Technology Frustration and Consumer Valuation Shift for Mobile Apps: An Exploratory Study

Full Paper

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Abstract

Consumer evaluation of products in a market is a predictor of the success or failure of a product. For digital products, the usage of a product is determined by the technology robustness associated with the design of the product. Bad designs, implementation and integration issues lead to frustration on the part of consumers using the product. In this study, we explore how technology frustration negatively influences the valuation of a product in digital markets. Furthermore, we hypothesize that market externalities, such as consumer passion for, and sustenance of, the product in question temper this negative effect. Finally, we contend that the negative effect of technology frustration is high for new and high priced products because of the higher expectations and hence more stringent evaluations for new and high priced products by consumers. We conducted empirical analysis and found support for our hypotheses. Managerial and research contributions are discussed.

Keywords

Consumer valuation, technology frustration, consumer passion, market sustenance, apps, android market

Introduction

Mobile applications (apps) are digital innovations using internet and mobile platforms. The popularity of mobile apps has resulted in the app entrepreneurship model, where app developers can appeal to and reach mass consumers relatively inexpensively. Apps are also becoming useful in several unprecedented ways, such as transforming healthcare delivery, enabling supply chains and leveraging crowd source concepts (Ghose and Han 2014). Revenue from app users is projected to increase from $10.3 billion in 2013 to $25.2 billion in 2017 (IDC 2013). The Apple store market has over 500,000 apps, ranging from work, play and everything in between, and the Android market has more than 40,000 apps.

While the apps market surge is unprecedented, not all are able to make money in the apps market space. Indeed, a number of apps and associated ventures have failed in a short period of time. Studies show a considerable skew in download rate of apps; for example, only 5 apps cover around 15% of all downloads, while over 50% of available apps achieve fewer than 500 downloads (Aitken and Gauntlett 2013). The reasons for skewed app market success rate is ascribed to technical, social and organizational reasons, albeit without a solid recommended solution on how to manage an app business model properly (Müller et al. 2011).

Prior research has suggested that managing business models for consumer oriented digital products needs a good customer value proposition, a solid revenue model, and the availability of key resources and processes to generate money (Johnson et al. 2008). A specific key resource and process for the apps is the technology front that involves the design, smooth functioning, and integration in the apps market space. Specific to digital business models, Bhardwaj et al. (2013) note that the scope, scale, speed, and sources of business value creation and capture are the four major components for value creation using a digital business strategy, such as that intended to be achieved using the app. In other words, the value creation from apps is highly influenced on its current evaluation by consumers in the market. Current consumer valuation of an app in the market reflects the net scope and scale of the app's usage, the speed at which it is proliferating, and whether consumers are willing to continue usage in the next time period or not. While consumers evaluate the apps at any instant, the extent to which technology remains an issue in this evaluation remains an unexplored question for both academicians and practitioners alike.

We focus on the technology frustration associated with apps in a market. At individual level, technology frustration is the emotional response of a negative computing experience with the technology (Bessière et al. 2006). Technology frustration originates when a consumer faces a challenge to deal with or use a technology, and the technology fails to fulfil the objective or desired functions. The underlying elements of technology frustration are crashing, network congestion, poor interfaces, confusing design, and usage problems. Often technology frustration leads to personal dissatisfaction and loss of self-efficacy, but may disrupt workplaces, slow functionalities, and reduce participation of an individual with the technology (Lazar et al. 2006), or may lead to an elevated levels of anxiety and anger on the part of the individual (Wilfong 2006) which, in turn, may result in a segment of the customers staying away from the technology (Lenhart 2003). Taken cumulatively, these individual technology frustration events aggregate to create a highly adverse overall response for the product in the market (Guchait and Namasivayam 2012).

In this study, we explore how technology frustration negatively influences the valuation of a product in digital markets. In addition to the main effects, we hypothesize that market externalities, such as consumer passion for, and sustenance of, the product in question temper this negative effect. In addition, we hypothesize that the negative effect of technology frustration is high for new and high priced products because of the greater expectations and hence more stringent evaluations that new and high priced products warrant. To test our hypotheses, we used a dataset that tracked cell phone apps in the android market, tracking more than 17000 apps for a week. We conducted empirical analysis and found support for our hypotheses. This study contributes to the information systems and consumer research literature in providing a new dimension of technology frustration associated with consumer evaluation of products. We discuss managerial implications and contributions of the study.

