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Editorial: "Are Technology Acceptance Models still fit for purpose?"

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Abstract

Technology acceptance research has been an important and fruitful research domain since the late 1980s. At the forefront has been the Technology Acceptance Model (TAM) and related models such as UTAUT. These models aim to explain and predict adoption of technology, so that adoption can be improved and decisions can be made regarding technology implementation. The predictor variables of adoption are Behavioural Intention (BI) and Actual Use (USE). The TAM defines two key determinants of BI, Perceived Ease of Use (PEOU, sometimes also abbreviated as PEU) and Perceived Usefulness (PU). Technology Acceptance Model research has been applied to many different technologies, in different fields of use, in different cultural contexts, and at different scales, globally. Whilst being robust, the approach does have limitations. These call into question, to greater and lesser degrees, the validity of the findings and/or the usefulness of the model under certain contexts. This issue examines the debates surrounding these limitations under the umbrella question of "TAMs: Are they still fit for purpose?" The commentary article and book review in this special issue directly address these debates and the articles demonstrate how researchers are responding to the debates, exploring them in different contexts, at different scales and for different technologies. The editorial concludes by proposing future directions for the field to continue its evolution and remain as an effective and important tool in understanding technology adoption in an age of frequent and rapid technological innovation in education.

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Introduction

Reports of the demise of technology acceptance model-based research (Mogaji et al., 2024; Al-Emran, 2023) are premature. Technology acceptance model-based research (TAMBR), which we define for this issue as that utilising theoretical models, such as the Technology Acceptance Model (TAM) (Davis, 1989; Davis et al., 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), aims to explain and predict the adoption and use of new technology. TAM has been a hugely influential theory of technology adoption since it was developed by Davis. It has spawned a school of research that has examined the influences upon intention to use and actual use of technology. This research has been applied to many different technologies, in different fields of use, in different cultural contexts, and at different scales, globally (Granic, 2022; Scherer et al., 2019). The impression that this research may be, in some circles, considered as mature and perhaps diminishing in popularity/efficacy (Al-Emran & Granic, 2021), probably stems from fact that the TAM, despite being over 30 years old, is still being employed by researchers, often in its original form, whilst technology itself, and the rate of technological change, has vastly transformed throughout the lifespan of TAM

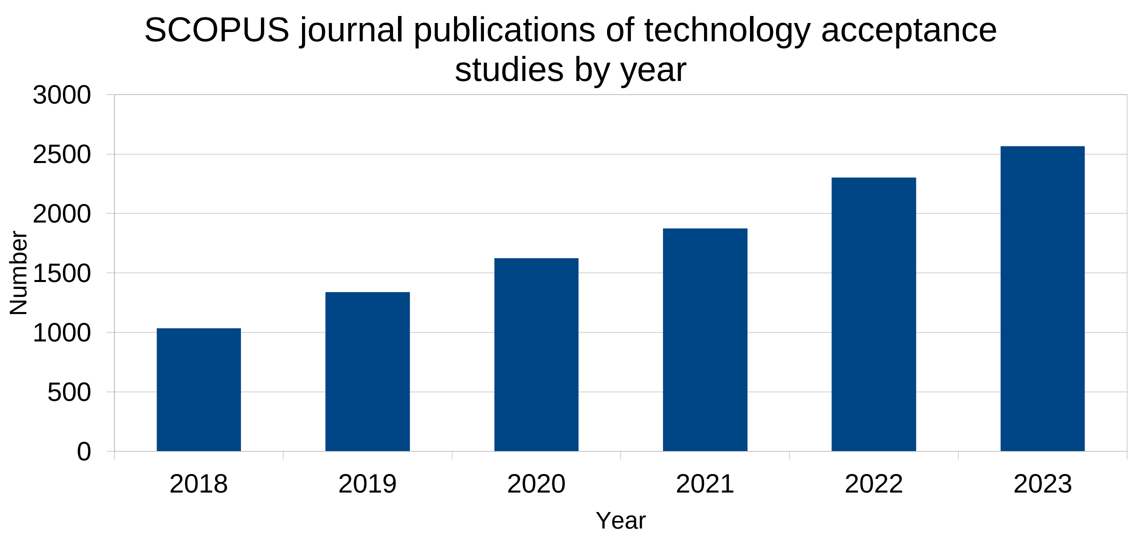
The case for continued research into technology acceptance is clear. We are now in an age where the introduction of new technology is a fact of life. We are also in an age where disruptive technologies and events are being forced upon us, and at a quicker pace than we have ever been used to. We only have to look at events in education within the past 4 years to see this. We have seen COVID-19 force many educators to pivot to online, and often asynchronous, learning, with a concomitant adoption of new technologies and associated pedagogies. In addition, more recently, the rapid development and use of Generative AI, such as ChatGPT, has been, and continues to be, a significant disruptive technology within higher education learning and teaching. GenAI is a technology that was adopted earlier and in larger numbers by students (Shaw et al., 2023) and as a result many educators had to react, rather than be proactive in their technology adoption. As a consequence, we have a situation where many universities are presently designing programs to support academic understanding and adoption of GenAI technologies now, and new technologies in the future. The imperative is high – our staff must be versed in new technologies to understand their pedagogical affordances, and the ethical challenges they present. As such it seems that a greater understanding of technology acceptance, the factors that influence it, and how to improve outcomes, is as important as ever.

