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A Meta-Analytical Review of Technology Acceptance Research

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Abstract

This paper reviewed the literature on technology acceptance using a meta-analytical approach. The objective of this review was two-fold: (a) to provide a comprehensive analysis of the factors contributing to technology acceptance and investigate their effects, depending on theoretical underpinnings; (b) to explore the conditions explaining the variance in the effects of predictors time-wise. This review analysed data from 693 papers. 21 independent predictors having differential effects on attitude, intention and use behaviour were found. The effects of the predictors were different depending on the theoretical frameworks they were related to. The analysis of the consistency of the role of the predictors suggested that there was no longitudinal change in their effect sizes.

Keywords: *meta-analysis, technology acceptance, technology adoption*

A Meta-Analytical Review of Technology Acceptance Research

1. Introduction

Technology acceptance research has been one of the fastest-growing streams in the Information Systems (IS) literature. The popularity of this research domain is due to the constantly developing nature of the technology. Fast technology development calls for fresh insight into the users' side of technology use. This is needed to capture changing users' demands, beliefs, preferences and expectations against contextual differences, such as culture, geographical location and the difference in technologies (Demoulin and Coussement, 2020, Pascual-Miguel et al., 2015). The scale to which the technology acceptance stream has grown and the current discourse around the future of this area have created the need to perform a meta-analytic review of the relevant work and offer future research avenues.

To this end, there are two gaps in the literature that this review paper aims to address. Firstly, there are a few systematic reviews and meta-analyses on technology acceptance (Dwivedi et al., 2019, Tsai et al., 2017). Still, they tend to focus on specific theories such as TAM (Scherer et al., 2019, King and He, 2006) or UTAUT (Tamilmani et al., 2019), and specific contexts, such as mobile banking, e-learning and e-government (Zhao et al., 2021, Jadil et al., 2021). However, a meta-analytic review of the factors of technology acceptance across theories might not only help put theories into perspective, but it could make it possible to focus on individual constructs more widely, examining whether attitude, intention or use behaviour can be regarded as a proxy for behaviour (Warshaw and Davis, 1985, Davis, 1985, Venkatesh et al., 2003, Turner et al., 2010, Straub et al., 1995, Tao, 2009, Calisir et al., 2009). Second, the fast-paced development of the technology has been fuelling the growth of the literature exploring the utilisation of new technology (Alexandrou and Chen, 2019, Nysveen and Pedersen, 2016). Considering the changes in technology use cases over the past decades, there is a need to aggregate the effects of factors and compare them across time.

Given the aforementioned gaps, this study pursued three objectives. The first objective was to conduct a meta-analysis to explore the predictors of technology acceptance and examine their relation to attitude, use intention and use behaviour. The second objective was to explore the effects of predictors depending on underpinning theories. By employing a subgroup analysis, which can identify the significance of the variance in factors across theories, the importance of the adopted theoretical foundations was examined. The third objective was to examine the variance in results in the technology acceptance literature across time to provide an understanding of the dynamics of the research on technology acceptance. That was made possible by identifying the changes in the power of researched constructs across time that explain which factors have received increasing importance.

2. Technology Acceptance

Among the most powerful theories that have been extensively used in the technology acceptance research stream until today are: Task-Technology Fit model (TTF), Diffusion of Innovation Theory (DOI), Delone and Mclean Success Model, Unified Theory of Acceptance and Use of Technology (UTAUT) and its extensions, as well as the original and extended TAM. They brought evidence about the role of the characteristics of innovation (e.g. relative advantage, compatibility, complexity), the fit of technology to tasks, the interdependence between the dimensions of IS success (e.g. information quality, system quality, service quality)

