ICIS 2019 Proceedings | Information Systems - The Heart of Innovation Ecosystems

How Story Works in Mobile App Stores? Exploring the Same-Side Effect from the Storytelling Perspective

Bingqing Xiong
University of Science and Technology of China, bxiong2-c@my.cityu.edu.hk

Mengyao Fu
City University of Hong Kong, mengyaofu3-c@my.cityu.edu.hk

Weiquan Wang
City University of Hong Kong, weiquan@cityu.edu.hk

How Story Works in Mobile App Stores? Exploring the Same-Side Effect from the Storytelling Perspective

Short Paper

Bingqing XIONG
University of Science and Technology of China-City University of Hong Kong Joint Program
Hefei, China
bxiong2-c@my.cityu.edu.hk

Mengyao FU
City University of Hong Kong
Hong Kong, China
mengyaofu3-c@my.cityu.edu.hk

Weiquan WANG
City University of Hong Kong
Hong Kong, China
weiquan@cityu.edu.hk

Abstract

The growing number of mobile apps has contributed to an innovation diffusion paradox whereby the accelerated pace with which mobile apps are being developed and updated has stymied their own diffusion. Due to consumers' limited personal involvement with mobile apps, storytelling, as an emerging and novel product recommendation format, is gaining traction as a promotional mechanism for diffusing mobile apps within the ecosystem. Storytelling is particularly amenable to the context of mobile app stores by giving affective meaning to the focal app being promoted and strengthening its association with other apps available from these stores. To this end, we construct a research model to illustrate how consumers' demand for related mobile apps is shaped by similarity in functional and visual attributes between these apps and the focal app being promoted via storytelling. Our model also sheds light on how the preceding effects could be mitigated by within-developer influence.

Keywords: Storytelling, same-side effect, functional similarity, visual similarity, within-developer influence

Introduction

Mobile app stores are digital platforms for diffusing mobile apps, a type of digital good that has permeated our daily lives. As of March 2018, there were approximately 3.8 million apps available in Google Play, the world's largest app store, while the Apple Store, its closest rival, boasted an estimated 3.2 million apps in July 2018[1]. Accompanying the explosion in downloads is the corresponding growth in the number of newly launched apps. Statistics generated from tracking monthly submissions to Apple App Store indicated that there were 11,564 submissions in January 2019 alone, representing an average of 413 submissions per day[2]. Comino et al. (2019) further noticed that the top 1,000 apps in five European countries are, on average,

[1] https://www.statista.com/statistics/268251/number-of-apps-in-the-itunes-app-store-since-2008
[2] http://www.pocketgamer.biz/metrics/app-store/submissions

being updated every 13 days on Google Play. Because industry reports have alluded to a positive relationship between app ratings and update frequency[3], developers are keen to continuously upgrade existing apps to new versions.

Yet, the accelerated growth of mobile apps has culminated in challenges for both consumers and platforms alike (Datta and Kajanan, 2013). For consumers, the burgeoning number of newly launched and frequently updated mobile apps implies that it is practically impossible for consumers to peruse the entire collection of available apps and they are constantly exposed to a mere fraction of such apps. Likewise, for mobile app platforms, it is difficult to introduce consumers to newly launched apps. Unless the release rate of new mobile apps slows down, it contributes to an innovation diffusion paradox within the mobile app ecosystem: even though the fast pace with which mobile apps can be developed and updated has fostered a climate of open innovation, the diversity and velocity in introducing new or upgraded apps has stymied their own diffusion. Consequently, one of the focal challenges for mobile app ecosystems stems from bolstering consumers' exposure to newly launched or updated apps.

