THE UNCONSCIOUS APP CONSUMER: DISCOVERING AND COMPARING THE INFORMATION-SEEKING PATTERNS AMONG MOBILE APPLICATION CONSUMERS

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Complete Research

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Abstract

The so-called privacy paradox – consumers expressing their need for privacy but acting in the opposite way – can be observed in the app market. Consumers download apps without a monetary payment, but need to provide personal data, without being aware of the amount and quality of data requested. Does this indicate that app users are unconscious consumers? This study analyzes consumers' use of information in the app purchase process. The results of our analysis reveal that information received from consumers' social environment is very important, whereas information about security and trustworthiness is not seen as crucial by many consumers. In a subsequent cluster analysis we can show, that consumers differ regarding their information preferences and at least some consumers indeed do not care about their privacy and security of personal data.

Keywords: Mobile applications, privacy paradox, unconscious consumer, consumer behavior.

1 Introduction

Consumers' use of mobile applications (apps) poses multiple challenges for research in consumer behavior. Apps are frequently considered as a fusion between fast moving consumer goods and traditional software products. In addition, apps are traded against an upcoming currency: privacy intrusion opportunities and verified personal data. However, in contrast to most economic exchanges consumers are usually unable to estimate the amount and the economic value of personal data they have to pay in advance. At the same time, consumers are concerned about their privacy and very sensible regarding the collection and use of personal data (Wenninger et al., 2012). Furthermore, the average user is not able to evaluate the quality and performance characteristics of the app.

As a result, app markets are characterized by highly asymmetrical information endowments of consumers and providers. With increasing information disparities in a market, the uncertainties of the market partners about the quality of the offers and the behavior of the other parties increase (Hirshleifer, 1973). If the market uncertainties cannot be reduced, it is unlikely that a contract is closed.

Nevertheless, current statistics do not show a disruption of the app market, but rather a booming app economy (Gartner Inc., 2012). Consumers download enormous numbers of apps and use them for everyday tasks, although many users do not know which or even that personal data is used by an app and that they give their personal data in exchange for the 'free' download of apps. Thus, they seem to have found strategies to overcome the information asymmetries in the market. But how do consumers break down informational barriers? Which information do they pay attention to in the purchasing channel in order to decrease their lack of information? Are consumers generally aware of the asymmetrical information endowments? Do they (consciously or unconsciously) ignore obvious risks?

This paper seeks to contribute to answering some of these questions and thereby to a better understanding of the processes that are used by consumers in dealing with the information asymmetries in the app market. Our findings should provide insights regarding suitable strategies which can reduce information asymmetries in the app market and therefore increase the probability of attracting and retaining customers. In particular, we are interested in whether consumers act 'unconsciously' when they download apps. Therefore, we aim to analyze if and what information consumers are using when purchasing apps.

The paper will first address the fundamental research question:

1. Which information and information sources are used by consumers before and during the app purchase process and how relevant are the various types and sources of information?

Starting from that, the fact that many consumers are concerned about their privacy, but download many apps in exchange for their personal data suggests that they are somehow able to deal with this contradiction. We assume that there are two possible explanations for this phenomenon. Either, consumers simply ignore the fact that they 'pay' for apps with their personal data or at least the risks associated, or they search for information about which and how much of their data they have to give in exchange and download an app if they do not perceive too many uncertainties. While, in general, consumers could also submit incorrect data in order to deal with privacy and security risks, this strategy is not applicable for many types of data, for example data which is generated through use of the app (e.g. movement profile). It can be assumed that consumers have different strategies for dealing with a lack of information on apps, for example depending on the operating system (OS) of their smart mobile device (SMD). Therefore, we will analyze the information preferences of customer segments, which can be targeted through specific marketing activities. For this, we also address the next two research questions:

2. Does consumers' use of information in the app purchase process depend on the type of the mobile ecosystem (operating system)?

3. Which customer segments can be identified with regard to their use of information in the app purchase process and how can they be characterized?

To answer these research questions, the remainder of this article is organized as follows. In the next section we will start with an overview of the relevant literature. We will give a summary of the characteristics of apps and app consumption as well as on privacy and personal data as currency in the app market. Following this, we will provide some insights into the context and design of our study and describe our methodology. Afterwards, we present and discuss the key findings of our study. Finally, we will point towards some limitations and conclude with some directions for further research.

2 Related literature

2.1 Privacy and personal data as currency in app markets

Apps, like traditional application software, can be characterized as closed and not integrated software packages, which are dependent on their underlying OS (Egele et al., 2011). Based on this, we define apps as application software programs, which use web and cloud applications and run on SMDs. They can be purchased and installed depending on their operating system and perform (highly fragmented) everyday tasks (Taylor, Voelker and Pentina, 2011). Importantly, mobile apps are embedded in mobile ecosystems, i.e. OS-based platforms which provide profile-bounded ubiquitous services for mobile devices.