Theoretical Background

Our theoretical framework is related to the prior work in the consumer evaluation and individual motivation. In this regard, existing research suggests a number of relevant concepts. For example, a stream of literature in information systems and marketing has pointed out that consumers evaluate products based on their expectations and related satisfaction (Oliver 1980). Similarly, other prior research has also suggested that individual and collective evaluations of products may be a result of consumers' validation that the product is of good quality or meets the requirements of needs that was referred by other consumers through word of mouth, or collective evaluations (Mudambi and Schuff, 2010; Negash et al., 2003).

We anchor to the expectation confirmation theory (ECT) and prior literature on consumer evaluations for this study. ECT posits that post-purchase or post-adoption satisfaction is a function of expectations, perceived performance, and disconfirmation of beliefs associated with a product (Oliver 1977; Oliver 1980). Applying to the digital products context, existing research has established that the confirmation or disconfirmation of consumer expectations is a highly influential factor in determining whether consumers continue or discontinue a product (Bhattacherjee 2001; Brown et al. 2012). When the product confirms to its objectives or intended goals of use, consumer evaluations increase (Aaker and Keller 1990; Dabholkar 1996). As much as technology issues are a precursor to a product's use or functionality, resulting consumer evaluations will be influenced or changed (i.e., shifted) by technology frustration. Based on these overarching premises, we propose a conceptual model (see Figure 1) for this study that presents three sets of relationships: (1) technology frustration has a direct impact on consumer evaluation shift, (2) two market externalities, i.e., consumer passion and market sustainance, moderate the relationship of technology frustration on consumer evaluation shift, and (3) two internal factors, e.g., age of the app and price of the app, also moderate the association of technology frustration on consumer evaluation shift. Next, we provide arguments for these relationships and draw testable hypotheses.

Hypotheses

Technology frustration deals with a set of emotional responses as a result of negative experiences with technology use. In the apps context, an app is always expected to perform or provide a specific functionality. When an app crashes, or is not well integrated in the market resulting in failures, the app would not meet the expected or required needs. In addition, confusing design and usage problems lead consumers to discontinue the app. Prior studies note that technology frustration leads to loss of the users' self-efficacy and subsequent personal dissatisfaction (Lazar et al. 2006). If being used in a work place, the slow functionalities or issues may lead to underutilization and lower employee productivity. Along with each user's dissatisfaction of an app, the negative word-of-mouth influence and other networking effects initiated by dissatisfied consumers will lead to fewer new consumers to adopt it, or positively review it, leading to a fewer number of positive ratings and a greater number of negative ratings. As a result, the overall consumer valuation will decrease. At a consumer or market level, shared understanding of technology frustrations felt at an individual level aggregates for a product or service to create a highly adverse response for the product in the market (Guchait and Namasivayam 2012). Thus, we hypothesize:

H1: Consumer technology frustration is negatively associated with consumer valuation shift for cellphone apps.

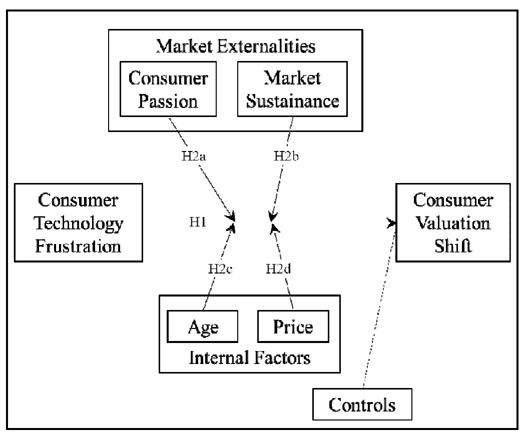

Figure 1: Conceptual Model

We argue that external market factors such as consumer passion and market sustainance of the app until the focal time are two moderating factors on the relationship between customer technology frustration and consumer valuation shift for several reasons. Consumer passion indicates the liking of consumers for an app due to its appeal, function or on the attribute that meets a specific consumer need. For example, a fitness app would have a good appeal for the consumer segment that want to stay fit, and hence, would have generated a niche of passionate consumers. These passionate consumers would then derive higher benefits, be beta testers, and help the app developer work towards the improvement of the app by providing feedback and, in general, help in mitigating the aspects related to technology frustration issues. Moreover, these satisfied consumers will generate positive word-of-mouth influence, resulting in higher consumer valuations. These passionate, satisfied consumers will therefore serve to temper the direct, negative effect that technology frustration would garner among general, non-involved adopters of the app.