In mobile app stores, recommendations of mobile apps are conventionally displayed in a fact-based format that highlights key product attributes and/or technical specifications (e.g., apps with 3D touch-enabled). However, mobile apps do not only comprise tangible attributes that correspond to functional features, they also embody intangible offerings, which tend to be experiential in nature (Lusch and Nambisan 2015). In this sense, conventional fact-based recommendation format often neglects the experiential aspects of the decision-making process that consumers undergo when downloading mobile apps. Consequently, mobile app stores have begun to innovate on the design of their recommender system by accentuating user experiences in the promotion of mobile apps. For example, the Apple App Store has recently introduced the 'Today' tab to incorporate rich story elements and collate apps into thematic categories for recommendation. In so doing, the Apple App Store downplays the tangible aspects of the mobile apps being promoted in favor of drawing consumers' attention to their intangible counterparts with unique storylines. An example of such a story is titled: 'Brave the open road' (as shown in Figure 1); it collates several focal apps related to travel to create a unifying promotional theme.

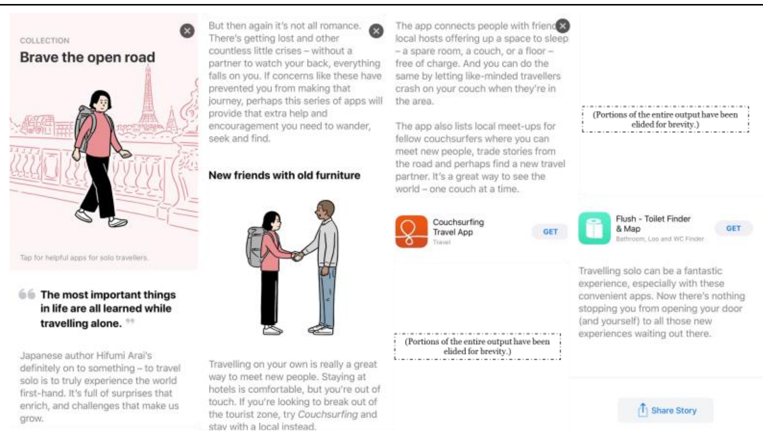

Figure 1. An Example of Storytelling on Apple App Store

Storytelling encapsulates experiencial and physical components to market product and/or service offerings (Yoo 2010). Indeed, past studies have discovered that storytelling, which induces an emotive response, enhances individuals' decision-making process in a variety of fields ranging from advertising to branding (Salzer-Mörling 2004). In the same vein, the introduction of mobile apps can be organized in a story-like format, encompassing elements such as causality, contextualization, and meaning. By facilitating emotive processing, storytelling exerts a salient effect on decision making by blending tangible and intangible attributes of mobile apps to illustrate how they can be utilized beyond functional situations. As contended by Kenter et al. (2016), storytelling plays a pivotal role in the symbolic representation and construction of contextual values, which in turn may aid consumers to better pinpoint what is meaningful and worthwhile

[3] http://www.businessinsider.com/app-update-strategy-and-statistics-2015-1

for them given the burgeoning number of newly launched and frequently updated mobile apps. By bundling focal mobile apps for easy reference, storytelling accelerates innovation diffusion within mobile app stores. A compelling story is able to not only persuade consumers to purchase focal apps, it can also entice consumers to consider related apps within the mobile app store (Dessart & Pidarti, 2019). Going back to our earlier example, it is conceivable that consumers who were exposed to the 'Brave the open road' story may be primed to explore related travel apps not promoted in the story.

Despite the touted benefits of storytelling, there is a dearth of research that has explored its impact on consumer behavior. We conceive ***storytelling*** as the *contextualization of product recommendations in a thematic fashion that conveys meaning to consumers* (Escalas, 2007). As alleged by Clarizia et al. (2018), the contextualization of product usage for a given scenario is an effective means of invoking targeted interest in the product. Apart from being an incredibly popular means of promoting mobile apps, storytelling also connects related products in a meaningful fashion that renders these products memorable to consumers (Austin 2010). We therefore anticipate that storytelling will not only draw consumers' attention to the focal app(s) being promoted, but also exert a same-side effect on related apps through strengthening their association with the focal app(s). To this end, this study endeavors to not only offer an in-depth understanding of the effects of storytelling on information goods with similar product attributes, but to also shed light on how these effects could be mitigated by within-developer influence.

