Mobile Application Adoption Predictors: Systematic Review of UTAUT2 Studies Using Weight Analysis

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Abstract. Mobile phone subscriptions are the largest form of consumer technology adopted across the world. Despite their potential, the research is very scant in understanding various predictors of consumer adoption towards mobiles technologies in particular mobile applications. This study intend to fulfil this purpose through weight analysis on mobile application adoption based studies that utilized UTAUT2 model. Studies needed for weight analysis were located through cited reference search method in Scopus and Web of Science bibliographic databases. The results of weight analysis revealed performance expectancy/ perceived usefulness, trust and habit as best predictors of consumer behavioural intention to mobile applications adoption whereas behavioural intention was the best predictor of use behaviour. There were also two promising predictors with perfect weight of one such as perceived risk on behavioural intention and habit on use behaviour. Further steps of this research involves meta-analysis to develop comprehensive conceptual model concurrent with weight analysis results for empirical evaluation on various mobile applications.

Keywords: UTAUT2, Weight analysis, Systematic Review.

1. Introduction

Marketing is an indispensable business function that serves as lifeline for any organisations survival since its core objective is to attract and retain customers to generate revenue [1]. Recent years has seen rapid explosion of mobile devices (m-devices) with a number of unique mobile subscribers reaching 5 billion in 2017 encompassing two thirds of global population elevating mobile to the highest scale of consumer technology worldwide [2]. Apart from providing entertainment to user's, mobile devices such as smartphones and tablets improves their productivity through plethora of mobile apps [3]. Examples of such applications include but are not limited to project management (slack), shopping (Amazon), business card (camcard), news organizer (flipboard), health/fitness (fitbit), note taking (evernote), transportation (uber), payment (square) and so on [4]. Unlike traditional advertising medium such as newspapers, televisions, magazine and radio, the unique characteristics of mobile platform enable marketers to reach right consumers anytime anywhere. This phenomenon is popularly referred as mobile advertising [5, 6]. The continuous advancement of wireless communication and network technologies such as 3G, 4G and 5G will make mobile advertising a popular form of advertising medium in the near future. The market research firm Statista's report reveals companies spend a whopping 105.95 billion USD on mobile advertising in 2017 and it is expected to reach 175.64 billion in 2020 [7]. However, despite the rise in mobile technologies, a research on Fortune 500 companies' mobile websites for their mobile readiness revealed just one-quarter of them had mobile-responsive websites and majority of the companies were unprepared[8] .

Given the preceding discussion on centrality of mobile advertising in marketing function to organisations, it would be impeccable to evaluate various predicators of consumer intention to adopt/use IT enabled mobile applications. The extended unified theory of acceptance and use of technology (UTAUT2) is the most comprehensive research model in the IS arena as on date in understanding various predictors influencing individuals to accept and make use of information technologies [see 9 for review]. Despite UTAUT2 model recent introduction in the year 2012, it has already garnered more than 3000 citations in Google Scholar alone spanning from IS field and beyond emphasising on its predictive ability. Thus, the objective of this study is to undertake weight analysis on consumer adoption/diffusion research of various mobile applications using UTAUT2 theory to evaluate the cumulative performance of various predictors. The study involves following steps to fulfil the objective:

- Locate empirical studies that utilized UTAUT2 model in understanding consumer intention/use behaviour of mobile applications.
- Conduct weight analysis of the empirical studies to understand the significance and insignificance of various relationships and their performance.
- Represent the predictors of consumer adoption to mobile applications in the form of sundial.

The next section of this paper describes the research method employed in this study; Section 3 presents the findings of weight analysis and systematic literature review followed by discussion in Section 4 and conclusion in Section 5.

2. Research Method

Since the purpose of this study is to synthesize the existing research findings on consumer adoption of mobile applications, a combination of "systematic review", "citation reference search" and "weight-analysis" approach were deemed appropriate [10-12]. Cited reference search for Venkatesh et al. [9] article in Scopus and Web of Science database from March 2012 to March 2017 resulted in 1,320 papers (823 from Scopus; 497 from Web of Science). On further scrutiny, we found 452 citations were common in both databases resulting in 868 unique citations for UTAUT2. Out of 868 articles, 16 empirical studies were found pertinent to mobile applications with relevant data for weight analysis. Weight analysis determines indicative predictive power of an independent variable over dependant variable. A weight is ratio between the number of times an independent variable found as significant predictor of dependant variable (a) to the total number of times an independent variable is examined as a predictor of dependant variable (b) and thus is calculated using formula (a)/(b) [13].