App markets are typical examples of so-called free or freemium markets, i.e. most apps include (at least) a free basic version. However, this does not mean that consumers do not have to pay for the benefits they derive. Although there is often no money involved in the economic exchange situation of an app purchase, the provider does not offer the app 'for free'. According to Skiera, Spann, and Walz's (2005) B2C-income types classification for the internet, which identifies price, contact and information as income types from B2C-exchanges, the most important income type of app providers is information. More precisely, private information of consumers is generated as the majority of apps receives, stores, or processes personal data, although sometimes other revenue mechanisms are used simultaneously (e.g. in-app advertising, monetary payment for the app). Consumers can benefit from 'free apps' in exchange for their personal data. Hence, personal data and privacy can be regarded as the predominant 'currency' in app markets (Grace et al., 2012) and the main revenue basis of providers of 'free apps'.

Regarding data quality, recent developments in mobile technology and an ever increasing digitalization of everyday tasks lead to an unprecedented precision of continuously updated and integrated personal data which is generated within mobile ecosystems like iOS and Android. Apps are embedded in a unique architecture which allows for an aggregation of fragmented pieces of personal data gained from SMD and apps and can be classified in a 4-tier model. The first tier includes basic consumer data which is required for enrollment within the mobile ecosystem and already generates first-class information to personalize the user profile, for example verified e-mail address, phone numbers, IMEI, UDID and, when using the app store, payment information like credit card and banking information (Felt et al., 2011). The second tier represents the ecosystem's ability to track and store the complete data generated by using the basic OS. The use of this data can be extended to a moving profile or a far-reaching profile of consumers' social environment. The third tier refers to the ability of a 3rd-party vendor to use specific data for consumers' app usage. Apps perform everyday tasks; therefore app usage data gives wide-reaching insights into consumers' everyday lives. In addition, the information can be recorded and personalized from the 3rd-party vendor by downlinking

to the OS, thereby allowing fundamental insights into consumers' behavior (Enck, 2011). Finally, a comprehensive user profile is composed by 4th-party aggregators like Google or Flurry, which represent the fourth tier. These aggregators gather information from thousands of app vendors and can create a holistic profile of users' lives.

2.2 Privacy paradox and app consumption characteristics

As discussed above, app purchase frequently requires a quid pro quo in the form of personal data. The personalized app data can be analyzed and used for gaining intimate insights into consumers' lives. The personalized, rich data about consumers generated from their app consumption is highly valuable for a variety of firms and organizations that intend to influence future consumer decisions. This value is also reflected in the market prices for such data: \$0.50 for an address, \$3 for the driver's license number, and \$55 for a package containing address, date of birth, social security number, credit record and military record (OECD, 2013).

In a market with complete information and rational choice, consumers are aware of the value of their data, able to evaluate the utility of app benefits (and risks), and only willing to pay a justified price. However, consumers do not have complete information concerning the apps they are buying. Indeed, software and apps are characterized by a high degree of experience and confidence attributes. Although all crucial information (in terms of services, personal data and trustworthiness) about the app can be gained before the actual purchase, an evaluation of the quality of the app can only take place after the download during usage. In addition, it is difficult for consumers to understand what kind of personal data is used by apps, as in some cases apps use personal data of consumers although this would not be necessary for the functionalities offered. For example, the 'Foodspotting' app captures user's e-mail address and usage data in return for offering restaurant information. More serious problems which can be increasingly observed in mobile markets are malware and security attacks (Felt et al., 2011). A popular example is social engineering, where consumers are tempted to agree with the offerings (i. e. interact with the app) (Nachenberg, 2011), because they do not (or sometimes cannot) realize the lurking fraud.

Despite the problems involved in app consumption, we observe that consumers download vast numbers of apps. Given the complexities behind app data usage, it is however questionable that consumers understand which data they give in exchange for the download of apps, let alone the value of their own data. Acquisti and Grossklags (2003) introduced the privacy paradox to explain such behavior. The paradox describes the observation that in the internet market consumers articulate their need for privacy, but act in the opposite way (Acquisti and Gross, 2006). Transferred to the app market, this paradox is presumably even more obvious. On the one hand, we know from various studies, that consumers highly value their privacy and are sensible about their personal data. They say they would not use the services, if their privacy is at risk (Wenninger et al., 2012). On the other hand, users download a drastically increasing number of apps every day without having exact information about the app (including the server-side they connect to). This might partly explain the fact, that most apps are only used one time (Localystics.com, 2011). However, in many cases the exchange of private data already took place before the first use.

But, why do consumers purchase apps without knowing what they actually get and what price they pay? Do we have to conclude that consumers are 'unconscious'? Do they make purchase decisions based on "minimal or virtually nonexistent" (p. 194) information processing (Dijksterhuis et al., 2005)? Dijksterhuis, Smith, van Baaren, and Wigboldus (2005) suggest that 'unconscious' consumer behavior is often triggered by environmental cues, i.e. by the consumption context. Research on the 'perception-behavior link' shows that consumer behavior is often highly imitative and influenced by the social environment, e.g. family and friends (Aarts and Dijksterhuis, 2000). Furthermore, research on 'automatic goal pursuit' implies that goal-directed behavior can proceed unconsciously, only guided by the environment.