Theoretical Foundation

Information Goods and Same-Side Effect

Characterized by costly development but negligible costs of reproduction and distribution, information goods are distinguishable from their physical counterparts (Wei and Nault 2013). In light of the distinction between the tangible (e.g., functionality) and intangible (e.g., graphical user interface) attributes of a product (Keller and McGill 1994; Lefkoff-Hagius and Mason 1990), information goods can be conceived as a multi-attribute product whereby interdependencies between the abovementioned two types of attributes may affect consumers differently (Lee et al. 2011). Specifically, as a consequence of their inherent intangible and reprogrammable nature, information goods tend to render digital operant resources in the likes of functional features and visual experience to be much more critical (Eaton et al. 2015). Aligned with past studies, we hence posit that consumers' evaluation of information goods are founded on the latter's: (1) functional (how well an information good fulfils its functional purpose as anticipated), and; (2) visual (how much an information good expresses and appeals visually) attributes.

For this reason, consumers would normally engage in comparisons of product attributes among information goods, a phenomenon labeled as same-side effects. Building on previous work on co-diffusive interactions (Dewan et al. 2010), we scrutinize the effects of cross-product interactions among related information goods. The term 'same-side' is borrowed from prior research on two-sided markets (e.g., Rogers 2003) to denote the mutual influence of similar products and characterize imitation effects or internal influence during innovation diffusion (Parker and Van Alstyne 2005). Increasingly, scholars have acknowledged that innovations do not diffuse in isolation and that interactions among overlapping innovations are often deterministic of the diffusion trajectories of innovations (Kim et al. 2000). In the same vein, we construe ***same-side effect*** as the primary driver of innovation diffusion for information goods and define it as the *extent to which interdependencies among information goods increase consumers' likelihood of acquiring both existing and related information goods*. In the case of mobile apps, same-side effects arise from the imitation effects of mobile apps during the diffusion process. For example, advances in digital reality have transformed human-computer interaction from hardware screens to gazes, gestures, and emotions (Nah et al. 2011), a trend that is evident from the increasing number of apps which have been released with virtual reality functions in mobile app stores.

Hypotheses Formulation

A common assumption underlying physical goods is that products with similar attributes will be favored by consumers (Lefkoff-Hagius and Mason 1993). The positive impact of product feature similarity on consumers' evaluations and purchase intentions can be accounted for by same-side effect in that imitation strategies such as design copies, market adaptions, or technological leapfrogging have been employed by manufacturers to distribute products with comparable functionality (Parker et al. 1991). Likewise, within mobile app stores, apps sharing comparable functionality are often catalogued into the same category for diffusion. Conceivably, we anticipate that consumers are more likely to prefer products with greater functional overlap (Lefkoff-Hagius and Mason 1993) and hypothesize that:

Hypothesis 1: Functional similarity between the focal app being promoted and related apps will positively influence consumers' demand for related apps.

Beyond functional benefits, there are also studies that have attested to the visual aspects of product preferences (e.g., Sirgy 1982). Visual attributes are distinct from their functional counterparts in that the former entails the visual appearance or expression of information goods whereas the latter relates to how they operate (Seo and Kim 2002). Visual and functional attributes may be activated differently when assessing information goods (Jiang and Benbasat 2004). Highlighting visual attributes of information goods might be disadvantageous for the diffusion of related information goods due to the intangibility of such goods: consumers' evaluation of information goods tends to be highly subjective (Chattaraman et al. 2009; Lefkoff-Hagius & Mason, 1990) so much so that they might simply go with the focal products under recommendation. In the same vein, consumers might also hold a negative opinion of the focal app being promoted together with any other visually related app if they view the visual style of the former unfavorably. We therefore hypothesize that:

Hypothesis 2: Visual similarity between the focal app being promoted and related apps will negatively influence consumers' demand for related apps.