3. Findings

This section presents and explains the findings from the systematic review and weight analysis.

3.1 Literature synthesis

The 16 mobile applications related studies included ten different countries: Malaysia was the most studied country with four empirical examination; whereas Jordon, China and the USA with two examinations each emerged as the second most studied countries. This is followed by six countries in third position such as Mozambique, France, Bangladesh, Portugal, Chile and the UK with one study each. Six major themes emerged based on the technology examined: 1) Mobile payments as a broader theme was the most examined technology with nine studies. Out of nine studies, six directly examined mobile payments, whereas three studies examined technologies such as NFC payments, mobile wallet and remote mobile payment to broadly fall under mobile payment classification. 2) Mobile banking was the second most popular technology examined with three studies, and finally the remaining four themes: 3) Mobile Apps [14]; 4) Mobile Internet [15]; 5) Mobile TV [16] and 6) Mobile advertising [17] were examined on one instance each. It was also found that only five studies employed Use behaviour (UB) as their outcome/dependant variable with all having behavioural intention (BI) as their immediate antecedent whereas BI was the most operated outcome/dependant variable with 11 studies (see Table 1).

Table 1: Summary of Mobile Application Studies

SN	Author name	D.V	Technology Examined	Country
1	Alalwan, Dwivedi, and Rana [18]	UB	Mobile Banking	Jordon
2	Baptista and Oliveira [19]	UB	Mobile Banking	Mozambique

3	Hew et al. [14]	BI	Mobile Apps	Malaysia
4	Jia et al. [20]	BI	Mobile Payment	China
5	Jia, Hall, and Zhu [21]	BI	Mobile Payment	China
6	Koenig-Lewis et al. [22]	UB	Mobile Payment	France
7	Mahfuz, Khanam, and Mutharasu [23]	UB	Mobile Banking	Bangladesh
8	Morosan and Defranco [24]	BI	NFC Payments	USA
9	Oliveira, Thomas, Baptista, and Campos [25]	BI	Mobile Payment	Portugal
10	Qasim and Abu-Shanab [26]	BI	Mobile Payment	Jordon
11	Ramírez-Correa et al. [15]	UB	Mobile Internet	Chile
12	Shaw [27]	BI	Mobile Wallet	USA
13	Slade, Williams, Dwivedi, and Piercy [28]	BI	Remote Mobile Payment	UK
14	Teo, Tan, Ooi, Hew, and Yew [29]	BI	Mobile Payment	Malaysia
15	Wong et al. [16]	BI	Mobile TV	Malaysia
16	Wong et al. [17]	BI	Mobile Advertising	Malaysia

[LEGEND: BI: Behavioural Intention; **D.V:** Independent Variable; **UB:** Use Behaviour]

3.2 External variables

Thirteen out of sixteen studies employed UTAUT2 constructs in combination with external variables. Whereas the remaining three studies (i.e. Jia, Hall [20]; Ramírez-Correa, Rondán-Cataluña [15]; Wong, Wei-Han Tan [16] adapted only UTAUT2 based constructs in understanding consumer intention to use various mobile applications. Table 2 presents findings of external variables analysis across thirteen studies to reveal eighteen unique external constructs and two unique external moderators. Trust was the most frequently utilised external construct with five studies followed by the second most used external constructs such as perceived risk, perceived security and innovativeness that were used on two occasions each. In addition, there were 14 more external constructs like: 1) exposure, 2) information searching, 3) knowledge, 4) website quality, 5) general privacy, 6) system-related privacy, 7) behavioural intention to recommend, 8) compatibility, 9) network externalities, 10) informal learning, 11) self-efficacy, 12) perceived transaction convenience, 13) perceived transaction speed and 14) mobile skilfulness that were used on one instance each. The hypothesis from all external constructs to consumer behavioural intention/use behaviour of various mobile applications were positive apart from perceived risk and system related privacy variable that were hypothesized negatively to BI. A (-) sign in Table 3 indicates the negative path relationship among the independent and dependant variable in examining consumer adoption of mobile applications. Finally, the two external moderators: Hofstede's cultural moderators and educational level were used together on three instances with two studies the former one was the most used.