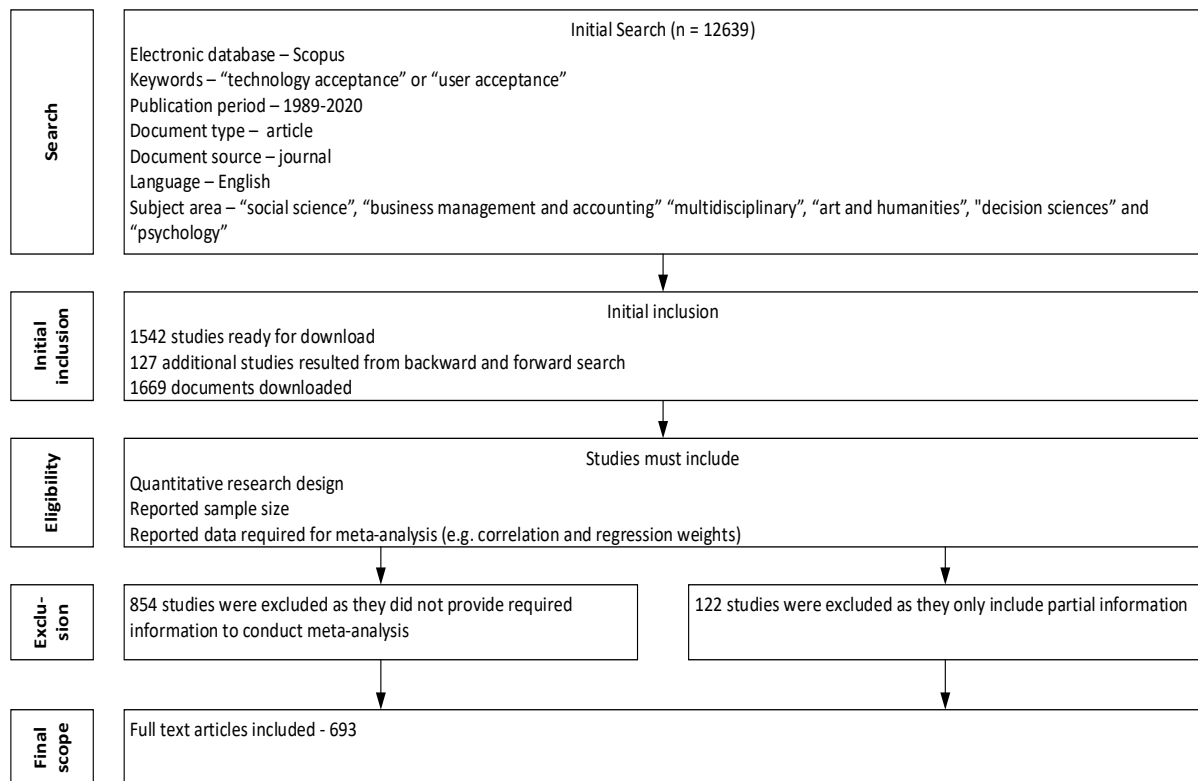
and the beliefs about internal and external factors affecting behaviour (e.g. social influence, performance expectancy) (Venkatesh et al., 2003). Many of the theories have been the subjects of revisions, resulting in integrated models, such as TAM-TTF (Tam and Oliveira, 2016, Dishaw and Strong, 1999) and UTAUT-TAM (Buabeng-Andoh and Baah, 2020). Scholars have often complemented theories with additional factors (e.g. privacy, trust) to test explored conditions that could explain adoption (Kumar et al., 2016, Vimalkumar et al., 2021).

Over the years technology acceptance research and theories has also been informed and underpinned by research and theories grounded in other disciplines that are concerned with human behaviour (Marikyan et al., 2020, Magsamen-Conrad and Dillon, 2020). To reflect on the development in technology acceptance research, a number of reviews have been conducted with a focus on particular theoretical models (Venkatesh et al., 2007, Dwivedi et al., 2019) and their extensions (Patil et al., 2020, Tamilmani et al., 2019). However, the focus on specific theories, domains or applications limits the scope of the papers included in the analysis, providing a partial insight into the underpinnings of use behaviour (King and He, 2006, Williams et al., 2011, Dwivedi et al., 2019). Therefore, to provide a comprehensive analysis of the research, this study identifies the factors of acceptance without limiting itself to specific theories and explores the difference in predictors depending on the theoretical underpinnings, the year of publication, technology applications and outlets.