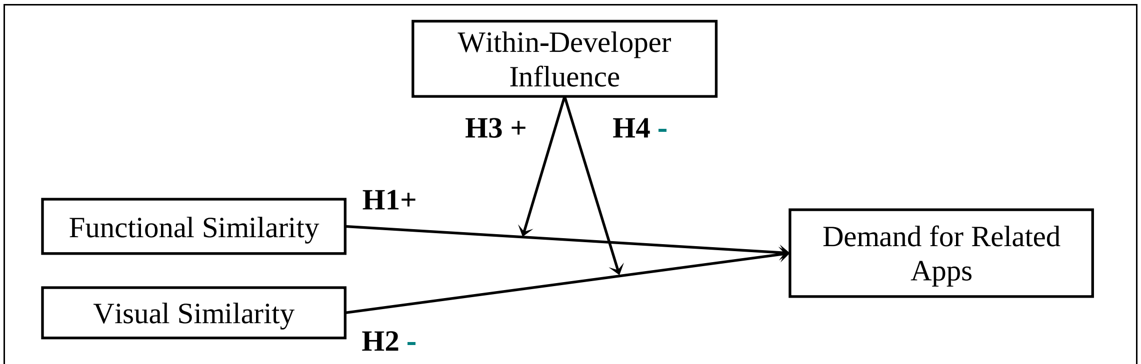

Figure 2. Research Model

Consumers' diagnosticity and evaluation of information goods from the same developer will undoubtedly be shaped by similarity in both functional and visual attributes (Jiang and Benbasat 2007). However, we expect the effects of functional and visual similarity on consumers' demand for related apps to differ. Whereas visual attributes are analogous with directly observable product appearance, functional attributes tap into product performance, which is invisible to consumers until consumption has actually taken place. Performance diagnosis of information goods thus demands greater cognitive effort as compared to their visual counterparts. In other words, we expect that within-developer influence would aid consumers in resolving the ambiguity inherent to related apps from the same developer, transferring positive associations if these apps do not deviate visually from the focal app being promoted (Pieters 2010). Conversely, if the focal app being promoted and a related app belong to the same developer, their functional attributes are likely to converge over time due to upgraded features of the reprogrammable nature of information goods (Wei and Nault 2013). This in turn bolsters the appeal of the related app by minimizing consumers' learning curve. We therefore hypothesize that:

Hypothesis 3: Within-developer influence will reinforce the positive relationship between functional similarity and consumers' demand for related apps.

Hypothesis 4: Within-developer influence will attenuate the negative relationship between visual similarity and consumers' demand for related apps.

Methodology

Data Collection and Analysis

To validate our research model, we will apply OLS regression analysis on a massive dataset containing mobile app descriptions and ranking data on the Apple App Store (IOS) (see Table 1).

Table 1. Description of Datasets

Dataset	**Description**
Set I: App Description	Descriptive information of all downloadable apps from the China IOS App Store. Contains app icons, app screenshots, developers' ID, textual descriptions, paid or free indicator, subcategory type, release date, updating date, and customer reviews for all 12,000 apps which are downloadable on the Apple App Store from March 15th to Sep 15th, 2018.
Set II: App Ranking Records	Consists of more than one million records on app ranking (approximately 10,000 records per day) from March 15th to Sep 15th in 2018, which include real-time ranking data for every app on the primary list. Additionally, ranking records will be randomly updated at several time periods during the day.
Set III: "Today" tab	Consist of 184 records for "Today" tab from March 15th to Sep 15th (184 days in total), each record includes the title, textural story, pictures, and apps' listing information.

Independent Variables:

The exogeneous variables are functional and visual similarity. Even though there could be other indicators (e.g., quality of apps, release date, and the number of versions), which will be incorporated into our data analysis as control variables. Two methods will be applied to calculate the degree of similarity between the focal app being promoted and related apps: Natural Language Procession (NLP) and Image Recognition. Adhering to the approach of Wang et al. (2018), ***functional similarity*** is detected by applying NLP on the textual descriptions and customer reviews of mobile apps. Each app will be mapped to a vector of features with weightings that are calculated based on the appearing frequency of each feature in the text. The functional similarity among apps will be computed by taking a cosine of their feature vectors. The functional similarity of app *i* and app *j* is defined as f_{ij}. The cosine similarities of all app-pairs form the square matrix F where $F_{ij} = f_{ij}$. ***Visual similarity*** is detected by conducting image matching analysis on app screenshot. We apply the Scale-Invariant Feature Transformation (SIFT) advocated by Lowe (1999) and adapted by Wang et al (2018). It extracts a core set of features (e.g., image scale, rotation, and illumination) from an image that mirrors its most crucial and distinctive informational components. We then match the image with another image. The visual similarity of app *i* and app *j* is defined as v_{ij}. The visual similarities of all app pairs form the square matrix V where $V_{ij} = v_{ij}$.