Table 2: Summary of External Variables

SN	External constructs	Frequency	Citations
1	Trust	5	Alalwan et al. [18]; Jia et al. [21]; Qasim & abu-shanab [26]; Shaw [27]; Slade et al. [28]
2	Perceived risk	2	Koenig-lewis et al. [22]; slade et al. [28]
3	Perceived security	2	Morosan & defranco [24]; oliveira et al. [25]
4	Innovativeness	2	Oliveira et al. [25]; wong et al. [17]
5	Exposure	1	Jia et al. [21]
6	Information searching	1	Jia et al. [21]
7	Knowledge	1	Koenig-lewis et al. [22]
8	General privacy	1	Morosan & defranco [24]
9	System-related privacy	1	Morosan & defranco [24]
10	Compatibility	1	Oliveira et al. [25]
11	Behavioural intention to recommend	1	Oliveira et al. [25]
12	Network externalities	1	Qasim & abu-shanab [26]
13	Self-efficacy	1	Shaw [27]
14	Informal learning	1	Shaw [27]
15	Perceived transaction speed	1	Teo et al. [29]
16	Perceived transaction convenience	1	Teo et al. [29]
17	Mobile skilfulness	1	Wong et al. [17]
18	Website quality	1	Mahfuz et al. [23]
SN	**External moderators**	**Frequency**	**Citations**
1	Hofstede cultural moderators	2	Baptista & oliveira [19]; Mahfuz et al. [23]
2	Educational level	1	Hew et al. [14]

3.3 Weight-analysis

3.3.1 Coding independent and dependent variables

This study employed generalized coding scheme adapted from Jeyaraj et al. [13] to uniformly code findings between various independent and dependant variables. The coding template was organised into 'rows' and 'columns'. Each row represents one of the 16 studies, whereas each column represents the path relationship between an independent and dependant variable. The intersection points between studies in "row" and path relationship in "column" represent the significance of the particular path relationship corresponding to that study. The coding scheme has four different values: 1) '+1' in the case where the path relationship examined was significant and hypothesized in positive direction; 2) '-1' in the case where the path relationship examined was significant and hypothesized in negative direction; 3) '0' in the case where the path relationship examined was insignificant; and 4) "Blank" when the relationship was not studied [13]. The thorough examination of 16 articles uncovered 63 unique path relationships employed among 31 independent and 12 dependent variables. However, the findings of this study is limited only to 31 path relationships on two dependant variables i.e. behavioural intention (comprising 27 independent variables) and use behaviour (comprising four independent variables) (see Table 3).

Since the objective of this study is to understand various predictors of consumer behavioural intention and use of mobile applications.

3.3.2 Consumer mobile applications predictor's findings

Table 3 presents the summary on weight-analysis findings of 16 studies mobile application studies. An independent variable is termed as well-utilized when examined by researchers in five or more studies and termed as experimental variable in case of less than five examinations. Furthermore, the independent variable qualifies as the best predicator of dependant variable when they are used in five or more studies (well-utilized) and have a weight of 0.80 or more. On the other hand, independent variable can be considered as a promising predicator when it is used in less than five studies (experimental) and have perfect weight of one [13].

Table 3 lists 27 independent variables on behavioural intention and four on use behaviour in understanding consumer adoption towards mobile applications. There were eight well-utilized independent variables/predictors (examined five or more instances) of behavioural intention such as performance expectancy/ perceived usefulness (examined 16 times), effort expectancy/ perceived ease of use (examined 14 times), social influence (examined 12 times), facilitating conditions (examined 9 times), hedonic motivation/ perceived enjoyment (examined 9 times), price value (examined 7 times), habit (examined 7 times) and trust (examined 7 times). Out of eight well-utilized predictors the best predictors of behavioural intention are the one with weights ≥ 0.80 which are performance expectancy/ perceived usefulness (0.81), trust (0.80) and habit (1.00). However, some independent variables, despite being used more than five times, yielded non-significant results consistently to emerge as the worst predictors of consumer behavioural intention towards mobile payment with weight < 0.80. The label of worst predictors may not necessarily appeal to the well utilized predicators having weight in between the range of 0.80 and 0.50 such as social influence (0.67), facilitating conditions(0.78) and hedonic motivation/perceived enjoyment (0.78) are worth of future examination [13].

