose value depended on other variables, and which also determined the value of yet other variables). Each possible structural model is based on theory that the model attempts to mirror. That is, if the theory says that attitude toward a technology depends on perception of its ease of use, which in turn is influenced by anxiety over whether we can use it or not, then this relationship can be described within a structural model (Figure 3.2).

Figure 3.2

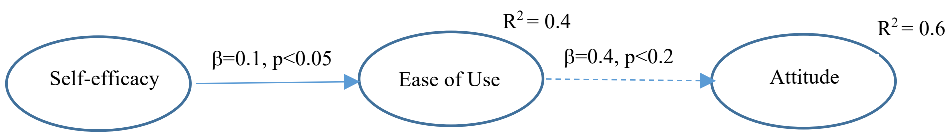
Example of a relationship in a structural equation model



The strength of association between each factor is reported by a standardised regression coefficient (β) (in the range 0.0 to 1.0 with the value determined by the strength of association) and its statistical significance (reported by its p value) is a measure of its validity. Each β is indicative of how many standard deviations the dependent factor's mean value adjusts given a one standard deviation adjustment of its independent variable. R^2 is a measure of how much the variance of a dependent variable is measured given its inputs and is used as an indicator of the power of the model: the more the model measures the influences on dependent factors, the more powerful it is. On the other hand, if the R^2 is low, it means the model is not sufficiently capturing the influencers of that factor, that others exist that are not included in the model. R^2 is therefore an indicator of the completeness of a model in each context. An example of a calculated SEM result is shown in Figure 3.3.

Figure 3.3

Example of a structural equation modelling result



Note: Structural models show significant paths (solid lines) and insignificant paths (dotted lines), along with the standardised regression co-efficient values (β) and measured variance (R^2) of a dependent factor.

In practice, many of these relationships exist simultaneously in a web of relations, and SEM measures the regression coefficients for all the paths between the various constructs that comprise the model simultaneously. Simultaneous measurement is important, because if one or more paths are removed, the rest of the model can change, and sequential measurement of regression coefficients may fail to detect it. Thus, a large part of this project is dedicated to determining the most parsimonious yet comprehensive model to measure attitudes; leaving out even one important factor can produce different results.

Thus, the SEM technique is used to quantitatively test theories of why people form attitudes towards actions, behaviours, or things, and, just like the variables that measure the factors, the SEM models are themselves only estimates of what is really forming peoples' attitudes. The technique, therefore, involves measuring how well the model fits the data, and this is represented by a small collection of 'fit' indices in the same way that the measurement model is evaluated using a set of fit indices (Section 3.5). It is accepted and required practice to measure and report these fit indices (see Hair et al., 2010), which are an indication of how well the model can be extrapolated to the population. These fit indices are reported for each CFA and SEM performed in this thesis.

3.7 Treatment of Ordinal Data

3.7.1 General Data Considerations

The quantitative models estimated in this thesis are done so using ordinal data measured using Likert scales deployed in surveys. The Likert scales in Paper 2 (Chapter 5) are seven-point bipolar scales from strongly disagree to strongly agree as anchors without descriptors at each anchor point. Thus, the scale is a continuum of equidistant contiguous but distinct categories and proper analysis would therefore avoid the use of parametric methods suited to analysis of continuous data. Often, though, the correlation matrix of confirmatory factor analysis is calculated using Pearson correlations, which assumes the data to be normally distributed, and thus continuous. When the data are ordinal, it has been shown that specific use of polychoric correlations provides more accurate representation of the measurement model than the Pearson correlations (Holgado–Tello et al., 2010).

Wu & Leung (2017) attempted to bridge the gap by showing that an eleven-point Likert scale from 0 to 10 can approximate continuous data for general social science research, making the point that the longer Likert scales act as interval scales and can produce acceptable results using methods suited for continuous data. Addressing the issue directly, Norman tested simulated ordinal data using continuous methods and stated that "parametric methods can be used without concern" (Norman, 2010, p. 625). Despite the assurance of some research that approximation is acceptable in social science research, this thesis respects the data by using only methods suited to their type to avoid approximations carrying through the analysis to the results.

3.7.2 Polychoric Correlation

Polychoric correlation is a statistical method used to estimate the correlation between two continuous latent variables based on the observed ordinal variables (Holgado–Tello et al., 2010, p. 155). It is used instead of Pearson correlation for CFA when the observed variables are ordinal or categorical, as Pearson correlation assumes linearity and normality, which may not hold for such variables. Weighted Least Squares (WLS) is an appropriate estimation method in CFA that can incorporate polychoric correlations into the estimation process, effectively handling non-normal and ordinal data, making it more appropriate than assuming normality, using Pearson correlations or Maximum Likelihood (ML) estimation (Coenders & Saris, 1995). For smaller sizes, a robust form of WLS should be used, such as Diagonally Weighted Least Squares (DWLS) (Flora & Curran, 2004). Using DWLS and polychoric correlations in CFA allows for a more accurate and robust analysis, especially when dealing with non-normal and ordinal data, providing a more realistic and reliable representation of the underlying latent variables.

Since the quantitative data in this project are Likert type, the confirmatory factor analyses and structural equation modelling were estimated using polychoric correlation input matrices and diagonal weighted least squares factor estimation (Wang, 2005). As both Appendix A (Investigating factor estimation effects) and Appendix 8.A (Chapter 8) show, there can be material difference of analysis outcome depending on the chosen factor estimation method, and so the extra care taken to use the correct analysis method for the type of data collected is justified and yields valid results.

CHAPTER 4 – IDENTIFYING KNOWN CONSTRUCTS

4.1 Preamble

The purpose of this paper was to identify the currently known factors used in contemporary technology acceptance models for educational technologies as a starting point, to collate 'what is currently known'. This was necessary because of the many different models used in the research field. The research followed firstly an inductive approach (Braun & Clarke, 2006) from seminal literature to organise the root of the taxonomy. It then used a deductive approach against that root to identify factors described by subsequent research to extend it, producing a more comprehensive taxonomy with primary, secondary, and tertiary groupings. This paper addressed the following research aims, objectives and hypotheses:

- **Research Aim 1**: To identify the types, characterisations and scope of factors affecting attitudes and intentions towards use of educational technologies.
- **Research Objective 1**: To search for the latent constructs related to educational technology use that have been shown to affect user attitudes and intentions.
- There were no research hypotheses related to this paper.

4.2 Statement of Authorship

Title of Paper	A taxonomy of factors affecting attitudes towards educational technologies for use with technology acceptance models.
Publication Status	Published
Publication Details	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

Principal Author (Candidate)

Name of Principal Author	Andrew C Kemp		
Contribution to the Paper	Conceptualisation, literature review, organisation of taxonomy, write-up.		
Overall percentage (%)	90%		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	23/6/2023

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
ii. permission is granted for the candidate in include the publication in the thesis; and
iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution

Name of Co-Author	Edward Palmer		
Contribution to the Paper	Supervised development of work, helped in data interpretation, manuscript conceptualisation, revisions and evaluation.		
Signature		Date	10/7/23

Name of Co-Author	Peter Strelan		
Contribution to the Paper	Supervised development of work, helped in data interpretation, manuscript conceptualisation, revisions and evaluation.		
Signature		Date	26/6/23

*4.3 Paper 1 - **A taxonomy of factors affecting attitudes towards educational technologies for use with technology acceptance models***

Abstract

The aim of this theoretical review was to identify the important factors shown to affect attitudes towards use of educational technologies by students or educators in higher education institutions and organise them into broad, intermediate and narrow groupings. This was done to assist the construction of more objective measurement instruments used in the evaluation of educational technologies. A qualitative review of the influential factors that affect user attitudes, intentions and motivations to use educational technologies was conducted, first by interrogating the fundamental behavioural theories underpinning technology acceptance models, and then by exploring the findings of later and contemporary empirical research conducted in the educational context. Identified factors were grouped to produce an ordered taxonomy of measurement constructs. This taxonomy provides each construct's lineage back through tertiary, secondary and primary taxonomic groups and provides a greater scope of measurement than commonly used models. Seven primary and twenty two secondary and tertiary taxonomic groups were defined, which collectively comprise sixty one measurement constructs. The taxonomy is designed to reduce measurement bias within studies and acts as a basis for consistent and objective benchmarking within and across institutions.

Introduction

Technology acceptance models (TAMs) are models that "provide an explanation of the determinants of computer acceptance that is general, capable of explaining user behaviour across a broad range of end-user computing technologies and user populations" (Davis et al., 1989, p. 985). The idea of TAMs was introduced by Davis (Davis, 1986, 1989) who drew on behavioural models including the Theory of Reasoned Action (TRA)

(Fishbein & Ajzen, 1975), expectancy theory (see Snead & Harrell 1994), self-efficacy theory (Bandura, 1981), cost-benefit decision processes (Beach & Mitchell, 1978), Innovation Diffusion Theory (IDT) (Tornatzky & Klein, 1982), and the Channel Disposition Model (Swanson, 1987). In doing so Davis concluded that a user's attitude to a technology is focused via the user's Perceived Usefulness and Perceived Ease of Use of the technology in question. Since that time, Davis' TAM has been expanded as the TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008).

Venkatesh et al (Venkatesh et al., 2003) conducted a revision of Davis' TAM, TAM2 (Venkatesh & Davis, 2000), C-TAM-TPB (Taylor & Todd, 1995), the TRA (Fishbein & Ajzen 1975), Theory of Planned Behaviour (Ajzen, 1991), the Motivational Model (Deci, 1971; Vallerand, 1997), the Model of PC Utilization (R. L. Thompson et al., 1991), the IDT (Rogers, 1995) and Social Cognitive Theory (Bandura, 1986) in 2003, which resulted in the construction of the Unified Theory of Acceptance and Use of Technology (UTAUT). The UTAUT differs from Davis' original TAM in that it adds a Social Norm construct as a direct influencer of Behavioural Intent to Use, and a Facilitating Conditions construct as a direct influencer of Actual Use. The construction of the UTAUT included judgements about strength or value of some constructs, and so does not include, *inter alia*, attitude, affect or self-efficacy while recent research demonstrates the mediating role of attitude in some situations (López-Bonilla & López-Bonilla, 2017; Moreno et al., 2017; S. Y. Park et al., 2012) and the variance of self-efficacy in different contexts (Tarhini et al., 2015). The UTAUT has been applied to both general and educational technologies and has internal reliability in various studies (Oye et al., 2014; Sumak et al., 2010), although its utility has not been universal in contrast to the TAM's more flexible structure (Ros et al., 2015).

More recently, the General Extended Technology Acceptance Model for E-Learning (GETAMEL) model was produced after extensive review in a broad variety of settings and covers a broad variety of educational technologies (Abdullah & Ward, 2016), and has been successfully used in over a hundred studies since its publication. The GETAMEL model comprises the five most-used constructs from reviewed research and so excludes constructs that have nonetheless been influential elsewhere.

The literature often reveals scant objective justification in how constructs are chosen or named, and measurement models vary considerably. Moore and Benbasat relate that "inadequate definition and measurement of constructs have been identified as major causes" of mixed and inconclusive outcomes (Moore & Benbasat 1991, p132). Considering further that structural equation modelling depends on calculating path coefficients concurrently, it stands to reason that variability in the number of paths and relationships alters the outcomes and inferences of models. It is therefore important that measurement models cover an inclusive scope and measure all likely factors in a way that brings consistency from study to study. We conjecture that this approach would improve validity and external reliability of study results, allowing for closer comparison of results across various settings. To this end, we propose a common lexicon and taxonomy to address this measurement problem.

The purpose of this review is to identify the important factors that influence intention to use educational technology and to organise them using a taxonomic structure. Noting Davis' point that "the size of the usage correlation varies greatly from one study to the next depending on the particular measures used" (Davis, 1989, p. 319) we should not forever exclude factors that have been shown to be less influential in other studies. *A priori* inclusion of all salient factors is important, because we cannot pre-empt technological developments or contextual influences which may elevate the importance of any factors. The taxonomy is an organised collection of such factors.

Methodology

Taxonomy formation

The taxonomy was formed adopting an 'empirical to deductive, deductive to empirical' approach (Nickerson et al., 2009) with the aim of producing a taxonomy that is concise, inclusive, comprehensive and extendable (ibid.). Following the example of Walter, Nutley and Davies (2003), we formed the taxonomy in stages using different source types.

In stage one, the theories that formed the basis of the TAM and UTAUT were interrogated to identify their included constructs and their associated authors' definitions to form the taxonomic root. The measurement intent of each construct was determined from the author definitions, which represents the "identify general distinguishing characteristics of objects" (Nickerson et al., 2009) stage of the empirical to deductive process. Constructs sharing same or similar distinguishing characteristics (for example a social factor, an attitude or feeling, a person's capacity, a technology attribute) were then collated into synonymous groups which became the primary groups of the taxonomic root. The deductive to empirical phase of taxonomy construction then began with re-examination of author definitions in the primary groups, which identified nuances allowing for the formation of secondary and, if required, tertiary levels. Tertiary levels were the limit of specificity in order to balance with parsimony, an approach adopted from Stoddard and Brownfield (2018). The co-authors were consulted to confirm the characterisation of the taxonomic groups and qualitative alignment of constructs within them.

The comprehensive review conducted by Abdullah and Ward (2016) was then used in stage two to expand the root by identifying additional constructs specifically relevant to educational technology. Only those which were not already represented, could form new taxonomic groups and which met the inclusion and exclusion criteria were added to the root. As a final check in stage three, 125 papers that cited the GETAMEL model were reviewed, as well as papers identified in a separate search using ["TAM" OR "UTAUT" OR "technology acceptance model"] as the search term and higher education and 2016-2019 as the filters. Redundant measurement constructs were not included to support parsimony.

Inclusion criteria:

- Higher education context or setting
- Educational technology used for instruction, or the delivery of instruction,
- Research subjects are educators or students in the higher education sector
- Research is peer reviewed, published in scholarly journals from 2004 onwards (the beginning of Web 2.0 capabilities),
- The construct is sufficiently defined to enable placement within the taxonomy,
- The presence of a significant ($p \leq 0.05$) regression co-efficient between the construct and either Behavioural Intent to Use (BI), or Attitude Towards Use (ATT), either directly or indirectly,

Exclusion criteria:

- Research subjects are professional staff,
- Research conducted in a primary or secondary education setting
- Redundant items

As with the root taxonomy, the co-authors were consulted to confirm taxonomic structure and make adjustments as required.

Results

Stage one classified thirty-one constructs, stage two, twenty-one, and stage three another nine, bringing the total number of included measurement constructs to sixty-one.

Stage 1 - Identification of the ontological foundations and formation of the taxonomic root

Table 1 lists the constructs described in the foundational behavioural theories that form the bases of the later major technology acceptance models. It also lists the constructs from two major technology acceptance models having causative relations with 'Behavioural Intent to Use'. The construct 'Facilitating Conditions' from the Unified Theory of Acceptance and Use of Technology is not included because the UTAUT posits that it moderates the relationship between Behavioural Intent and Actual Use. That is, according to the UTAUT, facilitating conditions does not influence behavioural intent but is downstream of it. However, facilitating conditions is included from the Model of PC Utilization.

Table 4.1

The Constructs That Comprise the Foundational Behavioural Intention Models

Ontological Root	Included Constructs	Authors' Definitions
TRA – Theory of Reasoned Action (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975)	Attitude Toward Behaviour	"the individual's positive or negative evaluation of performing the behaviour" (Ajzen & Fishbein, 1980, p. 6)
	Subjective Norm	"the person's perception of the social pressures put on him to perform the behaviour" (Ajzen & Fishbein, 1980, p. 6)
TPB – Theory of Planned Behaviour (Ajzen, 1991)	Attitude Toward Behaviour	Same as above as "The theory of planned behaviour is an extension of the theory of reasoned action" (Ajzen, 1991, p. 181)
	Subjective Norm	Same as above as "The theory of planned behaviour is an extension of the theory of reasoned action" (Ajzen, 1991, p. 181)
	Perceived Behavioural Control	people's "confidence in their ability to perform" a behaviour (Ajzen, 1991, p. 184)
MM – Motivational Model (Deci, 1971; Vallerand, 1997)	Extrinsic Motivation	Motivation to "performing a behaviour in order to achieve some separable goal" (Vallerand, 1997, p. 271)
	Intrinsic Motivation	Behaviour "performed for itself, in order to experience pleasure and satisfaction inherent in the activity" (Vallerand, 1997, p. 271), not for any external reward or results that come from it (Deci, 1971).

MPCU - Model of PC Utilization (R. L. Thompson et al., 1991)	Job-fit	"the capabilities of a PC to enhance an individual's job performance" (R. L. Thompson et al., 1991, p. 129)
	Complexity	"the degree to which an innovation is perceived as relatively difficult to understand and use" (Rogers & Shoemaker, 1971, p. 154)
	Long-term Consequences	"outcomes that have a payoff in the future [as opposed to] addressing current needs" (R. L. Thompson et al., 1991, p. 129)
	Affect Towards Use	"the feelings of joy, elation, or pleasure, or depression, disgust, displeasure, or hate associated by an individual with a particular act" (Triandis, 1980, p. 211)
	Social Factors	"the individual's internalization of the reference groups' subjective culture, and specific interpersonal agreements that the individual has made with others, in specific social situations" (Triandis, 1980, p. 210)
	Facilitating Conditions	"objective factors…that…make an act easy to do" (Triandis, 1980, p. 205)
IDF - Innovation Diffusion Theory (Rogers, 1995)	Relative Advantage	"the degree to which an innovation is perceived as being better than the idea it supersedes" (Rogers, 1995, p. 213).
	Complexity	"The degree to which an innovation is perceived as relatively difficult to understand and use" (Rogers, 1995, p. 230).
	Trialability	"the degree to which an innovation can be experimented with on a limited basis" (Rogers, 1995, p. 231)
	Observability	"the degree to which the results of an innovation are visible to others" (Rogers, 1995, p. 232)
	Compatibility	"the degree to which an innovation is perceived as being consistent with the existing values, past experiences and needs of potential adopters" (Rogers, 1995, p. 223)
AITI - Adoption of Information Technology Innovation (Moore & Benbasat, 1991)	Image	"the degree to which use of an innovation is perceived to enhance one's image or status in one's social system" (Moore & Benbasat, 1991, p. 195).
	Voluntariness of Use	"the degree to which use of the innovation is perceived as being voluntary, or of free will" (Moore & Benbasat, 1991, p. 195)
	Results Demonstrability	Relates to whether an innovation can be measured, observed and communicated. (Moore & Benbasat, 1991)
	Visibility	Relates to how immediately visible an innovation is, such as a hardware innovation. (Moore & Benbasat, 1991)

	Ease of Use	A renamed version of 'Complexity' (Rogers, 1995).
SCT – Social Cognitive Theory (Bandura, 1977, 1981, 1986) and adaptation to use of computers (Compeau & Higgins, 1995)	Outcome Expectations (Performance)	"a person's estimate that a given behaviour will lead to certain outcomes" (Bandura, 1977, p. 193)
	Outcome Expectations (Personal)	The "personal consequences of the behaviour" (Venkatesh et al., 2003, p. 432) in terms of esteem and accomplishment.
	Self-Efficacy	"Peoples' judgements of their capabilities to organize and execute courses of action required to attain designated types of performances. It is concerned not with the skills one has but with judgements of what one can do with whatever skills one possesses" (Bandura, 1986, p. 391).
	Affect	"liking for particular behaviours" (Compeau & Higgins, 1995, p. 196)
	Anxiety	"Evoking anxious or emotional reactions when it comes to performing a behaviour" (Venkatesh et al., 2003, p. 432)
TAM-O (Davis, 1986)	Perceived Usefulness	"the user's subjective probability that using a specific application system will increase his or her job performance within an organizational context." (Davis et al., 1989, p. 985)
	Perceived Ease of Use	"the degree to which the prospective user expects the target system to be free of effort." (Davis et al., 1989)
	Attitude Towards Use	Davis relates that the TAM was extended from the Theory of Reasoned Action. Accordingly, we adopt the definition for Attitude from the TRA: "the individual's positive or negative evaluation of performing the behaviour" (Ajzen & Fishbein, 1980, p. 6)
UTAUT (Venkatesh et al., 2003)	Performance Expectancy	"the degree to which an individual believes that using the system will help him or her to attain gains in a job performance" (Venkatesh et al., 2003, p. 447)
	Effort Expectancy	"the degree of ease associated with the use of the system" (Venkatesh et al., 2003, p. 450)
	Social Influence	"the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003, p. 451)

Formation of the taxonomic root using semantic groupings

The first step in building a taxonomy is to invert Table 4.1 so that constructs sharing a common or similar meaning or intention can be grouped using the authors' definitions as guides. Table 4.2 shows that there are five major core semantic groups that emerge naturally from the foundational behavioural theories. Closer consideration of definitions led to the creation of secondary and tertiary groupings, as shown in Tables 4.3-4.7.

Table 4.2

Semantic Groupings of the Core Constructs

Primary Construct Group and Semantic Intent	Identified Construct
Attitude and Affect: A person's attitude towards using the educational technology and the associated affectual state.	Attitude Towards Behaviour (TRA, TPB) Attitude Towards Use (TAM-O) Intrinsic Motivation (MM) Affect Towards Use (MPCU) Affect (SCT) Anxiety (SCT) [negative]
Social Factors: Perceptions of others' opinions on the use of the educational technology, including agreements and how one is perceived by others.	Subjective Norm (TRA, TPB) Social Influence (UTAUT) Social Factors (MPCU) Voluntariness of Use (AITI) Image (AITI) Outcome Expectations (Personal) (SCT)
Usefulness and Visibility: The value of using the educational technology in terms of meeting an operational need and the visibility to others.	Relative Advantage (IDF) Extrinsic Motivation (MM) Job-fit (MPCU) Long-term consequences (MPCU) Outcome Expectations (Performance) (SCT) Perceived Usefulness (TAM) Performance Expectancy (UTAUT) Compatibility (IDF) Results Demonstrability (AITI) Visibility (AITI) Observability (IDF)
Capability and Effort: The ease or difficulty of using the educational technology given one's abilities.	Complexity (IDF, MPCU) [negative] Ease of Use (AITI) Perceived Ease of Use (TAM)

	Effort Expectancy (UTAUT) Self-efficacy (SCT)
Environmental and Situational: The systemic or situational factors that affect the ability to use the educational technology.	Facilitating Conditions (MPCU) Facilitating Conditions (Triandis, 1977) Context of Opportunity (Sarver, 1983) Trialability (IDF)

Table 4.3

Semantic Groupings of the Attitude & Affect Primary Taxonomic Group

Attitude & Affect	
Secondary construct group and definition	Member constructs and definitions
Attitude: The individual's positive or negative evaluation of using the educational technology.	**Attitude Towards Behaviour (TRA, TPB); Attitude Towards Use (TAM-O)** The individual's positive or negative evaluation of using the educational technology.
Affect: The emotional or affectual state associated with the use of the educational technology.	**Intrinsic Motivation (MM)** The motivation to use the educational technology deriving from the expected pleasure or satisfaction thereof.
	Affect Towards Use (MPCU); Affect (SCT) The positive or negative feelings towards use of the educational technology.
	Anxiety (SCT) [negative] A state of unease, nervousness or apprehension with respect to using an educational technology.

Table 4.4

Semantic Groupings of the Social Factors Primary Taxonomic Group

Social Factors	
Secondary construct group and definition	Member constructs and definitions
Social Influence: The effect of a group's culture, norms and direct influences with respect to use of an educational technology.	**Subjective Norm (TRA, TPB); Social Factors (MPCU); Social Influence (UTAUT)** The person's perception of the social pressures to use the educational technology in terms of culture and norms.
	Voluntariness of Use (AITI)

	The degree to which use of the educational technology is voluntary.
Image & Esteem: How one is/will be perceived by others as a result of using the technology.	**Image (AITI); Outcome Expectations (Personal) (SCT)** The degree to which use of the educational technology will augment the esteem or image of the user within a social group.

Table 4.5

Semantic Groupings of the Usefulness & Visibility Primary Taxonomic Group

Usefulness & Visibility	
Secondary construct group and definition	Member constructs and definitions
Usefulness The degree to which use of an educational technology meets an operational need.	**Relative Advantage (IDF); Extrinsic Motivation (MM)** **Job-fit (MPCU); Long-term Consequences (MPCU); Outcome Expectations (Performance) (SCT); Perceived Usefulness (TAM); Performance Expectancy (UTAUT); Compatibility (IDF);** The degree to which use of an educational technology meets an operational need more than alternatives.
Visibility The degree to which use of the educational technology is observable to others.	**Results Demonstrability (AITI); Visibility (AITI); Observability (IDF)** The degree to which use of the educational technology is observable to others.

Table 4.6

Semantic Groupings of the Capability & Effort Primary Taxonomic Group

Capability & Effort	
Secondary construct group and definition	Member constructs and definitions
Ease of Use The degree to which the user perceives an educational technology to be easy to use.	**Complexity (IDF, MPCU) [negative]; Ease of Use (AITI); Perceived Ease of Use (TAM); Effort Expectancy (UTAUT)** The degree to which the user perceives an educational technology to be easy to use in terms of the interface and system that deploys it.
Self-efficacy A person’s perceived capability to use various attained computer skills to successfully engage with educational technology.	**Self-efficacy (SCT)** A person’s perceived capability to use various attained computer skills to successfully engage with educational technology.

Table 4.7

Semantic Groupings of the Environmental & Situational Primary Taxonomic Group

Environmental & Situational	
Secondary construct group and definition	Member constructs and definitions
Facilitating Conditions The degree to which the user perceives that external factors assist use of an educational technology.	**Facilitating Conditions (MPCU); Facilitating Conditions (Triandis)** The degree to which the user perceives that external factors assist use of an educational technology.
Opportunity The degree to which a person perceives that opportunity and access to the educational technology are present.	**Context of Opportunity (Sarver); Trialability (IDF)** The degree to which a person perceives that opportunity and access to the educational technology are present.

Ajzen's (1991) 'Perceived Behavioural Control' was considered as its child constructs 'Capability & Effort' and 'Environmental & Situational' for clear construction of the taxonomic root, although it can be considered to precede both in tables 4.6 and 4.7. Even though Ajzen did not specifically include 'Ease of Use' as a component of 'Perceived Behavioural Control', it is closely related to a person's self-efficacy and therefore contributes to Ajzen's intention of Perceived Behavioural Control. The final taxonomy combines both 'Capability & Effort' and 'Environmental & Situational' groups as secondary beneath 'Perceived Behavioural Control'. Rogers' (1995) 'Trialability' was placed alongside Sarver's (1983) 'Opportunity' as both relate to the opportunity to engage with an educational technology in a situational or access sense.

The inductive process represented in Tables 4.2 to 4.7 resulted in four primary groups: Attitude & Affect, Social Factors, Usefulness & Visibility, and Perceived Behavioural Control as represented in Table 4.8.

Table 4.8

The Taxonomic Root That Emerges From Semantic Alignment of the Fundamental Behavioural Theories, Davis' TAM and Venkatesh et al's UTAUT

Primary Taxonomy Group	Secondary Taxonomy Group	Tertiary Taxonomy Group	Measurement Construct
Attitude & Affect	Attitude		Attitude Towards Behaviour (TRA, TPB)
			Attitude Towards Use (TAM)
	Affect	Intrinsic Motivation	Intrinsic Motivation (MM)
		Affect Towards Use	Affect Towards Use (MPCU)
			Affect (SCT)
		Anxiety	Anxiety (SCT) [Neg]
Social Factors	Social Influence	Subjective Norm	Subjective Norm (TRA, TPB)
			Social Factors (MPCU)
			Social Influence (UTAUT)
		Voluntariness	Voluntariness of Use (AITI)
	Image & Esteem		Image (AITI)
			Outcome Expectations (Personal) (SCT)
Usefulness & Visibility	Usefulness		Relative Advantage (IDF)
			Extrinsic Motivation (MM)
			Job-fit (MPCU)
			Long-term Consequences (MPCU)
			Outcome Expectations (Performance) (SCT)
			Perceived Usefulness (TAM)
			Performance Expectancy (UTAUT)
			Compatibility (IDF)
	Visibility		Results Demonstrability (AITI)
			Visibility (AITI)
			Observability (IDF)
Perceived Behavioural Control	Capability & Effort	Ease of Use	Complexity (IDF, MPCU) [negative]

			Ease of Use (AITI)
			Perceived Ease of Use (TAM)
			Effort Expectancy (UTAUT) [negative]
		Self-efficacy	Self-efficacy (SCT)
	Environmental & Situational	Facilitating Conditions	Facilitating Conditions (MPCU, Triandis)
		Opportunity	Context of Opportunity (Sarver)
			Trialability (IDF)

Stages 2 and 3 - Incorporating subsequent research into the root taxonomy

The root taxonomy in Table 8 serves only as a foundational base that needs to be extended to cover contemporary and educational scope. In this section we incorporate new salient factors uncovered by later educational research to arrive at a full taxonomy.

Affect, attitude, and motivation

The Theories of Reasoned Action (TRA) and Planned Behaviour (TBP) relate the importance of attitude as an influencer of behaviour, and Davis' original TAM ('TAM-O') (1986) placed it as a precursor to behavioural intent. However, Davis' revised TAM ('TAM-R') (1989) removed it because "attitudes do not fully mediate the effect of perceived usefulness and perceived ease of use on behaviour" (Davis, 1989, p. 335). The TAM2 (Venkatesh & Davis, 2000), TAM3 (Venkatesh & Bala, 2008) and UTAUT (Venkatesh et al., 2003) models likewise do not feature attitude as a mediatory construct because it was found to be non-significant in the presence of usefulness and ease of use, and Teo (Teo, 2009a) later demonstrated that attitude did not affect total variance of behavioural intent, confirmed by Nistor and Heymann (Nistor & Heymann, 2010). However, attitude was influential as a distinct mediatory factor in a voluntary setting (López-Bonilla & López-Bonilla, 2011) and when PLS-SEM was used as the analysis method (López-Bonilla & López-Bonilla, 2017; H.-H. Yang & Su, 2017). Chau also demonstrated “significant positive impacts” (Chau, 2001, p. 30) when attitude was a precursor to both usefulness and ease of use and Teo et al (2017) found that teacher experience can impact attitude directly. Attitude can also relate to personal bearing instead of being directed to a technology, and Hao et al have shown the significant influence of personal innovativeness (“an individual’s willingness to take a risk and try a new technology”) (Hao et al., 2017, p. 107) on ease of use and thus to behavioural intent. Thus, attitude can sometimes be subsumed by other constructs, while in other settings, and measured in certain ways, it can appear distinctly. As such we retain the attitude construct within the taxonomy.