Consequently, the specific characteristics of the context of app consumption must be analyzed in order to understand consumer behavior in this context. The uniqueness of this purchase context could even classify it as a 'digital parallel consumer universe'.

First, system entry is only provided through the SMD. Consequently, purchasing apps and the perception of the risk involved in it is highly dependent on the mobile device the consumer is using (Ponemon Institute, 2011). Apps have to fulfil strict requirements in terms of design in order to generate a 'one face to the customer feeling' and are therefore frequently perceived as part of the underlying OS and SMD although they are separate 3rd-party products.

Second, apps and SMDs are highly integrated into consumers' lives used to perform highly fragmented everyday tasks. As they are often also highly playful and individualized, they might not even be perceived as highly complex software like traditional desktop applications (e.g. MS Excel).

Both aforementioned factors stimulate limited (e.g. buying another app from a known provider), habitual (e.g. buying habitually from the same app store) and impulsive (e.g. buying an app because of a sudden realization of a specific demand) buying decision styles, which correspond with only low levels of involvement. During such buying processes, consumers often do not search actively for information. If they perceive the risk involved in the app and the buying process to be low and/or if they trust the parties involved in it, their motivation to search for information can be expected to be particularly low.

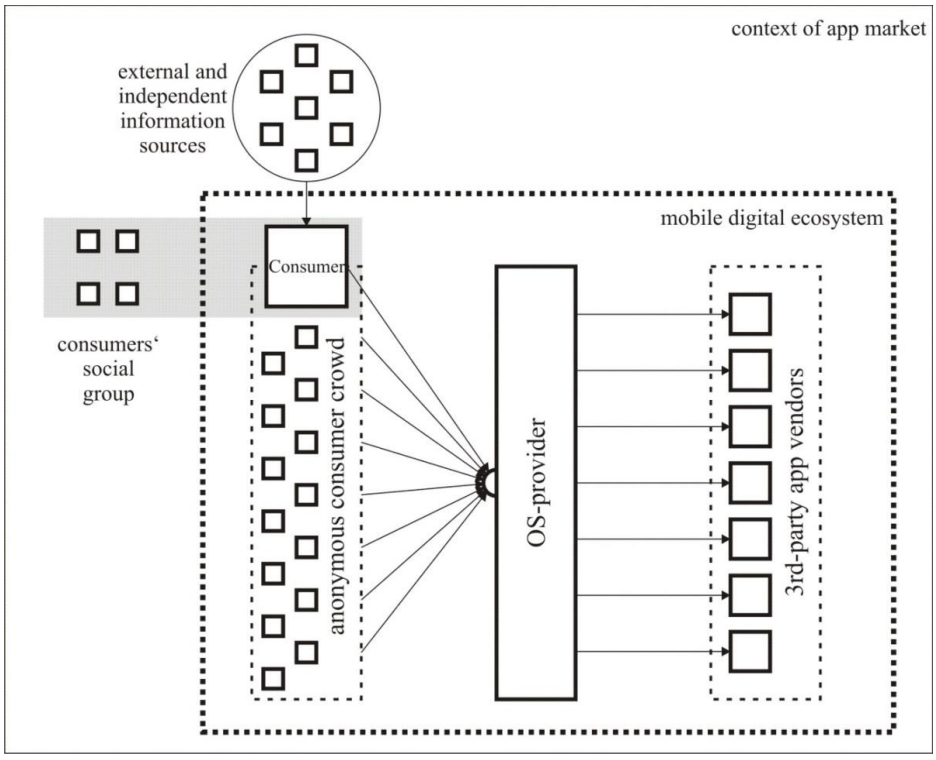

Figure 1. General framework of an app purchase decision-making process.

When purchasing apps, consumers do not only trust the information provided in the exclusive app purchasing channel, but also do they rely on trustful relationships to friends, family and acquaintances as well as on information from external and independent sources (e.g. journals, TV reports, newsletters, etc.).

Based on these considerations, we developed a general framework of an app purchase decision-making process which is presented in figure 1. The framework demonstrates the phases of which the

decision-making process consists and relates them to the specific context of the app market. This enables us to analyze the various information sources that are available to app consumers in the various stages of the purchase process.

The specific characteristics and the perception of apps might partly explain why consumers buy so many apps without exactly knowing what they buy and what they pay for it. Our following empirical study will further contribute to a better understanding of how consumers overcome the obviously high information disparities in app markets leading to an increasing consumption of apps. In particular, the aim of the study is to analyze the information and information sources consumers use during the app purchase process. By gathering information on the OS-provider, the 3rd-party vendor and the app itself, consumers reduce their lack of information compared to the providers and built up trust.