In addition to consumer passion, apps that have enjoyed sustained success in a market are more likely to command consumer support as a reflection of the apps' good usage and functionality. These apps are tested by consumers, have been evaluated and established through high download volumes in the market in the last many months. Thus, the scope of sustained apps to the idiosyncrasies associated with technology issues either has been resolved or is low. These apps have stood the test of time, and have commanded extensive positive support by consumers and are therefore more resilient to consumer frustrations. Consumers will be more forgiving with technology glitches associated with these apps because they either are passionate about them, or because they have sustained positive reviews, indicating that any glitches are anomalies and not the norm. Based on these arguments, we hypothesize:

H2a: The effect of consumer technology frustration on consumer valuation shift is lower for apps with high consumer passion.

H2b: The effect of consumer technology frustration on consumer valuation shift is lower for apps with high consumer sustainance.

We contend that internal market factors related to the app, such as age of the app and pricing of the app are prone negative consumer evaluations. For example, new apps that are introduced to the market recently will be evaluated more stringently than old apps, as they are not yet consumer-tested in the market. This is also perhaps due to the newness, and therefore greater interest and involvement (and hence, scrutiny) of new apps. Old apps may have gone through a lot of versioning and updates that would have resulted in a degree of robustness in terms of usability and functional integration in the app platform. Similarly, price of an app is sensitive to consumer evaluation as consumers have higher expectations for more expensive apps, and hence perform more stringent evaluations for products that command a price premium. When a relatively expensive product suffers from technological troubles or issues, consumers may find themselves being less tolerant of such mishaps, as their expectations have been negatively disconfirmed, leading to dissatisfaction with the app. Existing studies mention that price-stringent evaluations are taken very seriously by consumers even to the point of returning or discontinuing a product (Jones and Suh 2000; Parasuraman et al. 1994).

In sum, expectations are a direct function of price. Expectations associated with free apps is likely to be low, leading to positive disconfirmation of expectation even for relatively mediocre apps. As price of an app increases, so do expectations. Expensive apps are held to a higher standard, and technological blips and frustrations are progressively less tolerable. Thus, we argue that compared to the free or low-cost apps, the negative influence of technology frustration on consumer evaluation will be higher for more expensive apps. Based on these arguments, we hypothesize:

H2c: The negative effect of consumer technology frustration on consumer valuation shift is higher for new apps than for old apps.

H2d: The negative effect of consumer technology frustration on consumer valuation shift is higher for pricier apps than for low priced or free apps.

Method

Data and Variables

The data for this study comes from a secondary source. A consulting company engaged in tracking app businesses in android market collected the data. Our units of analysis are based on the tracking information about the apps for a two week span from 13 October 2014 to 27 October 2014. For the analysis purposes the first week is the focal reference week, and the second week is used as the reference for the increase in ratings and reviews to calculate the variables used in this study.

There were 39,015 apps that existed in the android market in the focal week of 13 October 2014 to 20 October 2014. We could not consider 14,028 dead apps for our analysis, which did not have any usage at all in terms of clicks or zero downloads in the market until the focal week. On close scrutiny, we found 10,000 apps were in a different language than English, had illegible names, or were duplicates in the market. In addition, we excluded 6688 apps as there were no change in ratings or number of people who rated or reviewed the apps in the focal week and the subsequent week. We were left with 17,299 apps for our analysis.

Table 1 provides a description of variables we used in this study. Table 2 provides the descriptive statistics pair-wise correlation amongst the key variables. The dependent variable in our model is the consumer valuation shift (CVS) in the week's span. This variable is calculated as the net change in the product of average rating and raters in that week, per original rater in the beginning of the week (see the calculation description in Table 1). Using both average ratings per week and the total number of raters provides both a measure of score, and a measure of popularity in a single variable that assesses overall rating impact. By measuring the change in overall impact score between the two time periods, an index is developed based on the benchmark measure of the first week. This index is our dependent variable, CVS. Aggregate measures of this kind have been used before, one famous one that uses a combination of two variables is Gross Rating Points, which combines two very different variables, frequency and reach, into an aggregate measure of overall size of an advertising campaign (Curran, 1999). Similarly, by combining two important app rating measures, namely average rating score and total number of raters, CVS truly measures the shift in an app's overall impact rating between two time periods, both in terms of quality and quantity.