Affect has generally not had as high an impact on behavioural intent as other constructs, and for this reason it was not included in the UTAUT model (Venkatesh et al., 2003). However, user enjoyment (“the extent to which the activity of using the computer is perceived to be enjoyable in its own right” (Martinez-Torres et al., 2008, p. 498)) has been shown to have “significant effect on intentions” (Davis et al., 1992, p. 1111) and so we retain it. User satisfaction, defined as “the degree to which users are satisfied and pleased with their prior use of an information system” (D. Y. Lee & Lehto, 2013, p. 195) is simply an affectual state, and so we place satisfaction in the affect group. Learning motivation, defined as “learner motivation to learn” (H. M. Huang & Liaw, 2018, p. 95), and learning goal orientation, defined as “an achievement-oriented motivation via task learning process” (Y. M. Cheng, 2011) have a drive element that pure affect does not and so we have placed learner motivation and learning goal orientation in a group called ‘Intrinsic Motivation’ parallel to affect. In recognising the implicit pleasure aspect of intrinsic motivation (Vallerand, 1997), we posit that motivation must be associated with affect, although its directional element is a distinguishing feature. In light of these considerations, we modify the ‘Attitude & Affect’ primary taxonomic group from the root taxonomy in Table 4.8 to ‘Attitude, Affect & Motivation’ (Table 4.9).

Table 4.9

Attitude, Affect and Motivation

Attitude, Affect & Motivation	Attitude		Attitude Towards Behaviour (TRA, TPB)
			Attitude Towards Use (TAM)
			Personal Innovativeness
	Intrinsic Motivation		Intrinsic Motivation (MM)
			Learner Motivation
			Learning Goal Orientation
	Affect	Affect Towards Use	Affect Towards Use (MPCU)
			Affect (SCT)
			Perceived Enjoyment
			User Satisfaction
		Anxiety	Anxiety (SCT) [Neg]

System and learning usefulness

Educational compatibility has been defined as "the degree to which an e-learning system is perceived as being congruent with a student's learning expectancy" (J. L. Chen, 2011, p. 1504). It is a reflection of learning usefulness, which we define as the ability of the learning resource to deliver desired learning outcomes. This is conceptually a different type of usefulness than system usefulness, which we define as the ability of the technology to produce a learning resource, and so we propose that an educational technology is useful only if it performs the double function of producing a learning resource that then helps the student achieve their learning goals. Another way that educational technology has been shown to be useful in a system sense is in 'quality of work life' (Tarhini et al., 2015), which has been defined "in terms of students' perception and belief that using the technology will improve their quality of work life such as saving expenses when downloading e-journals, or in communication when using email to communicate with their instructors and colleagues." (Tarhini et al., 2017, p. 311). This may be important in voluntary situations and so we include it addressing system usefulness. In light of the above considerations we therefore suggest that the usefulness construct be explicitly applied as both system and learning usefulness in educational technology research, and so we have modified Rogers' 'compatibility' (1995) to 'educational compatibility' in the final taxonomy and renamed 'Usefulness' to 'System and Learning Usefulness'.

Instructional attributes

Learning usefulness is itself supported by instructional design factors such as feedback, defined as "an important mechanism that helps to modify and reinforce those factors that assist in altering perceptions" (Martinez-Torres et al., 2008, p. 498), which can be adaptive (Tobing et al., 2008). Instructor-learner interaction ("the degree of online interaction between instructors and learners via the e-learning system" (Y. M. Cheng, 2013, p. 75)) and learner-learner interaction ("the degree of online interaction between learners and other learners via the e-learning system" (Y. M. Cheng, 2013, p. 75)) rely on the ability of the technology to enable these forms of social interaction important to learning. Collaboration, defined as "using features of cloud-based applications to facilitate students' collaboration" (Yadegaridehkordi et al., 2019, p. 85) has been shown to influence usefulness and ease of use and naturally sits alongside student-student interaction but has a groupwork emphasis. Teaching materials (H.A. Rajak et al., 2018) can be represented by both content features ("the characteristics and presentation of course content and information" (Tran, 2016)) and content richness ("the abundance of learning resources that users can access to enrich their learning activity" (D. Y. Lee & Lehto, 2013, p. 196)) which have both been found influential in attitude formation in the above studies. Rajak et al (2018) also provide evidence that design of learning contents is influential and because this represents how materials are assembled and presented we add it to the taxonomy. Finally, there is evidence that lecturers' positive attitudes to e-learning "contributes to the acceptance of [it]" (H.A. Rajak et al., 2018) by supporting usefulness (B.-C. Lee et al., 2009). In addition, technological pedagogical content knowledge ('TPCK'), defined as "a large body of sophisticated knowledge to understand how to use technology to improve the teaching" (Teo et al., 2017, p. 813) has influenced usefulness and behavioural intent (Teo et al., 2017). Both lecturers' characteristics and their knowledge are related and contribute to the successful deployment of a learning resource. Accordingly, we have formed a primary taxonomic group called 'Instructional Attributes' to house lecturer attributes, feedback, interaction and content attributes as per table 4.10, which could be considered in support of learning usefulness.

Table 4.10

Instructional Attributes

Instructional Attributes	Lecturer Attributes	Lecturer Characteristics
		Technological Pedagogical Content Knowledge (TPCK)
	Content Attributes	Content Features
		Content Richness
		Design of Learning Contents
	Feedback	Feedback
		System Adaptability
	Social Interactivity	Learner-Learner Interaction
		Instructor-Learner Interaction
		Collaboration

Perceived Behavioural Control

Abdullah and Ward (Abdullah & Ward, 2016) demonstrated that experience is the fifth most measured construct and they related it to users' growth of skills, implying that prior experience influences perceived ease of use or the self-efficacy that results from those skills thereby improving attitude. Another study showed that actual use of a wiki system positively influenced continued use (Yueh et al., 2015). Because there is more solid evidence that experience is related to skills growth, we have included it within the Ease of Use taxonomic group as an associated factor of perceived ease of use.

The review revealed that self-efficacy is a targeted, rather than general, concept that deals with how a person uses their skillset as opposed to the level of skills themselves (Bandura, 1981). For example, computer self-efficacy, defined as “a user’s assessment of his or her capability to use a computer” (Teo, 2009b, p. 304) is different to e-learning self-efficacy (“the personal confidence in finding information and communicating with an instructor within the e-learning system and the necessary skills for using the system” (S. Y. Park, 2009, p. 152)). Due to the variety of technological targets, we have modified the root taxonomy to include self-efficacy of various forms in their own section. As well as e-learning self-efficacy, students need accessibility (“the degree of ease with which a university student can access and use a campus e-learning system as an organizational factor” (S. Y. Park, 2009, p. 153)) and mobility (“the ability of using cloud applications via mobile devices freely without any time or place limitation” (Yadegaridehkordi et al., 2019, p. 85)), which we see as forming part of the opportunity taxonomic group, and training (“effort to teach and train their students to acquire E-learning skills” (Alenezi et al., 2011)), which we have placed within the facilitating conditions group. These modifications complete the Perceived Behavioural Control taxonomic group as per table 4.11.

Table 4.11

Perceived Behavioural Control

Perceived Behavioural Control	Capability & Effort	Ease of Use	Complexity (MPCU, IDF) [negative]
			Ease of Use (AITI)
			Perceived Ease of Use (TAM)

			Effort Expectancy (UTAUT) [negative]
			Experience
		Self-efficacy	Self-efficacy (SCT) (various forms)
	Environmental & Situational	Facilitating Conditions	Facilitating Conditions (MPCU, Triandis)
			Training
		Opportunity	Context of Opportunity (Sarver)
			Trialability (IDF)
			Accessibility
			Mobility

Cognitive Engagement

Our review noted the effects of cognitive absorption ("a state of deep involvement" (Saade & Bahli, 2005, p. 320)) and flow ("the state in which people are so involved in an activity that nothing else seems to matter" (Saade & Bahli, 2005, p. 318)) on attitudes, in addition to concentration ("degree to which users maintain exclusive, focused attention on their activity" (Liu et al., 2009, p. 602)), which we saw as sufficiently related to place in a taxonomic group called 'Absorption'. Alongside this, the concept of vividness ("the ability of a technology to produce a sensorially rich mediated environment" (Steuer, 1992, p. 80)) was discussed in terms of sensorial richness, relating it to cognitive processes and so is separate from content richness, which relates to media variety. B. C. Lee et al. (2009) discuss playfulness in terms of focussing attention and engaging curiosity and so has been used as a measure of flow. Together, absorption, vividness and playfulness therefore relate to the focus, attention and absorption of the learner and we have formed a primary taxonomic group called 'Cognitive Engagement' (Table 4.12).

Table 4.12

Cognitive Engagement

Cognitive Engagement	Absorption	Cognitive Absorption
		Concentration
		Flow
	Playfulness	Perceived Playfulness
	Vividness	Vividness

System Attributes

‘System Attributes’ is a proposed primary taxonomic group related to how the system itself performs as a separate consideration to the learning it produces – we relate this to ‘system usefulness’ as distinct from ‘learning usefulness’ of the resources so-produced. The advent of cloud computing brings with it considerations of security and privacy (“the degree to which students believe that cloud services are secure platforms for storing and sharing sensitive data” (Arpaci et al., 2015, p. 94)) of student information, which can affect student attitudes towards the technology. System usefulness depends on its function (“the perceived ability of an e-learning system to provide flexible access to instructional and assessment media” (Pituch & Lee, 2006, p. 225)), response to user inputs (“the degree to which a learner perceives that the response from the e-learning system is fast, consistent, and reasonable” (Pituch & Lee, 2006, p. 225)), and system interactivity (“learner-environment interaction consists of learners making use of a range of mechanisms for creating and modifying virtual worlds” (H. M. Huang & Liaw, 2018, p. 94)). There is evidence that personalisation, defined as “the process of changing interface, functionality, information content, or distinctiveness of a system to improve personal relevance” (Yadegaridehkordi et al., 2019, p. 86) also influences perceived ease of use in cloud systems. Function, response, interactivity and personalisation have been placed in a secondary taxonomic group called 'System Function & Response'. Information security and privacy is slightly different and may not necessarily relate to usefulness directly, although could certainly influence attitudes and intention to use a voluntary technology if a user was sensitive to such concerns. Table 4.13 shows the resultant system attributes primary taxonomic group.

Table 4.13

System attributes

System Attributes	Information Security & Privacy	Information Security & Privacy
	System Function & Response	System Functionality
		System Interactivity
		System Response
		Personalisation

The final taxonomy

The final taxonomy is presented in table 4.14.

Table 4.14

The Final Taxonomy

Primary Taxonomy Group	Secondary Taxonomy Group	Tertiary Taxonomy Group	Measurement Construct
Attitude, Affect & Motivation	Attitude		Attitude Towards Behaviour (TRA, TPB)
			Attitude Towards Use (TAM)
			Personal Innovativeness
	Intrinsic Motivation		Intrinsic Motivation (MM)
			Learner Motivation
			Learning Goal Orientation
	Affect	Affect Towards Use	Affect Towards Use (MPCU)
			Affect (SCT)
			Perceived Enjoyment

			User Satisfaction
		Anxiety	Anxiety (SCT) [Neg]
Social Factors	Social Influence	Subjective Norm	Subjective Norm (TRA, TPB)
			Social Factors (MPCU)
			Social Influence (UTAUT)
		Voluntariness	Voluntariness of Use (AITI)
	Image & Esteem		Image (AITI)
			Outcome Expectations (Personal) (SCT)
Usefulness & Visibility	System and Learning Usefulness		Relative Advantage (IDF)
			Extrinsic Motivation (MM)
			Job-fit (MPCU)
			Long-term Consequences (MPCU)
			Outcome Expectations (Performance) (SCT)
			Perceived Usefulness (TAM)
			Performance Expectancy (UTAUT)
			Educational Compatibility (IDF)
			Quality of Work Life
	Visibility		Results Demonstrability (AITI)
			Visibility (AITI)
			Observability (IDF)
Instructional Attributes	Lecturer Attributes		Lecturer Characteristics
			Technological Pedagogical Content Knowledge (TPCK)
	Content Attributes		Content Features
			Content Richness
			Design of Learning Contents
	Feedback		Feedback
			System Adaptability
	Social Interactivity		Learner-Learner Interaction
			Instructor-Learner Interaction
			Collaboration
Perceived Behavioural Control	Capability & Effort	Ease of Use	Complexity (IDF, MPCU) [negative]
			Ease of Use (AITI)

			Perceived Ease of Use (TAM)
			Effort Expectancy (UTAUT) [negative]
			Experience
		Self-efficacy	Self-efficacy (SCT) (various forms)
	Environmental & Situational	Facilitating Conditions	Facilitating Conditions (MPCU, Triandis)
			Training
		Opportunity	Context of Opportunity (Sarver)
			Trialability (IDF)
			Accessibility
			Mobility
Cognitive Engagement	Absorption		Cognitive Absorption
			Concentration
			Flow
	Playfulness		Perceived Playfulness
	Vividness		Vividness
System Attributes	Information Security & Privacy		Information Security & Privacy
	System Function & Response		System Functionality
			System Interactivity
			System Response
			Personalisation

Discussion

Building a reliable measure of factors affecting attitudes, intentions and behaviours required the incorporation of all factors shown or theorised to be influential. The inductive process initially identified a root taxonomy based on the foundational behavioural and motivational theories that underpin the TAM and UTAUT that had four primary groups: Attitude & Affect, Social Factors, Useability & Visibility and Perceived Behavioural Control. Consideration of more contemporary research slightly modified some of these groups and identified additional constructs, which were organised into three additional primary taxonomic groups: Instructional Attributes, Cognitive Engagement and System Attributes.

The taxonomy is as parsimonious as possible and does not include every synonymous measurement construct identified in reviewed research. In operationalisation it is recommended to include at least the primary taxonomic groups in research instruments, although the secondary and tertiary taxonomic groups provide for more targeted research, and within them, measurement constructs can be carefully chosen. For example, in the Usefulness & Visibility group, 'Relative Advantage' may be used when comparing two or more technologies, however 'Job Fit' could be more appropriate when appraising a single technology. The Usefulness & Visibility primary group can also be operationalised according to whether the research is measuring system usefulness or learning usefulness.

A second benefit of the use of the taxonomy is to manage convergent and discriminant validity of the measurement model. Referring to the taxonomy, it can be seen that 'Anxiety' and 'Self-efficacy' could conceivably co-vary. The taxonomy offers either 'User Satisfaction' or 'Perceived Enjoyment' within the 'Affect' group as alternatives to 'Anxiety'. In this way the taxonomy is a useful tool in the construction of a robust measurement model both in terms of operationalising the model to a particular context and also to improve discrimination between latent constructs.

We believe that the taxonomy is a tool to reduce measurement bias because it was constructed to include a comprehensive collection of factors, as recommended by Nickerson et al (2009), applicable to all educational technologies surveyed. It is intended that by including a fuller suite of relevant measurement constructs that a larger variance of Behavioural Intent may be accounted for, although individual research will demonstrate to what extent this occurs. A limitation of the taxonomy is that it may be appropriate to extend it as new technologies or contexts emerge.

The taxonomy is architecturally neutral in that while it is useful in advising what to measure, it leaves open the question of structure, which is the topic of further research. While structural model architecture is outside the scope of this paper, it is sufficient to say that closer review of each of the taxonomy's taxonomic groups could provide guidance on structural model construction.

Conclusion

A qualitative review was conducted of the precursor behavioural, motivational and attitudinal theories that underpinned the creation of both Davis' TAM and Venkatesh's UTAUT models, as well as of more recent educational technology research. Semantic alignment of the identified constructs allowed them to be grouped according to measurement intent. Arrangement of the constructs into primary, secondary and tertiary taxonomic groups produced seven primary and twenty two secondary and tertiary taxonomic groups, which collectively organise sixty one measurement constructs. The taxonomy is larger in scope than many of the currently used acceptance models because it includes and organises the variety of factors that the foundational behavioural theories and later empirical studies indicate are important in human decision making vis-à-vis educational technology use. It is intended that using this to operationalise measurement models could increase variance accounted for in measurement and structural models, and improve external validity of studies by introducing consistency and reducing measurement bias.

4.4 Postamble

The taxonomy provided a collated identification of known factors affecting attitudes and intentions towards educational technologies. This was an important first step because it provided a listing of all known constructs used in technology acceptance models used in either general or educational technologies. This revealed that a comprehensive model would likely include the seven primary constructs. The caveat is that even though each surveyed study measured and reported strength of each factor, it is not possible to indicate the relative strengths of each factor within the taxonomy because TAM path strengths vary depending on the model and cohort. As such, this taxonomy only lists factors without indication of relative strengths, and only when research is conducted would the relative strengths of each included factor become known.

This paper addressed the following research aim and objective:

- **Research Aim 1**: To identify the types, characterisations and scope of factors affecting attitudes and intentions towards use of educational technologies.
- **Research Objective 1**: To search for the latent constructs related to educational technology use that have been shown to affect user attitudes and intentions.

There remained two problems to address before constructing a theorised final model: exploring the nature of attitude and investigating whether any new constructs arose during the project. These are addressed in Chapters 5 and 6 respectively.

CHAPTER 5 – INVESTIGATING THE 'ATTITUDE PROBLEM'

5.1 Preamble

Attitude is one of the more perplexing constructs in technology acceptance research. While it is important and central as a precursor to firming intent, statistically it can sometimes be relevant and other times, not, depending on the model, cohort, technology, or analysis method. The purpose of this paper was to advise the status of attitude in the final model. This paper surveyed students' attitudes towards virtual reality and subsequent analysis investigated the effect, power, and position of attitude within an educational technology acceptance model. This paper helped to address the following research aims, objectives and hypotheses:

- **Research Aim 2**: To construct a comprehensive technology acceptance model suited to education
- **Research Objective 2**: To form a comprehensive, yet parsimonious, structural model that researchers can use to measure attitudes and intentions in a wide variety of educational settings.
- There were no research hypotheses related to this paper.

5.2 Statement of Authorship

Title of Paper	Exploring the specification of educational compatibility of virtual reality within a technology acceptance model.
Publication Status	Published
Publication Details	Kemp, A., Palmer, E., Strelan, P., & Thompson, H. (2022). 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

Principal Author (Candidate)

Name of Principal Author	Andrew C Kemp		
Contribution to the Paper	Conceptualisation, analysis, write-up		
Overall percentage (%)	90%		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	23/6/2023

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
ii. permission is granted for the candidate in include the publication in the thesis; and
iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution

Name of Co-Author	Edward Palmer		
Contribution to the Paper	Supervised development of work, helped in data interpretation, manuscript conceptualisation, revisions and evaluation.		
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Contribution to the Paper	Supervised development of work, helped in data interpretation, manuscript conceptualisation, revisions and evaluation.		
Signature		Date	26/6/23

Name of Co-Author	Helen Thompson		
Contribution to the Paper	Supervised development of work, helped in data interpretation, manuscript conceptualisation, revisions and evaluation.		
Signature		Date	03/07/2023

5.3 Paper 2 - ***Exploring the specification of educational compatibility of virtual reality within a technology acceptance model***

Abstract

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. 179 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.

Introduction

Compatibility was initially described by Rogers (1995), 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, 1995, p. 250). Hardgrave, Davis & Riemenschneider (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 TAM suited to engaging educational technologies.

Virtual reality 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 (H. M. 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.

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, Morris, Davis, & Davis, 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, 2009a; 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; H.-H. 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 & 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 ("the individual's positive or negative evaluation of performing the behaviour" (Ajzen & Fishbein, 1980, p. 6)) and educational compatibility ("the degree to which an e-learning system is perceived as being congruent with a student's learning expectancy" (Chen, 2011, p. 1504)) 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. Because these features have been shown to lead to improved learning outcomes (Makransky & Lilleholt, 2018), we hypothesise:

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, Higgins and Howell (1991) also demonstrated the influence of the organization as a whole. Accordingly, peer, superior and organizational 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 (Y. C. Chen et al., 2007, 2013; Y. C. Lin et al., 2010). Design quality has been shown to have some effect (B.-C. 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; Y. C. Chen et al., 2007; Y. M. Cheng, 2011; Y. Lee, 2006; Motaghian et al., 2013; Shen & Eder, 2009; S. 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)

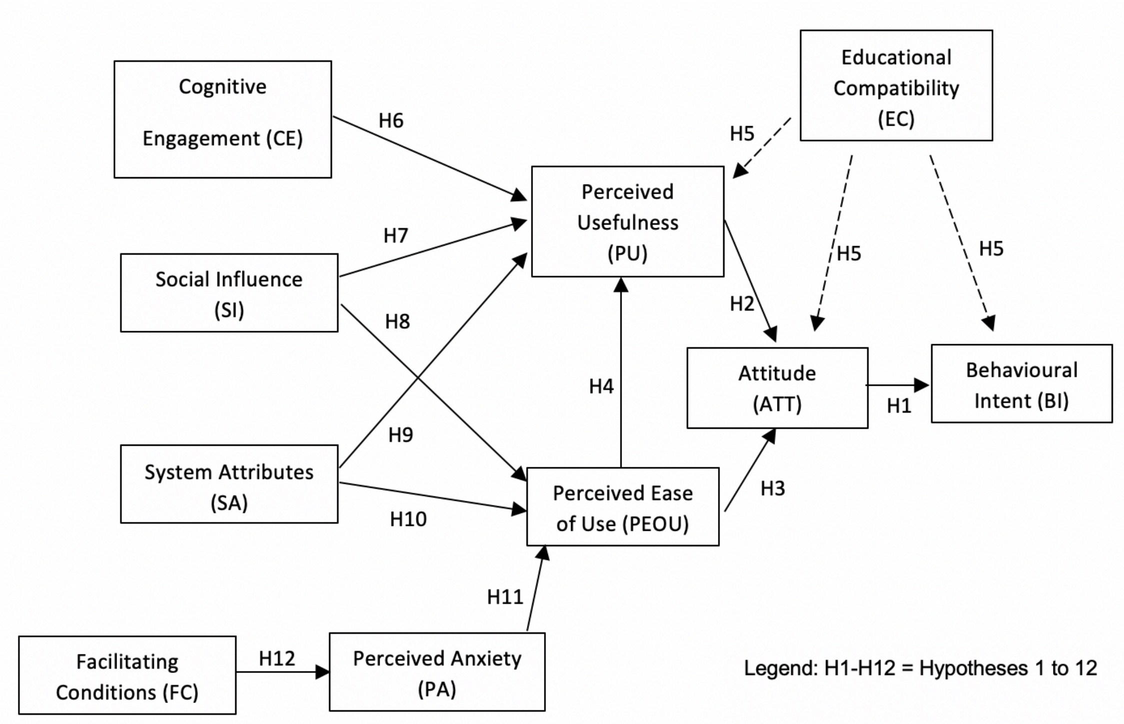
Facilitating conditions (FC) has been characterised as an external control construct (Venkatesh, 2000). External factors can include context of opportunity (Sarver, 1983) trialability (Rogers, 1995), and organizational and technical support infrastructure (Venkatesh et al., 2003). Venkatesh (2000) relates 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 5.1).

Figure 5.1

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; R. L. Thompson et al., 1991), facilitating conditions (Dečman, 2015; Taylor & Todd, 1995), perceived anxiety (Venkatesh et al., 2003), attitude (Taylor & Todd, 1995; R. L. Thompson et al., 1991), educational compatibility (Chen, 2011), cognitive engagement (Saade & Bahli, 2005; R. L. 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 1), 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

Ethical approval was granted for this research study. 182 responses were received, with 179 being valid. Two missing response items were imputed with the item median. Demographic data are represented in Tables 5.1 and 5.2.

Table 5.1

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 5.2

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) & 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 (Awang, 2012). Fit indices were chosen to report absolute (χ^2; RMSEA; SRMR), incremental (CFI, TLI) and parsimonious fit (χ^2/df) (Hooper et al., 2008; R. B. 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).

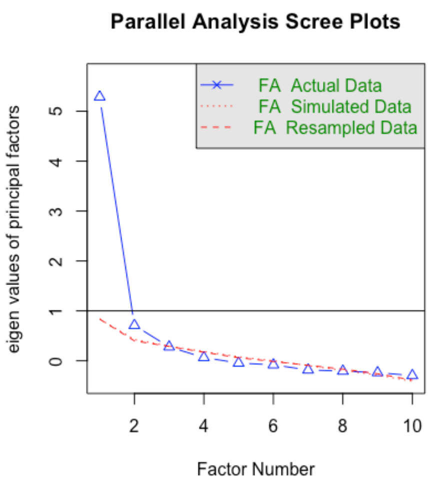
Results

Exploratory Factor Analysis

Parallel analysis suggested a 2-factor solution and produced the following scree plot as shown in Figure 5.2.

Figure 5.2

Parallel Analysis Scree Plot



The pattern matrix for a 2-factor solution with promax rotation is shown in Table 5.3 and the associated correlation matrix in Table 5.4.

Table 5.3

Pattern Matrix For a 2-factor Solution

	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 5.4

Correlation Matrix For a 2-factor Solution

	PU	EC-ATT
Factor 1	1.00	
Factor 2	0.68	1.00

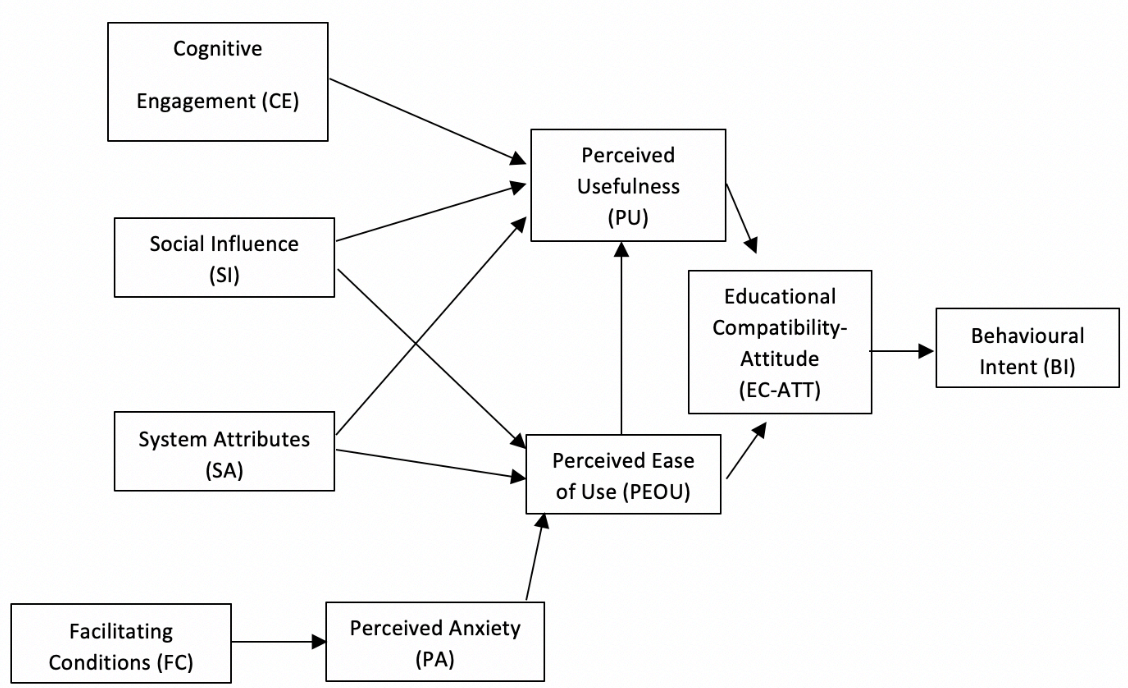
The attitude (PB items) and educational compatibility (EC items) items loaded cleanly onto one factor. This outcome indicated redundancy between EC and attitude (ATT) for our respondents. Perceived usefulness remained distinct from the combined ATT-EC factor with a 0.68 correlation. This finding is consistent 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 5.3.

Figure 5.3

Revised Structural 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 > 0.60 was used to confirm reliability of each construct (Awang, 2012). The convergent and discriminant validities are shown in Tables 5.5 and 5.6 respectively.

Table 5.5

Reliabilities and Convergent Validity of the Measurement Model

Construct	Item	Factor Loading (>0.60)	Composite Reliability (>0.60)	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 5.6

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 5.7 to 5.9 and Figure 5.4, whereas the subtracted model is shown in Tables 5.10 to 5.12 and Figure 5.5.

Table 5.7

Reliabilities and Convergent Validity of the Aggregate Measurement Model

Construct	Item	Factor Loading (>0.60)	Composite Reliability (>0.60)	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		

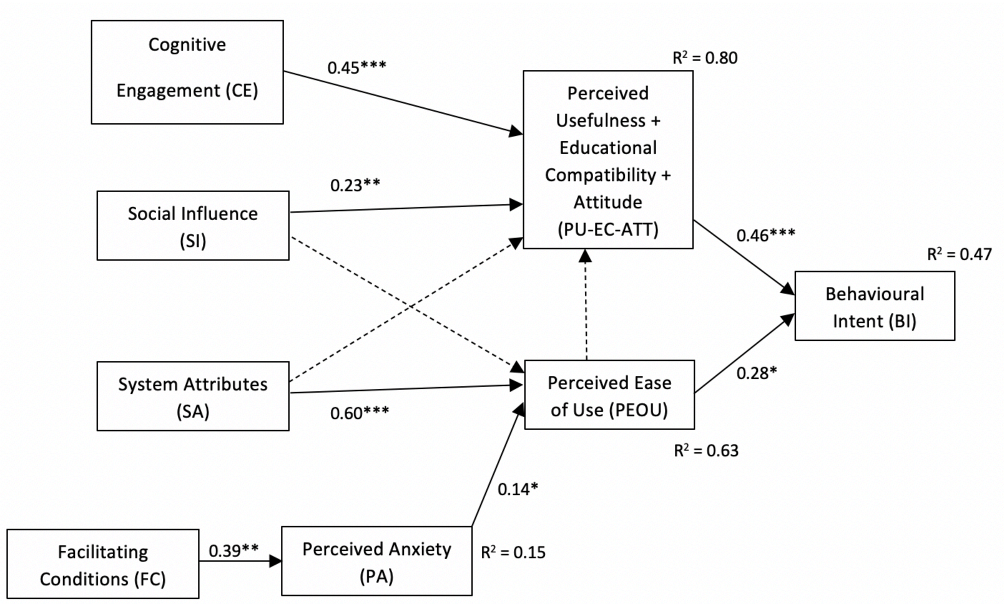
Table 5.8

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 5.4

Aggregate Structural Model



Note. Dashed lines indicate non-significant paths ($p < 0.001$ = ***, $p < 0.01$ = **, $p < 0.05$ = *).

Table 5.9

Aggregate Model Fit Indices

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

Note. Fit index thresholds from Hooper et al. (2008), Hu and Bentler (1999) and R. B. Kline (2015).