3 Research design

3.1 Survey design and data collection

A quantitative study using a standardized questionnaire was conducted in order to answer our research questions. The questionnaire was structured according to the software purchase process (Blackwell, Miniard and Engel, 2006; Buxmann, Diefenbach and Hess, 2011). As already mentioned, the app purchase is unique as access is only provided through the SMD and therefore, the process is clearly defined. The design of the survey is based on the general framework of an app purchase decision-making process presented in figure 1. We analyzed the information sources available to the consumers in the various stages of the app purchase process and developed items which represent them as shown in figure 2. The structure of the survey followed the chronology of the information consumers are confronted with during the app purchasing process, from gaining app attention to the download decision. Although some information might recurrently appear during the process from entering the app store to downloading the app, we avoided redundant questions. Only new information was taken into account. The survey questions were provided to the respondents on the basis of the sequenced process steps. The wording of some items was adapted depending on participants' OS-usage in order to fit to the specific characteristics of the respective OS. For example, the items contained the different store names (e.g. 'App Store' for iOS-users). Non-iOS-users received one additional question on the rating of the app developer, which does not apply to the iOS-context. However, this item was not included in the subsequent analysis.

In addition to the questions referring to information usage during app consumption, the survey included questions on system usage (software, hardware), consumers' experience with app consumption, app pricing preferences and socio-demographic data.

All items regarding consumers' information usage for app consumption were measured on 7-point Likert-scales ranging from "totally disagree" (1) to "agree completely" (7). Data collection took place in October and November 2012 in Germany. Consumers were invited to participate in an online survey via social media (Facebook, Xing, etc.) and university mailing lists. Altogether, 758 participants subscribed to the study. 521 participants who both use an SMD and already downloaded at least one app (filter questions) completed the whole survey and were included in the subsequent data analysis.

Of the remaining individuals, 42% (N = 219) were female and 58% were male (N = 302). As expected, most of the respondents were younger than 54 years (98.2%; N = 460). The largest group was between 18 and 24 years (49.7%; N = 259) old, followed by individuals between 25 and 34 years (38.6%; N = 201). Most of the participants were students (58.9%; N = 307) and employees (36.1%; N = 188), the remaining respondents were trainees (1.7%, N = 9), retirees, homemakers, and high-school

students (each 0.6%, N = 3). Respondents' OS-affiliation was identified according to the device manufacturer. 299 participants (57.4%) used iOS and 222 (42.6%) used non-iOS.

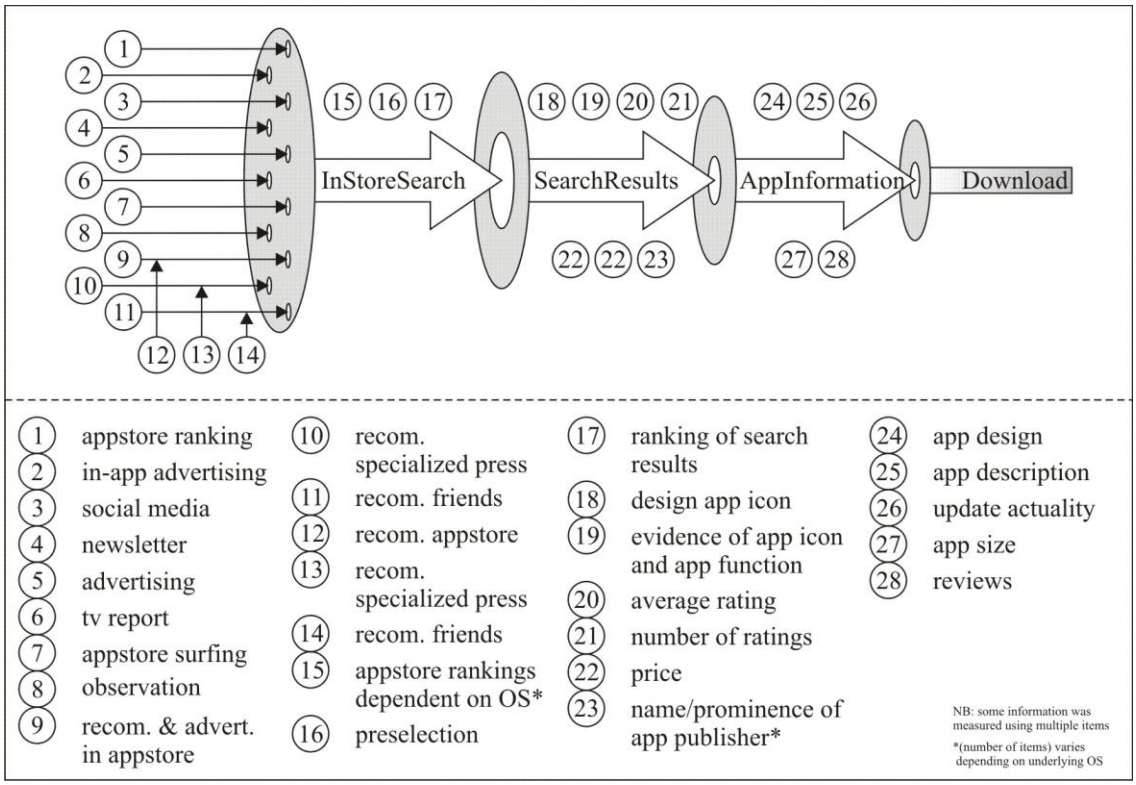

Figure 2. Purchase process and provided information.