3. Methodology

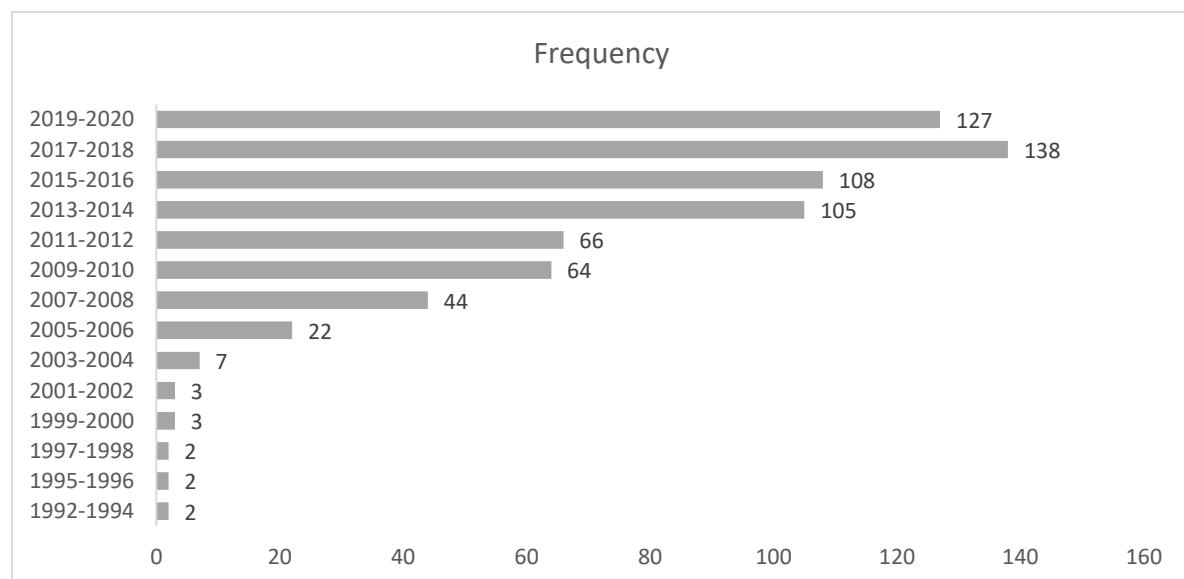
This study uses a meta-analytic approach to analyse the literature. The review of the literature was conducted in a systematic way in three steps to minimise potential biases (Figure 1) (Tranfield et al., 2003). First, we embarked on the planning stage by starting the preliminary review of the technology acceptance literature, proposing objectives and developing a research protocol. Second, we selected electronic databases, keywords, exclusion and inclusion criteria, the extraction of the material for data analysis and the analysis of the data. The Scopus electronic database was used as a source from which articles were searched and extracted, as it provides wide coverage of academic literature (Marikyan et al., 2019). The search of publications was based on the keyword “*technology acceptance*”, resulting in 12639 documents. After the filtration process, 1542 papers were left to download. Following the guidelines by Croom (2009) and Thomé et al. (2016), we conducted an additional backward and forward citation search, which made it possible to include all relevant papers. That resulted in an additional 127 articles. Then, we excluded articles that we could not use in the meta-analysis. As per Lipsey and Wilson (2001) and Cooper et al. (2019), this review only included studies that had a quantitative research design, and studies that reported the sample size and the type of analysis conducted (e.g. correlation, regression weights). In addition, we only included studies that examined at least one of the outcome variables, such as intention to use, attitude and use behaviour that we aimed to study. After applying those filtering criteria, 854 articles were excluded.

Figure 1: Literature search and the selection of studies eligible for meta-analysis