Dependent Variable:

We analyze whether the promotion of a focal app affects the demand of related apps in terms of download. We approximate the daily download quantity through the calibration method by Garg and Telang (2013) that is based on records of mobile app rankings. We conduct daily panel analysis based on the mean downloads for the entire day because mobile app rankings are updated at random times and idiosyncratic errors could occur if the period of analysis is too short (e.g., 2 hours). The download quantity of app *i* on day *t* is formulated as $D_{i,t} = \frac{1}{m(t)} * \sum_{k=1}^{m(t)} D_{i,t,k}$, where $m(t)$ refers to the number of ranking records of day *t*. To remove other unobservable time-varying variables, we will calculate the deviation of downloads from normal downloads of day *t*. The **downloads deviation** of app *i* of day *t* is formulated as $DD_{i,t} = D_{i,t} - E(D_{i,t})$ where the previous 60 days (before day *t*)' download records will be employed to detect the normal download rate $E(D_{i,t})$ for day *t*.

Table 2 offers a summary of variables in our study.

Table 2. Description of Variables				
Dataset	Description	Range	Data	Method
Functional Similarity	Continuous	[0,1]	Data Set I	Natural Language Procession
Visual Similarity	Continuous	[0,1]	Data Set I	Scale-Invariant Feature Transform
Within-Developer Influence	Binary	{0,1}	Data Set I	/
Downloads	Continuous	/	Data Set II	Calibration method
Deviation of Downloads	Continuous	/	Data Set II	Calibration method

Illustrative Data Analysis

We have conducted preliminary analysis on a select sub-sample to validate the operationalization of our key variables: functional similarity and visual similarity. For illustrative purpose, we have included an example of storytelling that was displayed on the 'Today' tab of the Apple App Store's homepage on April 1st, 2018. The story revolves around the theme – 'A great match of pictures and words' [https://itunes.apple.com/cn/story/id1342228547] and introduces one focal app: Butter Camera. To illustrate our data analytical procedures, we have compared the focal app being promoted against other five related apps belonging to the category of 'Photo & Video'. Detailed information of the five related apps (including price, developer, and category) is listed in Table 3 below.

Employing Natural Language Processing (NLP) to calculate functional similarity, we extracted functional features of the five related apps (see Table 3). We then compute pairwise cosine similarity using feature and weight vectors. Analytical results from our computation of cosine similarity are presented in the last column of Table 3: functional similarity. From the analytical results, we can deduce that, Lightbeauty Camera and FaceU exhibit high functional similarity with the focal app: Butter Camera.

Table 3 Functional Features and Similarity for Six Apps						
Name of Mobile App		**Price**	**Developer**	**Category**	**Functional Features**	**Functional Similarity**
Focal App	Butter Camera	Free	Wenrui Shan	Photo & Video	Filter, sticker, font, photo, legit, picture, creation, cat, text, one-click	100%
Related Apps	Lightbeauty Camera	Free	Shenzhen faceu technology Co. LTD	Photo & Video	photo, filter, take a photo, fine tuning, posture, effects, red net, one-click, style, appearance	26.04%
	MeituPic	Free	Xiamen Meitu Technology Co. LTD.	Photo & Video	Sticker, photo, selfie, beauty, figure, phone, anime, pinched, exclusive, fairy	6.33%
	Poco Camera	Free	POCO.CN	Photo & Video	Mobile phone, apps, pictures, lens, creative, cover, life, Chinese, photography, take a photo	3.54%
	FaceU	Free	Shenzhen faceu technology Co. LTD	Photo & Video	One-click, cute, photo, sticker, filter, video, take a photo, the whole network, share	34.40%
	Nomo Camera	Free	Blink Academy Co. LTD.	Photo & Video	picture, Nomo, account, subscribe, closure, terms, click, photo, photographer, expose	3.89%