So, and in response to these doubts regarding TAMBR, “Do these models based on work over 30 years old still have the explanatory and predictive power to contribute in the current research environment?” we draw from evidence suggesting that research in the discipline that employs technology acceptance models is buoyant. Indeed, examination of SCOPUS of articles published in indexed journals between 2018 and 2023 shows that the number of papers with technology acceptance, TAM or UTAUT as keywords shows some 10,743 journal articles published exhibiting a year-on-year increase during the period. (See Figure 1).

TAMBR has a sizeable body of research and within this work limitations of the approach have been identified and examined. So even though TAMBR remains popular, it is not a simple inference to conclude that because TAMs are still being used extensively, ergo they are still fit for purpose. In this special issue we attempt to discuss, using the identified limitations of TAMBR as a foundation, the future of this research and demonstrate how current researchers are responding to these criticisms.

Figure 1

SCOPUS journal article publications by year with keywords "technology acceptance", "TAM, "UTAUT"



Technology Acceptance Models

Technology acceptance models are a family of related models derived from Davis's TAM, which in turn drew upon the work of Fishbein and Ajzen's (1975) Theory of Reasoned Action (TRA). They include many extensions of the TAM, such as TAM2, extended TAM and others as well as UTAUT, which incorporates much of TAM into its own model and shares many similarities with it.

The TAM models aim to explain and predict adoption of technology, so that adoption can be improved and/or decisions can be made regarding technology implementation. The predictor variables of adoption are Behavioural Intention (BI) and Actual Use (USE). The TAM defines two key determinants of BI, Perceived Ease of Use (PEOU, sometimes also abbreviated as PEU) and Perceived Usefulness (PU), although an additional variable Attitude to Technology (ATT) is also incorporated into the model for some studies. The model also defines moderating factors, also known as external variables, such as subjective norm, experience and voluntariness, which are variables that moderate the influence of PEOU and PU under different contexts. Different versions and extensions of TAM have frequently developed and specified additional external variables to the model. For greater details on the development of TAM and its variants see Davis and Granic (2024), which provides a detailed description and explanation of the TAM.

The UTAUT model was synthesised from TAM and seven other technology models: TRA (Fishbein & Ajzen, 1975), Motivational Model (Davis et al., 1992), Theory of Planned Behaviour (Ajzen, 1985, 1991), Model of PC Utilisation (Thompson et al., 1991), Innovation Diffusion Theory (Rogers, 1962, 1995), Social Cognitive Theory and combined TAM and TPB (Bandura, 1986). It too uses Behavioural Intention and Actual Use as predictors of technology adoption. It proposes four antecedent variables, three of which: Performance Expectancy (PE), Effort Expectancy (EE) and Social Influence (SI) directly influence Behavioural Intention (BI), the fourth: Facilitating Conditions (FC) directly influences actual behaviour alongside BI. The model also defines a number of moderators on the antecedent variables, which originally included: gender, age, experience, and voluntariness of use, these like the moderator variables of TAM modify the impact of the four antecedent variables. Lampo (2020) contains a good explanation of the model.