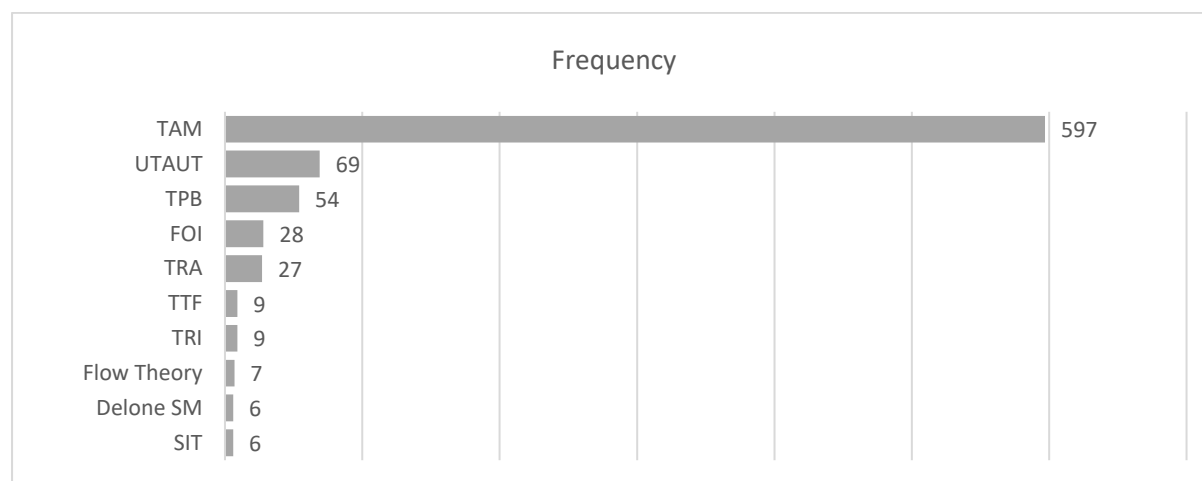
Third, after downloading the final sample of documents, we embarked on the extraction of data for the meta-analysis. Given that meta-analysis is a method by which the cumulative effects of relationships are assimilated from individual studies (Field, 2001), we had to collect data about the relationships between the factors of acceptance and dependent variables. The data collection started with the extraction of sample size, the coefficients of regression weights and p-values (King and He, 2006, Dwivedi et al., 2019). Then, the variance for each relation was calculated. Relationships that had been tested less than three times were excluded (Kapoor et al., 2014). During the final phase of data extraction, 122 articles were excluded due to insufficient information. As a result, the final scope of articles comprised 693 documents. Figure 2 illustrates the frequency of published papers by year.

Figure 2: Year of publication



The published research was based on 10 main underpinning theories with their extended versions, such as Technology Acceptance Models (TAM, TAM2, TAM3), Unified Theory of Acceptance and Use of Technology (UTAUT) and its extensions, and Technology Readiness Index (TRI)(Figure 3). The predominant number of papers utilised TAM as a theoretical framework.

Figure 3: Underpinning theories of published papers



For the analysis we used RStudio with *dmeter* and *metafor* packages (Harrer et al., 2019). The effect sizes of all identified determinants of acceptance were calculated using variance and relationship weights (beta) (Kapoor et al., 2014, Jeyaraj and Dwivedi, 2020). Given that the effect size is dependent on the number of the factors being investigated in the literature, this paper only included the variables that had been tested more than three times (Cooper et al., 2019).

To address the three objectives of the study, three types of analysis were used, namely, pooling effect sizes, sub-group analysis and the analysis of moderation effects. To address the first objective, a random-effect approach was used to pool (aggregate) effect sizes from all studies (Jeyaraj and Dwivedi, 2020). Prior to pooling the effect sizes, homogeneity across the synthesised papers was calculated by employing Q and I^2 statistics. This showed the variation across papers due to heterogeneity, above and beyond variation expected due to chance (Higgins et al., 2003). To address the second objective (variance in predictors due to a theory), we used a subgroup analysis. The idea behind the subgroup analysis is that effects are pooled and compared between the groups (e.g. high-ranked vs low-ranked journals, TAM-based studies vs UTAUT-based studies etc.). The results make it possible to study whether the difference between the groups is meaningful (Harrer et al., 2019). The third objective (the difference due to a publication year) was addressed using a moderation analysis. Moderation effects were examined by introducing control variables, which enabled us to calculate the variance in the outcome variable due to the interactive effect of the predictors with the year of publication.

4. Results and Discussion

4.1. The Determinants of Technology Acceptance

The first research objective was tackled by identifying the predictors of technology acceptance and pooling their effects on attitude, intention to use and use behaviour. In total, 21 determinants were identified, which are summarised in Table 1.