Table 5.10

Reliabilities and Convergent Validity of the Subtracted Measurement Model

Construct	Item	Factor Loading (>0.60)	Composite Reliability (>0.60)	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		

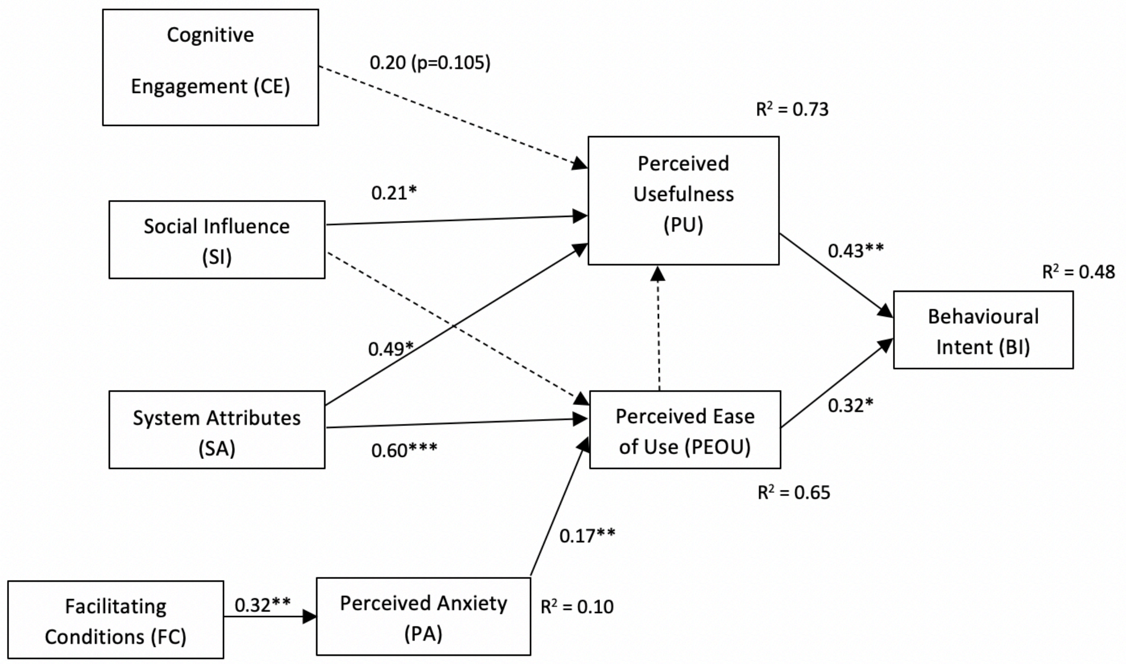
Table 5.11

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 5.5

Subtracted Structural Model



Note: Dashed lines indicate non-significant paths ($p < 0.001$ = ***, $p < 0.01$ = **, $p < 0.05$ = *).

Table 5.12

Subtracted Model Fit Indices

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

Note. Fit index thresholds from Hooper et al. (2008), Hu and Bentler (1999) and R. B. Kline (2015).

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 (β = 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 (β = 0.49, p<0.05). A comparison of the supported hypotheses between the two models is shown in Table 5.13.

Table 5.13

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

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 (Liao & Lu, 2008, Chen 2011). Compatibility has also had the same influences in non-educational settings (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 and Structural Equation Modelling

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 (β = 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 5.4) or subtracted model (Figure 5.5). 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, 2009a; 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 show 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 suggest 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: to explore the specification of educational compatibility in an educationally focused technology acceptance model, and 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 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. This may place limitations on the generalisability of these findings since instructional attributes was not included in the model for this reason, inclusion of which may change the values of path coefficients and model fit. 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.

Appendix 1

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

5.4 Postamble

The study of attitudes toward use of virtual reality as a teaching and/or learning technology was conducted to gain an understanding of the broad attitudinal landscape that existed on campus at the time of the survey. As stated in the study, Davis' Technology Acceptance Model (TAM) (Davis, 1986, 1989) was well-suited because it is a flexible and respected model that allows extension to include exogenous factors thought to be influential to attitudes and behaviour. Moreover, as a quantitative technique, it allows a more objective investigation of which factors are influential than qualitative techniques.

The model constructs were formed from six of the seven primary constructs of the taxonomy, which was presented in Chapter 4. Instructional attributes were not included because the respondents had little virtual learning experience to draw on to form attitudes. Therefore, instructional attributes is a subject of inquiry in the final model in the thesis.

The model behaved as expected, in that it produced statistically sound measurement and structural models which meant that the results could be trusted as reliable. The main conclusion was that affectual and cognitive factors associated with immersion and presence in a virtual reality environment were more likely to influence perceived usefulness of virtual reality than ease of use or personal ability factors. The fit statistics indicated that the model was a reliable indicator of factors affecting attitudes.

Of note for an educational technology, the 'educational compatibility' construct performed within the parameters of reliability and convergent discrimination. It was not, however, discriminant from general attitude. Analysis revealed that attitude and educational compatibility had no statistical effect and could therefore be omitted from the final model. The paper helped answer the following research aim and objective:

- **Research aim 2**: To construct a comprehensive technology acceptance model suited to education.

- **Research objective 2**: To form a comprehensive, yet parsimonious, structural model that researchers can use to measure attitudes and intentions in a wide variety of educational settings.

As a result of this study, the final model was constructed without attitude or educational compatibility despite these being part of the taxonomy presented in Chapter 4.

CHAPTER 6 – DISCOVERING NEW FACTORS

6.1 Preamble

Whereas Paper 1 (Kemp et al., 2019) identified and collated known factors already used in technology acceptance models, it was necessary to conduct research to uncover from students themselves whether more factors existed that were heretofore unaccounted for. The COVID-19 pandemic provided a rare opportunity to undertake this inquiry for two reasons: (a) most students were pushed into virtual classrooms for isolated instruction, and (b) the nature of the pandemic may have caused some factors to emerge more strongly than others.

The purpose of this piece of research was to therefore find any new factors that required inclusion into the final model.

Since the purpose was one of discovery, a qualitative enquiry of students themselves was required. The approach was to ask four open questions related to the positive and negative aspects of use of Zoom for learning, as well as anything else the student respondents thought important to raise. In addition, this piece of research focused on an aspect of an educational technology acceptance model hypothesised to be important: instructional attributes. For this reason, a specific question was included relating to the instructor's use of Zoom.

It was anticipated that the results of the thematic analysis would closely match the constructs presented in the taxonomy in paper one. This paper helped to address the following research aim and objective:

- **Research Aim 1**: To identify the types, characterisations and scope of factors affecting attitudes and intentions towards use of educational technologies.
- **Research Objective 1**: To search for the latent constructs related to educational technology use that have been shown to affect user attitudes and intentions.

6.2 Statement of Authorship

Title of Paper	Key factors for student learning via Zoom: a thematic analysis of technology acceptance.
Publication Status	Submitted to Educational Technology Research and Development

Principal Author (Candidate)

Name of Principal Author	Andrew C Kemp		
Contribution to the Paper	Co-conceptualisation, analysis of detail of thematic analysis, majority of writeup.		
Overall percentage (%)	75%		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	23/06/2023

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
ii. permission is granted for the candidate in include the publication in the thesis; and
iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution

Name of Co-Author	Sarah Dart		
Contribution to the Paper	Contribution to conceptualisation, co-analysis of first round of thematic coding with principal author, recommendations on write-up, written contribution to introduction, background, and method sections.		
Signature		Date	3/7/23

Name of Co-Author	Edward Palmer		
Contribution to the Paper	Supervised development of work, helped in data interpretation, manuscript conceptualisation, revisions and evaluation.		
Signature		Date	10/7/23

Name of Co-Author	Peter Strelan		
Contribution to the Paper	Supervised development of work, helped in data interpretation, manuscript conceptualisation, revisions and evaluation.		
Signature		Date	26/6/23

Name of Co-Author	Helen Thompson		
Contribution to the Paper	Supervised development of work, helped in data interpretation, manuscript conceptualisation, revisions and evaluation.		
Signature		Date	03/07/2023

6.3 Paper 3 - ***Key factors for student learning via Zoom: a thematic analysis of technology acceptance***

Abstract

Understanding student attitudes toward use of virtual classrooms is important in the contemporary context of online and blended learning experience. The recent COVID-19 pandemic prompted a pronounced shift to virtual classrooms and platforms like Zoom became integral to the learning process. Instructors and students were forced to quickly adapt. This study analysed student attitudes toward using Zoom for learning against a recently published taxonomy of factors known to influence educational technology acceptance. It was designed to uncover emergent themes that should be considered for inclusion in technology acceptance practice and research going forward. Thematic analysis was conducted of 169 text responses to four open questions administered to first year psychology students at an Australian university. Themes were mostly aligned with known factors from the taxonomy. However, health and well-being, and social comfort, emerged as new factors affecting student intentions to use Zoom for learning. Therefore, it is recommended these two new constructs are added to the taxonomy and considered for addition to future educational technology acceptance models.

Introduction

The COVID-19 pandemic caused a massive shift to purely online modes of delivery (Joia & Lorenzo, 2021; A. Lee et al., 2021; Wong, 2020). This resulted in rapid adoption of video-conferencing platforms that enabled real-time interactions between students and educators in a virtual classroom environment (Hamilton et al., 2020). Zoom was one of the most common software tools used for this purpose, given that it was a mature technology for online synchronous teaching (Correia et al., 2020; Tertiary Education Quality and Standards Agency, 2020). The rapid transition to online learning via Zoom has resulted in numerous and complex challenges for engaging students in effective learning designs resulting in pressure on teachers to rapidly adapt practice (Moorhouse, 2020). Understanding which factors are most critical to students' online learning experiences is necessary for developing effective methods of learning in this space.

Technology acceptance models are useful to examine how users' perceptions of a technology influence their decisions to ultimately use the technology. While many variations have been developed (Abdullah & Ward, 2016; Davis, 1986; Davis et al., 1989; Venkatesh et al., 2003), Davis' Technology Acceptance Model (TAM) is easily extendable with relevant factors to suit context, in this case, education. Previous research has sought to collate the predominant factors influencing user perceptions from the extant TAM literature, leading to a taxonomy of factors for educational applications of TAMs (Kemp et al., 2019). The taxonomy lists seven primary groupings of factors: attitude, affect & motivation, social factors, instructional attributes, cognitive engagement, system attributes, usefulness & visibility, and perceived behavioural control. This taxonomy is used as a basis for the present study. However, since the taxonomy was developed in 2019, there has been a substantial shift in the learning and teaching landscape caused by the COVID-19 pandemic. The unique circumstances associated with the pandemic and its dramatic impact on higher education practices may have meant new factors influencing student attitudes toward educational technologies have emerged.

Thus, this study's prime aim was to investigate student attitudes toward using Zoom during the COVID-19 period using Kemp et al.'s taxonomy as a comparative framework to identify if there were any factors which have not previously been accounted for. A qualitative research approach was therefore employed to allow unconstrained exploration of students' perspectives (Creswell, 2018). This adds to the research because understanding which factors should be included in educationally focused technology acceptance models can subsequently guide their construction and highlight which factors are influential. The findings also have implications for educators looking to improve the quality of learning experiences delivered via Zoom.

Background

Zoom is a virtual meeting tool that has been appropriated for educational use that provides users with an efficient environment for communication and collaboration in educational contexts. Its functionality includes video teleconferencing, interactive whiteboards, chat, breakout rooms and the ability to share screens. Zoom's functions allow students to communicate in ways that are not possible in face-to-face environments, such as with emoticons, or private chat with teachers (Kohnke & Moorhouse, 2020) that allow the teacher to monitor student engagement or provide feedback. However, lack of paralinguistic cues has a negative impact in some aspects of student engagement and communication (Kohnke & Moorhouse, 2020).

In investigating current student attitudes to this relatively new technology that has rapidly developed in its functionality and applications in higher education, it is helpful to cross-reference with factors that are known to affect attitudes toward educational technologies. Kemp et al.'s taxonomy (2019) collated three levels of factors (primary, secondary, and tertiary) based on published TAM research. Relevant to the present research are the seven primary factors. Recent research relating to these categories is briefly described to provide context for the analysis.

Attitude, affect and motivation

Some students have reported online learning to be 'worse than in-person schooling' (A. Lee et al., 2021, p. 91). Elsewhere students have indicated a preference for blended delivery (Ashton & Elliott, 2007) and face-to-face socialising with classmates (Ismaili, 2021) even if fully online courses are offered. Wong (2020) reported that students preferred face-to-face for small group activities, though the online mode is able to facilitate greater communication for shy students, and is tolerated for information delivery for larger classes. Behind student attitudes lie a number of factors, one of which may be e-learning readiness of the students themselves, incorporating aspects such as self-efficacy, motivation, online communication efficacy and motivation towards learning (James, 2021), as well as personality and behavioural characteristics (Cohen & Baruth, 2017).

Social factors

The Theory of Reasoned Action (Ajzen & Fishbein, 1980) and Theory of Planned Behaviour (Ajzen, 1991) suggest that social cues are important influencers of behaviour. During the COVID-19 disruption, faculty and students were forced into the online mode as a matter of public safety. This meant students' 'natural patterns of self-positioning and non-verbal engagement' (Ebner & Greenberg, 2020, p. 538), developed in face-to-face contexts, were altered to suit the online environment. Social cues are important in new situations when we are not entirely sure how to behave or are unsure how well we can perform (see Bandura, 1977; Sanna, 1992). Student behaviour can also be moderated in group settings (Karau & Williams, 1993). Given the rapid transition to online learning methods and technologies during the onset of COVID-19, we could likely expect that instructors and students would have been looking to others as guides to how to behave in the new setting.

Usefulness and perceived behavioural control

Students acknowledge the access and convenience advantages of online learning (Ashton & Elliott, 2007; Ismaili, 2021). Opportunity (Sarver, 1983), accessibility and individual agency (Dart et al., 2020) are important contributors to a student's control over their learning. Zoom supports this by making classes available regardless of student location (Sayem et al., 2017). Zoom also allows teachers and students to collaborate in small groups (Eraković & Topalov, 2021), use polls, share screens, communicate in non-verbal ways (Kohnke & Moorhouse, 2020) and conduct interactive tutorials (Sayem et al., 2017). These features of instruction, collaboration, communication, and presence are also part of traditional face-to-face classes, so the features of Zoom have supported efforts to move teaching from the face-to-face to online. Thus, Zoom appears *prima facie* useful because it allows some essential functions of teaching and because it facilitates access for remote students.

Instructional attributes

Instructional attributes can include instructor attitude, instructor knowledge, design and characteristics of teaching materials, instructor-learner interaction, learner-learner interaction, collaboration, and feedback (Kemp et al., 2019).

Teaching presence is important for online courses to reach their pedagogical objectives (Joia & Lorenzo, 2021; Van Wart et al., 2020) in terms of use of the technology and facilitating students' metacognition during studies (James, 2021). Dart and Woodlands (2022) have also described the importance of instructors developing knowledge facilitation skills that incorporate student-centric approaches. Student outcomes and satisfaction improve when instructors facilitate interaction rather than act as pedagogical sources of information (Arbaugh, 2002). Students have reported that interaction is more frequent in face-to-face settings and that lack of interaction in an online class would impede learning (Ismaili, 2021). Interaction and discussion that occurs in face-to-face classes 'support[s] the independent learning occurring through online work' (Ashton & Elliott, 2007, p. 175). Class discussion is also a critical success factor in online environments (Selim, 2007) and while student attitudes towards online learning vary, technology-mediated discussion can suit students who prefer anonymity or 'whose cultural expression gives them little capital in an English-dominant, vocally expressive classroom' (Ashton & Elliott, 2007, p. 176). Interaction and class engagement lead to a feeling of membership and influence, which promotes ‘e-learning stickiness’ (Luo et al., 2017, p. 155), or habitual use. Non-verbal forms of interaction also exist: students have come to value the emoticons, screen sharing and collaboration that Zoom can afford them (Eraković & Topalov, 2021), and interactive Zoom tutorials support student engagement and satisfaction (Sayem et al., 2017). Despite the theory and evidence that interaction and social engagement are important factors for satisfaction in Zoom (Van Wart et al., 2020), educators have acknowledged the difficulty in monitoring engagement in large classes (Moorhouse, 2020) or keeping students engaged in online environments (Ebner & Greenberg, 2020; Hamilton et al., 2020; A. Lee et al., 2021).

Anderson et al. (2001) argued that online learning may invoke feelings of separation. Instructors are called to offer more interactive teaching to combat the social distance students can feel in online environments (Volery & Lord, 2000), which requires a degree of technological competence. However while Lee et al. (2021) noted that many teachers turned to a technocentric approach as COVID-19 hit, it was soon realised that this did not satisfy students’ desires for actual human connection. Ebner & Greenburg (2020) also noted that technological acumen is insufficient when teaching through Zoom. Educators have also more recently become aware of the need to support students’ social and emotional well-being (Hamilton et al., 2020), with social presence and online comfort being important factors for student acceptance (Ismaili, 2021; Van Wart et al., 2020). In line with this, Lee et al. (2021) found that students feel more safe and trusting in Zoom environments where there are opportunities to give and receive feedback.

Cognitive engagement

Cognitive engagement encompasses perceived loss of time (‘time flies’), focus, enjoyment and vividness (Kemp et al., 2019; Saade & Bahli, 2005), and influences both perceived ease of use and usefulness. Yang & Kwok (2017) demonstrated that cognitive engagement leads to student enjoyment. Perceived loss of time is caused in part by playfulness (Saade & Bahli, 2005), and a user's cognitive immersion within a technology or learning activity, which relates to the learner's focus and learning engagement. An example of engaging content include worked example videos (Dart et al., 2020), where video length, colourful pens and synchronisation of narration and diagrams are carefully balanced to maintain interest. Interactive tools such as Mentimeter can also foster student engagement because of the quick student responses that others can see (Moorhouse & Kohnke, 2020), triggering the curiosity and interest of other students. While videos and technologies such as Mentimeter, Padlet and Go Soapbox are not features of Zoom, the screen-sharing function allows them to be used within a Zoom class. Screen fatigue can be a challenge (Kohnke & Moorhouse, 2020; Schade, 2020), which relates to physical and/or mental exhaustion that some report following extended use of Zoom (Ebner & Greenberg, 2020).

System attributes

System attributes such as ease of access, support and design (Volery & Lord, 2000) influence user attitudes toward online systems, with technology reliability and access being of high import (Selim, 2007). According to Yang and Kwok (2017), internet connectivity, system usability and technical issues are negative influences on student attitudes to online educational systems. Another aspect of online learning is privacy, where students' concerns about being recorded or identified can moderate their attitude towards using such technologies (Arpaci et al., 2015). Zoom experienced privacy issues initially (Young, 2021), with some issues being mitigated by adding per-meeting IDs and password access (Kohnke & Moorhouse, 2020). Finally, the design and function of the user interface has been shown to influence continued usage intention (Cho et al., 2009) and Eraslan Yalcin & Kutlu (2019) demonstrated that the user interface influences both perceived usefulness and ease of use.

With this background in mind, we developed a survey to understand students' attitudes toward Zoom for learning during the COVID-19 pandemic. The guiding research questions were:

1. What factors do students perceive as important in their decisions to use Zoom for learning?
2. What are the emerging factors (if any) that were not predominant pre-pandemic?

Methods

Participants and setting

The study was administered in Semester 2, 2020, by engaging students enrolled in a large first-year psychology subject at the University of Adelaide in Australia. The university is situated in metropolitan Adelaide and enrols approximately 23,000 students across three faculties. At the time of data collection, learning was delivered fully online because of COVID-19 pandemic restrictions. All synchronous classes were being conducted via Zoom following the rapid transition which occurred in Semester 1, 2020.

Data collection

Our research sought to uncover potentially unknown factors influencing students' attitudes to use Zoom for learning. Quantitative methods were thus a poor fit for answering the research questions as the key factors are not known. Therefore, a qualitative research approach was employed to enable rich and direct insights into student perspectives (Creswell, 2018; Trafimow, 2014), and thus allow the emergence of new influencing factors.

Data were collected through a voluntary, online anonymous survey hosted on the Qualtrics platform, and respondents received course credit for completing the survey. Ethics approval was granted by the School of Psychology Human Research Ethics Sub-

Committee. In this research we focus on the open-ended questions designed to understand what aspects of Zoom learning experiences students perceived to be working, be in need of improvement, and require instructor attention (Table 6.1).

Table 6.1

Open questions asked of respondents

Code	Question text
OQ1	What makes Zoom preferable for learning over other types of learning methods?
OQ2	What features of Zoom would you suggest improving to enhance learning?
OQ3	What could instructors do to improve your experience of learning via Zoom?
OQ4	Is there anything not covered by this survey that influences your use of Zoom for learning?

Out of a possible 742 students from the first-year psychology subject, 169 students completed the survey. This represented a 23% response rate. The demographic indicators of respondents are listed in Table 6.2, which are in broad alignment with the first-year psychology student cohort.

Table 6.2

Demographic indicators of respondents (n = 169)

Variable	Classification	Frequency	Percentage
Age	Up to 25	154	91%
	Over 25	15	9%
Gender	Female	121	72%
	Male	47	28%
	Neither male nor female	1	<1%
Origin	Domestic	151	89%
	International	18	11%

Data Analysis

Kemp et al.'s (2019) taxonomy was used to support identification of emergent factors influencing students' decisions to engage with Zoom, given the framework had mapped the TAM landscape in an educational context immediately prior to the pandemic's onset. The primary categories of the taxonomy of TAM factors were used to deductively code comments in the present study (Braun & Clarke, 2006). However, the authors remained open to new factors, and thus where a response made reference to a factor that did not align with an existing category, it was coded as a potential emergent factor.

To reduce bias and promote quality assurance in the data analysis process (Walther et al., 2013), two researchers coded textual responses independently using NVivo software (QSR International Pty Ltd. Version 12, 2018). After an initial round of coding, the researchers engaged in a discussion to compare preliminary coding outcomes and develop better shared understanding of theme definitions. A second round of coding was subsequently completed. Cohen's Kappa and percentage agreement were used as guides of confluence between coders. Cohen's Kappa is a measure of inter-rater agreement that takes into account agreement by chance and so is more robust than percentage agreement alone (Vieira et al., 2010). Greater than 92% agreement was achieved between two coders and Cohen's Kappa ranged from 0.74 to 0.99 for all categories, indicating at least substantial agreement (Landis & Koch, 1977). Finally, responses were analysed by the first author to identify the recurring ideas within responses coded to each primary taxonomic category. Those themes were then considered against the secondary taxonomic categories to identify potential gaps.

Results

The results are reported around the seven primary taxonomic groups of Kemp et al. (2019) of attitude, affect and motivation, social factors, usefulness and visibility, instructional attributes, perceived behavioural control, cognitive engagement, and system attributes. The analysis revealed that there was a gap in the primary taxonomic groups relating to health and well-being. Additionally, a gap was identified at the second level of the social factors grouping, relating to social comfort. Students referenced usefulness only in the context of accessing classes, rather than for learning. Therefore, usefulness and perceived behavioural control are reported together here, despite being considered separately in the taxonomy. Quotes which exemplify the underpinning themes are included.

Attitude, affect & motivation

Students provided a spectrum of attitudes towards learning with Zoom. However, comments tended to be negatively skewed, potentially a reflection of the COVID-19 situation forcing students online in rapid a chaotic transition, with many students stating their preference for face-to-face learning. For example, ‘I do not prefer zoom over any other learning methods known to me’, and ‘It isn’t preferable. It is currently the greatest inhibitor to my motivation to study and attend classes’. Other students were more pragmatic. They recognised the value of Zoom while still often preferring traditional methods: ‘It has been great during COVID, but I would prefer face-to-face’. Some students indicated the lack of social interaction was a key driver of their negative attitudes towards Zoom, for example ‘I just don’t like online learning and much preferred it when everything was in person’, and ‘Staring at a screen all day is never going to be preferable to being in a room full of other people who you are free to interact with’. Others had more positive attitudes, for example ‘Zoom allows for interaction with other students and tutors/lecturers which is not the case with recordings’. Capturing a number of positive aspects, one student related ‘I like Zoom plus lecture recording, I probably do prefer lecture recording. Zoom is good because its super user friendly and because I work/study I don’t lose time/ money travelling into uni’.

Social factors

Existing secondary taxonomic groups of ‘social influence’ and ‘image and esteem’ were not found to be explicitly represented in the data. However, the thematic analysis revealed an emergent theme relating to 'social comfort', a term we have employed to capture the feeling of preferring and enjoying being connected with others, for example 'I much prefer being able to go into class and physically interact with other classmates', and:

> The largest factor that causes me to prefer face-to-face learning over Zoom is the social aspect. While Zoom provides a useful alternative to this in circumstances where it is needed (e.g., social distancing, absent students), it can feel isolating and it is much more difficult to make friends. (Student respondent)

Contrary views were noted where respondents saw a positive in not having to be physically present with others: 'Zoom is more preferable for me because I don't have to meet people and I don't have to walk out of my room'. Another student related that 'sometimes it can be easier to talk as its not face-to-face and therefore you feel more comfortable'. Students expressed frustration with the social norms of their peers with regard to not interacting within Zoom classes, an implicit reference to social influence. This intersects with the instructional attributes secondary taxonomic category of social interactivity and is therefore covered in the section relating to instructional attributes where class interaction is discussed.

Usefulness and perceived behavioural control

Convenience and accessing learning at any time and place were major positives for students and one of the most highly mentioned. Students very much appreciated being able to manage sleep, personal routines, employment obligations and costs associated with travel. For some, the location convenience helped negate perceived negative effects of distance learning through Zoom. As one student commented, a substantial benefit of using Zoom was 'the ability to attend and interact with the class/lecture without having to physically go to class as transport to university from my house is quite strenuous and time consuming'. In addition to its benefits for access to learning, some students commented about Zoom's ease of use in terms of navigation and undertaking group work, which demonstrates that Zoom can be useful to facilitate group interactions.

Instructional attributes

Themes around instruction and student behaviour were the most predominant. In Kemp et al.'s (2019) taxonomy, instructional attributes was a term used to include both the student experience of learning and teaching practice. In the present study, we uncovered three broad themes aligned with instructional attributes: class interaction, instructor practice and feedback and information exchange.

The most prevalent theme to emerge from the thematic analysis was class interaction. Respondents generally acknowledged that their own peers were not interacting, for example 'I lacked the motivation to attend these zoom sessions as no one would really contribute', and 'A major issue with Zoom is the lack of participation from peers in breakout rooms'. A clue as to why students may not be participating is offered by this comment: 'I prefer face-to-face contact in person for trading of ideas and easier to grasp nuances in body language not always available via Zoom', and 'it is the lack of face-to-face interaction that fails it', as well as 'I prefer face-to-face to be able to see people and be able to read body language etc I feel people are not always natural when on zoom, I know I feel this way', or 'People are too shy to interact over zoom'.

Related to class interaction was student behaviour in breakout rooms, with suggestions to not overuse them because 'discussion just doesn't happen'. Within this theme, one student suggested more directed approach: 'When break out rooms and peer collaboration happen, the instructor should assure that all peers are interacting'. Other students provided suggestions on making instructions more explicit, such as 'I would benefit from an orientation on the use of zoom. What is expected RE: cameras/

microphones on or off. How discussion will be facilitated etc.'. and 'Give greater direction as well as feedback' and 'Being clear with instructions'.

We used the term 'instructor practice' to capture how instructors manage student behaviour and interaction, competency in use of Zoom as a platform, and the application of pedagogical principles and students provided some suggestions for how educators could act to improve this. Students discussed the importance of tailoring the lesson design to the platform, such as 'prepare classes to accommodate Zoom type of learning instead of a face-to-face type' and 'alter assignment tasks to suit online learning'. Another respondent suggested that educators should 'have a lesson plan which they follow - riddled with interactive activities to promote class engagement'. Students also noted the significance of their instructor's abilities in using Zoom smoothly and confidently. One respondent put it succinctly by suggesting 'become proficient in using all of Zoom's features for hosts'. Others reflected that 'some instructors don't seem to have a complete knowledge of how to use every feature of zoom properly' or 'Having an in depth understanding of how to use the program, and to not excessively or needlessly use complex functions for short activities'.

A small number of responses related to feedback specifically. These students appreciate that Zoom allows them to ask questions and receive quick responses, and that Zoom offers 'more feedback and interaction than other methods' which supports 'real-time learning where you can ask questions on the spot'. Interaction and feedback were closely related, and as one student eloquently put it: 'Zoom allows for interaction with other students and tutors/lecturers which is not the case with recordings. This also allows students to ask question and conduct discussions about content which helps to learn and understand the information'.

Cognitive engagement

Overall, the responses indicated that students are hopeful of more engaging learning activities as part of the Zoom learning experience because distraction was a key concern mentioned by several students, where ‘it is difficult to stay focused when watching a 2 hour zoom lecture at home and…it is much easier to lose focus in a zoom class’. Another student echoes this sentiment that a physical social setting helps engagement: ‘I think Zoom is fine how it is, though I just prefer face-to-face learning as I get easily distracted’. Students offer suggestions such as ‘make it fun’, provide more activities and to aim to make the experience more engaging.

System attributes

The responses revealed two main themes relating to system attributes: functional augmentation, and quality of connection, image, and audio. Functional augmentation suggestions included ‘greater ability to interact in a variety of different avenues’, for example by adding a ‘screen for cooperative activities’ or ‘making it easier to respond to the screen the teacher puts up’. One student advocated for adding native interactive capabilities beyond simple polling by adding ‘some quiz - like activities such as Kahoot but on the Zoom app’. Many students commented on the instructor’s use of the screen share functions: ‘make it easier to respond on screens the teacher puts up’ or ‘better screen sharing or use of drawing tools for visuals’. One student noted that the Zoom recording does not include the chat and another expressed frustration of using a small screen laptop when the instructor uses large dual monitors.

Students also highlighted that there were significant connectivity and quality issues, for example ‘Wi-Fi availability and high traffic on server can cause disruptions such as lags or lack of audio’. Comments about noise were accompanied by concerns about quality of the image and network capacity. One student put it succinctly: '[educators need to] have a better internet connection'.

Health and well-being as an emergent primary factor

A theme that emerged that was not related to any of the known taxonomic groups involved physical and mental well-being. On the positive side, one student related that 'I am physically disabled, so using Zoom in replacement of face-to-face lectures has been great as I have to travel a great distance to get to my campus', a sentiment that also relates to access and convenience. In terms of physical health, one student related that 'When using my computer for Zoom all day I get a sore back and eyes'. Whereas some students indicated that Zoom helps them communicate when they otherwise may not, one student informed that 'as a person with social anxiety the mic and photo aspects of zoom give me panic attacks and so aren't conductive to my mental health'. These types of comments indicate that Zoom can be associated with positive or negative health effects depending on each student's situation.