3.2 Methodology

As a first step we analyzed the information and information sources that are used by app consumers before and during the app purchase process. In order to reduce complexity and gain a better understanding of the underlying structure of our variables, we conducted a principal component analysis (PCA) (Hair, Anderson and Babin, 2010). The resulting factors represent the various types of information that are used by app consumers. As there are several ways to reduce uncertainties, we suggest that different user groups prefer different types of information. As a second step, we therefore grouped consumers regarding their preferred information behavior. We conducted a cluster analysis (Hair, Anderson and Babin, 2010) based on the extracted factors in order to identify consumer segments with similar information preferences.

4 Results

Altogether, 31 variables, which represent aspects of information used by app consumers, were included in factor analysis. The correlations among the variables in our data set as well as the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO = 0.795) proved that our data is suitable for factor analysis. This is also supported through Bartlett's test of sphericity ($X^2 = 4554.855$, $p < 0.01$).

Factors were extracted using the principle components analysis. We used the Kaiser-Guttmann rule to determine the number of factors. Eight factors with an eigenvalue larger than 1 were extracted. VARIMAX rotation was applied to account for interpretability of the factors.

Factor	Factor loading	Eigenvalue	% of variance
Anonymus reputation (Rep)		5.895	19.016
Reviews	0.782		
Average evaluation	0.697		
Number of evaluations	0.668		
Active search for reviews	0.614		
Reviews and evaluations more important than recommendations of friends	0.493		
App description	0.433		
External and independent information sources (Ext)		2.726	8.793
Commercials	0.779		
TV-reports	0.725		
Magazines	0.697		
Professional Journals	0.571		
Newsletters	0.566		
Social Media	0.454		
InApp Ads	0.393		
3rd-party vendor credibility (Cred)		2.573	8.299
Data protection regulations	0.822		
Active perception of data protection regulations	0.749		
Password protection	0.681		
App updates	0.530		
App size	0.455		
App developer/vendor	0.369		
Store (Sto)		2.095	6.757
App store surfing	0.797		
In-strore advertising	0.767		
Rankings	0.689		
Recommendation of store	0.643		
Social group (Soc)		1.729	5.576
Recommendations of family, friends, or acquaintances	0.847		
App use by family, friends, or acquaintances	0.825		
App attention through recommendations of family, friends, or acquaintances	0.811		
App Design (Des)		1.403	4.526
Icon Design	0.852		
Icon related to app content	0.826		
Screenshots	0.635		
Proactive provision of information to other users (Self)		1.313	4.235
Evaluations	0.871		
Reviews	0.856		

Table 1. Final results of principal component analysis.

The inspection of the factor loadings revealed that some variables cross-loaded on two factors, which caused problems regarding the interpretation of the factors. Therefore, a seven-factor structure shown in table 1 was preferred. The seven extracted factors explain 57.20% of overall variance. The highest factor loading per variable served as the basis for interpretative purposes. Only the variable ‘detailed

app description' cross-loaded on the two factors 'anonymous reputation' and '3rd party-vendor credibility' and was interpreted as an indicator of 'anonymous reputation', where its loading was higher. In order to check if a more suitable factor solution could be elicited, we further applied the OBLIMIN oblique factor rotation method, which delivered the same factors as the VARIMAX rotation.

The interpretation reveals that the factors match with the players who provide information on apps. Three factors include information consumers gather outside the mobile ecosystem. One of these factors was labeled 'anonymous reputation' (Rep). It refers to procedural reputation which is formed through a sequenced number of transactions and recommendations of anonymous consumers. Another factor includes information from 'external and independent sources' (Ext). The factor 'social group' (Soc) represents information consumers receive through their social relationships, in particular from family, friends, and acquaintances.

The information app users gather within the mobile ecosystem is also split-up into three components. One factor includes information on the app which is placed in the 'store' (Sto) itself. The information on the 3rd-party vendor consists of two dimensions. One dimension represents the 'credibility of the 3rd-party vendor' (Cred), whereas the other dimension refers to the 'app design' (Des).

The last factor refers to the app user's own engagement for a reduction of information asymmetries in app markets by providing 'information to other consumers' (Self).

The relevance of the various types and sources of information in the app purchase process was analyzed by calculating the means of the variables allocated to the seven factors, because these values can be better interpreted than the actual factor scores. The analysis reveals that consumers perceive information provided by their 'social group' as most important when making an app purchase decision (M = 5.694). Information placed in the 'store' (M = 4.298) and 'anonymous reputation' (M = 4.173) also seem to be highly influential whereas information about the 3rd-party vendor, both in terms of 'app design' (M = 3.686) and the 'vendor's credibility' (M = 3.135), only seem to play a minor role. In addition, app consumers do not rely very much on information from 'external and independent sources' (M = 2.634). Only few consumers seem to engage in the reduction of information asymmetries in the app market as the very little importance of the provision of information about apps 'to other consumers' (M = 1.703) indicates.