Table 1: Predictors of technology acceptance

Predictor	Definition	Reference
Attitude	<i>An individual's positive or negative feelings (evaluative affect) about performing the target behaviour</i>	Fishbein and Ajzen (1975)
Effort expectancy	<i>The degree of ease associated with the use of the system</i>	Venkatesh et al. (2003)
Experience	<i>Prior use of technology</i>	Venkatesh et al. (2003)
Facilitating conditions	<i>The degree to which an individual believes that an organisational and technical infrastructure exists to support use of the system.</i>	Venkatesh et al. (2003)
Innovativeness	<i>The willingness of an individual to try out any new information technology.</i>	Agarwal and Prasad (1998)
Perceived enjoyment	<i>Conceived as the extent to which the activity of using computers is perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated.</i>	Davis et al. (1992)
Perceived ease of use	<i>The degree to which a person believes that using a particular system would be free of effort.</i>	Davis (1989)
Performance expectancy	<i>The degree to which an individual believes that using the system will help him or her to attain gains in job performance.</i>	Venkatesh et al. (2003)
Perceived playfulness	<i>The strength of one's belief that interacting with the given technology will fulfil the user's intrinsic motives.</i>	Lin et al. (2005)
Perceived privacy risk	<i>Potential loss of control over personal information.</i>	Featherman and Pavlou (2003)
Perceived risk	<i>Perceived uncertainty in the given situation.</i>	Im et al. (2008)
Perceived security risk	<i>Individual's perception of security risk</i>	Alexandrou and Chen (2019)
Perceived usefulness	<i>The degree to which a person believes that using a particular system would enhance his or her job performance.</i>	Davis (1989)
Perceived value	<i>Consumers' cognitive trade-off between the perceived benefits of the applications and the monetary cost for using them.</i>	Venkatesh et al. (2012)
Relative advantage	<i>The degree to which using an innovation is perceived as being better than using a precursor.</i>	Venkatesh et al. (2003)
Satisfaction	<i>Users' affect with (feelings about) technology use.</i>	Spreng and Olshavsky (1993)
Self-efficacy	<i>Judgement of one's ability to use a technology to accomplish a particular job or task.</i>	Venkatesh et al. (2003)
Social influence	<i>The degree to which an individual perceives that important others believe he or she should use the new system.</i>	Venkatesh et al. (2003)
Subjective norm	<i>The individual's perception that most people who are important to him think he should or should not perform the behaviour in question.</i>	Fishbein and Ajzen (1975)
Trust	<i>Individual's expectations about the motives and behaviours of a trustee.</i>	Doney and Cannon (1997)
Perceived behavioural control	<i>The perceived ease or difficulty of performing the behaviour</i>	Ajzen (1991)

The analysis of pooled effect sizes for each outcome variable demonstrated that out of 15 predictors of attitude, 11 were significant (Table 2). The predictors mostly reflect the positive perceptions about how technologies are used and what outcomes the utilisation can bring, such as perceived playfulness, perceived ease of use and perceived enjoyment. Experience, perceived privacy risk, perceived risk, perceived security risk and self-efficacy had non-significant effects. The non-supported effect of experience can be explained by the assumption that when it comes to attitude, experience can weaken trust in technology, underpinning a positive attitude (Tong, 2010). A plausible interpretation of the nonsignificant effect of all three risk variables could be that attitude to technology is an affective state and may be more psychologically distant than actual use or intentions. Given the technological advancements,

the benefits that new technologies promise may reduce the uncertainty of technology use (Marikyan et al., 2019). Therefore, in a situation of general technology evaluation, risks may seem abstract and irrelevant. The effect of self-efficacy was not confirmed either. Prior literature provided evidence that self-efficacy has a mediated affect through cognition (Kulviwat et al., 2014). Thus, it is assumed to be an indirect predictor of technology acceptance.

Table 2: The predictors of attitude

Independent Variable	Total Effect Size	95% - CI	P-Value
Performance expectancy	0.5296	[0.1562; 0.9030]	0.0203
Perceived usefulness	0.4288	[0.4069; 0.4508]	0.0001
Perceived enjoyment	0.4109	[0.3540; 0.4677]	0.0001
Trust	0.2879	[0.2275; 0.3482]	0.0001
Perceived ease of use	0.2544	[0.2332; 0.2757]	0.0001
Perceived playfulness	0.2381	[0.1635; 0.3127]	0.0002
Subjective norm	0.2085	[0.1492; 0.2679]	0.0001
Social influence	0.1849	[0.0788; 0.2910]	0.0019
Innovativeness	0.1235	[0.0620; 0.1850]	0.0017
Facilitating conditions	0.118	[0.0099; 0.2261]	0.0345
Self-efficacy	0.1166	[-0.0186; 0.2517]	0.0848
Perceived privacy risk	0.1156	[-0.0158; 0.2470]	0.0785
Experience	0.0782	[-0.0580; 0.2143]	0.1651
Perceived security risk	0.0029	[-0.1617; 0.1674]	0.9704
Perceived risk	-0.0469	[-0.1392; 0.0453]	0.3021

The highest number of factors were identified to be the predictors of intention to use (Table 3). Out of 21 factors, the effects of only two were not found to be significant. The variables with significant effects embrace all positive and negative beliefs about the consequences of technology utilisation, as well as the beliefs about personal abilities and control over behaviour. Although the effects of privacy and security risks were not supported, the overall perception of risks was found to determine the willingness to embark on technology utilisation.