Discussion

Most themes that emerged from the analysis were able to be aligned with the primary categories of Kemp et al.'s taxonomy except for health and well-being, and social comfort. Health and well-being had no equivalent in the taxonomy at any level. This indicates that health and well-being could be considered as an additional primary category and should therefore be considered for future research involving technology acceptance models. Additionally, students highly valued social comfort, which suggests that it can be categorized as an extension of the social factors identified by Kemp et al. (2019). However, social comfort seems to be distinct from the influence of peers and important individuals, indicating that it should be treated as a separate aspect within the broader category of social factors. Hence, it can be regarded as a new secondary grouping within the primary group of social factors. Implications for the key factors that emerged from these findings are discussed below, aligned to the primary taxonomic categories.

Attitude, affect and motivation

In terms of attitude, affect and motivation, comments revealed why learning using Zoom can be problematic. Dissatisfaction was based in the disruption to established teaching and learning norms, with zoom learning being a confronting transition for those who enjoy face to face environments (see Ismaili, 2021; Wong, 2020). However, these data were collected during COVID-19 and so were likely confounded by those experiences which affected much more than learning. Within that context, some students did find value and satisfaction being able to continue their studies even with the disruptions at the time. Some of the comments alluded to preferences for being with others and not enjoying online learning in general, leading to dissatisfaction and loss of motivation, and so social factors were likely partly responsible for the attitudes that were identified in this research.

Social factors

Whereas the taxonomy characterised social factors through the lenses of social norms and influence from others, these results showed that simply being around others is another influential social determinant of behaviour. This aligns with other research that students prefer and enjoy being with others during class (Ashton & Elliott, 2007; Ismaili, 2021; A. Lee et al., 2021; Wong, 2020) because of the greater sense of social connection and presence. Ebner & Greenberg (2020) reported that the familiar social and para-linguistic cues stemming from social proximity support student engagement and interaction, leading to a sense of membership and influence within the social group (Luo et al., 2017). This implies that the screen was not able to convey the expected implicit signals people pick up from each other in physical settings and this may contribute to reduced class interaction. It is possible that students are uncertain how to act in the absence of physical cues leading to an infinite loop of inaction and lack of engagement. The effect of the loss of physical social cues and how this affects behaviour needs to be more fully explored. Considering this information, we suggest that social comfort be added as a new secondary level grouping to Kemp et al.'s (2019) primary social factors group. The practical implications are that instructors could coach students towards new standards of engagement and encourage use of Zoom features (such as emoji, chat and Zoom reactions) to reduce the sense of isolation.

Usefulness and perceived behavioural control

The results echoed other research identifying major advantages of online learning platforms such as improved access, convenience and student agency (Ashton & Elliott, 2007; Dart et al., 2020; Ismaili, 2021). In our case, students specifically called out benefits such as financial benefits in terms of cost and being able to better manage employment, and health benefits by managing sleep. In addition to convenience and logistics, respondents also pointed out Zoom's capacity to navigate and undertake group work. Our results are therefore in line with other well-established research on the benefits of e-learning in general. This indicates that students could be given a choice of attendance mode to help them balance their own lives, and if pitched this way may improve attitudes towards its use.

Instructional attributes

Students focused on the design of the learning itself, which relates to the pedagogical aspect of the technological pedagogical content knowledge (TPACK) paradigm (Mishra & Koehler, 2006; Selim, 2007). Respondents recommended that instructors deliberately design their lessons to suit the online synchronous context and be better prepared to direct and manage student behaviour in class. These findings are in line with Arbaugh (2002) who suggested that student-centric constructivist approaches may be more accepted than teacher-centric objectivist pedagogy. Students' wishes for their instructors to be competent using Zoom also touch on the technology aspect of TPACK. The implication is that improving familiarity and competency with Zoom will enable instructors to plan and design their lessons for the platform, thereby addressing a few of the student concerns.

The responses indicated a situation where students said they value interaction with others in a social and learning sense yet are not able to behave this way in Zoom. Instructors have also expressed frustration and difficulty getting students to engage (Ebner & Greenberg, 2020; Hamilton et al., 2020; A. Lee et al., 2021). Social loafing theory (Karau & Williams, 1993; Sanna, 1992) suggests that students do not consider there is anything to gain by participating, or that they lack the self-efficacy to be competent amongst peers, that others can take up the slack, or that students are mimicking others' behaviour. Thus, lack of engagement may be linked to not being sure how to act, not having confidence in group settings when no one else is interacting, and a preference for others to make the effort. Responses indicated that the removal of face-to-face group cues may be contributing to all these possible causes.

These results aligned with recent studies that showed that online learning is characterised by lower interaction than face-to-face learning (see Ismaili, 2021), which is concerning because class interaction is linked to student satisfaction (Arbaugh, 2002). Ashton & Elliot (2007) showed that in-class interaction supports individual online learning, and so if in-class interaction is not being replicated in the virtual classes then this can logically affect the efficacy and satisfaction of online learning in general. Student responses indicated their preference for instructors to actively manage class interaction and support the idea that instructors may need to work towards establishing new virtual social norms that support class interaction and communication. As Kohnke and Moorhouse (2020) point out, there are non-verbal ways to communicate and interact in Zoom in addition to speaking with the camera on, and these need to be fully explored.

Cognitive engagement

Whereas cognitive engagement is associated with student enjoyment (S. Yang & Kwok, 2017) and influences student intention to engage with the learning (Moon & Kim, 2001), our results indicated that students' experience in this area was poor. Many commented on how easy it was to become distracted and lose focus, mostly due to isolation issues or being in a familiar home environment. Respondents provided suggestions to remedy this, such as to simply make it fun, or to include more activities or a wider range of capabilities within the Zoom platform. In all, respondents painted a picture of instructors grappling with how to effect their practice through Zoom, that instructors need to go beyond what works in face-to-face settings, and that students also need to learn to adapt. Given the low engagement reported by students in this study, it is unsurprising that their attitudes towards learning through this platform were generally also negative.

System attributes

In terms of system attributes our results focused on functional augmentation and quality of service. The former related to suggestions to incorporate more interactive features as native features of the platform, whereas currently a user can use third party applications and screen share to show them. Considering student complaints that they lose focus easily and do not feel engaged, incorporation of interaction features into the Zoom platform would make these functions more immediately available for instructors, who might begin to use them if easily available on the interface (see Cho et al., 2009). In terms of service quality, students recommended higher quality internet connection and audio quality and these results were in agreement with Selim (2007), and instructors could consider this as part of their technology setup.

Health and well-being

Health and well-being was the only theme to emerge from this study that was not accounted for in Kemp et al.'s taxonomy. The results showed that health and well-being can manifest as physical health in terms of managing physical disabilities and social isolation during pandemics, through to mental health and well-being. While most students merely had negative attitudes and low satisfaction towards learning through Zoom, a minority expressed negative health effects such as anxiety or sore back or eyes. While these effects can be due to the technology itself, some of these effects were also likely associated with the social isolation due to the pandemic, and the connection with the social influence of being with others is interesting and demonstrably important. Thus, social connection and well-being would appear to be somewhat linked, implying that a construct should be considered for TAM models where this may be influential, though it should always be considered in context.

Conclusion

We surveyed students during the COVID-19 pandemic for their attitudes towards Zoom for learning against known factors relating to technology acceptance. Although many students expressed a preference for face-to-face learning, they often also acknowledged that learning via Zoom was beneficial and convenient. Students were concerned about lack of engagement with other students, instructional style, and instructors' ability to manage the class to support engagement and interaction. These results indicated that instructors would further support students by improving their Zoom efficacy, actively designing for the synchronous online environment, including more engaging tasks, and learning new ways to facilitate different kinds of communication through Zoom. The broad theme of broken social connections was apparent, implying instructors would do well to help to rebuild it. We also noted an important comfort and well-being dimension to learning via Zoom where physical and mental health can be affected both positively and negatively depending on the student and situation, which has both practice and research implications. We recommend that health and well-being be added as a new primary construct in Kemp et al.'s (2019) taxonomy, and that social comfort be added as a new secondary construct within social factors.

Limitations and further research

This study was restricted to one university in a Western setting with 169 respondents. This limitation could be addressed in future research by exploring the Zoom learning experience across multiple universities and including diverse learning contexts in different countries. This study highlighted that student engagement in Zoom fell far short of most student expectations, however future research could explore how factors such as cultural communication norms, students' learning readiness, physical and mental health affect how a student might engage. In terms of TAM research, the social comfort and well-being aspect should be explored with a view to incorporating it into TAM models pertaining to educational technologies involved in distance learning. Finally, this study was conducted during COVID-19 lockdowns when many, (or all), students were forced to use this particular technology, which may influence the generalisability of the results at other times.

6.4 Postamble

This study was conducted to discover any new constructs that are required to be included in the final model, and it achieved this purpose by revealing the themes of social and personal comfort, and health and well-being. Social and personal comfort related to comfort with learning either in person or via use of technologies, and health and well-being include physical, mental, and psychological aspects. The other themes to emerge from the analysis aligned with the taxonomy from Paper 1 (Chapter 4).

This study also served to demonstrate that different factors can exhibit relative strengths, which was not apparent in the taxonomy presented in Chapter 4. For example, in Chapter 4, 'access' was but one of many factors, and it was a tertiary factor within 'perceived behavioural control' > 'environmental & situational' > 'opportunity'. However, as this paper demonstrates, access is by no means an insignificant factor for students, especially during the pandemic. This example serves to demonstrate that factor strengths become apparent only during measurement.

This study helped answer the following research aim and objective:

- **Research aim 1**: To identify the types, characterisations and scope of factors affecting attitudes and intentions towards use of educational technologies.
- **Research objective 1**: To search for the latent constructs related to educational technology use that have been shown to affect user attitudes and intentions.

As a result of this study, all important constructs for a comprehensive educational technology acceptance model had been identified, ready for inclusion into the final putative model that was tested in Paper 4 (Chapter 7).

CHAPTER 7 – THE FINAL MODEL

7.1 Preamble

This final paper of the research project assembled a putative technology acceptance model suited to educational technologies. Its design was informed by the results of the first three papers and it was deployed and in a real-world context to test its utility and effectiveness. Specifically, this final paper addresses the following research aims, objectives and hypotheses:

Research Aim 1: To construct a comprehensive technology acceptance model suited to education, and investigate:

(a) Whether its education-specific constructs improve its power when applied to educational technologies, and

(b) If it can explain the majority of variance of intent to use such technologies.

Research Objective 2: To form a comprehensive, yet parsimonious, structural model that researchers can use to measure attitudes and intentions in a wide variety of educational settings.

Research Objective 3: To test this model in a real-world educational setting.

Research Hypothesis 1: A suitably constructed and relevant model will explain a majority of the variation of intention to use an educational technology (> 60%).

Research Hypothesis 2: The inclusion of constructs specific to educational technology and learning will increase the overall power of the model when applied to an educational technology.

7.2 Statement of Authorship

Title of Paper	Testing a novel extended educational technology acceptance model using student attitudes towards virtual classrooms
Publication Status	Submitted to British Journal of Educational Technology

Principal Author (Candidate)

Name of Principal Author	Andrew C Kemp		
Contribution to the Paper	Conceptualisation, analysis and write-up.		
Overall percentage (%)	90%		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	23/06/2023

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
ii. permission is granted for the candidate in include the publication in the thesis; and
iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution

Name of Co-Author	Edward Palmer		
Contribution to the Paper	Supervised development of work, helped in data interpretation, manuscript conceptualisation, revisions and evaluation.		
Signature		Date	10/7/23

Name of Co-Author	Peter Strelan		
Contribution to the Paper	Supervised development of work, helped in data interpretation, manuscript conceptualisation, revisions and evaluation.		
Signature		Date	26/6/23

Name of Co-Author	Helen Thompson		
Contribution to the Paper	Supervised development of work, helped in data interpretation, manuscript conceptualisation, revisions and evaluation.		
Signature		Date	03/07/2023

7.3 Paper 4 - ***Testing a novel extended educational technology acceptance model using student attitudes towards virtual classrooms***

Abstract

Many technology acceptance models used in education were originally designed for general technologies and later adopted by education researchers. This study extends Davis' technology acceptance model to specifically evaluate educational technologies in higher education, focussing on virtual classrooms. Prior research informed the construction of the model, which contains perceived usefulness, perceived ease of use, behavioural intent, access & convenience, system attributes and self-efficacy. Education-specific constructs include cognitive engagement, feedback, instructor practice and class interaction & communication. Additionally, a new construct called comfort & well-being is introduced. 427 valid responses on a 5-point Likert scale were received from university students. Exploratory factor analysis, confirmatory factor analysis and structural equation modelling were used to analyse the data. The model accounted for 78% of variance of behavioural intent, with comfort & well-being demonstrating the strongest influence. Cognitive engagement and access & convenience influenced perceived usefulness, and system attributes and self-efficacy influenced perceived ease of use. Feedback, instructor practice and class interaction & communication were not significant as educational constructs for this cohort. Based on this analysis, a final extended educational technology acceptance model (EETAM) is proposed for further use and testing.

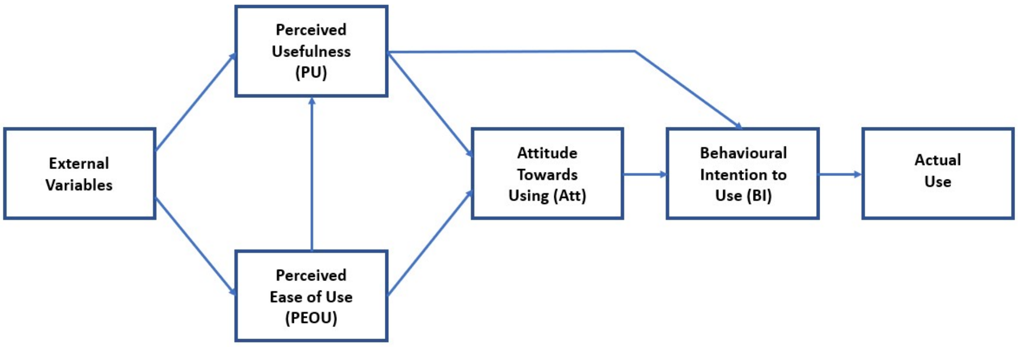
Introduction

Technology acceptance models

Technology acceptance models (TAMs) such as the seminal model developed by Davis (1986; Davis et al., 1989) (Figure 7.1) have been used to assess user attitudes toward technologies. The TAM's central constructs were perceived usefulness, perceived ease of use, attitude, and behavioural intent to use the technology. The model proposes that perceived usefulness and perceived ease of use mediate the effect of external factors to subsequently influence attitude and intention to use a technology.

Figure 7.1

The Original Technology Acceptance Model (TAM)



Note. Adapted from Davis (1986)

A systematic review of the literature by the authors (unpublished) revealed that extended TAMs are the most used model to appraise educational technologies, followed by the TAM itself, the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) and its extensions, followed by the General Extended Technology Acceptance Model for E-Learning (GETAMEL) (Abdullah & Ward, 2016), Technology Acceptance Model 2 (Venkatesh & Davis, 2000) and Technology Acceptance Model 3 (Venkatesh & Bala, 2008). It is notable that none of these prominent models include factors specific to education or learning and are general in nature.

Over time, researchers have extended the TAM to suit different educational contexts resulting in a wide variety of technology acceptance models. Extended TAMs incorporate a wide range of external factors theorised to influence perceived usefulness and perceived ease of use and vary in size and design. Some models are quite compact (e.g., Arpaci, 2017; Bao et al., 2013; Mahdi, 2014; Zacharis, 2012), while others are larger (e.g., Altanopoulou & Tselios, 2017; Baby & Kannammal, 2020; Binyamin et al., 2019; Teo et al., 2019). In our review, few models included factors specific to pedagogy or learning, such as instructional design (Alshammari, 2020), communication and collaboration (Alyoussef, 2020), instructor engagement (Barclay et al., 2018), teacher support (Hoi & Mu, 2021), instructor attitude towards students (Y. Lee et al., 2014), and motivation and content quality (Zain et al., 2019). Most other studies in our review featured only factors that are relevant to general technologies such as social norm, facilitating conditions, self-efficacy, prior experience, anxiety, playfulness, enjoyment, and satisfaction. While some of these are important to education, they are not specific to it.

Abdullah and Ward (2016) proposed an extended TAM known as the General Extended Technology Acceptance Model for E-Learning (GETAMEL), which incorporated the five most commonly used external factors: experience, social norm, enjoyment, anxiety, and self-efficacy. However, it remained uncertain whether the chosen factors represented a comprehensive selection for educational purposes, since none were pedagogical in nature. In our review, examples of the GETAMEL in educational research included investigating students' intention to use e-learning (Chang et al., 2017), adoption of the Blackboard learning management system (Matarirano, Panicker, et al., 2021), an extended version to investigate Blackboard adoption by lecturers (Matarirano, Jere, et al., 2021) and video demonstrations to predict student intention to use digital technologies (Sprenger & Schwaninger, 2023).

Since our review returned a variety of models without specific focus on education and learning, this study's prime aim was to develop an extended educational technology acceptance model specified for educational technologies in a variety of settings. After designing the model based on prior empirical research, we tested it by investigating student attitudes and intentions to use virtual classrooms for learning over the last half of 2021 and the first half of 2022 across two Australian universities.

Virtual classrooms

While the focus of this paper is the proposed technology acceptance model, a brief review of virtual classrooms is necessary because we used this technology to test the hypothesised model. Virtual classrooms offer improved learner access (Ashton & Elliott, 2007; Sayem et al., 2017; Correia et al., 2020; Willermark, 2021) and have been used in both fully online and hybrid modes. However, Raes et al. (2020) found that hybrid classes resulted in loss of relatedness to peers and lower student motivation, and Ruthotto et al. (2020) found that larger virtual class sizes result in reduced student participation and lurking. Ratan et al. (2022) found that social presence, perceived learning gains and satisfaction are higher in synchronous virtual classes than asynchronous, with social presence mediating the perceived benefit of active learning. Pi et al. (2020) highlighted the importance of instructor presence and active teaching strategies in maintaining student focus, with interaction being an important driver of student satisfaction in online classes (Martin et al., 2012). The evidence suggest that students struggle with focus and attention in virtual classrooms, however innovative and adapted practice to mitigate these effects is important to research to understand more fully.

Purpose of this research

The primary aim of this research was to determine the effectiveness of the hypothesised technology acceptance model by deploying it in a real-world setting to evaluate virtual classrooms. Indications of a successful model include the amount of variance explained of the dependent variable (see Peterson, 2000), goodness of fit tests, convergence and divergence of the measurement model, and a functioning structural model (see Hair et al., 2010; Hooper et al., 2008; Hu & Bentler, 1999). Passing these statistical tests strengthens its prospects to be used and tested for other educational technologies and contexts, and the model's performance is presented here.

Development of the research model

General considerations

Kemp et al. (2019) suggested seven primary factor groups that were relevant to student attitudes towards educational technologies: attitude, affect and motivation, social factors, usefulness and visibility, instructional attributes, perceived behavioural control, cognitive engagement, and system attributes. These primary factor groups emerged from a systematic review of the extant literature which collated most factors used by researchers up to that point. Each primary factor group included secondary and tertiary sub-groups, for example, instructional attributes included lecturer attributes, content attributes, feedback, and social interactivity. The taxonomy suggested that each of the seven primary factor groups should be incorporated in some way in a technology acceptance model suited to educational technologies, a recommendation which we have adopted.

COVID-19 had a significant impact on education globally causing disruptions in learning delivery (Hamilton et al., 2020; Joia & Lorenzo, 2021). It was therefore important to explore how student attitudes towards learning technologies may have evolved during this period. Student attitudes to using Zoom for learning were investigated in a separate qualitative study (Paper 3, Chapter 6), revealing that social comfort and well-being, cognitive engagement, instructor practice, class interaction and feedback, access and convenience, and system attributes were important considerations. Based on these results the inclusion of a comfort and well-being factor into the theorised extended model, in addition to the primary taxonomic factors from Paper 1 (Chapter 4), was proposed.

The inclusion of attitude in extended TAMs has been a subject of some uncertainty. Some researchers have found consistent evidence that attitude is redundant in TAMs

(Davis, 1989; Teo, 2009a; Venkatesh & Bala, 2008, Nistor & Heymann, 2010). However other research has shown that attitude can be influential (López-Bonilla & López-Bonilla, 2011; López-Bonilla & López-Bonilla, 2017; H. Yang & Su, 2017). On balance the evidence that attitude is statistically redundant in TAMs was more convincing and so attitude was omitted from the model.

This previous research suggested that an effective extended educational technology acceptance model should include perceived usefulness, perceived ease of use, cognitive engagement, class interaction & communication, feedback, instructor practice, access & convenience, system attributes, self-efficacy, and comfort and well-being. These factors represent all of the primary factor classes suggested by the taxonomy, except attitude, in addition to the factors suggested by the qualitative study in Paper 3 (Chapter 6). Table 7.1 shows the alignment between the factors suggested by the prior studies and the final model.

Table 7.1

Origin of Factors Included in the Hypothesised Model

Taxonomy	**Qualitative Study**	**Final model factors**
Attitude, affect & motivation	Attitude	Not included
Social factors	Social comfort	Comfort & well-being
Not present	Health & well-being	Comfort & well-being
Usefulness & visibility	Convenience	Access & convenience
Usefulness & visibility		Perceived usefulness
Instructional attributes	Instructor practice	Instructor practice
Instructional attributes	Class interaction	Class interaction & communication
Instructional attributes	Feedback	Feedback
Perceived behavioural control	Access	Access & convenience
Perceived behavioural control		Perceived ease of use

Perceived behavioural control		Self-efficacy
Cognitive engagement	Cognitive engagement	Cognitive engagement
System attributes	System attributes	System attributes

Note. 'Taxonomy' refers to Paper 1 (Chapter 4), 'Qualitative Study' refers to Paper 3 (Chapter 6).

Each of the final model factors and their relevance to our twelve hypotheses (H1 to H12) are explored below.

Comfort and well-being

The relevance of social comfort and well-being in technology acceptance research became apparent in (authors, submitted) qualitative study of student attitudes towards Zoom for learning. Socially isolated learning and using Zoom for prolonged periods was associated with physical and mental health effects and decreased well-being. Social isolation included the sense of being apart from others even while seeing, hearing, or interacting with them over Zoom, and many respondents expressed the desire to physically be around others. Ebner and Greenberg (2020) highlighted the importance of non-verbal engagement and social cues resulting from physically being with others, which led us to hypothesise that social comfort and well-being might directly influence a student's intention to use a virtual classroom. Thus, we defined comfort and well-being as the positive or negative comfort one experiences from use of a technology and health effects associated with its use. Accordingly, it is included in the hypothesised model as a direct antecedent to behavioural intent.

H1 Comfort & well-being positively, and directly, influences behavioural intent

Perceived usefulness and perceived ease of use

Perceived usefulness and perceived ease of use are core constructs of the TAM model (Davis, 1986; Davis et al., 1989) that also have homologues in the Unified Theory of Acceptance and Use of Technology, namely performance expectancy and effort expectancy respectively (Venkatesh et al., 2003). Davis' TAM model posits that perceived usefulness and perceived ease of use together mediate the effects of other external variables on behavioural intent to use a technology, and that additionally, that perceived usefulness mediates some of the effect of perceived ease of use. Even though the relationship between perceived ease of use and perceived usefulness may not be strong in all cases (Sheppard & Vibert, 2019), we include it in our list of hypotheses due the long-standing acceptance of the TAM model (Eraslan Yalcin & Kutlu, 2019).

H2 Perceived usefulness positively influences behavioural intent

H3 Perceived ease of use positively influences behavioural intent

H4 Perceived ease of use positively influences perceived usefulness

Cognitive Engagement

Cognitive engagement encompasses cognitive absorption (Liu et al., 2009; Saade & Bahli, 2005), loss of time (Saade & Bahli, 2005), and playfulness (B. Lee et al., 2009) that can lead to improved student enjoyment (S. Yang & Kwok, 2017). Playfulness and loss of time lead to a sense of cognitive immersion within a task. However, gratuitous time on task can negatively affect cognitive engagement due to loss of interest or boredom, that can be remedied by shorter videos (Dart et al., 2020) or providing quick student interactions (Moorhouse & Kohnke, 2020). In the qualitative study of attitudes towards Zoom (Paper 3, Chapter 6) students said that they wanted more engaging activities to stave off boredom and distraction. Students stated that enjoyment and making it fun were important to making the learning experience more engaging. Thus, cognitive engagement includes being absorbed, focused, and entertained to an extent that a user continues to engage with the material or activity. Cognitive engagement has been shown to strongly influence perceived usefulness (Kemp et al., 2022), as a result it is included in the hypothesised model upstream of perceived usefulness.

H5 Cognitive engagement positively influences perceived usefulness

Feedback

Traditionally, educators make students aware of the required standards and students' achievement, with students taking responsibility to close the gap (Boud & Molloy, 2012). However, Askew & Lodge (2000) described co-constructivist feedback as encompassing all dialogue that supports learning, which can occur during or outside of class between educator and students. In our qualitative review (authors, submitted) most students aligned with Askew and Lodge's concept, for example where feedback encompassed discussion over Zoom, and a closely related theme was interaction with the class as opposed to more formal treatments described by Sadler (1989) and Boud & Molloy (2012). Because such co-constructivist feedback supports students' perceptions of real-time learning, we hypothesised that feedback positively influences the perceived usefulness of virtual classrooms, and further that such feedback can be broadly characterised according to Askew & Lodge's interpretation depending on the research question or activity.

H6 Feedback positively influences perceived usefulness

Instructor Practice

Instructor practice encompasses general instructor characteristics and teaching paradigm (B. Lee et al., 2009; Arbaugh, 2002), instructor attitudes towards, and control of, the technology (H.A. Rajak et al., 2018; Selim, 2007), and the instructor's technological pedagogical content knowledge (Mishra & Koehler, 2006; Teo & Zhou, 2017). It can also include management of feedback and class cooperation (Krause et al., 2009), design of learning contents (H.A. Rajak et al., 2018; B. Lee et al., 2009) and content features (D. Y.

Lee & Lehto, 2013; Tran, 2016). As such, instructor practice encompasses the instructor's approach and method of teaching, including content, and also how the instructor manages the class and student behaviour. With the abundance of research pointing to the importance of all these factors, we hypothesised that effective instructor practice positively influences students' perceived usefulness of virtual classrooms.

H7 Instructor practice positively influences perceived usefulness

Class Interaction & Communication

Kemp et al. (2019) included a sub-class of instructional attributes called social interactivity, which encompassed learner-learner and instructor-learner interaction (Cheng, 2013) and collaboration (Yadegaridehkordi et al., 2019). These attributes describe all forms of interaction and communication and allow for class discussion (Selim, 2007) and the kind of feedback that Askew & Lodge (2000) described. Interaction and communication in virtual classrooms can to feelings of group membership (Luo et al., 2017) and suit students with different confidence and English levels (Ashton & Elliott, 2007). A predominant theme in our qualitative study (Paper 3, Chapter 6) was class interaction, including behaviour of peers in learning groups and breakout rooms. Thus, class interaction and communication can possibly overlap with the broader interpretation of feedback suggested by Askew & Lodge (2000), however, we do not presume to restrict researchers to this interpretation and leave class interaction and communication as separate to formal feedback in the model to aid broader application. Because of the research demonstrating the importance of class interaction and communication, we hypothesise that it positively influences students' perceived usefulness of virtual classrooms.

H8 Class interaction & communication positively influences perceived usefulness.

Access and Convenience

Sarver (1983) argued that a person's chosen path is blocked unless one has the opportunity to proceed. In the current context, it relates to the opportunity for a student to access learning. All other things being equal, virtual classrooms afford this opportunity of access when off-campus, or when the access is not at the same time as the live class (in the case of recordings). Selim (2007) demonstrated that system factors such as navigation, access and interface are critical factors to educational technology acceptance. While navigation and interface are system attributes, they enable satisfactory access to learning. In our qualitative study, access and convenience was the most highly mentioned theme by students (Paper 3, Chapter 6) however, there was little indication of whether access and convenience influenced perceived usefulness, perceived ease of use, or both. For this reason, we hypothesised that it has potential to influence both usefulness and ease of use.

H9 Access & convenience influences perceived usefulness

H10 Access & convenience influences perceived ease of use

System attributes

System attributes includes aspects of technology such as response and user control over learning activity (Martinez-Torres et al., 2008; Pituch & Lee, 2006), the user-friendliness of the interface layout (Eraslan Yalcin & Kutlu, 2019), system functionality (Cho et al., 2009) and internet connectivity and drop-outs (Selim, 2007). These attributes encapsulate how a system works as a technology, as opposed to its usefulness as a learning tool. In other recent research, students have also mentioned that such attributes as connectivity and response, audio, and video quality affect how easy it is to use Zoom as a learning tool (Paper 3, Chapter 6). System attributes of virtual reality was also shown to influence only perceived ease of use when perceived usefulness was tailored to learning

(Kemp et al., 2022), we therefore hypothesise that system attributes has an influence on ease of use in our proposed model.

H11 System attributes positively influences perceived ease of use

Self-efficacy

Self-efficacy has been conceptualised as 'a person's judgement of what one can do with whatever skills one possesses' (Bandura, 1986, p. 391) and so this concept is not about a user's actual skills, but their perception of them. Thus, self-efficacy is technology-dependent, including concepts such as computer self-efficacy (Teo, 2009b) and e-learning self-efficacy (Park, 2009), and a user may experience a sense of anxiety when contemplating using a technology in which they have low perceptions of self-efficacy (Venkatesh, 2000) or little experience. As such, the importance of self-efficacy in a model will depend on the experience a user has with a technology, and so the questionnaire that supports the model should be tailored to the technology being measured. Since self-efficacy is technology-dependent, we include it in the model and hypothesise that perceived self-efficacy influences perceived ease of use.