Instances of worst predictors with weight < 0.50 comprise effort expectancy/perceived ease of use (0.67) and price value (0.29). Furthermore, there were 19 experimental variables used in understanding consumer behavioural intention towards mobile payment. Out of nineteen experimental variables only three variables: 1) perceived risk, 2) perceived security and 3) innovativeness were examined on two instances each with rest sixteen variables were examined on once instance each. The discussion is restricted to experimental variables examined more than one instance. Perceived Risk emerged as the promising predicator with weight of one.

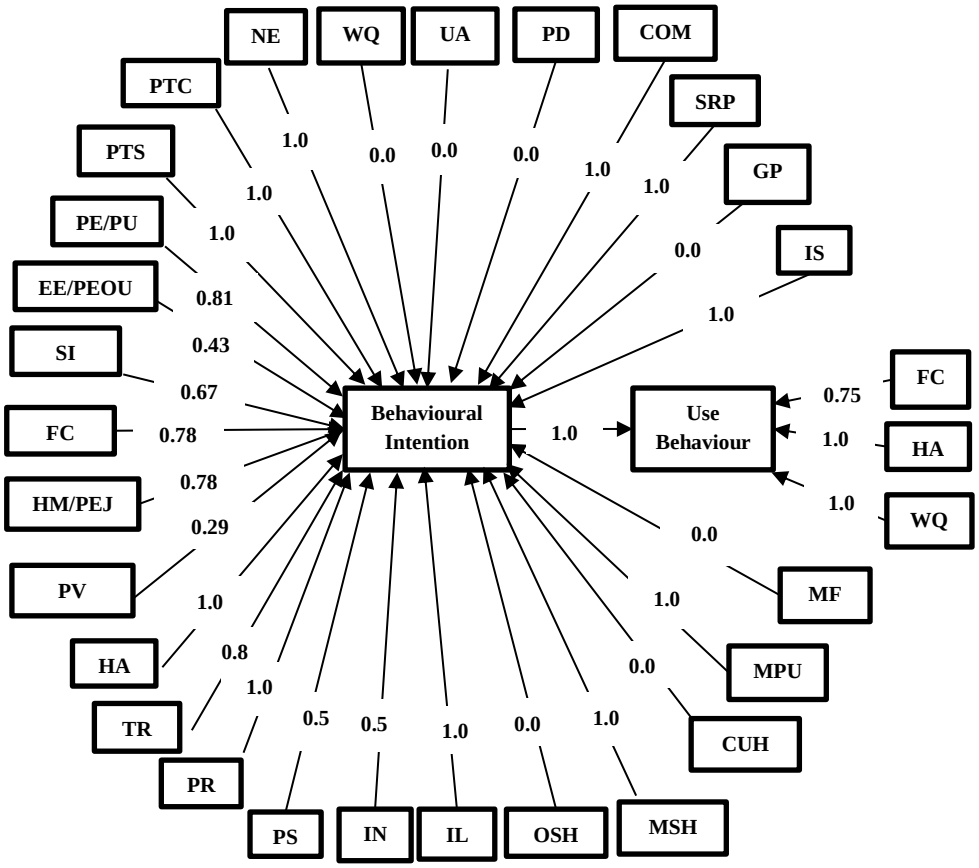
There were four independent variables in understanding consumer use behaviour towards mobile applications. Among the four, behavioural intention was the only well utilized and best predicator with significant values on all five occasions. The remaining three: 1) facilitating conditions (examined 4 times, significant 3 times), habit (examined 2 times, significant 2 times) and website quality (examined 1 times, significant 1 times) are experimental variables. Habit emerged as the promising predicator with weight of one among experimental variables examined more than one instance. Figure 1 presents sundial of consumer mobile applications adoption predictors and their corresponding

weight. Surprisingly none of the sixteen studies on consumer mobile applications employed UTAUT2 moderator's relationships in their original form.