Variable	**Description and Operationalization**	**References**
Dependent Variables		
Consumer Valuation Shift (CVS)	The change in the net consumer rating of the app, considering both the total raters who rated the app and the ratings that the app received in the span of the week. The CRS index is calculated as follows: CVS = (R2N2-R1N1)/N1. Where, R2= Average rating of the app in week 2 R1= Average rating of the app in week 1 N2= Total number of raters of the app in week 2 N1= Total number of raters of the app in week 1	(Perdikaki and Swaminathan 2013; Ülkü et al. 2012)
Independent Variables		
Consumer Technology Frustration (CTF)	Frustration felt by the consumers for the app in the market. This variable is coded by mining the text reviews of each app in the weeks' time. The index measures the percentage of reviewers that discuss technical issues, frustrating problems, challenges in and crashing of the app within the focal week.	(Bessière et al. 2006; Guchait and Namasivayam 2012)
Consumer Passion (CP)	A powerful and persistent urge by the consumers to use or buy or interact with the app. This variable is coded as the ratio of 5-star ratings out of the total number of ratings submitted for each app in the focal week.	(Belk et al. 2003; Denegri-Knott and Molesworth 2013)
Market Sustainance (MS)	To what extent consumers have sustained the app in the market. The variables is operationalized by measuring the total download volume of the app until the focal week. This was a range variable with unequal ranges. We coded download volume as a continuous variable by taking the mid-point of the range provided. (E.g. if the download range is 10,000-50,000, we used the midpoint 30,000 as the number of downloads). We then divided the number of downloads 1,000,000.	(Lee and Raghu 2014)
Age of the app (AGE)	How long the app has existed in the android market since its release. The variable was coded as the difference between the focal week and the release date of the app.	
Price of the app (PRICE)	The price of the app in US$.	
Control Variables		
Game_app	Whether the app is an application app. The variable is coded as 1=game app, 0=not a game app.	
Category Dummy (C_N)	The category of the app, as pre-defined in the android market. We coded dummy variables for each category to include in the analysis. We have the following 12 categories: C_Adventure, C_Card, C_Medical, C_Business, C_Health, C_Travel, C_Weather, C_Sports, C_Music, C_News, C_Entertainment	

Table 1: Description of Variables

The focal independent variable in this study is consumer technology frustration (CTF) which indicates the frustration in using the app. This variable is coded by mining the text reviews of each app in the week's time. The index measures the percentage of reviewers that discuss technical issues, frustrating problems, challenges in usage, and crashing of the app. Thus it provides an aggregate measure of consumer frustration with the app in the market. The reviews were coded using a hermeneutic coding process to code the customer technology frustration by the consulting firm. We looked for words like “crash”, “frustrating”, “issues” etc. to find the percentage of apps that showed users frustration while operating an app.

The second independent variable is consumer passion (CP), for the app in the market that reflects the appeal of the app to the consumers as a powerful and persistent product, and is measured by calculating the percentage of consumers that rate the app with highest rating in the market. The third independent variable is market sustainance that is operationalized as to what extent the app is sustained in the market through downloads until now from its release date. The download volume varies from 0 to 3,000,000, with average download of 27,000 for the apps in our sample. The third dependent variable is the price of the app in the market. The price of the apps varies from free to 112US$. The final dependent variable is the age of the app since its release date. The average app in our sample is 2.5 years old, with the maximum age being 7 years and minimum is one year. We coded a variable Game_app indicating whether the app is a game based application since, in the android market, 66% apps are game related. We also coded 12 dummies indicating the category of the app.