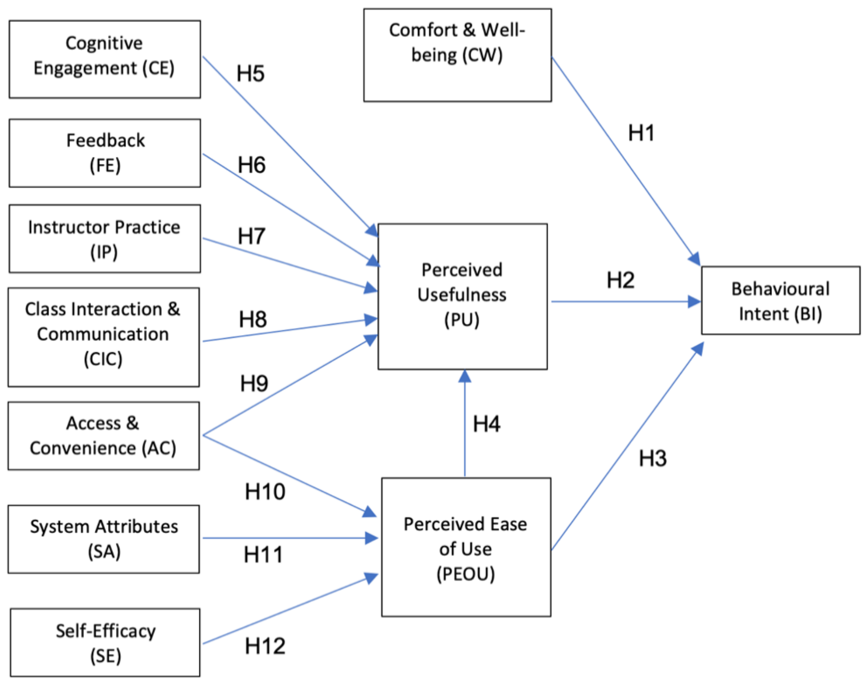
H12 Self-efficacy positively influences perceived ease of use

Hypothesised model

The theoretical and empirical research indicate a suitable hypothesised structural model includes the factors considered above and is presented in Figure 7.2.

Figure 7.2

Hypothesised Model



Methods

Construct operationalisation

Students were administered a voluntary questionnaire consisting of 46 question items, indicating their responses on a 5-point Likert scale for each question (1 = *Strongly disagree*; 5 = *Strongly agree*). Since the collection of constructs was novel, we drew on various research to collect and adapt questionnaire items. Items related to perceived usefulness, perceived ease of use and behavioural intent were adapted from Davis (1989) and Dečman (2015), cognitive engagement items from Liu et al., (2009), B.C. Lee et al., (2009) and Saade & Bahli (2005), feedback and system attributes items were adapted from Martinez-Torres et al., (2008), instructor practice from B.C. Lee et al., (2009), class interaction and communication from Cheng (2013) and Yadegaridehkordi et al., (2019) and self-efficacy items from Venkatesh et al., (2003). The comfort & well-being and access & convenience were new constructs suggested by prior qualitative research (Paper

3, Chapter 6) and were drafted for this study and subject to face validity by the research team.

Demographic data of the respondents

A total of 489 responses were received over second semester 2021 and first semester 2022 from students at two large Australian universities. Students from one of the universities received course credit for completing the questionnaire, and the study and treatment of results was given ethical approval by the relevant university ethics review committees. Exclusion of duplicate and incomplete responses resulted in a total of 427 valid responses. The breakdown in terms of age and gender is shown in Table 7.2.

Table 7.2

Personal Demographics of the Sampled Cohort

Age group	Female	Male	Non-binary	Prefer not to say	Totals
16-17	14	4	-	-	18
18-25	289	80	4	2	375
26-35	11	12	2		25
36+	8	-			8
Not specified	1				1
Totals	323	96	6	2	427

379 responses came from students who attended one university, 20 were from the other university, and 29 did not say. 402 students reported using Zoom only, 17 reported using Blackboard Collaborate only, 17 reported using both virtual classrooms, and three did not report which virtual classroom they used. 374 students were in 1st year, 44 students were in 2nd year, six in 3rd year, three in their 4th or greater year of undergraduate study, and one did not say. In terms of study major, 146 students listed Psychology, 76 listed

Physical and Mathematical Science, 67 Health and Medical Science, 48 Arts and Social Science, 16 Computer Science and IT, 10 Business and Law, and 40 did not say.

Analysis approach

Exploratory factor analysis was conducted on the four instructional attributes constructs (cognitive engagement, instructor practice, feedback, class interaction and communication) since they had not been used previously in this configuration that we were aware of. Thereafter, we verified the complete measurement model before proceeding to path analysis of the structural model (Anderson & Gerbing, 1988). The analyses were conducted using R version 3.6.0 (R Core Team, 2013) and RStudio version 1.2.1335 (RStudio Team, 2015). We chose diagonally weighted least squares (DWLS) to estimate the factors due to the ordinal nature of the data 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.

25% of the data (n = 100 rows) was randomly selected to perform the exploratory factor analysis using Horn’s parallel analysis method (Çokluk & Koçak, 2016) using a promax (oblique) rotation with a cut-off of 0.3 to inform the number of factors to extract. Confirmatory factor analysis and structural equation modelling were conducted on the remaining rows using diagonally-weighted least squares as the robust estimation method which incorporates the polychoric correlations necessary for ordinal data (Holgado–Tello et al., 2010; Li, 2016). Convergent and discriminant validity (Hair et al., 2010) were estimated along with fit indices (Hooper et al., 2008; R. B. Kline, 2015) using recommended cut-off values (Hu & Bentler, 1999).

Results

Exploratory factor analysis

The number of factors was estimated using Horn's parallel analysis method (Çokluk & Koçak, 2016) and was determined to be four factors, shown in Table 7.3. The item CIC4 did not adequately load onto its factor and so was excluded. Otherwise, the four instructional attributes factors were confirmed as hypothesised (Figure 7.2). The associated scree plot is shown in Figure 7.3.

Figure 7.3

Scree Plot from the Exploratory Factor Analysis Showing Inflection After Four Factors

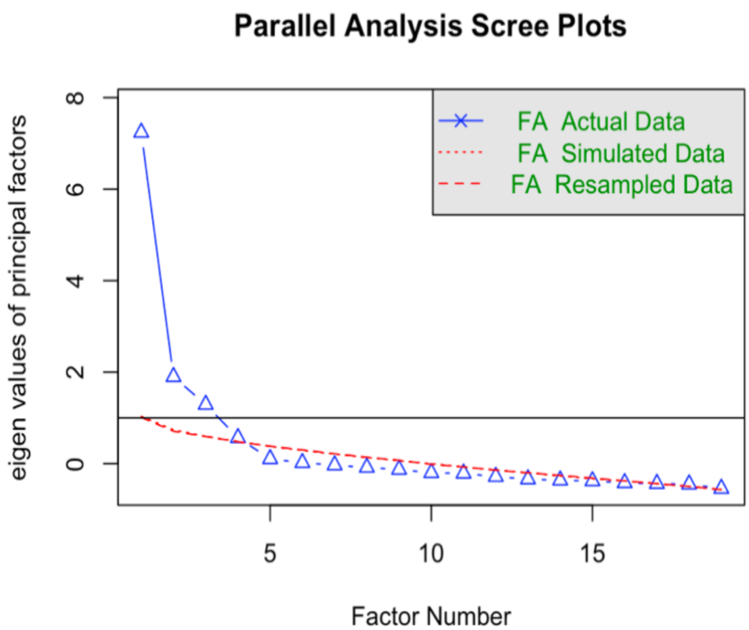


Table 7.3

Pattern Matrix from the Exploratory Factor Analysis, Cut-off = 0.4

Item	Class Interaction and Communication	Cognitive Engagement	Instructor Practice	Feedback
Proportional variance %	0.209	0.144	0.128	0.127
Cumulative variance %	0.209	0.353	0.481	0.608
CE1		0.837		
CE2		0.856		
CE3		0.764		
CE4		0.608		
FE1				0.671
FE2				0.706
FE3				0.814
FE4				0.753
IP1			0.641	
IP2			0.810	
IP3			0.841	
IP4			0.599	
CIC1	0.760			
CIC2	0.842			
CIC3	0.916			
CIC4				
CIC5	0.705			
CIC6	0.666			
CIC7	0.796			

Note. CE = cognitive engagement, FE = Feedback, IP = Instructor practice, CIC = Class interaction and communication. Specific items are listed in Appendix A.

Confirmatory factor analysis and structural equation modelling

The initial run of the CFA showed that an item from comfort and well-being (CW2), and two items from self-efficacy (SE1 and SE2) were below the 0.6 threshold for factor loading (Hair et al., 2010), so were excluded, and the CFA was re-run. Table 7.4 shows the factor loadings, composite reliability and average variance extracted of the resultant measurement model.

Table 7.4

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	0.864	0.91	0.71
	PU2	0.842		
	PU3	0.826		
	PU4	0.840		
Perceived ease of use (PEOU)	PE1	0.837	0.87	0.62
	PE2	0.686		
	PE3	0.819		
	PE4	0.802		
Comfort and Well-being (CW)	CW1	0.836	0.85	0.65
	CW3	0.851		
	CW4	0.720		
Cognitive engagement (CE)	CE1	0.718	0.89	0.67
	CE2	0.815		
	CE3	0.847		
	CE4	0.877		
Instructor Practice (IP)	IP1	0.683	0.83	0.55
	IP2	0.883		
	IP3	0.670		

	IP4	0.716		
Feedback (FE)	FE1	0.652	0.85	0.59
	FE2	0.928		
	FE3	0.835		
	FE4	0.629		
Class Interaction and Communication (CIC)	CIC1	0.783	0.93	0.67
	CIC2	0.832		
	CIC3	0.847		
	CIC5	0.824		
	CIC6	0.824		
	CIC7	0.815		
Access and Convenience (AC)	AC1	0.754	0.84	0.57
	AC2	0.797		
	AC3	0.791		
	AC4	0.679		
Self-Efficacy (SE)	SE3	0.814	0.85	0.75
	SE4	0.910		
System Attributes (SA)	SA1	0.743	0.79	0.48
	SA2	0.667		
	SA3	0.707		
	SA4	0.662		

Table 7.4 indicated that the average variance extracted by system attributes construct was slightly less than the ideal threshold 0.50; this is likely due to two of the indicators loading in the 0.66-0.67 range. Fornell and Larker (1981) found this to be an acceptable situation when the composite reliability is high and above its threshold, which is the case here. Seeing as the construct's AVE was only slightly less than the recommended threshold, the reliability was high, and it theoretically made sense, we retained the system attributes construct in the model. Table 7.5 shows the discriminant validity of the measurement model.

Table 7.5

Discriminant Validities of the Measurement Model

	PU	PE	CE	FE	IP	CIC	CW	AC	SA	SE
PU	**0.84**									
PE	0.59	**0.79**								
CE	0.85	0.45	**0.82**							
FE	0.64	0.52	0.59	**0.77**						
IP	0.39	0.53	0.26	0.57	**0.74**					
CIC	0.48	0.36	0.50	0.42	0.41	**0.82**				
CW	0.72	0.42	0.77	0.45	0.18	0.45	**0.80**			
AC	0.60	0.56	0.34	0.44	0.43	0.28	0.47	**0.76**		
SA	0.80	0.72	0.68	0.72	0.61	0.42	0.67	0.79	**0.70**	
SE	0.28	0.60	0.10	0.23	0.44	0.28	0.08	0.51	0.41	**0.86**

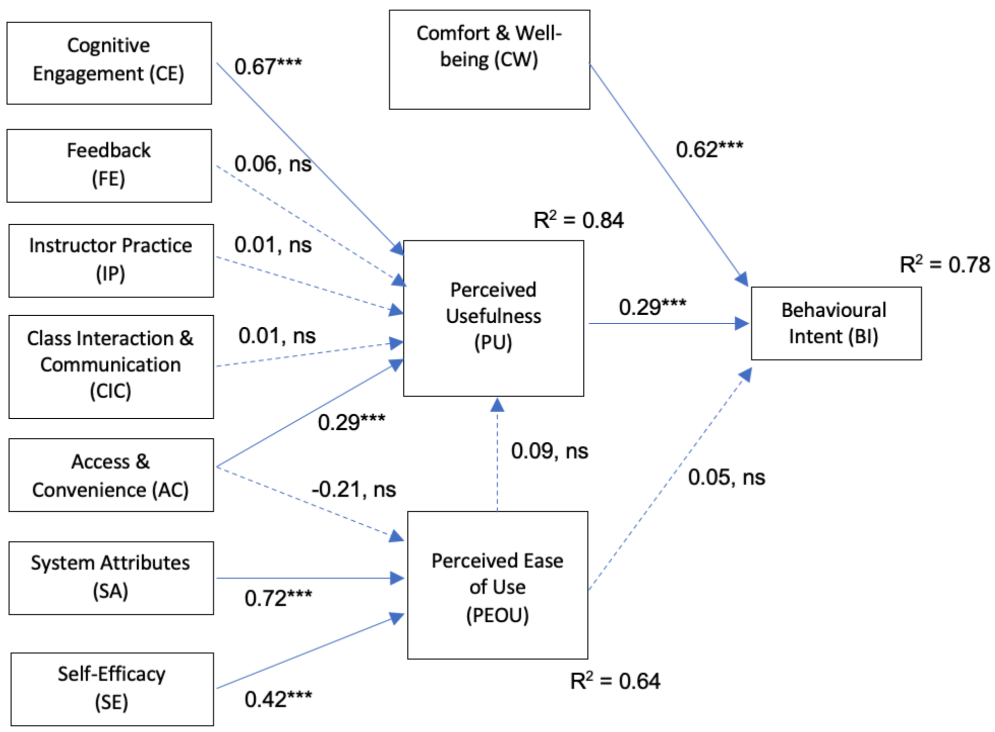
Note. Square root of the average variance extracted on the diagonal, correlations on the off diagonal. PU = perceived usefulness, PE = perceived ease of use, CE = cognitive engagement, FE = feedback, IP = instructor practice, CIC = class interaction and communication, CW = comfort & well-being, AC = access and convenience, SA = system attributes, SE = self-efficacy.

Table 7.5 shows the discriminant validity of the measurement model, which demonstrated that perceived usefulness and cognitive engagement were possibly congruous. This is a similar result as that seen in a study of the educational compatibility of virtual reality (Kemp et al., 2022). This pattern may indicate that students believe that cognitive engagement makes a learning technology useful. However, these results alone do not warrant sufficient justification to alter Davis' core perceived usefulness factor, and it may instead indicate factor specification requires further attention. Table 7.5 also showed that access and convenience was not discriminant from system attributes. A possible explanation is that convenient access to learning is seen as a system attribute by students, a result that may be tested in a future study. However, because access and convenience was a prominent unique theme in Paper 3 (Chapter 6) it was justified to keep it as a separate construct to observe its behaviour.

The structural equation model was analysed using the measurement model indicated by Tables 7.4 and 7.5 and shown in Figure 7.4.

Figure 7.4

Structural Equation Model Results



Note. *** = $p < 0.001$; ns = not significant. While the path from access and convenience to perceived ease of use was insignificant, it was marginally so with p = 0.052.

The results showed that comfort and well-being strongly influenced students' intent to use the virtual classroom, and that comfort and well-being and perceived usefulness together explained 78% of the variance of intent. Of the four instructional attributes, only cognitive engagement showed any significant influence on perceived usefulness. Cognitive engagement and access and convenience explained 84% of variance of perceived usefulness highlighting the importance of these two factors. Feedback, instructor practice and class interaction and communication all showed no significant effect on perceived usefulness. Access and convenience showed a moderate influence on usefulness, but not to ease of use. Perceived ease of use was influenced strongly by system attributes and moderately by self-efficacy with 64% of its variance explained. Lastly, perceived ease of use did not influence perceived usefulness or behavioural intent. The goodness of fit statistics are shown in Table 7.6 and the summary of the hypotheses results is shown in Table 7.7.

Table 7.6

Goodness of Fit Statistics

Fit Category	Name of Index	Level of Acceptance	Value
Absolute fit	χ^2, df, p	$p > 0.05$	1837.564, df=779, p = 0.000
	RMSEA	< 0.06	0.057 (0.054 – 0.060)
Incremental fit	CFI	> 0.9	0.959
	TLI	> 0.95	0.954
	SRMR	< 0.08	0.062
Parsimonious fit	χ^2/df	< 3	2.36

Note. Acceptance thresholds are referenced from Hooper et al. (2008), Hu and Bentler (1999) and R. B. Kline (2015).

Table 7.7

Summary of Hypotheses

Number	Description	Result
H1	Comfort & well-being positively, and directly, influences behavioural intent	Supported
H2	Perceived usefulness positively influences behavioural intent	Supported
H3	Perceived ease of use positively influences behavioural intent	Not supported
H4	Perceived ease of use positively influences perceived usefulness	Not supported
H5	Cognitive engagement positively influences perceived usefulness	Supported
H6	Feedback positively influences perceived usefulness	Not supported
H7	Instructor practice positively influences perceived usefulness	Not supported
H8	Class interaction & communication positively influences perceived usefulness	Not supported
H9	Access & convenience influences perceived usefulness	Supported
H10	Access & convenience influences perceived ease of use	Not supported
H11	System attributes positively influences perceived ease of use	Supported

H12	Self-efficacy positively influences perceived ease of use	Supported

Discussion

Comfort and well-being

The effect of comfort and well-being was a stand-out feature of these results, exhibiting a strong 0.62 standardised loading onto behavioural intent. This factor was included based on the results of the qualitative student survey which indicated that many students preferred face-to-face teaching environments and that prolonged use of virtual classrooms can impact health. This result reflected student preferences for being around others in the learning environment, and their health and well-being influences their intention to use a virtual classroom. Considering the generalisability of this construct, it is envisaged that it would be relevant for technologies that have potential to impact a person's psychological, mental or physical balance and health, for example, virtual environments, simulations, or technologies designed to connect people.

Instructional attributes

The exploratory factor analysis of the instructional attributes factors confirmed the hypothesised structure where cognitive engagement, feedback, instructor practice and class interaction and communication were distinct factors. This result supported the inclusions of these factors within the taxonomy of Kemp et al. (2019), and the findings of the qualitative study where these factors were voluntarily offered by students (Paper 3, Chapter 6).

The exploratory factor analysis confirmed the nature of the factors, but surprisingly the structural model indicated that feedback, instructor practice and class interaction and communication did not have statistically significant influence on perceived usefulness. This contradicted other research highlighting the importance of these factors (Cheng, 2013;

H.A. Rajak et al., 2018; Lee et al., 2009; Tobing et al., 2008; Yadegaridehkordi et al., 2019). Possible explanations include that the sample size was insufficient, or that the analysis did not pick up strong and coherent patterns in the responses. The research was conducted across two universities with no standardisation of learning experience, possibly contributing to the heterogenous nature of responses. Additionally, the demographic data indicated that students were studying a variety of majors implying variations in their learning experiences. The inconsistent nature of student learning experiences likely resulted in an incoherent picture that was reflected in the statistical results. Despite these findings, we believe that feedback, instructor practice or class interaction and communication remain important, but that these factors were not sufficiently controlled to allow a coherent picture to emerge in this analysis.

General considerations

Cognitive engagement exhibited the highest path loading of the model at 0.67 onto perceived usefulness which is unsurprising considering the high correlation between the two (Table 7.5). A similar result is seen in Kemp et al. (2022). These results imply that students associate cognitive engagement with usefulness. In the current study, cognitive engagement and access and convenience accounted for 84% of the variance of perceived usefulness, which is a relatively high figure (see Peterson, 2000). It also appears that a lot of the variance explained of usefulness comes from cognitive engagement. This finding is intuitive when concerning educational technologies, seeing as engagement leads to student achievement and satisfaction (Janssen et al., 2016; Makransky & Lilleholt, 2018; Parong & Mayer, 2018).

Access and convenience showed a moderate influence on perceived usefulness, but not on perceived ease of use, indicating that students see that one of the uses of virtual classrooms is to provide access to learning. However, students did not feel that access to learning made it easier to use. Thus, the results provided statistical indication that access is associated with perceived usefulness but not perceived ease of use. Because the relationship between access and ease of use was not affected by different learning experiences of students (for example, different subjects and instructors), we concluded that this was a bona fide result, and it is not needed to include this relationship in the model going forward.

Ease of use was influenced by system attributes and self-efficacy and measured 64% of variance, implying that there may be other unaccounted for factors. Notably, perceived ease of use had no significant influence on perceived usefulness, mirroring the result from Sheppard and Vibert (2019). It is possible that this relationship between perceived ease of use and perceived usefulness might not be always relevant. This might indicate that nowadays peoples' experience with information systems is enough that ease of use no longer impacts a user's sense of usefulness.

Final model performance

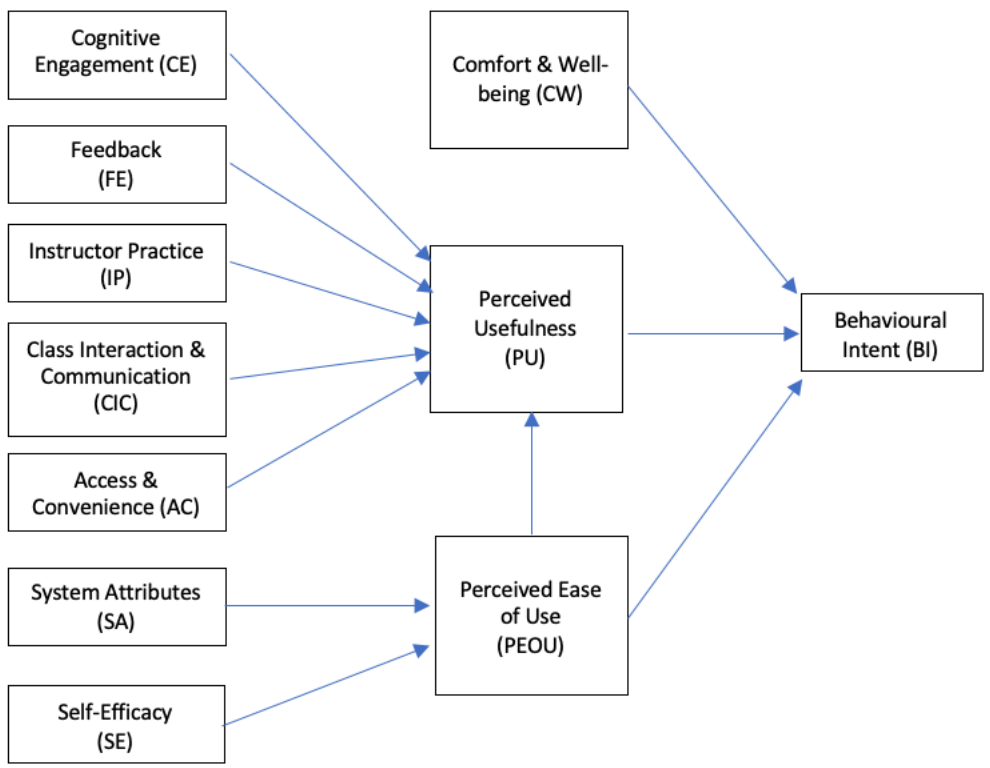
This model includes Davis' central constructs of usefulness, ease of use and intent, while omitting attitude. It extends Davis' TAM in two important ways that other models do not: firstly, by including instructional attributes important to learning and teaching, and secondly by inclusion of comfort and well-being.

The model accounted for 78% of variance of behavioural intent which is quite high and suggests that the model accounts for most influences on a student's intent to use virtual classrooms. If feedback, instructor practice and class interaction & communication were significant for this cohort the model's explained variance may increase further, although this requires testing. The goodness of fit statistics inferred that the model was able to replicate the population sufficiently well. The measurement model showed good reliability but only moderate average variance extracted in the range of 0.48-0.71, which may indicate that the questionnaire items require tightening. The discriminant matrix showed that cognitive engagement and perceived usefulness were not discriminant for this cohort, and this deserves closer attention in terms of construct operationalisation. If it persists in future research, it may support the idea that students associate cognitive engagement with usefulness of a technology.

The model's explained variance and fit led us to conclude that it is an adequate model for further use. Despite the associations of feedback, instructor practice and class interaction & communication failing to achieve significance, we submit that the final model retain these instructional attributes factors for reasons made clear in the discussion. Based on these considerations, a final suggested extended educational technology acceptance model (EETAM) is provided in Figure 7.5.

Figure 7.5

The Proposed Extended Educational Technology Acceptance Model (EETAM)



Conclusion

The research aimed to develop and test an extended educational technology acceptance model (EETAM) using exploratory factor analysis, confirmatory factor analysis, and structural equation modelling, drawing on prior research to inform and refine the model. The final model includes a new factor called comfort and well-being and accounted for 78% of behavioural intent to use virtual classrooms. While three of the instructional attributes constructs did not associate as anticipated, this was interpreted as a sign of the disparate learning environments and activities of respondents. Further testing in other settings and under controlled conditions is suggested to explore the model's behaviour as a comprehensive and parsimonious educational technology acceptance model.

Appendix A

Survey Instrument

Item code	Item text
Perceived Usefulness (PU)	
PU1	Using virtual classrooms helps me learn more quickly
PU2	Learning using virtual classrooms enables my achievement of learning goals
PU3	Virtual classrooms make my learning easier
PU4	Virtual classrooms are useful for my learning
Perceived Ease of Use (PE)	
PE1	I think it is easy to use virtual classrooms
PE2	I think it is easy to learn how to use virtual classrooms
PE3	I think using virtual classrooms is clear and understandable
PE4	I think it is easy to become skilful at using virtual classrooms
Cognitive Engagement (CE)	
CE1	Using virtual classrooms is fun
CE2	Using virtual classrooms makes learning more interesting
CE3	Virtual classrooms allow me to focus more intensely on a learning task
CE4	I become absorbed in learning when using virtual classrooms
Feedback (FE)	
FE1	Feedback I get through virtual classrooms is given in a timely manner

FE2	The feedback I get from virtual classrooms encourages me to continue using it
FE3	The feedback provided by virtual classrooms is useful
FE4	I am able to access feedback through virtual classrooms easily
Instructor Practice (IP)	
IP1	My instructor is skilled at using virtual classrooms
IP2	My instructor’s use of virtual classrooms aligns well with the rest of the course
IP3	My instructor provides instruction or guidance on what I should do in virtual classrooms
IP4	The amount of content my instructor delivers via virtual classrooms is appropriate
Class Interaction & Collaboration (CIC)	
CIC1	I can establish personal contact with other learners in virtual classrooms
CIC2	I can exchange knowledge with other learners in virtual classrooms
CIC3	I can learn in groups and cooperate with other learners in virtual classrooms
CIC4	Learning works best with other learners in virtual classrooms
CIC5	Interaction with others is easy in virtual classrooms
CIC6	I can communicate with others when I use virtual classrooms
CIC7	I can collaborate with others using virtual classrooms
Comfort and Well-being (CW)	
CW1	I am comfortable with the lack of in-person interaction in virtual classrooms
CW2	I get aches in my eyes, head, neck or back when using virtual classrooms [R]
CW3	I prefer learning in person instead of through virtual classrooms [R]
CW4	Using virtual classrooms feels socially isolating [R]
Access & Convenience (AC)	
AC1	Virtual classrooms offer flexibility in learning as to time and place
AC2	Virtual classrooms allow me to access learning material when I choose
AC3	Virtual classrooms allow me to take part in learning activities where I choose
AC4	Using virtual classrooms makes learning inconvenient [R]
System Attributes (SA)	
SA1	The general quality of the virtual classroom experience is high
SA2	Virtual classrooms allow me to control the rhythm of my learning activities
SA3	I think virtual classrooms are reliable technologies
SA4	When using virtual classrooms the system response is fast
Self-Efficacy (SE)	
SE1	My technical abilities make me feel apprehensive about using virtual classrooms [R]
SE2	Technically, virtual classrooms are somewhat intimidating for me [R]
SE3	I am confident in using virtual classrooms even if there is no one around to show me how to do it
SE4	I am confident in using virtual classrooms even if I have only online instructions for reference

Behavioural Intent (BI)	
BI1	Given the choice, I will use virtual classrooms for my learning
BI2	Given the choice, I will use virtual classrooms in the next semester
BI3	Given the choice, I plan to use virtual classrooms frequently for my learning

7.4 Postamble

As discussed in the chapter, the EETAM model was demonstrated to be statistically sound as measured by its fit statistics, meaning that there is high confidence that it is able to reproduce population data. However, not all of the model's paths were statistically significant and this required consideration as to the integrity of the model.

With the insignificance of paths associated with feedback, instructor practice, and class interaction and communication it is a legitimate question to ask is if they should be retained within the model. Firstly, this was a confirmatory technology acceptance model and as such was constructed as a result of research that informed its included factors. In this case, there was qualitative (Askew & Lodge, 2000; Y. M. Cheng, 2013; Kemp et al., 2019; Mishra & Koehler, 2006; Yadegaridehkordi et al., 2019; Chapter 6 (Paper 3)) and quantitative (Binyamin et al., 2019; Chung & Ackerman, 2015; H. M. Huang & Liaw, 2018; Ros et al., 2015) evidence to support the inclusion of these particular factors, providing solid basis for their inclusion as relevant influencers of attitude and behaviour.

Despite such theoretical support, it is foreseeable that a factor's path will not demonstrate significance if it is not relevant to the respondents of a particular study, or if the respondents perceive varied experience vis-à-vis that hypothesised relationship. This can be seen, for example, in Abdullah et al. (2016) where there was no significant path between experience and perceived usefulness, and subjective norms and perceived usefulness, despite prior theoretical, and experimental (Abdullah & Ward, 2016), support. Another example is found in Paper 2 (Chapter 5) where cognitive engagement's association with perceived usefulness was non-significant (Figure 5.5) despite it being significant with different data (Figure 5.4). Furthermore, both Figures 5.4 and 5.5 failed to reproduce Davis' (1986) theoretical relationship between perceived ease of use and perceived usefulness, however this did not constitute grounds to remove that path from Davis' model. These few examples serve to show that different data will result in different path relationships depending on the data. The data simply relay what is occurring in the real world, in this case, a heterogenous student experience vis-à-vis these factors. Thus, "the same model applied in different settings will yield different results, and therefore, inform different practice implications" (p.33 this thesis). On this basis alone, statistical insignificance of the path relationships in one setting do not merit their removal from the model if there is no corresponding theoretical support. Instead, it is simply a sign that the relationships were not relevant for this cohort of students, and therefore acted as a possible diagnostic vis-à-vis the learning environment.

There are therefore two strong reasons to retain the factors within the model: theoretical support, and an indication that these factors reflected a heterogenous student experience, which would change from cohort to cohort. As such, the model is presented in its entirety. It is up to researchers if any of the model's factors should be omitted from the before deployment in their particular setting, or, if one or more paths do not achieve significance, then it could be considered as indication that the associations in question were not apparent for their cohort.

Based on the research included and considered in this thesis, the final model (Figure 7.8) has emerged which has performed well under real-world conditions and addressed the following research aims, objectives and hypotheses:

Research Aim 1: To construct a comprehensive technology acceptance model suited to education, and investigate:

(a) Whether its education-specific constructs improve its power when applied to educational technologies, and

(b) If it can explain the majority of variance of intent to use such technologies.

Research Objective 2: To form a comprehensive, yet parsimonious, structural model that researchers can use to measure attitudes and intentions in a wide variety of educational settings.