Themes

Researchers on TAMBR have highlighted a number of themes that characterise research using TAM, in particular, but which can also be applied to all TAMBR to some degree, including that which uses UTAUT. The debates around these themes identify some of the limitations of the model and as such call into question, to greater and lesser degrees, the validity of the findings and/or the usefulness of the model under certain contexts. We will be using these debates to structure the issue's response the guiding theme of this special issue.

We have grouped these themes into the three areas where they relate to model functionality: Outputs, Inputs and Structure:

Outputs: For much TAMBR BI (Behavioural Intention) is the focus of the research. Many studies finish at prediction of BI and do not continue onto examine actual use (USE). Nistor (2014) citing Bagozzi (2002) and Straub and Burton-Jones (2007) noted that few studies using TAM examine the intention – behaviour link, this is also re-iterated by Scherer, Siddiq and Tondeur (2019) who noted that the link between user intentions and actual use is often omitted in many empirical studies using TAM. TAM and UTAUT assume that BI is a reliable indicator of USE. For many studies the objective of the work is to predict BI and thus whilst the weight of evidence is clear that TAM and UTAUT are effective at predicting BI, it is less strong that they are equally effective at predicting USE, i.e. actual adoption.

Inputs: There are questions relating to the methods employed within technology acceptance research, particularly the data collection methods. Are they suitable for the findings to be used with confidence in predicting adoption/acceptance of new technologies?

Within TAMBR there is a marked reliance on surveys and questionnaires for data collection, with a resultant prioritisation of user perceptions (Xue et al., 2024; Fajriyanto et al., 2024; Williams et al., 2015). This can be seen as a limitation of the research as self-reporting does not always match to actual activity with a variety of different elements impacting directly on self-reporting accuracy (Andrews et al., 2015). A number of researchers have called for a diversification of data collection techniques, they cite a conspicuous absence of experimental methodologies, such as keyboard logging, cognitive walkthroughs, activity logs, which are prevalent in user acceptance testing and longitudinal studies. Davis himself with others (Riedl et al., 2020), have proposed the emerging field of NeuroIS as an alternative, claiming it would be a novel approach to data collection that could enhance the depth and accuracy of user acceptance research. Certainly research employing these methods could potentially provide more objective data types, contrasting sharply with the subjective data typically garnered through traditional surveys (Polson et al., 1992; Lyon et al., 2021).

More recently, some researchers have expounded data-driven predictive analysis based approaches (Alwabel & Zeng, 2021) as an alternative to TAMBR, which they claim is explanatory, but not predictive in focus.

Model Structure: The core constructs - PEOU and PU for TAM and PE, EE, SI and FC for UTAUT - have endured and have been shown to be reliable (and valid) constructs within the models (King & He, 2006), However, a characteristic of research in the field is for researchers to incorporate of an increasing number of moderating factors into the model to adapt the model to be better suited to different contexts (Adbullah & Ward, 2015; Granic & Marangunic, 2019; Granic, 2022; Lampo, 2022). This is both a strength of TAM and UTAUT, endowing them with versatility, which has enabled the models to be applied to a huge variety of technologies, across many different contexts and at different levels of granularity from acceptance in small scale environments through to wide ranging international studies. However, this flexibility of the models is also considered by some as a weakness, impacting the ability of TAMBR findings to be effectively generalised (Tremblay-Cantin et al., 2023; Turner et al., 2013). Whilst the addition of moderating factors can improve the predictive power of the model for specific technologies and/or cases (Sohn & Kim, 2020) it is often at the expense of enabling the findings to be applicable beyond the focus of the individual study (Turner et al., 2010).

Alongside this, in addition to the plethora of these moderating factors, there is variance in the structure of the model adopted. Some TAM models include Attitude to Technology (ATT) as an antecedent of BI alongside PEOU and PU, whilst other do not (Scherer et al., 2019). The fluid structure of TAM, in particular, but it is a characteristic shared with UTAUT, has allowed the development of enhanced and extended versions of the model. It is common for many studies to have as an outcome the identification of different moderating factors or to categorise moderating variables into classes for particular studies, but again these reduce opportunities for the generalisability of results.

The predictive ability of the models has been called into question, with researchers noting that variations in correlations between the model's variables between studies are not typically considered or accounted for (Li et al., 2008).