Factor	OS	N	Mean value	P
Rep	iOS	287	4.1278	0.002
	non-iOS	210	4.2349	
Ext	iOS	286	2.7303	0.126
	non-iOS	206	2.5014	
Cred	iOS	281	2.8885	0.369
	non-iOS	201	3.4784	
Sto	iOS	288	4.5269	0.786
	non-iOS	209	3.9833	
Soc	iOS	290	5.8310	0.002
	non-iOS	217	5.5115	
Des	iOS	291	3.7331	0.734
	non-iOS	216	3.6235	
Self	iOS	295	1.7661	0.011
	non-iOS	213	1.6150	

Table 2. Results of t- test of factor mean values for iOS- and non-iOS-users.

We further analyzed if consumers' use of information in the app purchase process is related to the mobile ecosystem in which the app purchase takes place. We conducted a t-test and compared the mean values of the factors for the consumers in both groups (iOS vs. non-iOS). The results can be obtained from table 2. The analysis reveals that iOS-consumers attribute higher relevance to information from their social group and are more actively engaged in the depletion of information asymmetries in the app market than non-iOS-users, who rely more on reputation built through reviews and evaluations of anonymous actors than consumers in the iOS ecosystem.

In the next step of our data analysis we conducted both hierarchical and nonhierarchical cluster analyses in order to identify customer segments with regard to their information requirements in the app purchase process. The cluster analysis was based on the seven factors extracted in the previous PCA. Only those cases without missing values in the relevant variables were included, which reduced the sample size to 430 cases. First, we applied the single linkage algorithm in order to identify outliers in the data set (Hair, Anderson and Babin, 2010). Two outliers were removed which reduced the effective data set to 428 cases. Second, in order to determine the appropriate number of clusters, we applied the Ward algorithm. We extracted the 2-, 3-, 4-, 5-, 6-, 7-, 8-, 9- and 10-cluster solutions and calculated the F-values for each cluster. The 6-, 7-, 8-, 9-, and 10-cluster solutions showed a low percentage of F-values greater than 1, proving that the variance of most variables was lower within the clusters than within the whole sample, thus indicating satisfactory cluster solutions. Third, we applied a nonhierarchical procedure. The mean values resulting from the Ward algorithm were used as initial values in the subsequent application of the k-means cluster algorithm for 6, 7, 8, 9, and 10 clusters. The calculation and inspection of the F-values of the resulting cluster solutions revealed lower percentages of F-values greater than 1 than for the Ward algorithm solutions. The 6-cluster solution resulting from the k-means algorithm was preferred, because it revealed a low percentage of F-values greater than 1 and could be well interpreted. Table 3 shows the F- and t-values of the 6-cluster-solution. T-values are used for the interpretation of the clusters. Positive (negative) t-values indicate a higher (lower) value of a variable in the cluster compared to the complete data set.

Finally, a one-way analysis of variance (ANOVA) was used in order to assess statistical differences of the mean values of the clusters. The results reveal that significant differences between the clusters exist ($p < 0.001$ for all seven factors). Hence, discriminant customer segments can be identified based on the seven factors.

F- and t-values		k-means algorithm													
		Rep		Ext		Cred		Sto		Soc		Des		Self	
Cluster	N	F	t	F	t	F	t	F	t	F	t	F	t	F	t
1	105	0.914	-0.009	1.191	0.303	0.891	-0.105	0.670	0.016	0.450	0.280	0.321	1.187	0.273	-0.431
2	43	0.447	0.404	0.680	-0.027	0.987	0.064	0.420	0.412	0.859	-0.002	0.752	0.200	0.727	2.363
3	91	0.914	-0.020	0.856	-0.074	0.772	-0.175	0.307	0.992	0.347	0.249	0.410	-0.684	0.298	-0.263
4	66	0.837	-0.930	0.665	-0.351	0.473	-0.610	0.681	-0.783	0.533	0.343	0.417	-0.495	0.252	0.030
5	81	0.528	0.535	0.971	0.019	0.711	0.924	0.701	-0.730	0.475	0.203	0.526	-0.417	0.349	-0.283
6	42	1.140	0.080	1.420	-0.052	0.864	-0.246	0.762	0.026	0.438	-2.167	0.805	-0.107	0.521	-0.274

Table 3. F-and t-values of 6-cluster solution by k-means algorithm.