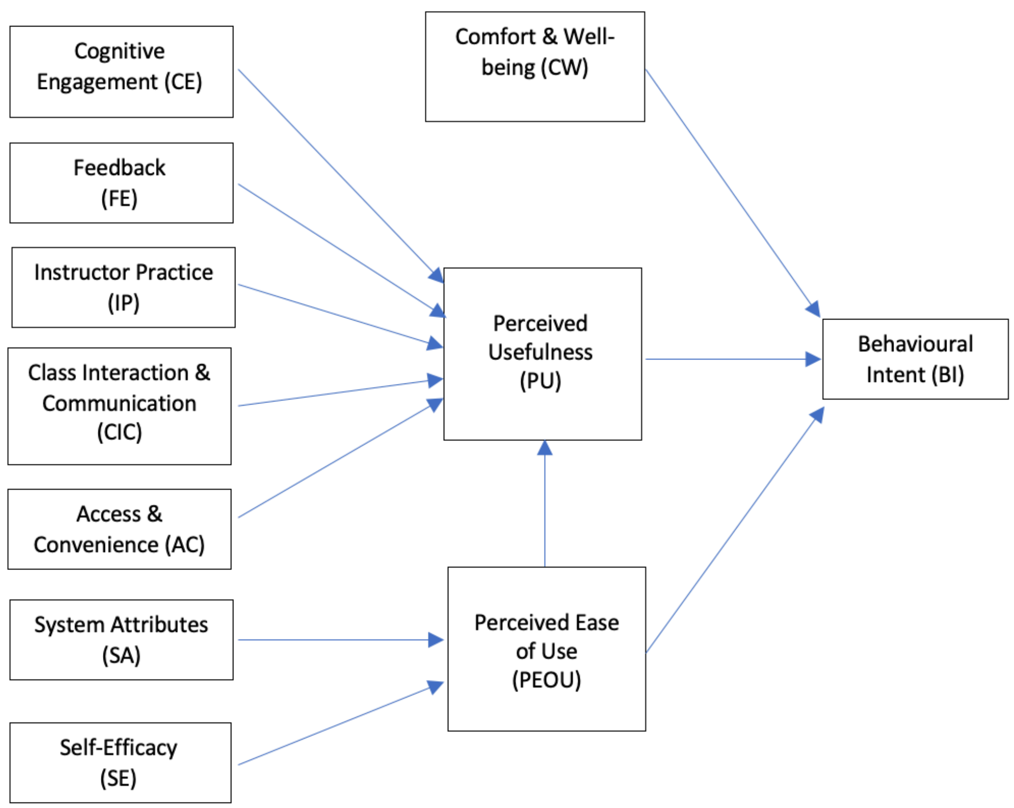
Research Objective 3: To test this model in a real-world educational setting.

Research Hypothesis 1: A suitably constructed and relevant model will explain a majority of the variation of intention to use an educational technology (> 60%).

Research Hypothesis 2: The inclusion of constructs specific to educational technology and learning will increase the overall power of the model when applied to an educational technology.

Figure 7.6

The Extended Educational Technology Acceptance Model (EETAM)



CHAPTER 8 – THE EFFECT OF INSTRUCTIONAL ATTRIBUTES

8.1 Introduction

One main reason for developing a technology acceptance model specifically suited to educational technologies is the belief that it will more adequately measure users' attitudes and intentions compared to other general models that do not include constructs directly related to learning and teaching. For this reason, this doctoral project included the following research aim and hypothesis:

- Research aim 2(a): To investigate whether its education-specific constructs improve its power when applied to educational technologies.
- Hypothesis 2: The inclusion of constructs specific to educational technology and learning will increase the overall power of the model when applied to an educational technology.

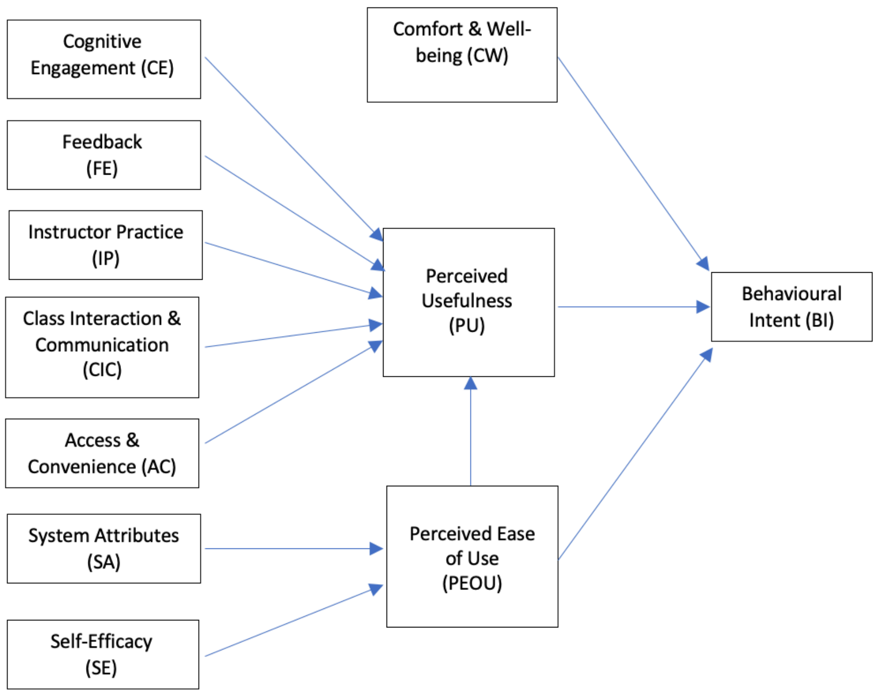
A full treatment of this question was beyond the scope and purpose of Paper 4 (Chapter 7), and so it is addressed in this chapter.

To achieve the research aim and answer the hypothesis it was necessary to compare two models using identical data and analysis technique. The full model includes all of the educational constructs and relationships that are apparent in the final model in Paper 4 (Chapter 7) and which is shown in Figure 8.1 (the EETAM), and a general model that excludes the four related to education: cognitive engagement, feedback, instructor practice, and class interaction and communication.

Since the analysis technique and model workup have been addressed in previous chapters, only the comparison will be addressed here.

Figure 8.1

The Extended Educational Technology Acceptance Model (EETAM)



8.2 Methods

The demographics, data and model for this investigation are identical to those used for Paper 4 (Chapter 7). Ordinarily, diagonally weighted least squares would be best to estimate the factors owing to the ordinal nature of the data, however, the general model (without the educational constructs) failed to converge using this method. As a way forward, It was possible to compare the models using Maximum Likelihood (ML) estimation, however it was known that ML estimation can distort results (Coenders & Saris, 1995). To test whether ML estimation would permit an acceptable comparison the EETAM model was estimated using both DWLS and ML methods and the results compared (see Appendix 8.A). It was found that the majority of parameters were consistently and generally underestimated by ML. This was consistent with the results from Appendix A, which conducted the same comparison but on the model from Chapter 5 (Paper 2). Since both the EETAM and general models converged successfully using ML, and the caveat of global underestimation effects when estimating using ML was understood, and moreover all other aspects of the comparison were equivalent, both models were compared using ML in order to continue with the comparison.

8.3 Results

Table 8.1 provides the comparison of the reliabilities, factor loadings and average variance extracted for both models. Tables 8.2 and 8.3 provide the discriminant validities of both models. Figures 8.2 and 8.3 show the differences between the two structural modelling and Table 8.4 provides the comparison of goodness of fit.

Table 8.1

Reliabilities and Average Variance Extracted of the EETAM and General Measurement Models

Construct	Item	Factor loading (> 0.60) EETAM / General	Composite reliability (> 0.70) EETAM / General	Average variance extracted (> 0.50) EETAM / General
Perceived usefulness (PU)	PU1	0.809 / 0.780	0.88 / 0.88	0.64 / 0.64
	PU2	0.798 / 0.811		
	PU3	0.795 / 0.797		
	PU4	0.787 / 0.806		
Perceived ease of use (PEOU)	PE1	0.725 / 0.726	0.79 / 0.78	0.48 / 0.48
	PE2	0.638 / 0.625		
	PE3	0.760 / 0.754		
	PE4	0.654 / 0.649		
Comfort and Well-being (CW)	CW1	0.725 / 0.768	0.79 / 0.79	0.55 / 0.56
	CW3	0.797 / 0.755		
	CW4	0.710 / 0.716		
Cognitive engagement (CE)	CE1	0.543 / NA	0.82 / NA	0.77 / NA
	CE2	0.698 / NA		
	CE3	0.816 / NA		

	CE4	0.851 / NA		
Instructor Practice (IP)	IP1	0.681 / NA	0.76 / NA	0.44 / NA
	IP2	0.809 / NA		
	IP3	0.591 / NA		
	IP4	0.558 / NA		
Feedback (FE)	FE1	0.633 / NA	0.78 / NA	0.48 / NA
	FE2	0.803 / NA		
	FE3	0.777 / NA		
	FE4	0.504 / NA		
Class Interaction and Communication (CIC)	CIC1	0.712 / NA	0.89 / NA	0.57 / NA
	CIC2	0.822 / NA		
	CIC3	0.807 / NA		
	CIC5	0.698 / NA		
	CIC6	0.752 / NA		
	CIC7	0.746 / NA		
Access and Convenience (AC)	AC1	0.668 / 0.663	0.74 / 0.74	0.43 / 0.42
	AC2	0.744 / 0.732		
	AC3	0.735 / 0.721		
	AC4	0.420 / 0.444		
Self-Efficacy (SE)	SE3	0.753 / 0.795	0.79 / 0.78	0.66 / 0.64
	SE4	0.863 / 0.803		
System Attributes (SA)	SA1	0.655 / 0.634	0.73 / 0.74	0.41 / 0.42
	SA2	0.616 / 0.627		
	SA3	0.663 / 0.707		
	SA4	0.610 / 0.623		

Note. All loadings were significant at the $p < 0.001$ level. Figures are indicative only since the data are treated as continuous.

Table 8.2

Discriminant Validities of the EETAM Measurement Model

	PU	PE	CE	FE	IP	CIC	CW	AC	SA	SE
PU	**0.80**									
PE	0.54	**0.70**								
CE	0.85	0.39	**0.74**							
FE	0.59	0.43	0.54	**0.69**						
IP	0.32	0.41	0.15	0.52	**0.67**					
CIC	0.49	0.32	0.44	0.38	0.32	**0.76**				
CW	0.71	0.40	0.79	0.43	0.13	0.45	**0.74**			
AC	0.45	0.46	0.25	0.36	0.34	0.22	0.30	**0.66**		
SA	0.73	0.66	0.64	0.68	0.57	0.42	0.64	0.68	**0.64**	
SE	0.28	0.53	0.13	0.20	0.32	0.30	0.18	0.45	0.42	**0.81**

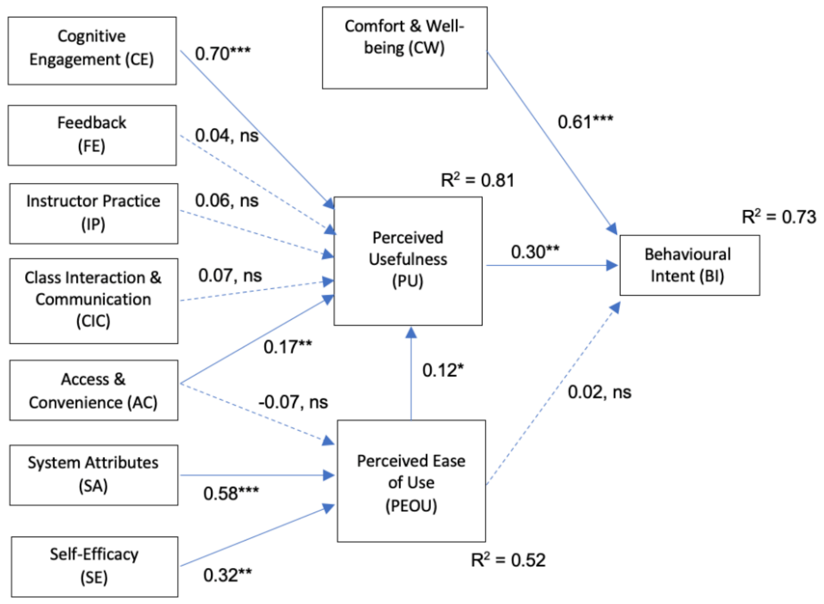
Table 8.3

Discriminant Validities of the General Measurement Model

	PU	PE	CW	AC	SA	SE
PU	**0.80**					
PE	0.59	**0.69**				
CW	0.29	0.40	**0.75**			
AC	0.51	0.47	0.36	**0.65**		
SA	0.50	0.65	0.64	0.70	**0.65**	
SE	0.39	0.56	0.21	0.45	0.43	**0.80**

Figure 8.2

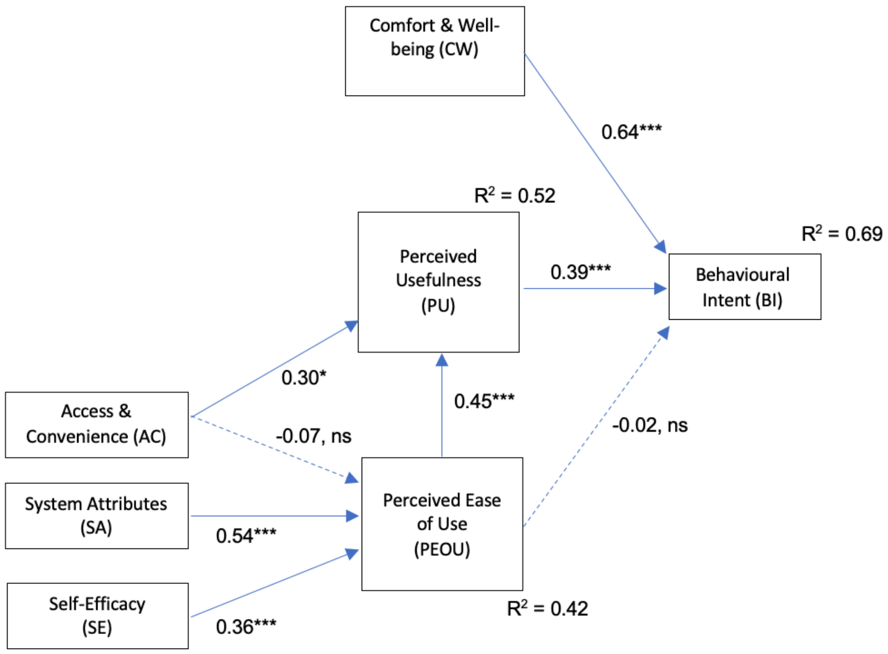
EETAM Structural Model



Note: * = (p<0.05), ** = (p<0.01), *** = (p<0.001).

Figure 8.3

General Structural Model



Note: * = (p<0.05), ** = (p<0.01), *** = (p<0.001).

Table 8.4

Goodness of Fit Statistics of the EETAM and General Models

Fit Category	Name of Index	Level of Acceptance	Value (EETAM / General)
Absolute fit	χ^2, df, p	$p > 0.05$	1460.706, df = 779, p = 0.000 / 608.055, df = 261, p = 0.000
	RMSEA	< 0.06	0.054 (0.050 – 0.058) / 0.067 (0.60 – 0.74)
Incremental fit	CFI	> 0.9	0.898 / 0.907
	TLI	> 0.95	0.887 / 0.893
	SRMR	< 0.08	0.065 / 0.095
Parsimonious fit	χ^2/df	< 3	1.87 / 2.33

Note. Threshold values are taken from Hooper et al. (2008), Hu & Bentler (1999) and R. B. Kline (2015).

Table 8.5 shows a comparison of the variance explained between the two models.

Table 8.5

Comparison of Total Variance Explained (R^2) of the Endogenous Variables

	EETAM model	General model
Behavioural intent	0.73	0.69
Perceived usefulness	0.81	0.52
Perceived ease of use	0.52	0.42

Note: EETAM = Extended educational technology acceptance model, which includes the instructional attributes.

8.4 Discussion

Estimation method

The first point to address is the estimation method used to calculate the loadings of items onto factors, and loadings between factors within the structural model. It was necessary to use robust maximum likelihood with robust standard error calculation instead of the recommended diagonally weighted least squares (Holgado–Tello et al., 2010) to achieve general model convergence. This may be due to the fact that the model became mis-specified when the instructional attributes were removed (Yang-Wallentin et al., 2010), meaning the population model was unable to adequately reproduce the data. One interpretation is that cognitive engagement drives most of the influence of perceived usefulness (due to collinearity observed in Paper 4, Chapter 7), and so without that influence, perceived usefulness is less important, destroying most of the model's influence. In support of this interpretation, Table 8.2 shows that perceived usefulness and cognitive engagement were not discriminant, which was also seen in Paper 4 (Chapter 7).

Even though the optimal estimation method was not able to be applied, the same estimation method was applied to both models, the only change being the inclusion or not of the factors relating to education. The application of a sub-optimal estimation method influenced the values of loadings and fit statistics, an effect which is demonstrated by Appendix C which shows that use of the maximum likelihood estimator can distort findings when used against ordinal data. However, the consequences of this are diminished by use of the robust version of the method and equalised by use of the same technique on both models. Since the only aim was to compare the effect of exclusion of certain factors across two models under the same conditions, not to derive a real-world solution of a single model in a particular context, the influences of the estimation method on the results can be viewed as having been controlled for, allowing this project to meet research aim

2(a) and test hypothesis 2. In other words, while the specific loading values are distorted, the effect of excluding certain factors is nonetheless apparent in the comparison.

Effects on model power

Germane to this discussion is the effect of removal of the instructional attributes on the power of the model. Figures 8.2 and 8.3 and Table 8.5 show that the effect of including instructional attributes is to increase the variance explained of behavioural intent, perceived usefulness, and perceived ease of use. The effect is strongest on perceived usefulness, increasing it from 0.52 to 0.81. The variance explained of behavioural intent increases from 0.69 to 0.73 when instructional attributes are included. This is a small amount and likely due to the small factor loading between perceived usefulness and behavioural intent. It is likely that the effect would be larger in models where the loading between perceived usefulness and behavioural intent were larger, which is generally the case in TAM models. In the EETAM, the inclusion of comfort and well-being probably took a lot of power away from perceived usefulness, as demonstrated by its much higher factor loading.

Effect of instructional attributes

The non-significance of feedback, instructor practice and class interaction & communication was unexpected. Were the loadings of these factors onto perceived usefulness significant, it is possible that perceived usefulness would become stronger in the model and have a higher loading onto behavioural intent, and that therefore the change of variance explained by including these constructs could be higher, however this requires testing. In Paper 4 (Chapter7) it was concluded that the heterogeneity of the teaching and learning experiences of respondents contributed to the non-significance of these three factors, and so by re-applying the model in a controlled teaching environment this assumption can be tested.

Without the influence of feedback, instructor practice and class interaction & communication the comparison rests on the effects of cognitive engagement. Inclusion of cognitive engagement into the model has increased the variance explained of behavioural intent, perceived usefulness, and perceived ease of use to varying degrees. As discussed in Paper 4 (Chapter 7), cognitive engagement is not exclusive to learning but is fundamental to learning effectiveness, and so these results support the hypothesis that instructional attributes improve the power of the model, however further testing is required to provide further support.

Table 8.6 shows how the results relate to the relevant research aim and hypothesis.

Table 8.6

Relation of the Results to the Research Aim and Hypothesis

	EETAM model	General model
Research aim 2(a): To investigate whether its education-specific constructs improve its power when applied to educational technologies.	Met	Met
Hypothesis 2: The inclusion of constructs specific to educational technology and learning will increase the overall power of the model when applied to an educational technology.	Supported but more testing is required	N/A

Note. EETAM = Extended Educational Technology Acceptance Model

8.5 Conclusion

A comparison of the Extended Educational Technology Acceptance Model and a general model was conducted to test whether inclusion of four instructional attributes (cognitive engagement, feedback, instructor practice and class interaction & communication) resulted in the model power improving when applied to an educational technology, in this case virtual classrooms. This comparison directly addresses research aim 2(a) and hypothesis 2. The results showed that inclusion of cognitive engagement marginally improved the power of the overall model, and markedly improved the variance explained of perceived usefulness of virtual classrooms. Feedback, instructor practice and class interaction & communication were ineffectual due to their non-significant loadings onto perceived usefulness. The findings support that inclusion of constructs specific to educational technology and learning will increase the overall power of the model when applied to an educational technology (hypothesis 2), however, further study in a controlled teaching environment is recommended to investigate the effects of inclusion of feedback, instructor practice and class interaction & communication.

Appendix 8.A Comparison of DWLS and ML estimations for the EETAM

Table 8.A.1

Convergent Validity ML vs DWLS Estimations of the EETAM Model

Construct	Item	Factor loading (> 0.60) ML / DWLS	Composite reliability (> 0.70) ML/DWLS	Average variance extracted (> 0.50) ML/DWLS
Perceived usefulness (PU)	PU1	0.809 / 0.864	0.88 / 0.91	0.64 / 0.71
	PU2	0.798 / 0.842		
	PU3	0.795 / 0.826		
	PU4	0.787 / 0.840		
Perceived ease of use (PEOU)	PE1	0.725 / 0.837	0.79 / 0.87	0.48 / 0.62
	PE2	0.638 / 0.686		
	PE3	0.760 / 0.819		
	PE4	0.654 / 0.802		
Comfort and Well-being (CW)	CW1	0.725 / 0.836	0.79 / 0.85	0.55 / 0.65
	CW3	0.797 / 0.851		
	CW4	0.710 / 0.720		
Cognitive engagement (CE)	CE1	0.543 / 0.718	0.82 / 0.89	0.77 / 0.67
	CE2	0.698 / 0.815		
	CE3	0.816 / 0.847		
	CE4	0.851 / 0.877		
Instructor Practice (IP)	IP1	0.681 / 0.683	0.76 / 0.83	0.44 / 0.55
	IP2	0.809 / 0.883		
	IP3	0.591 / 0.670		
	IP4	0.558 / 0.716		
Feedback (FE)	FE1	0.633 / 0.652	0.78 / 0.85	0.48 / 0.59
	FE2	0.803 / 0.928		
	FE3	0.777 / 0.835		
	FE4	0.504 / 0.629		
Class Interaction and	CIC1	0.712 / 0.783	0.89 / 0.93	0.57 / 0.67
	CIC2	0.822 / 0.832		

Communication (CIC)	CIC3	0.807 / 0.847		
	CIC5	0.698 / 0.824		
	CIC6	0.752 / 0.824		
	CIC7	0.746 / 0.815		
Access and Convenience (AC)	AC1	0.668 / 0.754	0.74 / 0.84	0.43 / 0.57
	AC2	0.744 / 0.797		
	AC3	0.735 / 0.791		
	AC4	0.420 / 0.679		
Self-Efficacy (SE)	SE3	0.753 / 0.814	0.79 / 0.85	0.66 / 0.75
	SE4	0.863 / 0.910		
System Attributes (SA)	SA1	0.655 / 0.743	0.73 / 0.79	0.41 / 0.48
	SA2	0.616 / 0.667		
	SA3	0.663 / 0.707		
	SA4	0.610 / 0.662		

Table 8.A.2

Discriminant Validity ML Estimation

	PU	PE	CE	FE	IP	CIC	CW	AC	SA	SE
PU	**0.80**									
PE	0.54	**0.70**								
CE	0.85	0.39	**0.74**							
FE	0.59	0.43	0.54	**0.69**						
IP	0.32	0.41	0.15	0.52	**0.67**					
CIC	0.49	0.32	0.44	0.38	0.32	**0.76**				
CW	0.71	0.40	0.79	0.43	0.13	0.45	**0.74**			
AC	0.45	0.46	0.25	0.36	0.34	0.22	0.30	**0.66**		
SA	0.73	0.66	0.64	0.68	0.57	0.42	0.64	0.68	**0.64**	
SE	0.28	0.53	0.13	0.20	0.32	0.30	0.18	0.45	0.42	**0.81**

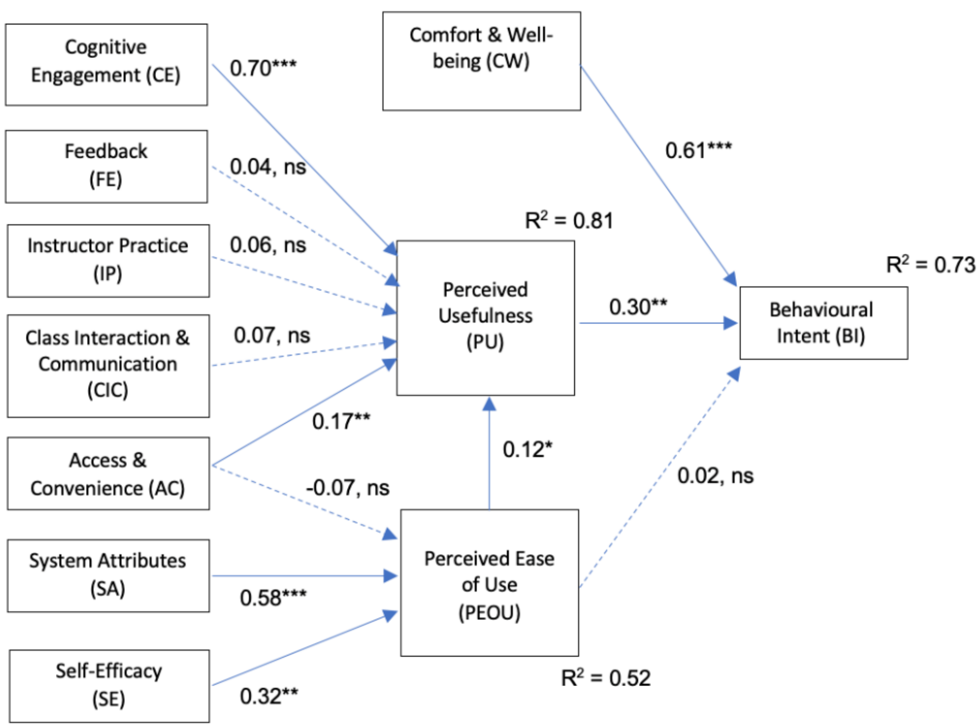
Table 8.A.3

Discriminant Validity DWLS Estimation

	PU	PE	CE	FE	IP	CIC	CW	AC	SA	SE
PU	**0.84**									
PE	0.59	**0.79**								
CE	0.85	0.45	**0.82**							
FE	0.64	0.52	0.59	**0.77**						
IP	0.39	0.53	0.26	0.57	**0.74**					
CIC	0.48	0.36	0.50	0.42	0.41	**0.82**				
CW	0.72	0.42	0.77	0.45	0.18	0.45	**0.80**			
AC	0.60	0.56	0.34	0.44	0.43	0.28	0.47	**0.76**		
SA	0.80	0.72	0.68	0.72	0.61	0.42	0.67	0.79	**0.70**	
SE	0.28	0.60	0.10	0.23	0.44	0.28	0.08	0.51	0.41	**0.86**

Figure 8.A.1

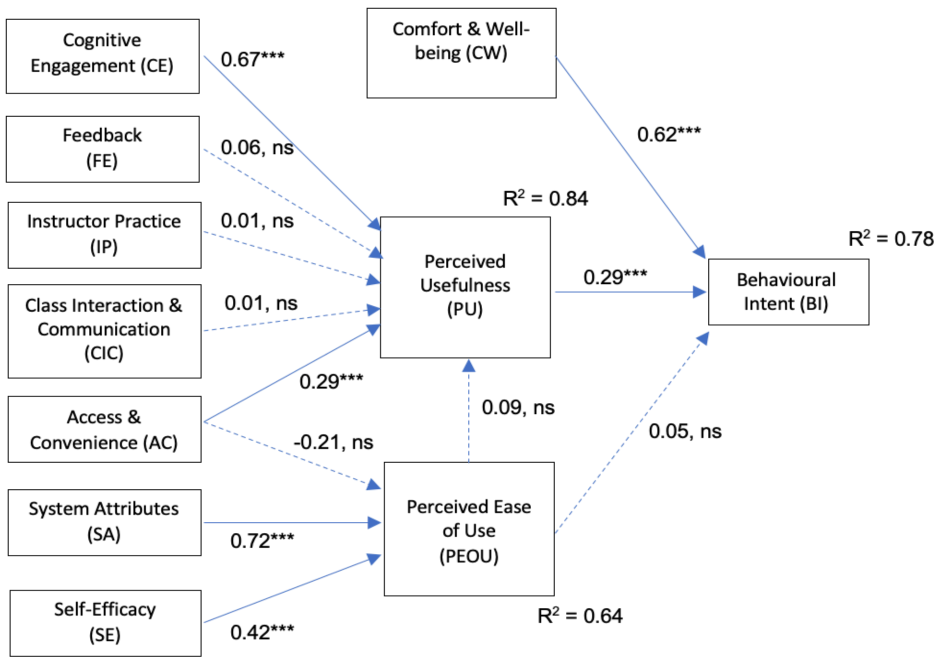
Structural Model ML Estimation



Note: * = (p<0.05), ** = (p<0.01), *** = (p<0.001).

Figure 8.A.2

Structural Model DWLS Estimation



Note: * = (p<0.05), ** = (p<0.01), *** = (p<0.001).

Table 8.A.4

Fit indices ML vs DWLS estimations

Fit Category	Name of Index	Level of Acceptance	Value (ML/DWLS)
Absolute fit	χ^2, df, p	p > 0.05	1460.706, df = 779, p = 0.000 / 1837.564, df=779, p = 0.000
	RMSEA	< 0.06	0.054 (0.050 – 0.058) / 0.057 (0.054 – 0.060)
Incremental fit	CFI	> 0.95	0.898 / 0.959
	TLI	> 0.95	0.887 / 0.954
	SRMR	< 0.08	0.065 / 0.062
Parsimonious fit	χ^2/df	< 3	1.87 / 2.36

Note. Threshold values are taken from Hooper et al. (2008), Hu & Bentler (1999) and R. B. Kline (2015).

CHAPTER 9 – DISCUSSION

9.1 Summary of research objectives and hypotheses

This thesis presented three research aims, three research objectives, and two research hypotheses, which are presented in Tables 9.1-9.3 for context ahead of the discussion.

Table 9.1

Status of research aims

Research aims		Status
1	To identify the types and characterisations and scope of factors affecting attitudes and intentions towards use of educational technologies.	This aim has been met by Paper 1 (Chapter 4) and Paper 3 (Chapter 6).
2(a)	To construct a comprehensive technology acceptance model suited to education and investigate whether its education-specific constructs improve its power when applied to educational technologies.	This aim has been met by Paper 4 (Chapter 7) and Chapter 8, with support from Paper 2 (Chapter 5) to help specify the model.
2(b)	To construct a comprehensive technology acceptance model suited to education and investigate if it can explain the majority of variance of intent to use such technologies.	This aim has been met by Paper 4 (Chapter 7), with support from Paper 2 (Chapter 5) to help specify the model.