Next, we calculated visual similarity via SIFT. In so doing, we extracted a core set of visual features (e.g., image scale, rotation, and illumination) that have been marked with green points in Figure 3. These green points depict the most crucial and distinctive informational components for the app screenshot. Screenshots from the five related apps were matched with the one from the focal app being promoted. Analytical results pertaining to visual similarity are listed on the comparison chart to portray the degree of matching in screenshots between the focal app being promoted and each of the five related apps (see Figure 3). From the analytical results, we can infer that, Poco Camera shares the highest visual similarity with the focal app being promoted whereas Nomo Camera has the lowest visual similarity.

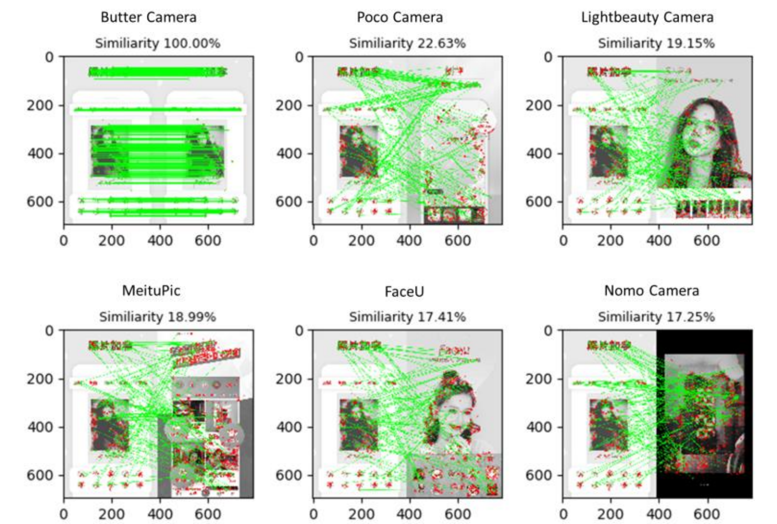

Figure 3 Virtual Similarity for Six Apps

Empirical Model

To validate our research model, we will conduct data analyses on the daily panel as follows. We denote the download deviation of the recommended mobile app *i* during day *t* with DD_{it}, the download deviation of the related app *j* during day *t* with DD_{jt} where t = 1, ...T. First, we denote the download deviation of the related mobile app *j* during day *t* with D_{jt}, where t = 1~ T. We modeled DD_{it} as a function of mobile app recommendations on the list L (the treatment variable), $DD_{it} = \alpha L + \beta D_{it} + \lambda_i + \varphi_t + \varepsilon_{it}$. Second, we modeled DD_{jt} as a function of network effect from app *i*: $DD_{jt} = \gamma N_i + \beta D_{jt} + \lambda_j + \varphi_t + \varepsilon_{jt}$. Comparing the equation for DD_{it} and DD_{jt}, both of the promotion effect (denotes as α) from recommendation for app *i* and the same-side effect (denotes as γ) from recommendation for app *j* can be observed.

Table 4 offers detailed descriptions for all variables in our empirical model.

Table 4. Description of Variables

	Symbol	Noting	Consideration
Dependent Variables	DD_{it}	Download deviation of recommended mobile app *i* during day *t*	$DD_{it} = \alpha L + \beta D_{it} + \lambda_i + \varphi_t + \varepsilon_{it}$
	DD_{jt}	Download deviation of related mobile app *j* during day *t*	$DD_{jt} = \gamma N_i + \beta D_{jt} + \lambda_j + \varphi_t + \varepsilon_{jt}$
Independent & Control Variables	D_{it}	Time-varying attributes of the original app D_{it}	Time-varying characteristics of the original app D_{it} include: Price, updating version, release date, and the number of apps from the same developer