Table 3: The Predictors of intention to use

Independent Variable	Total Effect Size	95% - CI	P-Value
Attitude	0.4971	[0.4688; 0.5254]	0.0001
Satisfaction	0.4192	[0.3113; 0.5271]	0.0001
Perceived usefulness	0.3470	[0.3265; 0.3676]	0.0001
Perceived enjoyment	0.2890	[0.2331; 0.3450]	0.0001
Perceived playfulness	0.2759	[0.1052; 0.4466]	0.0042
Performance expectancy	0.2746	[0.2294; 0.3197]	0.0001
Perceived value	0.2502	[0.1365; 0.3640]	0.0003
Trust	0.2477	[0.2037; 0.2917]	0.0001
Subjective norm	0.2257	[0.1888; 0.2625]	0.0001
Perceived ease of use	0.2204	[0.1987; 0.2420]	0.0001
Self-efficacy	0.2141	[0.1371; 0.2912]	0.0001
Perceived behavioural control	0.2019	[0.1513; 0.2525]	0.0001
Social influence	0.1920	[0.1570; 0.2270]	0.0001
Innovativeness	0.1859	[0.0960; 0.2758]	0.0003
Facilitating conditions	0.1802	[0.1175; 0.2429]	0.0001
Relative advantage	0.1742	[0.1225; 0.2258]	0.0001
Experience	0.1665	[0.0451; 0.2879]	0.0105
Effort expectancy	0.1254	[0.0891; 0.1617]	0.0001
Perceived security risk	0.0888	[-0.0777; 0.2553]	0.2677
Perceived privacy risk	0.0566	[-0.0916; 0.2047]	0.4243
Perceived risk	-0.0982	[-0.1424; -0.0539]	0.0001

Use behaviour has been predicted by 14 factors, which in general can be described as beliefs about the risks, positive outcomes and personal capabilities (Table 4). Trust, performance expectancy and social influence were found to have non-significant effects. These findings contradict the general argument in the research that these variables are important when using technology (Venkatesh et al., 2003, Rahi et al., 2019, Al-Saedi et al., 2020). The perception of the degree to which technology can perform well in delivering services is not important, as people might set a new threshold of expectations for future technology use. Similarly, trust may not play an important role when users have already been engaging with the technology. Also, due to prior experience, the first-hand knowledge about the outcomes of adoption diminishes the influence of the opinions of other people about technology.

Table 4: The predictors of use behaviour

Independent Variable	Total Effect Size	95% - CI	P-Value
Intention to use	0.4573	[0.4160; 0.4987]	0.0001
Attitude	0.3740	[0.2453; 0.5026]	0.0001
Perceived usefulness	0.3359	[0.2697; 0.4021]	0.0001
Perceived enjoyment	0.3233	[0.2147; 0.4320]	0.0025
Satisfaction	0.3172	[-0.0039; 0.6383]	0.0500
Performance expectancy	0.2580	[-0.1217; 0.6390]	0.1191
Facilitating conditions	0.2489	[0.1404; 0.3575]	0.0002
Innovativeness	0.2413	[0.0333; 0.4493]	0.0307
Perceived ease of use	0.2295	[0.1466; 0.3125]	0.0001
Perceived behavioural control	0.1943	[0.0270; 0.3616]	0.0280
Self-efficacy	0.1640	[0.0289; 0.2992]	0.0226
Trust	0.1297	[-0.0263; 0.2858]	0.0881
Social influence	0.0606	[-0.3695; 0.4907]	0.7155
Perceived risk	-0.1513	[-0.2639; -0.0387]	0.0235