Table 9.2

Status of research objectives

Research objectives		Status
1	To search for the latent constructs related to educational technology use that have been shown to affect user attitudes and intentions.	This objective has been met by Paper 1 (Chapter 4) and Paper 3 (Chapter 6).
2	To form a sufficient, but still parsimonious, structural model that researchers can use to measure attitudes and intentions in a wide variety of educational settings.	This objective has been met by Paper 4 (Chapter 7) and Paper 2 (Chapter 5).
3	To test this model in a real-world educational setting.	This objective has been met by Paper 4 (Chapter 7).

Table 9.3

Status of hypotheses

Hypotheses		Status
1	A suitably constructed and relevant model will explain a majority of the variation of intention to use an educational technology (> 60%).	Supported – Paper 4 (Chapter 7).
2	The inclusion of constructs specific to learning and pedagogy will increase the power of the model when applied to an educational technology.	Supported – Chapter 8, and 9.3.4 below.

This discussion will firstly address the scope and limitations of technology acceptance models to establish a justification of this research, followed by discussion of the main findings from the papers.

9.2 Scope and limitations of educational technology acceptance models

The literature review provided insight into the breadth and diversity of technology acceptance models in terms of model architectures, factor inclusions and technology targets. It emerged that there had been no coherent approach across the field to the design of models, leading to difficulty in identifying a starting point to select a comprehensive model suitable to assess educational technologies. Most TAMs were extended versions of Davis' TAM, which demonstrated a need by researchers to extend the core model to adequately address research questions.

The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) was formed as a consolidation of previous studies concerning technology in general and brought together the most central factors to form a parsimonious model. The model includes only performance expectancy, effort expectancy, social norm and facilitating conditions as independent factors and intention to use and actual use of a technology as dependent factors, It was designed for general technologies and so, by design, includes no factors that are specific to learning or pedagogy, enabling it to be used broadly. Accordingly, the model informs how influential each of the included factors are without consideration of any instructional attributes, such as *inter alia* feedback, class interaction, instructor practice or student engagement.

A noted feature of the UTAUT model is the effect of social influence. As only one of three determinants of behavioural intention, social influence is known to be important before and during the introduction of a new technology, and its influence attenuates over time (Venkatesh & Davis, 2000). This effect was known when the UTAUT was proposed.

Therefore, its influence on behaviour could reasonably be expected to wane as a user's experience grows, and this expectation is indicated by the inclusion of the experience moderator on this relationship. Once accounted for, the model suggests that only performance and effort expectancy remain as primary influencers to behavioural intent. In essence, the UTAUT is very similar to the TAM except for the influence of facilitating conditions on actual use, a relationship that again attenuates for experienced users for the same reasons stated above. At its core, the model says that for experienced users, only performance and effort expectancy influence behavioural intent, with social norms and facilitating conditions additionally influencing inexperienced users of a system.

Whereas the UTAUT was an aggregate model to appraise technologies in general, the General Extended Technology Acceptance Model for E-Learning (GETAMEL) (Abdullah & Ward, 2016) was built specifically to appraise educational technologies and so it can be considered a welcome advancement. It extended the TAM by adding the five most used external factors, which were identified from a meta-analysis of 107 prior studies: experience, anxiety, self-efficacy, social norm, and enjoyment. The study did not aim to demonstrate that the five chosen factors were the most suitable for an educationally focussed model; the included factors being incorporated based only on their frequency and of use within the surveyed research.

Of the five factors, Abdullah & Ward (2016) themselves reported that experience is related to skills growth, and Yueh et al. (2015) found that continued use leads to an increase in actual use, implying that continued use, increasing experience, and skills growth are associated with a reduction of anxiety and an increase in self-efficacy. Thus, it could be said that there is some redundancy in the self-efficacy, computer anxiety and experience constructs, all being measures that reflect one's ability and comfort with using a computer system. As a result of this consideration, the GETAMEL model could be said to measure only three different constructs, namely self-efficacy (with experience and anxiety associated with this), social norms and enjoyment.

A benefit of the meta-analysis that led to the GETAMEL model is that it highlighted that the three user groups (teacher, student, and employee) valued different system characteristics of E-Learning systems, which is useful in the consideration of future studies. For example, within the constraints of GETAMEL's five factors, teachers were influenced by what their peers were doing and required development and/or technical support. Students were more influenced by their enjoyment and their own computer literacy, and employees were influenced by whether their peers use the system and their own computer skills. This result implied that external factors could be chosen based on what the study is designed to measure, and the population being studied as well as the context.

Despite the focus on the educational context, the GETAMEL did not include factors specific to learning and pedagogy and so the effect of these on teachers and students remains unknown. The choice to base the GETAMEL on the five most frequently used constructs instead of constructs with qualitative significance for education raises doubts about its ability to accurately assess attitudes in educational settings. Indeed, Matarirano, Jere, et al., (2021) employed the model and concluded that "it may not be the best model to measure adoption of technology by lecturers" (Matarirano, Jere, et al., 2021, p. 73).

The literature review revealed that only a minority of models directed at educational technologies included constructs specific to teaching, learning or pedagogy, raising doubts that most may not be as well-equipped in educational contexts as might be expected. Do educational technology acceptance models require education-specific constructs? Just as self-efficacy comes in as many forms as there are competencies, it is argued here that technology acceptance models can come in as many flavours as there are technology contexts. For example, one can imagine models with constructs specific to settings and users such as flying and airline pilots, construction managers and civil engineering, software developers, or plant operators; these fields all come with their own types of technologies and user needs and so it is reasonable that industry-specific constructs would need to be measured. The finding from the literature review that most technology acceptance models deployed in educational settings did not include education-specific constructs strengthened the premise of this research project, which had as one aim to identify, describe and incorporate instructionally relevant constructs.

9.3 Findings from the papers and associated discussion

There were five major findings from this research project:

1. Attitude is redundant with educational compatibility and can be safely excluded from the model.
2. Instructional attributes are relevant and should be included within an educational technology acceptance model.
3. Comfort & well-being is an important factor for students when considering using an educational technology.
4. Cognitive engagement improved the power of the model and influenced how students perceived usefulness.
5. The final model is statistically sound and measured 78% of variance in behavioural intent, indicating that the model is robust and has substantial power.

These findings are each discussed below.

9.3.1 Attitude is redundant with educational compatibility, and can be safely excluded from the model

Paper 2 (Chapter 5) found that attitude had no statistical power in the model, nor did its presence improve the model's statistical fit. This finding aligns with other research. For example, Davis (1989) removed attitude from the original TAM (TAM-O) to produce what is known as the revised TAM (TAM-R). Since then, attitude has been omitted from the TAM2 (Venkatesh & Davis, 2000), Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) and the TAM3 (Venkatesh & Bala, 2008) as it was found to be statistically non-significant in the presence of perceived usefulness and perceived ease of use. Despite these findings, attitude has been found to be statistically significant in some settings such as when use is voluntary or when the data are analysed using PLS-SEM (López-Bonilla & Lopez-Bonilla, 2017; López-Bonilla & López-Bonilla, 2011; H.-H. Yang & Su, 2017), or when attitude was a precursor to both perceived usefulness and perceived ease of use (Chau, 2001). Teo (2009a), Nistor & Heymann (2010) and Ursavas (2013) have concluded that whereas attitude is an important consideration in the formation of intention, it has no statistical power in acceptance models since it is subsumed by more powerful usefulness and ease of use constructs.

Educational compatibility being collinear with attitude was another finding of Paper 2 (Chapter 5) as determined by exploratory factor analysis. Lai et al. (2012) demonstrated that educational compatibility influences perceived usefulness, perceived ease of use, and attitude, but arrived at this conclusion using a modified acceptance model that incorporated Theory of Reasoned Action and Theory of Planed Behaviour constructs and structures, so it is difficult to compare directly with the model in this thesis. Chen (2011) also incorporated educational compatibility into a modified Unified Theory of Acceptance and Use model, demonstrating its influence in usage intention. This would indicate that educational compatibility should be included in an educationally focused acceptance model. However, the results of Paper 2 (Chapter 5) also demonstrated that educational compatibility and attitude were semantic synonyms and statistically collinear. The collinearity of attitude and educational compatibility is supported by Lai (2013) who reported a high correlation between these two constructs.

Given the high correlation, demonstrated collinearity using exploratory factor analysis in Paper 2 (Chapter 5) and the semantic similarities, it can be surmised that educational compatibility and attitude are likely redundant constructs. Given also that attitude can be safely excluded from technology acceptance models, the case for also excluding educational compatibility is reasonable. For these reasons, neither attitude nor educational compatibility were included in the final model. The finding that attitude can be omitted from the final model directly supported:

- Research aim 2(a): To construct a comprehensive technology acceptance model suited to education and investigate whether its education-specific constructs improve its power when applied to educational technologies.
- Research aim 2(b): To construct a comprehensive technology acceptance model suited to education and investigate if it can explain the majority of variance of intent to use such technologies.
- Research objective 2: To form a comprehensive, yet parsimonious, structural model that researchers can use to measure attitudes and intentions in a wide variety of educational settings.

Notwithstanding these findings, there was indication that educational compatibility and perceived usefulness were possibly closely related as demonstrated by the failure of latent factor discrimination in Table 5.6 of Paper 2 (Chapter 5). This implies that student perceptions of usefulness could be enhanced if the technology in question not only performed its function of delivering learning, but that the learning was also compatible with the students' perceived educational needs. Cognitive engagement might also come to bear and closely relate to usefulness in the same way. The implications for teaching therefore include that the technology needs to be cognitively engaging and be compatible with student learning needs.

9.3.2 Instructional attributes are relevant and should be included within an educational technology acceptance model

The taxonomy represented by Paper 1 (Chapter 4) included a section of instructional attributes in four categories of specific constructs included in technology acceptance models, each demonstrating influence of either learner attitude or intention to use an educational technology: lecturer attributes, content attributes, feedback, and social interaction. Paper 3 (Chapter 6) surveyed 169 students whose responses concerning instructional attributes were coded into three main categories, namely class interaction (n = 108), instructor practice (n = 53) and feedback (n = 11). Paper 4 (Chapter 7) performed an exploratory factor analysis on responses from students, which confirmed that class interaction and communication, instructor practice, and feedback were distinct factors that were suitable inclusions of an educationally focused technology acceptance model. Accordingly, these factors were included in the final model.

As discussed in Paper 4 (Chapter 7), these three instructional attributes did not converge to a significant regression value in the structural model. One possibility for this is that they were incorrectly specified, however Table 7.4 demonstrated a suitable convergent validity of these constructs and so it can be concluded from this that factor specification was adequate.

One possibility for the results is that the constructs were irrelevant for the context, technology, or survey respondents. Considering that the survey was administered to students in respect of learning using virtual classrooms that can involve class interaction, collaboration, feedback and instructor management of the class and activities, this is doubtful. Firstly, Ashton & Elliott (2007) emphasised that interaction in face-to-face settings supports student learning outside of class, and Luo et al. (2017) proposed that class interaction leads to a sense of membership and student belonging, with less interaction occurring in online classes (Ismaili, 2021). While there is also evidence from Paper 3 (Chapter 6) that class interaction is lacking in virtual classrooms, non-verbal forms of interaction are available, such as emoticons and chat (Eraković & Topalov, 2021), while Sayem et al. (2017) reported that interactive Zoom tutorials support student satisfaction and engagement. Support for class interaction being important and influential for student success is therefore evident.

Many students highlighted the importance of instructor practice, which can encompass use of the technology, class management and provision of feedback. This is supported by Fathi and Yousefifard (2019) who showed that an instructor’s technological, pedagogical content knowledge (TPACK) (Mishra & Koehler, 2006) is fundamental to student success. Teo et al. (2017) demonstrated that TPACK influences an instructor’s attitude towards teaching online, which further supports student satisfaction (Sun et al., 2008). Further than attitude, James (2021), and Joia and Lorenzo (2021), highlighted the importance of instructor presence in facilitating student engagement. This compares to the results of Paper 3 (Chapter 6) concerning lack of instructor engagement with and management of the class and group activities, but student engagement can be difficult to monitor in online classes (Ebner & Greenberg, 2020; Moorhouse, 2020). Engagement with the instructor is also a way for students to feel less isolated in online environments (Volery & Lord, 2000) and support social and emotional well-being (Hamilton et al., 2020). Indeed, there is evidence that students feel safer and have greater trust in Zoom environments where feedback can be shared (A. Lee et al., 2021).

The findings from Paper 1 (Chapter 4) and Paper 3 (Chapter 6) that instructional attributes are important are thus amply supported by evidence in the extant literature. Accordingly, the conclusion in Paper 4 (Chapter 7) that student experience of the instructional attributes was simply too varied for the responses to reflect coherent variance patterns makes practical sense. Given this result appears to be a result of research design, the continued inclusion of these instructional attributes constructs in the final model is reasonable and recommended for further research to explore.

The results could also highlight the importance of instructor practice in terms of ensuring that the class is run effectively with adequate student engagement and feedback. Semantically, instructor practice, feedback, and class interaction and collaboration are functions of the instructor as opposed to student beliefs or attitudes. All of the student-centric constructs in the final model converged sufficiently, however, the instructor-centric constructs did not. These results imply that disconnected instructor practice led to an inconsistent and varied student learning experience. It could therefore be proposed that the model has successfully identified that the instructor practice was disconnected from student experience, providing a varied experience for students, and causing non-significant constructs in the final structural model. If this is the case, it may have diagnosed problems with instructor practice for the student respondents in Paper 4 (Chapter 7).

The results support the finding that instructional attributes are relevant and should be included in the final model, and that future use of the model carefully control for instructor practice. The implication here is also that teaching using technology should endeavour to ensure that the technologies used for teaching enable instructional attributes such as feedback and class interaction and communication. The finding directly supports:

- Research aim 1: To identify the types and characterisations and scope of factors affecting attitudes and intentions towards use of educational technologies.
- Research aim 2(a): To construct a comprehensive technology acceptance model suited to education and investigate whether its education-specific constructs improve its power when applied to educational technologies.
- Research objective 1: To search for the latent constructs related to educational technology use that have been shown to affect user attitudes and intentions.

- Hypothesis 2: The inclusion of constructs specific to learning and pedagogy will increase the power of the model when applied to an educational technology.

9.3.3 Comfort & well-being is an important factor for students when considering using an educational technology

Paper 3 (Chapter 6) revealed the importance of two themes that had previously not been a feature of quantitative technology acceptance research, namely social comfort, and well-being. Both attributes have been explored in other research and so are not new in and of themselves, however, they have not been included as factors in technology acceptance models to the knowledge of the author.

Social comfort was the name given to one's comfort or preference with being around others in the learning environment. This can manifest as a student's preference for being physically present with other students and the instructor (Ismaili, 2021; Wong, 2020), or at least having some face to face contact in a blended setting (Ashton & Elliott, 2007), leading to a negative impression of purely online learning (A. Lee et al., 2021). A possible reason for such a preference is the presence of familiar social cues in face to face settings (Ebner & Greenberg, 2020) that facilitate communication and motivation for learning (James, 2021) and which help develop the personality and behavioural characteristics of students (Cohen & Baruth, 2017).

Paper 3 (Chapter 6) revealed that social comfort can have a connection with well-being for students with social anxiety, who may subsequently develop a preference to learn online and not enter face to face environments. The COVID-19 pandemic uncovered a preference of many students to remain socially isolated during times of pandemic for the health benefits that afforded, and one student stated that online learning was easier because they were physically disabled, and that face-to-face learning was more problematic. These cases, though relatively small, highlight a possible connection between a person's comfort and well-being, whether that comfort is derived from physical proximity to others or by remaining in the comfort of a familiar and safe individual environment. Other responses provided evidence that students experienced direct health drawbacks from some educational technologies. For example, one student stated that Zoom gave them headaches, sore neck, and eyes. The importance of health was also raised by Sagnier et al. (2020) who revealed the negative effects of cyber sickness on intention to use virtual reality for learning. It is reasonable to surmise that the effects of social comfort and well-being can influence a student's satisfaction and enjoyment (Estriegana et al., 2019), which can in turn influence attitude and intention to use the technology.

The responses from Paper 3 (Chapter 6) indicated that comfort and well-being considerations played directly onto a student's intent to attend learning in either the face-to-face or online environments. Conversely, there was no indication that these themes influenced perceived usefulness or perceived ease of use. This indicated inclusion of comfort & well-being into the final model and its placement as a direct contributor of behavioural intent within the final model. This represented a departure from Davis' model architecture where all external constructs are mediated by perceived usefulness and perceived ease of use. In support of this model structure, the quantitative analysis in Paper 4 (Chapter 7) provided strong evidence that social comfort and well-being directly influenced behavioural intent to use an educational technology. This supports dedicated attention as to how students are affected by an educational technology in terms of both health, but also their preferences for learning setting that may affect well-being and influence attendance behaviour.

The finding that comfort and well-being is an important factor for students when considering using an educational technology directly supports:

- Research aim 1: To identify the types and characterisations and scope of factors affecting attitudes and intentions towards use of educational technologies.
- Research aim 2(b): To construct a comprehensive technology acceptance model suited to education and investigate if it can explain the majority of variance of intent to use such technologies.
- Research objective 1: To search for the latent constructs related to educational technology use that have been shown to affect user attitudes and intentions.
- Research objective 2: To form a comprehensive, yet parsimonious, structural model that researchers can use to measure attitudes and intentions in a wide variety of educational settings.
- Hypothesis 1: A suitably constructed and relevant model will explain a majority of the variation of intention to use an educational technology (> 60%).

9.3.4 Cognitive engagement improved the power of the model and influenced how students perceived usefulness

In the general educational context, Rotgans and Schmidt (2011, p. 465) characterised cognitive engagement as "a psychological state in which students put a lot of effort to truly understand a topic". Greene (2015) associated it with cognitive processing depth and student motivational profiles, and Chi et al. (2018) characterised it as a student's investment in learning, also linking it to motivation. The common factor with these treatments is the effort a student puts into learning due to motivation and the depth with which learning occurs. In contrast, in technology acceptance research cognitive engagement has been discussed more as something that happens to a student as they interact with a technology, or activity via a technology. For example Saade and Bahli (Saade & Bahli, 2005) described cognitive engagement as a state of deep involvement and flow where someone may lose track of time, and Lee et al. (2009) discussed it in terms of playfulness, where users maintain a focus on their activity (Liu et al., 2009). It is this latter characterisation that this thesis adopts in alignment with the literature that forms its foundations.

Paper 4 (Chapter 7) demonstrated that cognitive engagement and perceived usefulness were at the borderline of discrimination and were possibly collinear (Table 7.5). Statistical remedies to collinearity in structural equation models include combining the factors, respecifying the factors (changing the question items), or removal of one of the factors (Kock & Lynn, 2012). Theoretically none of these were viable options because cognitive engagement is semantically a different construct to perceived usefulness, and so it makes no sense to combine them. A conclusion that could be drawn from the results is that students answer questions about cognitive engagement and perceived usefulness in a way that produces similar variance patterns. Such high correlation between cognitive engagement and perceived usefulness has been revealed in two separate factor analysis studies within this thesis (Tables 5.8, 5.11 and 7.5), where the only commonality was that the study subjects studied first year psychology, otherwise, the questions, model, technology target, year and cohort were all different. This confluence could be interpreted that students perceive usefulness through the lens of whether it engages them, whereas in technology acceptance research generally, usefulness it is normally perceived through the lens as being useful for learning or making learning easier or more efficient. Thus, these results possibly indicated that whereas educators generally see an educational technology as useful if it helps students learn, students possibly see an educational technology as useful if it engages them.

In support of this argument, removal of cognitive engagement from the final model (Chapter 8) reduced the explained variance of perceived usefulness from $R^2 = 0.81$ to 0.52, reduced the explained variance of perceived ease of use from $R^2 = 0.52$ to 0.42, and reduced the explained variance of behavioural intent from $R^2 = 0.73$ to 0.69. Additionally, without cognitive engagement, perceived usefulness appeared to have become more prominent on its own within the model (compare Figures 8.6 and 8.7): the path coefficient from perceived usefulness to behavioural intent increased from $\beta = 0.30$ to 0.39, the path coefficient from ease of use to usefulness increased from $\beta = 0.12$ to 0.45, and the path coefficient from access & convenience to usefulness increased from $\beta = 0.17$ to 0.30. These results indicated that when usefulness is not fed by engagement it acts more as it is specified (as a standard usefulness function), but when coupled with engagement it loses prominence and acts more as a conduit for cognitive engagement. Moreover, the path coefficient from cognitive engagement to perceived usefulness was 0.70 (Figure 8.6) and 0.67 (Figure 7.6) depending on the estimation method, revealing a substantial connection.

Since feedback, instructor practice, and class interaction & communication were all non-significant, the specificity of cognitive engagement to learning and pedagogy is important to address Hypothesis 2. Paper 3 (Chapter 6) helps to directly answer this question. Cognitive engagement can occur during both educational use of a technology technologies, for example virtual reality (as Paper 1, Chapter 4 demonstrates), but also for general use of a technology in terms of playfulness and flow (B.-C. Lee et al., 2009; Saade & Bahli, 2005). However, responses in Paper 3 (Chapter 6) indicated that cognitive engagement can also be seen as important and necessary for successful learning via technology: students indicated that instructors needed to make online lessons more engaging and interesting, and Davis et al. (1992) showed that such engagement influences intention, with this also applying to the educational setting (Eraković & Topalov, 2021; Sayem et al., 2017). It could therefore be argued that cognitive engagement is not just an attribute of use of technology in general but an important aspect of learning with technology.

Thus, while cognitive engagement is a feature of general technology use, there is strong support that it is as germane to learning as the other instructional attributes identified by Paper 1 (Chapter 4), namely feedback, class interaction & communication, and instructor practice. In support of this, Paper 4 (Chapter 7) showed that cognitive engagement strengthened the explained variance of perceived usefulness, perceived ease of use and behavioural intent vis-à-vis use of virtual classrooms. Since cognitive engagement is an important and fundamental aspect of successful learning, then these findings provide support for hypothesis two, that constructs specific to learning and pedagogy will increase the power of the model. This supports cognitive engagement being conscientiously designed into learning activities using educational technologies and also being included in educational technology acceptance models.

The finding that cognitive engagement improved the power of the model and influenced how students see usefulness directly supports:

- Research aim 1: To identify the types and characterisations and scope of factors affecting attitudes and intentions towards use of educational technologies.
- Research aim 2(a): To construct a comprehensive technology acceptance model suited to education and investigate whether its education-specific constructs improve its power when applied to educational technologies.
- Research objective 1: To search for the latent constructs related to educational technology use that have been shown to affect user attitudes and intentions.
- Research objective 2: To form a comprehensive, yet parsimonious, structural model that researchers can use to measure attitudes and intentions in a wide variety of educational settings.
- Hypothesis 2: The inclusion of constructs specific to learning and pedagogy will increase the power of the model when applied to an educational technology.

9.3.5 The final model was statistically sound and measured 78% of variance in behavioural intent, indicating that the model is robust and has substantial power

The quality of the final model necessarily rests on the quality of the measurement and structural models (Anderson & Gerbing, 1988) and the appropriateness of the analysis method (Chapter 3).

The final model included instructional attributes that had not been included in a prior model but which were specified using question items from various validated sources. It was therefore necessary to perform an exploratory factor analysis (Table 7.3), which confirmed that the constructs were correctly specified. The rest of the model constructs were informed by research conducted in Paper 1 (Chapter 4) and Paper 3 (Chapter 6). The complete measurement model was analysed for reliability and convergent and discriminant validity (Tables 7.4 and 7.5) which demonstrated adequate quality of the inherent factors to proceed to structural modelling. The structural model was informed by theoretical considerations of how the constructs have been shown to relate to each other in prior research (including Paper 2 (Chapter 5). The model showed good fit with all indices falling within generally accepted thresholds (Table 7.6) (Hooper et al., 2008; Hu & Bentler, 1999; P. Kline, 1994).

The analysis method included consideration of the kinds of variables and type of data. Given that the variables were reflective in nature, factor analysis was the appropriate method to analyse the data (see Section 3.4.3). The ordinal nature of the data warranted careful treatment as the data could not be assumed to be normal. Thus, weighted least squares regression was chosen as the appropriate method (see Coenders & Saris, 1995; Flora & Curran, 2004; W. C. Wang, 2005) as opposed to maximum likelihood, which assumes normality (Mîndrilă, 2010).

The above considerations of model design and analysis method provide confidence that the results are sound and a true representation of student attitudes towards at least virtual classrooms. The model can be presumed to be applicable to other educational technologies since most constructs were derived from the extant literature that informed the taxonomy in Paper 1 (Chapter 4). Paper 4 (Chapter 7) demonstrated the statistical robustness of the final model, in that the fit statistics (Table 7.6) indicated that the theorised model was a strong predictor of the population. The amount of variance explained of behavioural intent (R^2 = 0.78) indicated that the model explained most of the influences of student behavioural intent. This figure can be considered alongside the results of Paper 3 (Chapter 6), which described the factors that are important to students vis-à-vis use of Zoom which were subsequently included in the final model. Together, the high explained variance of behavioural intent in Paper 4 (Chapter 7) and the evidence from Paper 3 (Chapter 6) imply that the final model is comprehensive. Overall, the model provides guidance on what considerations are likely to improve student intention to use an educational technology, and each factor should be considered in-turn where possible to maximise student engagement.

The finding that the final model is statistically sound and measured 78% of variance in behavioural intent, indicating that the model is robust and has substantial power directly supports:

- Research aim 2(b): To construct a comprehensive technology acceptance model suited to education and investigate if it can explain the majority of variance of intent to use such technologies.
- Research objective 2: To form a comprehensive, yet parsimonious, structural model that researchers can use to measure attitudes and intentions in a wide variety of educational settings.

- Hypothesis 1: A suitably constructed and relevant model will explain a majority of the variation of intention to use an educational technology (> 60%).

9.4 Limitations and future research

9.4.1 Students as subjects

The author acknowledges the scope of respondents was constrained to university students studying first year psychology. Whereas Paper 1 (Chapter 4) and Paper 2 (Chapter 5) included both students and instructors, Paper 2 (Chapter 5) attracted such a small number of teaching staff that their responses were not likely to be generalisable to the broader teaching community. Papers 3 and 4 (Chapters 6 and 7) included only students as respondents. Future research could include educators and broader cohorts of students, for example from different countries, cultures, and levels of schooling.

9.4.2 Uncontrolled nature of learning experiences

The results from Paper 4 (Chapter 7) indicated that the instructional attributes of feedback, instructor practice and class interaction & communication were not significant influencers of perceived usefulness. This was an unexpected finding since these factors were shown to be influential in other studies (Paper 1 (Chapter 4) and Paper 3 (Chapter 6)). It was concluded in Paper 3 (Chapter 6) that the uncontrolled nature of the student learning experience led to such high variance of responses that no pattern was evident within the responses, leading to non-significant results. This provides a direction for future research where the final model can be deployed within a controlled teaching and learning environment, where the learning experience is common to all study participants.

9.4.3 Technology targets

The research conducted as part of this thesis appraised two educational technologies, namely virtual reality, and virtual classrooms. Since it was beyond the scope of this research project to deploy the model against as many educational technologies as there are available, the project had as a primary objective to design and demonstrate a viable technology acceptance model using one technology. Since Paper 4 (Chapter 7) demonstrated that the model itself was sound, it remains for future research to deploy and validate the model using other technology targets. Technologies that engage the comfort and well-being construct would be suitable, for example, artificial intelligence (AI) and its various forms where users necessarily relate to bots and other forms of AI as opposed to real people.

CHAPTER 10 – CONCLUSION

This chapter will conclude the thesis by summarising the key research findings in relation to the research aims, objectives and hypotheses.

The main research aim of the project was to construct a comprehensive yet parsimonious technology acceptance model that is suitable to apply to educational technologies. It was hypothesised that by carefully ensuring that all relevant constructs were included that it would measure the majority of variance explained of the dependent variable, behavioural intent. This was indeed the case, where the final model explained 78% of variance for behavioural intent, and included constructs relating to comfort and well-being, cognitive engagement, instructor practice, feedback, class interaction and communication, access & convenience, system attributes and self-efficacy as exogenous variables to the core constructs of perceived usefulness, perceived ease of use, and behavioural intent.

It was also hypothesised that by including relevant instructional attributes that the model power would increase, as measured by the variance explained of behavioural intent. Paper 4 (Chapter 7) and section 9.3.4 of the discussion support the hypothesis that inclusion of instructional attributes does indeed increase the power of the model, however this finding was limited due to the other instructional attributes not converging as expected. As explained in section 9.3.2 of the discussion, it is likely that this was due to the incoherent nature of learning experience for the student respondents of Paper 4 (Chapter 7), and unlikely due to the ineffective nature of the instructional attributes constructs themselves. In fact, it was proposed in section 9.3.2 that this result was due to the model functioning correctly and diagnosing the effects of varied teacher pedagogical content knowledge (TPACK) on the student experience. Thus, while Paper 1 (Chapter 4) and Paper 3 (Chapter 6) both support the inclusion of instructor attributes, feedback, and class interaction and communication into the final model, Paper 4 (Chapter 7) was unable to confirm this. Even so, the results indicated that TPACK must be carefully considered for instructors to influence student attitudes and intentions regarding use of the educational technology. If this is true then the model may have actually highlighted a problem to do with student experience, although this remains to be tested.

One of the objectives of the research project was in response to a perceived lack of consistency in the field of technology acceptance modelling, and it was resolved to ensure that all required constructs were included in the final model. This was achieved by firstly forming the taxonomy of factors that are relevant to technology acceptance modelling in educational settings followed by asking students to provide their views. Paper 3 (Chapter 6) revealed the importance of comfort and well-being in students' determination to use an educational technology, at least in terms of virtual classrooms. The responses indicated that this would be relevant to any technology that might affect a student's well-being or comfort in any way, either physically, mentally, or psychologically. This was confirmed quantitatively in Paper 4 (Chapter 7) where comfort and well-being was the strongest direct influence on a student's behavioural intent to use virtual classrooms, followed by perceived usefulness. This finding contributes to the field of knowledge by firstly including it as a construct within educational technology acceptance models but also demonstrates its importance to students. Conceivably, this will be an important consideration for users of technologies such as virtual reality and artificial intelligence.

In terms of the model itself, an interesting finding was that cognitive engagement was key to students' perceived usefulness. Whereas a common conceptualisation of perceived usefulness is to do with utility of the technology, it can also be a way to view educational compatibility, in other words, does the technology help the student to learn? The findings of both Paper 2 (Chapter 5) and Paper 4 (Chapter 7) both revealed the importance of cognitive engagement and its close relationship to perceived usefulness for students. This can possibly be interpreted to mean that students perceive an educational technology to be useful if it is engaging, not as much that it helps them learn.