	N_i	Network effect from the focal app *i*, N_i	N_i includes three dimensions: Functional similarity, visual similarity, and within-developer influence
	λ_i	Time-invariant app specific heterogeneity captured by the app fixed effects λ_i	Product fixed effects (λ_i) to control for app specific time-invariant heterogeneity, including any observable (e.g., paid/free pricing type) and unobservable time-invariant app characteristics (e.g., inherent quality of the app)
	φ_t	Time fixed effects	Daily controls (φ_t) to account for time trends
	ε_{it}	Other unobserved time-varying variables ε_{it}	Unobserved error term (ε_{it}) is assumed to be orthogonal to other independent variables

Future Analysis

As we process our preliminary data analysis, we found that app screenshots contain much more information than that in the app icons. Meanwhile, to better incorporate the role of storytelling into our study, we have extracted storytelling data with detailed story elements. For future data analysis, all app screenshots will be taken into account with a uniform format. Furthermore, we will ascertain the aggregate effect of the focal apps being promoted on consumers' demand of a related app via hierarchical regression analysis. Moreover, we would perform Difference in Difference (DID) testing to rule out heterogeneity among mobile apps as a potential confound and utilize Propensity Score Matching (PSM) and Heckman's (1979) two-step approach as a robustness check to avoid selection bias and time lag effects.

Conclusion

While past studies have scrutinized the impact of discrete recommendation styles on firms' own products, they have largely ignored the presence of same-side effect on related ones. To this end, we advance a research model that postulates how functional and visual similarity among mobile apps can shape consumers' demand for apps associated with a focal app being promoted through storytelling. We further describe the design of empirical study for validating our research model that is grounded in the similarity detection method advocated by Wang et al. (2018). Findings from this study can yield invaluable insights that can be harnessed by mobile app developers and store owners to exploit storytelling as a means of diffusing mobile apps.

Acknowledgement

The work described in the paper was partially supported by grants from the Research Grants Council of Hong Kong S.A.R. (Projects No. CityU 11505917 and No. CityU 11504316).

References

Austin, M. 2010. *Useful fictions: evolution, anxiety, and the origins of literature Choice Reviews Online*, (Vol. 48).

Chattaraman, V., Rudd, N. A., & Lennon, S. J. 2009. "Identity salience and shifts in product preferences of Hispanic consumers: Cultural relevance of product attributes as a moderator," *Journal of Business Research*, (62:8), pp.826-833.

Clarizia, F., Colace, F., Lombardi, M., and Pascale, F. 2018. "A context aware recommender system for digital storytelling," in *Proceedings - International Conference on Advanced Information Networking and Applications*, pp. 542–549.

Comino, S., Manenti, F. M., and Mariuzzo, F. 2019. "Updates Management in Mobile Applications: iTunes versus Google Play," *Journal of Economics and Management Strategy*, (28:3), pp.392-419.

Datta, D., and Kajanan, S. 2013. "Do App Launch Times Impact their Subsequent Commercial Success? An Analytical Approach," *2013 International Conference on Cloud Computing and Big Data*, pp. 205–210.

Dewan, S., Ganley, D., and Kraemer, K. L. 2010. "Complementarities in the diffusion of personal computers and the internet: Implications for the global digital divide," *Information Systems Research*, (21:4), pp. 925–940.

Eaton, B., Elaluf-Calderwood, S., Sørensen, C., and Yoo, Y. 2015. "Distributed tuning of boundary resources: the case of Apple's iOS service system," *MIS Quarterly: Management Information Systems*, (37:1), pp. 217–243.

Escalas, J. E. 2007. "Self-Referencing and Persuasion: Narrative Transportation versus Analytical Elaboration," *Journal of Consumer Research*, (33:4), pp. 421–429.

Garg, R., and Telang, R. 2013. "Inferring app demand from publicly available data," *MIS Quarterly*, (37:4), pp. 1253–1264.

Jiang, Z., and Benbasat, I. 2004. "Virtual product experience: Effects of visual and functional control of products on perceived diagnosticity and flow in electronic shopping," *Journal of Management Information Systems*, (21:3), pp. 111–147.