Variable	Obs	Mean	Std. Dev.	Min	Max	*1*	*2*	*3*	*4*	*5*	*6*	*7*
CVS	17299	4.35	2.84	-6.58	16.96	1.00						
CTF	17299	7.93	13.62	0	100	0.04	1.00					
CP	17299	0.57	0.20	0	1	-0.02	-0.24	1.00				
MS	17299	0.27	0.77	0	3	0.03	0.10	-0.07	1.00			
AGE	17299	2.53	1.13	1.02	6.89	-0.02	-0.06	0.14	-0.08	1.00		
Price	17299	1.79	3.95	0	111.99	0.08	0.06	0.05	-0.03	0.13	1.00	
Game_app	17299	0.66	0.47	0	1	-0.04	-0.04	-0.17	0.05	-0.26	-0.12	1.00

The category dummies have mean<0.05, and std dev <0.20; and correlations are less than 0.1.
All correlations greater than 0.10 are statistically significant at p<0.01

Table 2. Descriptive Statistics and Correlations amongst Key Variables

Estimation Models

We used the ordinary least squares (OLS) estimation to model the consumer rating shift model because the CVS is a continuous variable.

$$CVS_i = \beta X_i + \varepsilon \qquad (1)$$

Where, CVS_i is the dependent variable, X_i is a set of explanatory variables, β is a vector of parameters and ε are disturbances associated with each observation.

Results

	1	2	3	4	5	6
	Direct Effects Model	Consumer Passion Interaction	Market Sustainance Interaction	Age Interaction	Price Interaction	All Interaction Terms
VARIABLES	**CVS**	**CVS**	**CVS**	**CVS**	**CVS**	**CVS**
CTF	**-0.005*** (0.002)**	-0.019*** (0.003)	-0.021** (0.002)	-0.019*** (0.004)	-0.003*** (0.002)	-0.029*** (0.006)
CP	0.283** (0.114)	0.633*** (0.121)	0.275** (0.114)	0.283** (0.114)	0.278** (0.114)	0.635*** (0.121)
MS	0.091*** (0.028)	0.074*** (0.028)	0.111*** (0.030)	0.091*** (0.028)	0.092*** (0.028)	0.104*** (0.030)
AGE	-0.084*** (0.020)	-0.081*** (0.020)	-0.085*** (0.020)	-0.085*** (0.023)	-0.087*** (0.020)	-0.068*** (0.023)
PRICE	0.054*** (0.006)	0.054*** (0.006)	0.054*** (0.006)	0.054*** (0.006)	0.064*** (0.007)	0.063*** (0.007)
CTF X CP		**-0.054*** **				**-0.057*** **

		(0.007)				**(0.007)**
CTF X MS			**-0.004**** **(0.002)**			**-0.006***** **(0.002)**
CTF X AGE				**-0.045***** **(0.001)**		**-0.050**** **(0.001)**
CTF X PRICE					**-0.001**** **(0.000)**	**-0.001**** **(0.000)**
Game_App	-0.275 (0.054)	-0.277 (0.054)	-0.275 (0.054)	-0.275*** (0.054)	-0.269*** (0.054)	-0.230 (0.059)
Constant	4.414*** (0.097)	4.023*** (0.108)	4.407*** (0.097)	4.415*** (0.113)	4.386*** (0.098)	4.154*** (0.105)
Observations	17,299	17,299	17,299	17,299	17,299	17,299
R-squared	0.36	0.31	0.30	0.30	0.28	0.28
Adj R-Sq.	0.24	0.22	0.22	0.21	0.21	0.20
F-Statistics	14.06***	18.38***	13.85***	13.44***	13.47***	17.34***

Standard errors in parentheses
*Significance levels: *** p<0.01, ** p<0.05, * p<0.1*
The focal independent variables and interaction terms are mean centered in the interaction effect models
Models include all the category dummies and none of them are significant
F-stat differences are significant across models to test interaction effects' contribution to the models

Table 3: Results of Estimation Models

We first tested the direct relationship between consumer technology frustrations on consumer valuation shift and reported the results (see Column 1 of Table 3). We then included one interaction term each to test their individual interaction effects on consumer valuation shift (Column 2-5, Table 3), and finally, tested for joint effects of all interaction terms in a model (Column 6 of Table 3).

We find support for H1 as the coefficient for consumer technology frustration is negative and significant in the direct effect model (Column 1 of Table 3, β = -0.005, $p<0.01$). This result shows that with every two units of consumer frustration with the app, there is a 1% reduction in consumer valuation in a week for the app. A practical implication of this result is that for every two consumers who indicate frustrating experiences with the app in their reviews, one new customer is lost in the next week.