The results of the pooled effects of the factors show that each outcome variable has different predictors. Such results provide evidence for the debate on whether attitude, intention to use or use behaviour can be used as a proxy for technology adoption (Warshaw and Davis, 1985, Davis, 1985, Venkatesh et al., 2003, Turner et al., 2010, Straub et al., 1995, Tao, 2009, Calisir et al., 2009). Specifically, research in sociology and psychology suggested that attitude explains behaviour (Ajzen and Fishbein, 1980, Baldinger and Rubinson, 1996). Other scholars argued about the need to focus on use intention, although the findings of the degree to which this translates into actual behaviour were not consistent (Turner et al., 2010, Davis, 1985, Straub et al., 1995, Calisir et al., 2009). Given that the explanatory strength of attitude, use intention and actual behaviour is different, future research could consider the types of beliefs specific to a technology pre-adoption phase and actual use. The focus on the factors which matter for users in specific situations (i.e. when assessing technology prior to use, when considering the predisposition towards its use in the future and after having experience of interacting with technology) will help improve the predictive power of future technology adoption theories.

4.2.Theory-based Variance

The subgrouping of predictors based on theories results in different total effects sizes for all outcome variables, as demonstrated by p-values below 0.05 and Q-test results showing the difference between subgroups (Table 5). There are three types of observations resulting from the subgroup analysis. First, although there is variance in effect sizes among theories, some of the theoretical models are consistent in their predictive strength irrespective of the outcome

variable. For example, TRI and TAM are among the top three theories with the strongest effects on attitude, intention to use and actual use behaviour, ranging between 0.32 and 0.51. Second, the importance of the theories varies depending on the outcome variable. For instance, UTAUT (B=0.32) plays a more significant role when examining attitude, while it becomes the least important when investigating use intention (B=0.20). Delone and McLean's IS Success Model (B=0.39) and TAM (B=0.32) are the strongest theoretical frameworks in the studies focusing on intention. The factors of Social Cognitive Theory (SCT) have medium effects on intention (B=0.29), but very weak effects on attitude (B=0.06). Third, the highest variance in the effects of theories is found when examining the predictors of use behaviour. In addition, there are fewer theories that are employed for studying the actual use of information systems, compared to the research focusing on two other outcome variables. These findings mean that each theoretical framework has a different contribution to the research on technology adoption from the perspectives of users' attitudes, use intention and actual use behaviour.

Table 5: Subgroup Analysis – Dominant theory

Name	Total Effect Size	Subgroup Differences Q	Subgroup Differences P-Value
DV - Attitude			
TRI	0.4117	107.09	0.0001
TAM	0.3250		
UTAUT	0.3182		
Flow	0.2954		
TPB	0.2919		
TRA	0.2833		
DOI	0.2617		
TTF	0.2015		
SCT	0.0658		
DV – Intention to Use			
TRI	0.4527	107.14	0.0001
Delone Model	0.3975		
TAM	0.3281		
TRA	0.3014		
TTF	0.3007		
SCT	0.2944		
TPB	0.2672		
Flow	0.2244		
DOI	0.2100		
UTAUT	0.2015		
DV – Use Behaviour			
TRI	0.5106	253.01	0.0001
TRA	0.4555		
TAM	0.3492		
UTAUT	0.2862		
DOI	0.2176		
TPB	0.2104		

4.3. Longitudinal change

Moderation analysis by the publication year demonstrated that the effect sizes of almost all predictors have not changed significantly over time, as demonstrated by p values > 0.05 and small effect sizes (Table 6). Only perceived usefulness, effort expectancy and relative advantage have significant effects, although they are close to zero, which suggests that there is almost no meaningful change in the effects of variables on adoption. Perceived usefulness has a very weak positive effect (B=0.0181, p<0.05) when examining attitude. This shows that when evaluating technology, the increase in the strength of the belief that technology can enhance users' performance is minimal. The effects of effort expectancy (B=-0.0164, p<0.05) and relative advantage (B=-0.0390, p<0.05) are weak and negative when explored in relation to intention to use. In contrast to perceived usefulness, relative advantage is measured in juxtaposition to alternative systems and reliant on a clear understanding of the capabilities of

the systems being compared. When measuring future use intention, people started paying slightly less attention to the advantages of new systems over incumbent ones. Such an assumption is also supported by the non-significant change of the effect of relative advantage in relation to use behaviour. The weakened effect of effort expectancy means that over time the belief about the degree to which the system is effortless to operate has become less critical. A plausible interpretation is that with the wider embeddedness of technologies, users have become more technically skilled in operating ICT systems. However, such a small change in the effects of relative advantage and effort expectancy demonstrates that they still have almost the same influence on adoption decisions as at the outset of technology acceptance research.