Jiang, Z., and Benbasat, I. 2007. "The Effects of Presentation Formats and Task Complexity on Online Consumers' Product Understanding," *MIS Quarterly*, (31:3), pp. 497–520.

Keller, P.A. and McGill, A.L., 1994. Differences in the relative influence of product attributes under alternative processing conditions: Attribute importance versus attribute ease of imagability. *Journal of Consumer Psychology*, (3:1), pp.29-49.

Kenter, J. O., Jobstvogt, N., Watson, V., Irvine, K. N., Christie, M., and Bryce, R. 2016. "The impact of information, value-deliberation and group-based decision-making on values for ecosystem services: integrating deliberative monetary valuation and storytelling," *Ecosystem Services*, (21), pp. 270–290.

Kim, N., Chang, D. R., and Shocker, A. D. 2000. "Modeling Intercategory and Generational Dynamics for A Growing Information Technology Industry," *Management Science*, (46:4), pp. 496–512.

Lee, S., Ha, S., & Widdows, R. 2011. Consumer responses to high-technology products: Product attributes, cognition, and emotions. *Journal of Business Research*, (64:11), pp.1195-1200.

Lefkoff-Hagius, R., & Mason, C. H. 1990. The role of tangible and intangible attributes in similarity and preference judgments. *ACR North American Advances*, (17:1), pp.135-143.

Lefkoff-Hagius, R., and Mason, C. H. 1993. "Characteristic, Beneficial, and Image Attributes in Consumer Judgments of Similarity and Preference," *Journal of Consumer Research*, (20:1), pp. 100-110.

Lowe, D. G. 1999. "Object recognition from local scale-invariant features," in *iccv*, (92:2), pp. 1150-1157

Lusch, R. F., and Nambisan, S. 2015. "Service innovation: A service-dominant logic perspective.," *MIS quarterly*, (39:1), pp. 155-175.

Nah, F., Eschenbrenner, B., and DeWester, D. 2011. "Enhancing brand equity through flow and telepresence: A comparison of 2D and 3D virtual worlds," *MIS Quarterly*, (35:3), pp.731-748.

Park, C. W., Milberg, S., & Lawson, R. 1991. Evaluation of brand extensions: the role of product feature similarity and brand concept consistency. *Journal of consumer research*, (18:2), pp.185-193.

Parker, G. G., and Van Alstyne, M. W. 2005. "Two-Sided Network Effects: A Theory of Information Product Design," *Management Science*, (51:10), pp.1494–1504.

Pieters, R. 2010. Looking more or less alike: Determinants of perceived visual similarity between copycat and leading brands. *Journal of Business Research*, (63:11), pp.1121-1128.

Rogers, E. M. 2003. "Diffusion of innovations. Free Press," New York, (551).

Salzer-Mörling, M. 2004. "Storytelling and branding," *Att mobilisera för regional tillväxt, Studentlitteratur, Lund*, pp. 145–155.

Seo, J., and Kim, G. J. 2002. "Design for presence: A structured approach to virtual reality system design," *Presence: Teleoperators and Virtual Environments*, (11:4), pp. 378–403.

Sirgy, M. J. 1982. "Self-Concept in Consumer Behavior: A Critical Review," *Journal of Consumer Research*, (9:3), pp. 287-300.

Vargo, S. L., and Lusch, R. F. 2008. "Service-dominant logic: continuing the evolution," *Journal of the Academy of marketing Science*, (36:1), pp. 1–10.

Wang, Q., Li, B., and Singh, P. V. 2018. "Copycats vs . Original Mobile Apps : A Machine Learning Copycat-Detection Method and Empirical Analysis," *Information Systems Research*, (29.2), pp. 273-291.

Wei, X., and Nault, B. R. 2013. "Experience information goods: 'Version-to-upgrade,'" *Decision Support Systems*, (56:1), pp. 494–501.

Yoo, Y. 2010. "Computing in everyday life: A call for research on experiential computing," *MIS quarterly,* (34:2), pp. 213–231.