Based on the t-values, the first cluster was labeled 'social prestige consumers' (24.5%). They are highly influenced by their social group and by design elements. In addition, external and independent information sources are also more important to them than for the average consumer. The second cluster was labeled 'co-creators' (10%). They are those consumers who most actively provide information to other consumers by reviewing and evaluating apps. At the same time they are also interested in information provided by other anonymous consumers and information offered within the

app store. The third cluster was labeled ‘OS-associated consumers’ (21.3%). For these consumers the app store is the most important information source followed by information from their social group. The consumers in this customer segment do not rely on reputation built through reviews of anonymous consumers and do not care much about the credibility of the app vendor or design aspects. Consumers in the fourth cluster are characterized by their interest in information from their social group. Therefore, we called them ‘social group dependents’ (15.4%). They mostly gather information from their social group and rely less on other information sources. Consumers in the fifth cluster care a lot about security and credibility. They are ‘security seekers’ (18.9%). They also use information from anonymous consumers and their social group, but are neither interested in information provided by the store nor by external and independent sources. The sixth cluster includes the ‘egomaniacs’ (9.8%). These consumers do not use much information from other sources. Interestingly, they show a particular low interest in information from individuals in their social group. They seem to rely mostly on themselves but do not share their knowledge or information with others.

For a more detailed description of the clusters we further compared them regarding socio-demographic characteristics, in particular age, gender, occupation, income, OS-affiliation, and experience. As shown in table 4 significant differences between the consumer segments could be found except for age. For example, in the ‘co-creator’ and ‘egomaniac’ clusters females are extremely underrepresented, whereas males are particularly underrepresented in the ‘social group dependent’ cluster. Students are also more likely to be ‘social group dependent’ than employees, while employees are more likely to be ‘security seekers’ than students, indicating that security concerns are higher when smartphones are (also) professionally used. Furthermore, with increasing experience regarding app downloads, consumers’ likelihood to be ‘co-creators’ is increasing, possibly because they have gathered more knowledge about apps which allows them to share it with other consumers.

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6			
	'Social prestige'	'Co-creator'	'OS-associated'	'Social group dependent'	'Security seeker'	'Egomaniac'	Complete sample (N = 428)	X^2 (df)	Significance level
Gender								29.789 (5)	0.000
female	49.5%	14.0%	30.8%	54.5%	40.7%	23.8%	38.6%		
male	50.5%	86.0%	69.2%	45.5%	59.3%	76.2%	61.4%		
Occupation								54.070 (30)	0.005
others	0.0%	2.3%	2.2%	0.0%	2.4%	2.3%	1.3%		
HS students	0.9%	0.0%	0.0%	1.5%	0.0%	0.0%	0.5%		
students	61.9%	65.1%	53.8%	77.3%	43.2%	57.1%	58.9%		
trainees	1.0%	0.0%	2.2%	0.0%	0.0%	4.8%	1.2%		
employees	36.2%	32.6%	40.7%	21.2%	51.9%	31.0%	36.9%		
retirees	0.0%	0.0%	1.1%	0.0%	0.0%	4.8%	0.7%		
homemakers	0.0%	0.0%	0.0%	0.0%	2.5%	0.0%	0.5%		
Income (in €)								30.667 (20)	0.06
≤ 400	12.4%	14.0%	3.3%	12.1%	9.9%	21.4%	11.0%		
401 -1000	45.7%	48.8%	44.0%	56.1%	35.8%	38.2%	44.6%		
1001 - 2500	22.9%	9.3%	28.6%	22.7%	33.3%	19.0%	24.3%		
2501 - 5000	17.1%	23.3%	20.9%	7.6%	17.3%	14.3%	16.8%		
> 5000	1.9%	4.6%	3.2%	1.5%	3.7%	7.1%	3.3%		
OS-affiliation								17.865 (5)	0.003
iOS	35.2%	32.6%	30.8%	40.9%	59.3%	42.9%	40.2%		
non-iOS	64.8%	67.4%	69.2%	59.1%	40.7%	57.1%	59.8%		
Experience (number of downloaded apps)								18.808 (5)	0.002
≤ 30	71.4%	55.8%	75.8%	87.9%	84.0%	76.2%	76.2%		
> 30	28.6%	44.2%	24.2%	12.1%	16.0%	23.8%	23.8%		

Table 4. Differences in socio-demographic and OS-usage characteristics between the clusters.

We further assessed if the consumers in the different clusters can be differentiated with regard to their experience in app purchasing. However, no significant differences regarding the number of apps consumers had already purchased could be found between the segments. Finally, we analyzed the differences of the consumer segments in terms of their attitudes towards various pricing aspects. The analysis reveals that there are significant differences between the clusters regarding all five pricing issues we raised in our questionnaire. The results are shown in table 5.

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6			
	'Social prestige'	'Co-creator'	'OS-associated'	'Social group dependent'	'Security seeker'	'Egomaniac'	Complete sample (N = 428)	F	Significance level
Pricing variables									
Free apps are preferred	6.12	5.09	6.26	6.05	6.48	5.60	6.06	7.478	0.000
Fee-based apps have higher quality	3.77	4.05	3.69	3.02	3.24	3.25	3.53	3.287	0.006
Ads are accepted in free apps	4.78	4.51	5.08	4.20	4.70	4.29	4.66	2.328	0.042
Higher evaluations increase willingness to pay	4.06	4.88	3.98	2.88	3.52	3.44	3.78	7.465	0.000
Free basic version is important	5.05	4.95	4.85	4.64	4.96	4.29	4.84	1.315	0.257

Table 5. Attitudes towards pricing in the six clusters.