Table 3: Weight analysis summary approach adapted from Jeyaraj et al. [13]

SN	Independent Variable	DV	Sig (a)	In-Sig	Total (b)	Weight (a/b)
1	Performance expectancy/ Perceived Usefulness	BI	13	3	16	0.81
2	Effort expectancy/Perceived ease of use		6	8	14	0.43
3	Social Influence		8	4	12	0.67
4	Facilitating Conditions		7	2	9	0.78
5	Hedonic motivation/ Perceived enjoyment		7	2	9	0.78
6	Price Value		2	5	7	0.29
7	Habit		5	0	5	1
8	Trust		4	1	5	0.8
9	Perceived Risk(-)		2	0	2	1
10	Perceived security		1	1	2	0.5
11	Innovativeness		1	1	2	0.5
12	Informal learning		1	0	1	1
13	Online shopping habit		0	1	1	0
14	Mobile shopping habit		1	0	1	1
15	Cell phone Usage habit		0	1	1	0
16	Mobile payment usage habit		1	0	1	1
17	Masculinity Vs Femininity		0	1	1	0
18	Information searching		1	0	1	1
19	General privacy		0	1	1	0
20	System-related privacy(-)		1	0	1	1
21	Compatibility		1	0	1	1
22	Power distance		0	1	1	0
23	Uncertainty avoidance		0	1	1	0
24	Website quality		0	1	1	0
25	Network externalities		1	0	1	1
26	Perceived Transaction Convenience		0	1	1	0
27	Perceived Transaction Speed		1	0	1	1
28	Behavioural Intention	UB	5	0	5	1
29	Facilitating Conditions		3	1	4	0.75
30	Habit		2	0	2	1
31	Website quality		1	0	1	1

[Legend: D.V: Independent Variable; In. Sig : Number of insignificant path values; Sig (a): Number of significant path values]



[LEGEND: CUH: Cell Phone Usage Habit; **COM:** Compatibility; **EE/PEOU:** Effort Expectancy/Perceived Ease Of Use; **FC:** Facilitating Conditions; **GP:** General Privacy; **HA:** Habit; **HM/PEJ:** Hedonic Motivation/ Perceived Enjoyment; **IL:** Informal Learning; **IS:** Information Searching; **IN:** Innovativeness; **MF:** Masculinity Vs Femininity; **MPU:** Mobile Payment Usage Habit; **MSH:** Mobile Shopping Habit; **NE:** Network Externalities; **OSH:** Online Shopping Habit; **PR:** Perceived Risk; **PS:** Perceived Security; **PTC:** Perceived Transaction Convenience; **PTS:** Perceived Transaction Speed; **PE/PU:** Performance Expectancy/ Perceived Usefulness; **PD:** Power Distance; **PV:** Price Value; **SI:** Social Influence; **SRP:** System-Related Privacy; **TR:** Trust; **UA:** Uncertainty Avoidance; **WQ:** Website Quality.]

FIG. 1. Consumer mobile applications adoption predictors a Sundial

4. Discussion

Literature synthesis reveals the deployment of UTAUT2 theory to understand consumer adoption of six different mobile applications in ten different countries underscoring generalizability of UTAUT2 theory across various technological and cultural contexts. Utilitarian value based mobile applications were the most studied

with mobile payments (9 studies) and mobile banking (3 studies) together comprising 12 out of 16 studies. The findings revealed that only five (around 31%) studies employed UB as endogenous variable whereas the remaining 11 studies comprising (69%) employed BI as endogenous variable. This pattern is comprehensible since popular mobile applications are still evolving and it is difficult to measure actual consumer use of these technologies, in such cases BI can be good indicator of future technology use. However, Wu and Du's [30] meta-analysis on BI and UB caution the researchers notion of considering BI as surrogate of UB as it's not appropriate for studies to report user behaviour without assessing actual system usage. In addition, they caution all stakeholders in research community should be circumspect of such studies not investigating user behaviour but only behavioural intention [30].