We find support for H2a which predicted that negative effect of consumer technology frustration on consumer valuation shift is low for apps with high consumer passion. The interaction term of CTF X CP is negative and significant in the interaction effects model (refer to column 6 of Table 3, β = -0.057, $p<0.01$). The interaction hypotheses H2b predicted that for the apps with high market sustainance, the technology frustration will have a lower effect than for the apps for which consumer passion is low. We find support for this hypothesis as the interaction term CTF X MS is significant and negative in the interaction effects model (Column 6 of Table 3, β = -0.006, $p<0.01$). Similarly, H2c is also supported with the interaction term CTF X AGE being significant on CVS in the interaction model (see Column 6 of Table 3; β = -0.050, $p<0.05$). Finally, H2d is also supported with the interaction term CTF X PRICE being significant on CVS (Column 6 of Table 3; β = -0.001, $p<0.05$).

Amongst other findings, we also find CP, MS, and PRICE have positive and significant direct effects on CVS, while AGE has a negative significant direct effect. These results were not hypothesized due to their intuitive nature, but are nonetheless noteworthy. We also find that in some models, a game app has a negative consumer evaluation shift (see Columns 4 and 5 in Table 3). Plausibly, a game app is prone to more stringent evaluation than other apps, and frustration levels seem higher if problems occur during app usage. The categorical control variables are not significant in our models.

We tested for multicollinearity by computing variance inflation factors (VIFs) for all estimation models. The highest VIF was 2.0 in the direct-effect models, confirming that multicollinearity is not a serious concern. To reduce potential high multicollinearity issues due to the number of interaction terms in the models, all continuous variables were mean-centered by subtracting the corresponding variable mean from each value (Aiken and West 1991). The VIF of any individual variable in any of the interaction effect models was less than 7.0. Furthermore, mean VIFs in all the models were less than 5.0. Thus, we find that multicollinearity is not a serious concern in the estimation.

Discussions

This study finds that technology frustration is a critical negative determinant to influence consumer valuation shift of apps. Second, we find that with a high level of passionate consumers in the market about the apps helps to mitigate this effect to some extent. A third finding is that if the app has sustained in the market for a good period of time, the influence of technology frustration on consumer valuation shift is lower than those apps which have sustained for less period of time. Fourth, reviews of new apps reflect a higher shift in technology frustration on consumer evaluations, compared to older apps. Finally, higher priced apps bear more consumer technology frustration on the valuations, mostly due to the price-sensitive stringent mindset of consumer evaluations for price-premium products.

Another managerial implication of this study is that irrespective of a great proposition that an app is useful for customers, the technical design and integration plays a highly valuable role in consumer acceptance of the app. Hence, developers should pay more attention to the technical aspect of the apps. Moreover, app developers should be careful in the design and development aspects of an app—which is often a forgotten aspect due to the low-cost development regime of apps developments. In addition, identifying passionate consumers and pricing of the apps play important role for an apps success. Finally, as much as an app's release is important, taking feedbacks from consumers and tracking almost on every day basis is highly influential for an app's success. While such feedbacks and market mechanisms such as release controls and exist strategy are seen in consumer oriented products such as movies or music products, apps markets need to implement such system.

This study contributes to research in identifying technological, market externalities and internal factors associated with digital product success. Contextualizing to apps market, the study suggests the integral role of these three complementary factors, and thus, contribute to evaluate the components of a digital business strategy (Bharadwaj et al., 2013).

The study is cross-sectional in nature, and hence is limited to the associational interpretation of results than drawing any causal inferences. We plan to extend this study to multiple week's panel data analysis to provide more insights and robust evidences. In addition, future research may explore nuances associated with technology frustration with a deeper lens. Another interesting aspect for the future research would be to include the "dead apps" and look for commonalities between the groups of apps and the business value associated with it. Possibly, exploring willingness to pay in the apps market can establish the nuances associated with establishing a business case for apps.

In conclusion, the objective of this study was to explore to what extent technology frustration influences consumer valuation of apps. In addition, we posed the research question as to how market externalities such as passionate consumers and sustainance of the app in the market; and whether market internal factors such as pricing and age of the app moderate the influence of technology frustration on consumer evaluations. We analyzed secondary data for more than 17,000 android apps and found support for all our hypotheses. This study contributes to the research on the digital business strategy for apps markets.