Additional multiple comparisons between the clusters by conducting Bonferroni and Tukey-HSD post hoc tests reveal, for example, that 'co-creators' would be willing to pay more for an app compared to the other groups (except 'OS-associated') if it has very positive evaluations. This documents their belief in the necessity of 'neutral' evaluations, which might be the reason why they actively engage themselves in providing reviews and evaluations. Furthermore, they also have a significantly lower preference for free apps than users in the other clusters (except 'egomaniacs'). 'Social group dependents' do significantly less perceive fee-based apps to be of higher quality than consumers in the other groups (except 'security seekers') undermining their preference for recommendations from their friends and family.

5 Discussion, limitations and future research

Our paper deals with the question whether consumers really fall prey to the privacy paradox and are 'unconscious' when buying apps. We show that seven types of information, from various sources, both from inside and outside the mobile ecosystem, are relevant for app purchasing. Our study reveals that compared to the other types of information, consumers perceive information about the use of personal data by the 3rd-party app vendor as less important. They consider information from their social group and the app store more relevant. However, it is questionable whether this type of information is crucial for the reduction of the most important uncertainties involved in app consumption, i.e. which personal data must be offered by the consumer in exchange for the apps' benefits. A more detailed analysis of consumer segments, based on their information behavior, reveals that only in one of six segments consumers pay a lot of attention to their privacy, security and the trustworthiness of the app. So, does this mean that (almost all) app consumers are indeed 'unconscious' and simply ignore that they pay with their personal data when they download 'free' apps?

As discussed earlier, we assume that there are several ways for consumers to deal with the information asymmetries in app markets. We therefore have reason to believe, that different consumers use different strategies to reduce their lack of information. These strategies could depend on consumers'

OS-affiliation as the context of app consumption is mainly determined by the digital ecosystem. Although we indeed found some significant differences regarding the information preferences of iOS- and non-iOS-consumers, app users in both groups showed low interest in information on the 3rd-party vendor's credibility. 21.3% of the consumers in our sample (OS-associated) mainly rely on the information provided by the store which is often not useful with regard to issues like privacy or the trustworthiness of the app. Up to this point, we can therefore not give a clear answer to the question whether app consumers are 'unconscious'. Our research suggests that at least some consumers might indeed be unconscious, because they do not seem to search for relevant information which could reduce the information asymmetries in the app market.

From these findings we conclude that consumers do also apply other mechanisms for dealing with the information asymmetries in app markets. Trust in several information sources could be such a strategy. Some of the trust relationships in app markets are very special, because apps are purchased in closed systems (mobile ecosystem). We assume that the main relationship exists between the consumer and the OS-provider. The OS-provider, owning the monopolistic purchase channel, determines the rules and sets the standards for the descriptions of the apps offered. Hence, it is the 'one face to the customer'. Although the OS-provider is only the intermediary between the consumers and the app-vendors, many consumers are presumably not aware of the fact that they buy their apps from the app vendor. Consequently, we assume that the relationship between the consumers and the 3rd-party vendor is not very close. Due to the exclusivity of the purchase channel, consumers might even trust 3rd-party vendors they do not know, because they have already built up trust towards the OS-provider.

It should be noted that the app market is very dynamic and innovative. Providers implement and update OS-versions frequently. For example, with the introduction of recent OS (e.g. iOS7), multiple privacy and security issues have changed. Whereas technical leaks were closed, other changes indeed might decrease the probability that consumers search for and find information regarding privacy and personal data issues. The easy-to-use orientation is generally strengthened in new OS versions. For example, when searching for apps, consumers will see only one app on the first page of the search result, which could lead them to the conclusion that there is only one suitable app available for their purpose and decrease their motivation to search for alternatives. Such changes strengthen the habitualization of the app-purchase process and support the particular trust mechanism. This increases the privacy paradox in mobile ecosystems.

Due to the exploratory nature of our research, our study has some limitations. For example, while in this paper we refer to the 'consumption' of apps, it must be recognized that we limit our considerations to 'purchasing' apps. However, we are aware, that consuming apps also includes app usage and deletion, which should be considered in future studies related to the topic.

Our sample is not representative of all app consumers, as it includes a large group of students. In addition, we only have very general information on the demographic characteristics of our respondents, which limits our ability to relate app consumers' information seeking behavior to demographic characteristics. In particular, it would have been valuable to know more on participants' occupation and primary usage of their mobile devices (business and/or private) as this could probably also contribute to explaining their information behavior. With regard to consumers' OS usage, we discussed only differences between iOS and non-iOS users, which is rather broad. In future research, the differences in the specifications of OS should be considered in more detail.

Our study was only a first step toward a better understanding of the information search process involved in app consumption. Based on the above considerations we identified two major topics for future research. First, the relevance of trust relationships in mobile ecosystems for dealing with information asymmetries in app markets and hence, their impact on the purchase process should be investigated. Second, detailed knowledge of consumers' perception of apps and the underlying purchase process is necessary in order to understand their information processing behavior and buying decision styles.

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