While this research achieved its stated objectives, the findings indicated that some aspects could be investigated further. Firstly, the perceived usefulness factor may respond favourably to re-specification to measure both educational compatibility and cognitive engagement. Paper 2 (Chapter 5) showed that educational compatibility is a possible driver of student perceptions of usefulness, and Paper 2 (Chapter 5) and Paper 4 (Chapter 7) both indicated that cognitive engagement is either highly correlated with usefulness, or collinear with it. Together, this highlights the difference between a general and educational TAM: the former asks, 'is this technology useful to perform a task', whereas the latter asks, 'does this technology engage students and help them learn'? Thus, research dedicated to investigating making the usefulness factor specific to student engagement and learning effectiveness is indicated.

A second area of future research would investigate the influence of instructor practice on student comfort and well-being, since design of learning can be determined by lecturers and professional staff, such as learning designers. An important consideration that came to light was class management which appeared to affect student attitudes, and which could conceivably affect student comfort with the mode (blended, online or face to face). Indeed, Escobar-Rodriguez & Monge-Lozano (2012) highlighted the importance of instructor training, and also the support offered to the instructor by the technology, which aligns with this avenue for future research and the results of Paper 3 (Chapter 6). He et al. (2023) showed also that educational and emotional support can improve educational technology acceptance, which is relevant for the further exploration of the comfort and well-being factor.

Finally, this research project did not address inclusivity and universal design considerations, which would conceivably influence ease of use and perceived behavioural control. Papers 2 (Chapter 5) and 4 (Chapter 7) both demonstrated that ease of use was only weakly influential and re-specifying this factor to perceived behavioural control that incorporated access, abilities and divergence parameters may strengthen it.

A final point can be made about the use of TAMs in general, which may be seen as a problem or weakness: TAMs are mostly employed to state ‘what is’ and rarely are used as part of a quality review of a technology within its educational setting, with a view to improving the student experience. As Granić (2022) suggests, TAMs can be used to attempt to predict future student behaviour if a given technology is employed. Since technology acceptance modelling is more or less matured, a next phase of TAM research could concentrate on their use as management tools to improve student experience and satisfaction.

In summary, a comprehensive extended educational technology acceptance model (EETAM) was designed and tested. It was found to measure the majority of variance of behavioural intent to use an educational technology and demonstrated the importance of comfort and well-being as a direct determinant of intent to use the technology. In terms of instructor attributes, cognitive engagement improved the power of the model. Whereas the findings and extant literature support the inclusion of instructor practice, feedback, and class interaction and communication within the model, further testing controlling for these factors is recommended.

APPENDIX A – INVESTIGATING FACTOR ESTIMATION EFFECTS

A.1 Introduction

Section 3.7 (Treatment of ordinal data) highlighted the care to be taken when analysing data, that techniques that assume normality can produce biased results when used on non-normal data. Likert data across five categories can exhibit non-normality, and since this type of data is common in technology acceptance research, and used in this doctoral thesis, care was taken to use methods suited to non-normal data.

By way of confirmation, the model and data from Paper 2 (Chapter 5) were used to compare the effects of using a method that assumes data normality on the collected ordinal data. While there is no direct link with the stated research aims, objectives or hypotheses, this study serves to demonstrate the importance of using the most appropriate factor estimation technique, which serves to support trust in the results.

Technology acceptance models (TAMs) (Davis, 1986; 1989) have been used extensively in the social sciences and use factor analysis and structural equation modelling to determine model parameters. As described in Chapter 3, factor analysis fits a distribution curve to observed data and correlates that with an assumed normal distribution of the latent variable. Most TAMs deploy surveys with Likert scales generally ranging from 5 to 7 categories to collect data from respondents, and so the collected data are ordinal. Despite this, some TAM research uses analysis methods that assume normality and linearity of the input data which may distort results (Coenders & Saris, 1995).

Maximum likelihood is a common factor estimation technique in technology acceptance research which is listed as the default method in software such as SPSS. As explained in Section 3.7 (Treatment of ordinal data), maximum likelihood estimation fits a normal curve over the data that provides the best fit. Maximum likelihood is best suited to data that are normal, linear, and large enough sample size (Mîndrilă, 2010) and results become less reliable as these conditions are violated.

Studies have been conducted to assess whether the ordinal nature of the data affects results when using methods that assume data normality. Norman (2010) conducted a study using simulated data and concluded that parametric methods can be used on ordinal data without concern. Wu & Leung (2017) concluded that ordinal data with ten categories approximates continuous data and so have recommended this threshold if using parametric methods on ordinal data. Despite Norman's assurances and acknowledging that most quantitative acceptance studies use Likert scales with five categories, Holgado-Tello et al. (2010) recommend estimating polychoric correlations between observed variable distributions and the latent variables. Polychoric correlations involve fitting a distribution over ordinal data histogram to minimise the residuals between the curve and data values (Coenders & Saris, 1995), and as such the distribution is more accurate for non-normal data.

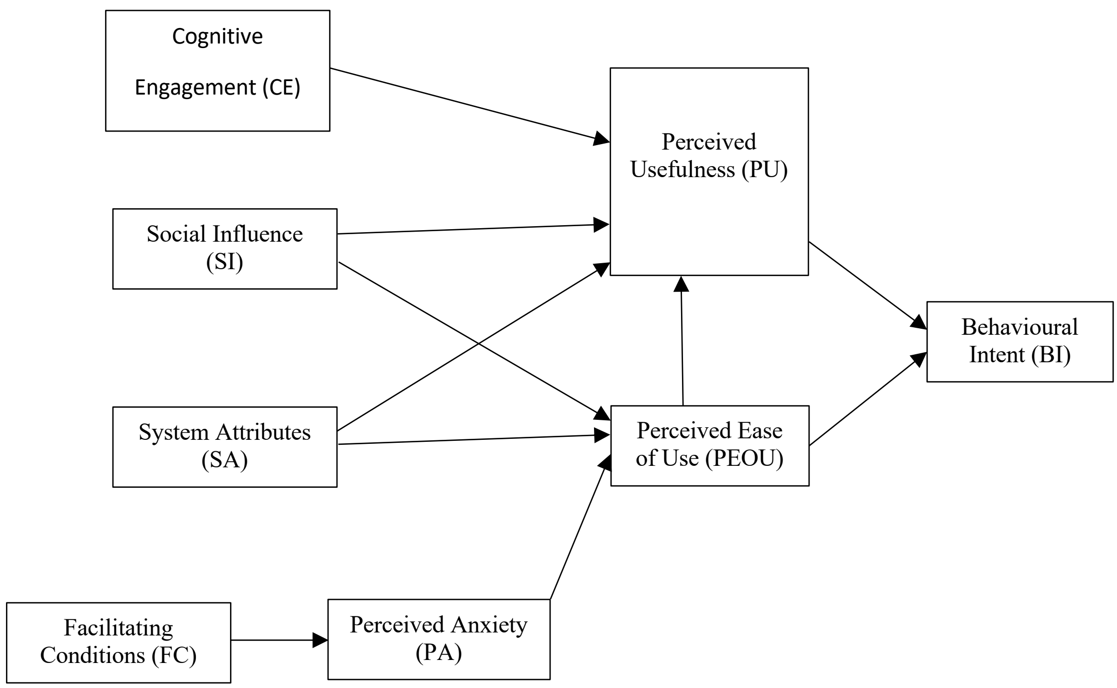
With research such as Norman's (2010) suggesting little consequence to using continuous methods on ordinal data, does it matter in the real world what method is used? This study takes real data collected for Paper 2 (Chapter 5) and compares the results of the confirmatory factor analysis and structural equation modelling using diagonally weighted least squares (DWLS) (Flora & Curran, 2004), which uses polychoric correlations, and maximum likelihood (ML), which uses Pearson correlations. The results demonstrate the effects that can result from using different correlation types and estimation methods on ordinal data and provide justification for the analysis methods used in this doctoral research project.

A.2 Method

The model used in this analysis comes from Kemp et al. (2022) (Paper 2, Chapter 5) which examined the nature of educational compatibility of virtual reality within an Australian higher education institution. That study concluded that educational compatibility and attitude were redundant, and that power of the model, as measured by total variance measured of behavioural intent, was not affected by including those constructs. As a result, a parsimonious model was produced that omitted attitude and educational compatibility, and that model is the basis of this comparison using the same data. The model is represented in Figure A.1.

Figure A.1

Model Used for this Study



The analysis followed Anderson & Gerbing's (1988) recommended two-stage process of analysing the measurement model followed by the structural model. It was conducted in RStudio version 1.2.1335 (RStudio Team, 2015) using R version 3.6.0 (R

Core Team, 2013) using the following packages: psych version 1.8.12 (Revelle, 2019), lavaan version 0.6.4 (Rossel, 2012) and polycor version 0.7-10 (Fox, 2019). The data were specified as ordinal for the diagonally weighted least squares estimation (Holgado-Tello et al., 2010) and continuous for the maximum likelihood estimation.

A.3 Results

Table A.1 lists the parameters for convergent validity of the various indicators depending on which estimation method was used. Questionnaire items are listed in Kemp et al. (2022) (Paper 2, Chapter 5).

Table A.1

Convergent Validity of the Model as a Result of Two Estimation Methods

Construct	**Item**	**Factor Loading (>0.60) DWLS / ML**	**Composite Reliability (>0.60) DWLS / ML**	**Average Variance Extracted (>0.50) DWLS / ML**
Perceived Usefulness (PU)	PU1	0.920 / 0.914	0.93 / 0.92	0.78 / 0.74
	PU2	0.908 / 0.879		
	PU3	0.833 / 0.815		
	PU4	0.871 / 0.835		
Perceived Ease of Use (PEOU)	PE1	0.899 / 0.863	0.94 / 0.91	0.79 / 0.72
	PE2	0.870 / 0.835		
	PE3	0.949 / 0.899		
	PE4	0.840 / 0.785		
	SI1	0.884 / 0.833	0.78 / 0.76	0.64 / 0.62

Social Influence (SI)	SI2	0.711 / 0.728		
Facilitating Conditions (FC)	FC2	0.889 / 0.891	0.87 / 0.87	0.76 / 0.77
	FC3	0.858 / 0.860		
Perceived Anxiety (PA)	rPA1	0.880 / 0.800	0.85 / 0.83	0.74 / 0.74
	rPA2	0.844 / 0.887		
Cognitive Engagement (CE)	CE1	0.860 / 0.842	0.91 / 0.88	0.78 / 0.71
	CE2	0.905 / 0.904		
	CE4	0.880 / 0.782		
System Attributes (SA)	SA1	0.774 / 0.759	0.86 / 0.84	0.61 / 0.57
	SA2	0.800 / 0.743		
	SA3	0.675 / 0.680		
	SA4	0.858 / 0.834		

Note: DWLS vs ML estimation. DWLS = diagonally weighted least squares, ML = maximum likelihood.

Table A.1 shows that factor loadings and average variance extracted were generally underestimated by maximum likelihood. Table A.2 shows the square root of the average variance extracted (across the diagonal, bold) and correlations between factors (off-diagonal) for diagonally weighted least squares / maximum likelihood respectively.

Table A.2

Discriminant validity of the measurement model using two estimation methods

	PU	PEOU	CE	SI	FC	PA	SA

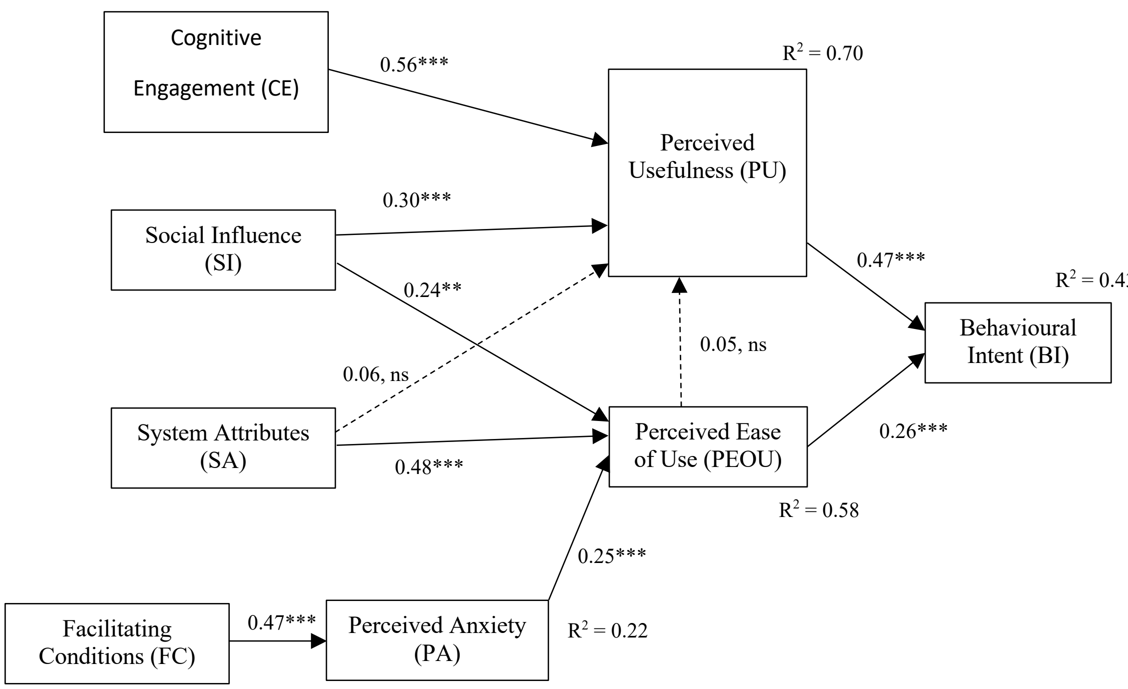
PU	**0.88 / 0.86**						
PEOU	0.58 / 0.59	**0.89 / 0.85**					
CE	0.78 / 0.77	0.58 / 0.55	**0.88 / 0.84**				
SI	0.64 / 0.62	0.57 / 0.57	0.51 / 0.46	**0.80 / 0.79**			
FC	0.46 / 0.43	0.52 / 0.48	0.49 / 0.41	0.43 / 0.42	**0.87 / 0.88**		
PA	0.**23** / 0.15	0.44 / 0.36	0.23 / 0.13	0.20 / 0.14	0.47 / 0.32	**0.86 / 0.86**	
SA	0.73 / 0.74	0.70 / 0.69	0.82 / 0.80	0.59 / 0.59	0.62 / 0.60	0.29 / 0.19	**0.78 / 0.75**

Note: DWLS / ML estimation. DWLS = diagonally weighted least squares, ML = maximum likelihood.

Table A.2 shows that the factor correlations were generally underestimated by the maximum likelihood method. Figures A.2 and A.3 show the compared structural models estimated by diagonally weighted least squares and maximum likelihood respectively.

Figure A.2

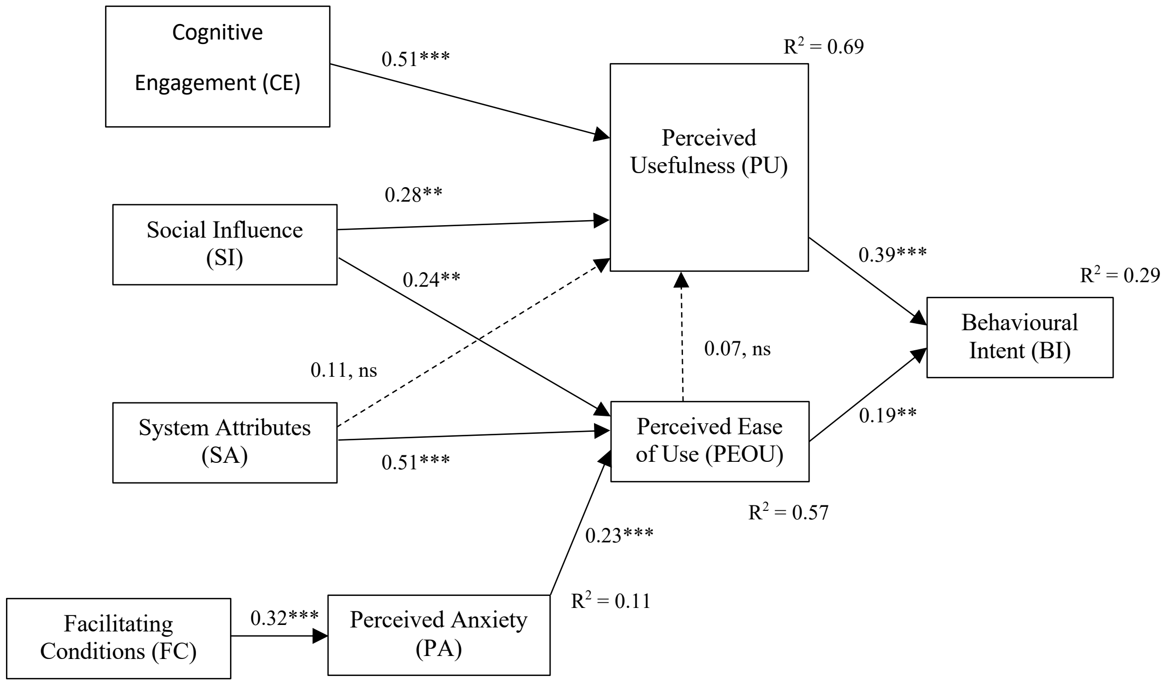
Structural Model – Estimation by Diagonally Weighted Least Squares



Note: * = (p<0.05), ** = (p<0.01), *** = (p<0.001).

Figure A.3

Structural model and path coefficients – estimation by maximum likelihood



Note: * = ($p<0.05$), ** = ($p<0.01$), *** = ($p<0.001$).

Comparison of Figures A.2 and A.3 reveals that, in general, standardised regression coefficients between factors was underestimated by the maximum likelihood method, though there were some exceptions. In addition, the amount of variance explained was also underestimated to various amounts. The path from cognitive engagement to perceived usefulness and from perceived ease of use to behavioural intent became less significant because of maximum likelihood.

Table A.3

Structural model fit indices – DWLS vs ML estimation

Fit Category	Fit parameter	Acceptance level	**Value** (DWLS / ML)
Absolute fit	χ^2, df, p	p > 0.005	347.237, df=194, p = 0.000 / 306.950, df=231, p = 0.000
	RMSEA	< 0.08	0.07 (0.055 – 0.078) / 0.06 (0.045 – 0.069)
Incremental fit	CFI	> 0.9	0.98 / 0.96
	TLI	> 0.95	0.98 / 0.95
	SRMR	< 0.08	0.05 / 0.06
Parsimonious fit	χ^2/df	< 3	1.79 / 1.33

Note: DWLS = diagonally weighted least squares, ML = maximum likelihood. Cut-off values as recommended (Hair et al., 2010).

Table A.3 revealed that fit indices were generally underestimated by maximum likelihood, especially the χ^2 and parsimonious fit. Table A.4 lists the effects of using maximum likelihood, instead of diagonally weighted least squares, to estimate factors in the measurement model.

Table A.4

Effect of Maximum Likelihood (ML) Estimation on Measurement Model Parameters

Parameter	**Effect of ML estimation**
Item loadings	Generally underestimated
Average variance extracted (AVE)	Generally underestimated

Composite reliability	Generally underestimated
Factor correlations	Generally underestimated

Table A.5 lists the effects of using maximum likelihood, instead of diagonally weighted least squares, to estimate factors in the structural model.

Table A.5

Effect of Maximum Likelihood (ML) Estimation on Structural Model Parameters

Parameter	**Effect of ML estimation**
Path regressions	Generally underestimated
Significance of path regressions	Some paths less significant
% variance explained	Underestimated
Absolute fit	Underestimated
Incremental fit	Underestimated
Parsimonious fit	Underestimated

Tables A.4 and A.5 both demonstrated that maximum likelihood underestimated all of the parameters in the measurement and structural models.

A.4 Discussion

Chapter 3 (Methods) reviewed considerations around treatment of ordinal data, which is germane to technology acceptance modelling since most studies are conducted using questionnaires that collect Likert-type data over five categories. There are theoretical studies that recommend estimating polychoric correlations between ordinal observed variables and presumed continuous latent variables (see Holgado-Tello et al., 2010) whereas some suggest that use of continuous methods is of no consequence (Norman, 2010).

Given the possibility of bias in the results within this doctoral research project this study was performed to investigate whether choice of estimation method matters when ordinal data are used. The results show that in nearly every case, maximum likelihood underestimated the calculated parameters to varying degrees. This mostly agrees with Mîndrilă (2010), however Mîndrilă stated that χ^2 is over-estimated when maximum likelihood is used, which is the opposite to the result here. What is clear and important is that this study confirmed that parameters were biased by the maximum likelihood method.

It needs to be acknowledged that the bias did not materially change the results in that the model remained the same (Figures A.2 and A.3). The most striking change was the amount of variance explained of behavioural intent, that fell from 43% to 29%, which has the potential to mislead the reader to thinking that the model is weaker than it actually is. There are some further potentials for danger. Firstly, the significance of some paths was reduced. In this study this did not result in any model changes, but if a path was already borderline it could result in a path becoming non-significant and being removed from the model entirely. Similarly, the underestimation of factor loadings has the potential to remove some measurement items from the observed variables if they fall under the 0.6 threshold (Hair et al., 2010), which would potentially alter the outcome and behaviour of that factor within the model.

A.5 Conclusion

This short supplementary study confirmed the admonitions of Holgado-Tello et al. (2010) and Mîndrilă (2010) who recommend that polychoric correlations be calculated instead of Pearson correlations for factor analysis when observed variable data are ordinal. This means using either weighted least squares (Coenders & Saris, 1995) or diagonally weighted least squares if the sample size is small (Flora & Curran, 2004). This study should be read in conjunction with Chapter 3 (Methods) and serves as a justification for the methods used in Papers 2 (Chapter 5) and 4 (Chapter 7).

APPENDIX B – Thematic classifications and coding for Paper 3 (Chapter 6)

Table B.1

Kappa's Score and Percentage Agreement Between the Two Coders (Andrew Kemp and Dr Sarah Dart) for the First Round of Coding

	Kappa	Agreement (%)
Attitude, Affect & Motivation	0.74	93.1
Cognitive Engagement	0.99	99.9
Health & Well-being	0.84	98.8
Instructional Attributes	0.85	92.9
Perceived Behavioural Control	0.81	94.2
Social Factors	0.91	97.8
System Attributes	0.83	95.0
Usefulness & Visibility	0.76	97.1

Tables B.2 to B.9 represent further coding of subthemes carried out by Andrew Kemp.

Table B.2

Primary Construct from Taxonomy: Attitude, Affect and Motivation

Secondary Construct: Attitude	
Theme: Preference for learning using Zoom	
General Positive Comments, n=8	General Negative Comments, n=49
Exemplar comment: "I much prefer zoom to a recording if we have to do online learning because I like that it's live because it keeps me more up to date with content and you can ask questions."	Exemplar comment: "I don't find it preferable however it is convenient location wise."
Exemplar comment: "more motivation to learn"	Exemplar comment: "Personally the delivery method of zoom is off. I lacked the motivation to attend these zoom sessions as no one would really contribute.

	That's not the fault of zoom or the instructors."
	Exemplar comment: "I have found zoom learning to be a confronting transition and have avoided the use where possible. I do not like contributing to tutorials via zoom and would prefer online discussion boards for tutorials instead."

Table B.3

Primary Construct from Taxonomy: Cognitive Engagement

Secondary Construct: Absorption	
Theme: Engagement, interaction and focus	
General Positive Comments, n=1	Suggested Improvements, n=16
Exemplar comment: "The live aspect of it results in you having to be attentive during the zoom and therefore more actively engaged."	Exemplar comment: "make it more interactive to regain or maintain focus. It is too easy to get distracted."

Table B.4

Primary Construct from Taxonomy: Instructional Attributes

Secondary Construct: Content Attributes	
Theme: Interactive content	
General Positive Comments, n=3	Suggested Improvements, n=23
Exemplar comment: "Some had implemented some interactive learning but to stay engaged in class I think it is imperative to use in future learning."	Exemplar comment: "Have a lesson plan which they follow - riddled with interactive activities to promote class engagement."
Secondary Construct: Feedback	
Theme: Zoom enables feedback	

General Positive Comments, n=7	Suggested Improvements, n=4
Exemplar comment: "It enables any questions students have to be answered quickly"	Exemplar comment: "Give greater direction as well as feedback"
Secondary Construct: Lecturer Attributes	
Theme: Zoom lesson planning and integration	
General Positive Comments, n=0	Suggested Improvements, n=24
	Exemplar comment: "Prepare classes to accommodate Zoom type of learning instead of a face-to-face type."
	Exemplar comment: "Be prepared, confident and take charge of the tutorial, otherwise it doesn't flow or feel like we are learning. It almost feels like a waste of time."
Theme: Design for engagement	
General Positive Comments, n=0	Suggested Improvements, n=25
	Exemplar comment: "Create a more interesting zoom session that allows us to get more involved."
Theme: Facilitation of student behaviour	
General Positive Comments, n=0	Suggested Improvements, n=14
	Exemplar comment: "When break our [sic] rooms and peer collaboration happens, the instructor should assure that all peers are interacting."
	Exemplar comment: "encourage more people to get involved by turning on their cameras and asking direct questions to get more students involved in the discussions, as I found that a lot of people didn't turn their cameras on or talk throughout the sessions"
Theme: Instructor Zoom self-efficacy	

General Positive Comments, n=0	Suggested Improvements, n=15
	Exemplar comment: "Become proficient in using all of Zoom's features for hosts."
Secondary Construct: Social Interactivity	
Theme: Learner-instructor interaction	
General Positive Comments, n=19	Suggested Improvements, n=0
Exemplar comment: "If the lecturer is not busy, you can ask questions right away."	
Theme: Learner-learner interaction	
General Positive Comments, n=9	Suggested Improvements, n=0
Exemplar comment: "Better to engage with peers"	Exemplar comment: "Not overuse the breakout rooms - the discussion just doesn't happen."
Theme: Class interaction	
General Positive Comments, n=43	Suggested Improvements, n=10
Exemplar comment: "Gives you the opportunity to interact possibly more frequently and receive feedback"	Exemplar comment: "make sure people put their camera on and encourage everyone to speak up and not just sit there in silence."

Table B.5

Primary Construct from Taxonomy: Perceived Behavioural Control

Secondary Construct: Capability & Effort	
Theme: Easy to use	
General Positive Comments, n=5	Suggested Improvements, n=1
Exemplar comment: "It's easier to do group work."	Exemplar comment: "[make it] easier to use certain functions"
Secondary Construct: Environmental & Situational	
Theme: Accessibility and convenience	
General Positive Comments, n=92	Suggested Improvements, n=0
Exemplar comment: "The ability to attend and interact with the class/lecture without having to physically going [sic] to class as	

transport to University from my house is quite strenuous and time consuming."	

Table B.6

Primary Construct from Taxonomy: Social Factors

Secondary Construct: Social Influence	
Theme: Behaviour of peers	
General Positive Comments, n=0	General Negative Comments, n=16
	Exemplar comment: "I lacked the motivation to attend these zoom sessions as no one would really contribute."

Table B.7

Primary Construct from Taxonomy: System Attributes

Secondary Construct: System Function & Response	
Theme: Connection, image and audio quality	
General Positive Comments, n=0	General Negative Comments, n=34
	Exemplar comment: "Wi-Fi availability and high traffic on server can cause disruptions such as lags or lack of audio."
Theme: Functionality improvements	
General Positive Comments, n=0	Suggested Improvements, n=53
	Exemplar comment: "Perhaps some quiz - like activities such as kahoot but on the Zoom app for teachers to assist in learning."
Theme: Interface improvements	
General Positive Comments, n=0	Suggested Improvements, n=5
	Exemplar comment: "Many features of zoom feel hidden away in menus, in my

	experience it takes 5-10 minutes of class time to teach the class how to use a feature (ie. raising hand feature, whiteboard, etc.)"

Table B.8

Primary Construct from Taxonomy: Usefulness & Visibility

Secondary Construct: System & Learning Usefulness	
Theme: Class participation and interaction	
General Positive Comments, n=13	Qualified support, n=8
Exemplar comment: "Zoom allows for interaction with other students and tutors/lecturers which is not the case with recordings."	Exemplar comment: "Student's ability to participate compared to a lecture. However not as good as in person tutorials etc."

Table B.9

Non-existent Primary Construct from Taxonomy

Theme: Social comfort	
General Positive Comments, n=4	General Negative Comments, n=20
Exemplar comment: "sometimes it can be easier to talk as its not face to face and therefore you feel more comfortable."	Exemplar comment: "The largest factor that causes me to prefer face-to-face learning over Zoom is the social aspect. While Zoom provides a useful alternative to this in circumstances where it is needed (e.g., social distancing, absent students), it can feel isolating and it is much more difficult to make friends."
Theme: Physical and mental health	
General Positive Comments, n=10	General Negative Comments, n=3

Exemplar comment: "allows for more interactive experience during social distancing"	Exemplar comment: "When using my computer for Zoom all day I get a sore back and eyes."
Exemplar comment: "I am physically disabled, so using ZOOM in replacement of face-to-face lectures has been great as I have to travel a great distance to get to my campus"	Exemplar comment: "as a person with social anxiety the mic and photo aspects of zoom give me panic attacks and so aren't conductive to my mental health."

The emergent themes from tables B.2 to B.9 were then collated into aggregate themes according to their aspect of learning and teaching affected (Table B.10). Attitude was not included because students' attitude and preferences were of a binary form either for or against using Zoom for learning, often due to factors which can be represented by the themes delineated below. As such attitude was a result of the application of the ideas represented by the parent themes.

Table B.10

Summary of themes presented in Tables B.2 to B.9

Parent theme from thematic analysis	Included subthemes
Class interaction (n=108)	Class interaction (n=43) Class participation and interaction (n=21) Leaner-instructor interaction (n=19) Behaviour of peers (n=16) Learner-learner interaction (n=9)
System functionality (n=101)	Functionality improvements (n=53) Connection, image and audio quality (n=43) Interface improvements (n=5)
Access and convenience (n=98)	Accessibility and convenience (n=92) Easy to use (n=6)
Engagement with learning (n=68)	Interactive content (n=26) Design for engagement (n=25)

	Engagement, interaction and focus (n=17)
Instructor practice (n=53)	Zoom lesson planning and integration (n=24) Instructor Zoom self-efficacy (n=15) Facilitation of student behaviour (n=14)
Comfort and well-being (n=37)	Social comfort (n=24) Physical and mental health (n=13)
Feedback and information exchange (n=11)	Zoom enables feedback (n=11)

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