The two independent variables of technology acceptance model (TAM) i.e. perceived usefulness similar to performance expectancy (16 studies) and perceived ease of use (14 studies) similar to effort expectancy emerged as the most utilized variables emphasising TAM's dominance in individual adoption research. However, the most frequently used predicators does not necessarily translate into best predicators [13]. For instance, effort expectancy, despite being the second most examined independent variable on 14 instances, was significant on just six occasions with weight of 0.43 to become the worst predictor of consumer behavioural intention to mobile applications. Surprisingly price value the latest addition to the UTAUT2 model was the worst predicator of BI with lowest weight of 0.29 among relationships that are examined five or more times. A meta-analytic study on price value construct found the construct inappropriate to examine mobile applications that are available to users free of cost as they were prone to insignificant results in determining consumer adoption to those technology[31]. Researchers need compelling reason to include the worst predicators as independent variables in evaluating consumer adoption towards mobile payment. On the other hand, researchers should continue using four best predictors in understanding consumer adoption of mobile applications three of them performance expectancy/perceived usefulness (0.81), trust (0.80) and habit (1.00) were on behavioural intention, whereas behavioural intention (1.00) the fourth and final one was on use behaviour all having weights of ≥ 0.80. Moreover, there were only two promising predictors with perfect weight of one used more than one instance such as perceived risk (1) and habit (1). Adoption to innovative product such as mobile applications that are entirely new to market can involve great element of risk. However, UTAUT and TAM, the most popular theoretical models in understanding individual technology adoption, have often overlooked constructs such as perceived risk, privacy concerns and trust [22]. Weight analysis finding confirms the notion of Koenig-Lewis et al. [22] with trust emerging as best predicator and perceived risk as promising predicator of consumer adoption to mobile applications. Researchers should continue using promising predicators in future studies to enable more testing and ascertain their suitability as the best predicator.

As far as habit is concerned, it emerged as best predictor of behavioural intention and promising predictor of use behaviour. HA→BI path was the most examined habit based relationship with all five significant instances and the remaining two significant relationships were for the path HA→UB. UB is less utilized as dependant variable of HA than BI, since HA→UB is better hypothesis in understanding consumer adoption of well-established and mature technologies, whereas BI is better predictor of habit and

subsequent UB for new and rarely used technology applications such as our case under investigation i.e. mobile applications [32]. Moreover this belief is strengthened through meta-analysis study that focussed on habit construct which revealed habit as not an optimal construct to examine technology users at early stage of adoption where sufficient time hasn't elapsed in using technologies to form habit [33].

5. Conclusion

This paper aimed to understand the predictors of consumer adoption to mobile application through weight analysis. The results of weight analysis divulged the most/least/best/worst and promising predictors of consumer adoption for mobile applications and provided comprehensive review on this subject. The results also revealed that more than 80% of the studies employed external variables since UTAUT2 and other popular technology acceptance theories have disregarded predictors such as trust (best predictor) and perceived risk (promising predictor) in consumer adoption for mobile applications. Moreover, none of the studies employed UTAUT2 moderating variables due to the complexity of their relationship amongst various constructs. In addition, despite being the most frequently used predictor; effort expectancy produced the most insignificant results. This calls for researchers to be more cautious while operationalizing their constructs from existing theory/model to make necessary adaptations or omit irrelevant constructs depending upon context rather than having obligation to replicate all the constructs in underpinning model/theory. Despite precautionary measures taken for coding and analysis the findings of the study is not without its limitations. The studies involved for weight analysis were limited only to two databases such as Web of Science and Scopus restricting the number of empirical studies. Future weight analysis should include a large number of studies from wider range of databases to minimize publication bias. Although weight analysis is good indicator on significance of predictors it does not take sample size into consideration like meta-analysis to provide true effect size. Thus, the next stage of this research is as follows: 1) to conduct meta-analysis and develop research model in combination with weight analysis; 2) to collect data on selected mobile applications through questionnaires; and 3) to analyse the collected data and empirically examine the research model through statistical techniques.

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