Table 6: Moderation Analysis – Publication Year

Independent Variable	Effect size	Moderator: P-value
DV - Attitude		
Perceived security risk	0.0492	0.0874
Perceived usefulness	0.0181	0.0242
Social influence	0.0133	0.5086
Perceived risk	0.0123	0.2903
Perceived privacy risk	0.0081	0.6976
Self-efficacy	0.0071	0.6923
Perceived ease of use	0.0039	0.0984
Trust	0.0023	0.7048
Experience	0.0007	0.6612
Perceived usefulness	-0.0009	0.7016
Perceived enjoyment	-0.0032	0.5844
Subjective norm	-0.0042	0.5597
Innovativeness	-0.0086	0.1114
Facilitating conditions	-0.0149	0.4001
Performance expectancy	-0.0209	0.6378
Intention to use	-0.0426	0.3600
DV - Intention to Use		
Perceived privacy risk	0.0379	0.0719
Perceived security risk	0.0148	0.4864
Self-efficacy	0.0083	0.3946
Perceived enjoyment	0.0069	0.3718
Perceived behavioural control	0.0046	0.4236
Attitude	0.0045	0.1214
Social influence	0.0041	0.2381
Subjective norm	0.0035	0.2381
Perceived risk	0.0032	0.6609
Perceived value	-0.0004	0.9812
Perceived ease of use	-0.0010	0.6829
Performance expectancy	-0.0014	0.8601
Perceived usefulness	-0.0015	0.4759
Trust	-0.0046	0.4752
Satisfaction	-0.0063	0.6754
Experience	-0.0075	0.4431
Perceived playfulness	-0.0147	0.4952
Facilitating conditions	-0.0158	0.1519
Effort expectancy	-0.0164	0.0024
Innovativeness	-0.0164	0.3071
Relative advantage	-0.039	0.0254
DV - Use Behaviour		
Social Influence	0.0711	0.1999
Perceived enjoyment	0.0256	0.2120
Satisfaction	0.0191	0.7776
Perceived risk	0.0090	0.3599
Trust	0.0083	0.6141
Perceived usefulness	0.0045	0.4643
Self-efficacy	0.0027	0.8448
Intention to use	0.0013	0.7189
Perceived ease of use	-0.0004	0.9603
Attitude	-0.0005	0.9555
Performance expectancy	-0.0074	0.9085
Facilitating conditions	-0.0141	0.4587
Innovativeness	-0.0151	0.3079
Perceived behavioural control	-0.0272	0.1352
Relative advantage	-0.0507	0.0831

5. Conclusion

5.1. Theoretical Contributions

This meta-analytical review makes several contributions to the literature. First, this review produced comprehensive data on all key predictors of technology acceptance, in contrast to prior research, which mostly focused on particular theories (King and He, 2006, Williams et al., 2011, Dwivedi et al., 2019). The adopted approach provided a complete picture of the underpinnings of technology use. The analysis of the predictors of attitude, intention to use and use behaviour contributes to the debate as to which outcome variable works better as a proxy for acceptance (Warshaw and Davis, 1985, Davis, 1985, Venkatesh et al., 2003, Turner et al., 2010, Straub et al., 1995, Tao, 2009, Calisir et al., 2009). The findings are important since the focus on a single variable can over-stress or underemphasise the importance of the conditions underpinning technology acceptance. Also, a comparative insight into the strength of predictors depending on technology acceptance theories adds to the discussion about the contribution of theories to advances in the field (Venkatesh et al., 2007, Benbasat and Barki, 2007). Secondly, the paper provided a longitudinal insight into technology acceptance research, which is missing in prior meta-analytic studies. Such an insight brings evidence about the dynamics in technology acceptance research and helps understand how the determinants of users' behaviour change along with the progress in technology and new users' practices.

5.2. Limitations and Future Research Avenues

Given that the focus of this paper was to provide a comprehensive view of the predictors of technology adoption, this study is limited in the analysis of factors for the moderation analysis. Future research could examine the role of context-specific or individual-specific (e.g. personality) factors moderating the strength of predictors in different technology adoption models. Another limitation is that meta-analytic reviews usually exclude qualitative studies. However, future research can use techniques of coding qualitative data and quantitatively analyse the findings. Thirdly, future research could use the strongest relationships between predictors, attitude, intention to use and use behaviour to verify them empirically.

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