Discussion

This Special Issue contains five research papers, a commentary article by Ronny Scherer and a review of Fred Davis' very recently published book on TAM (2024), written with Andrina Granic. What these articles give us is a clear idea of how current researchers are applying technology acceptance research, and indication of how researchers are responding to the debates we have outlined above. As can be seen from Table 1 the research is wide ranging and the papers demonstrate some of the defining characteristics of TAMBR.

Table 1

A summary of the papers contained of the special issue by key characteristics

Author(s)	Model	Technology	Data Source	Scale	Outputs	Structure
Kavitha and Joshith	TAM	AI	Survey/Questionnaire	National	BI	Modifications to structure suggested
Enang and Christopoulou	TAM and UTAUT	ChatGPT	Survey	Dept	BI and ATU	None
Soares, Lerigo-Sampson, and Barker	UTAUT	Online marking rubrics	Interviews	Institution	BI, USE (willingness to use)	None
Yang, Li, Chen, and Wu	TAM	Online teaching	Questionnaire	National	BI and USE	Uses external variables suggested from other studies for context
Sun, Yuan, and Liu	TAM	Digital pedagogy	Case study of published material	Multi-institutional	BI and USE	Combined TAM with ANT

Each of the papers in the special issue has a contribution to make to the debates spotlighted above. Ronny Scherer's commentary article directly addresses many of the debates. It examines the core structure of TAM analysing the internal setup of the model and how the components interface and interact, then considers the model from a measurement perspective, noting the influence data collection and sources have upon the robustness of the model and then finally take a critical view of the structure and causal relationship within the model. He calls for a diversification of the data sources being employed within TAM research proposing the future should move towards longitudinal evidence and an examination of the causal assumptions underlying the relationships within the model. This dovetails with Davis and Granic's book (2024), which alongside a comprehensive account of the development of the TAM and review of recent research to give a detailed overview of the current state of the research area, also calls for an expansion of the data collection techniques employed by researchers and proposes a new approach based on NeuroIS. The empirical papers demonstrate how current researchers are adjusted their research in response to some of the debates. Joshith and Kavitha apply TAM at a national scale looking at the acceptance of AI at a macro level. Both Soares, Lerigo-Sampson and Barker and Enang and Christopoulou's studies, that examine online marking rubrics and ChatGPT respectively, consider actual use of technology. In addition, both studies, along with that of Joshith and Kavitha, draw their data from academic samples as opposed to students. Sun, Yuan and Liu employ case study research drawing upon published material for their work on the acceptance and adoption of digital pedagogy at two different international universities and Yang, Li, Chen and Wu's study looks at the impact of the pandemic in forcing the adoption of online teaching on the subsequent willingness to use online learning techniques. Both of these studies focus on actual use of technology.

The articles show researchers are incorporating the debates in the area and responding to the issues being raised. We can see three out of five of the studies employ the full range of the models and examine actual use or adoption of technology and four out out of five draw upon data sources beyond student surveys. Four out of five of the studies do not propose additional external variables or extensions to the models. However, except for one, all of the studies still rely upon survey or questionnaire data.

The Future

TAM (and UTAUT)'s one size fits all scope and their ability to be adapted to different contexts has served TAMBR well, up until now. It is perhaps holding it back at this time. In the ever changing technological environment and combined with the speed of these changes, research needs to emphasise prediction more. To assist this TAMBR researchers now need to think more about examining the internal structure of the model. Refocussing data collection away from self-reporting to the inclusion of methods that measure actual use (potentially NeuroIS, definitely longitudinal and possibly borrowed from User Acceptance testing and Software Engineering/Usability). This would precipitate a move towards measuring activity rather than intention, and especially towards research that specifically measures the conversion of BI to USE. Analysis of weightings, correlations between variables, co-correlations and redundancy between external moderating factors and the core predictors and their antecedents consolidated between different studies and contexts should enable the outputs of the model to be predictive as well as explanatory. Such development would supplement the already robust and excellent explanatory powers of the core models with greater predictive ability and generalisability.

The TAMs have evolved and developed over the past 30 years and so have remained useful and relevant. Perhaps TAMs were fit for purpose because they fitted all purposes – the flexibility and adaptability of the model enabled this. Now TAMs needs to adapt again and extend again, but this time so that they fit with the wider set of contexts without having to be extended and adapted for specific contexts and instead the focus should be on the internal structure of the models to make their findings more generalisable. Key to this is the data we collect, data that enables the analysis of actual behaviour and actions as well as intentions

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