REFERENCES

Aaker, D. A., and Keller, K. L. 1990. "Consumer Evaluations of Brand Extensions," *The Journal of Marketing*), pp. 27-41.

Aitken, M., and Gauntlett, C. 2013. "Patient Apps for Improved Healthcare from Novelty to Mainstream," *IMS Institute for Healthcare Informatics*), pp. 1-65.

Belk, R. W., Ger, G., and Askegaard, S. 2003. "The Fire of Desire: A Multisited Inquiry into Consumer Passion," *Journal of consumer research* (30:3), pp. 326-351.

Bessière, K., Newhagen, J. E., Robinson, J. P., and Shneiderman, B. 2006. "A Model for Computer Frustration: The Role of Instrumental and Dispositional Factors on Incident, Session, and Post-Session Frustration and Mood," *Computers in Human Behavior* (22:6), pp. 941-961.

Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., and Venkatraman, N. 2013. "Digital Business Strategy: Toward a Next Generation of Insights," *MIS Quarterly* (37:2), pp. 471-482.

Bhattacherjee, A. 2001. "Understanding Information Systems Continuance: An Expectation-Confirmation Model," *MIS quarterly*), pp. 351-370.

Brown, S. A., Venkatesh, V., and Goyal, S. 2012. "Expectation Confirmation in Technology Use," *Information Systems Research* (23:2), pp. 474-487.

Curran, C. M. (1999). Misplaced marketing-A best buy in advertising: schools selling students as media audiences. Journal of Consumer Marketing, 16(6), 534-536.

Dabholkar, P. A. 1996. "Consumer Evaluations of New Technology-Based Self-Service Options: An Investigation of Alternative Models of Service Quality," *International Journal of research in Marketing* (13:1), pp. 29-51.

Denegri-Knott, J., and Molesworth, M. 2013. "Redistributed Consumer Desire in Digital Virtual Worlds of Consumption," *Journal of Marketing Management* (29:13-14), pp. 1561-1579.

Ghose, A., and Han, S. P. 2014. "Estimating Demand for Mobile Applications in the New Economy," *Management Science* (60:6), pp. 1470-1488.

Guchait, P., and Namasivayam, K. 2012. "Customer Creation of Service Products: Role of Frustration in Customer Evaluations," *Journal of services Marketing* (26:3), pp. 216-224.

IDC. 2013. "Worldwide and U.S. Mobile Applications Download and Revenue 2013-2017 Forecast: The App as the Emerging Face of the Internet."

Johnson, M. W., Christensen, C. M., and Kagermann, H. 2008. "Reinventing Your Business Model," *Harvard Business Review* (86:12), pp. 50-59.

Lazar, J., Jones, A., Hackley, M., and Shneiderman, B. 2006. "Severity and Impact of Computer User Frustration: A Comparison of Student and Workplace Users," *Interacting with Computers* (18:2), pp. 187-207.

Lee, G., and Raghu, T. 2014. "Determinants of Mobile Apps' Success: Evidence from the App Store Market," *Journal of Management Information Systems* (31:2), pp. 133-170.

Lenhart, A. 2003. *The Ever-Shifting Internet Population: A New Look at Access and the Digital Divide*. Pew Internet & American Life Project.

Müller, R. M., Kijl, B., & Martens, J. K. (2011). A comparison of inter-organizational business models of mobile app stores: there is more than open vs. closed. Journal of theoretical and applied electronic commerce research, 6(2), 63-76.

Oliver, R. L. 1977. "Effect of Expectation and Disconfirmation on Postexposure Product Evaluations: An Alternative Interpretation," *Journal of applied psychology* (62:4), p. 480.

Oliver, R. L. 1980. "A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions," *Journal of marketing research*), pp. 460-469.

Perdikaki, O., and Swaminathan, J. 2013. "Improving Valuation under Consumer Search: Implications for Pricing and Profits," *Production and Operations Management* (22:4), pp. 857-874.

Ülkü, S., Dimofte, C. V., and Schmidt, G. M. 2012. "Consumer Valuation of Modularly Upgradeable Products," *Management Science* (58:9), pp. 1761-1776.

Wilfong, J. D. 2006. "Computer Anxiety and Anger: The Impact of Computer Use, Computer Experience, and Self-Efficacy Beliefs," *Computers in Human Behavior* (22:6), pp. 1001-1011.