"Mobile apps in retail: Effect of push notification frequency on app user behavior"

AUTHORS	Atilla Wohllebe (iD) Dirk-Siegfried Hübner (iD) Uwe Radtke (iD) Szilárd Podruzsik (iD)

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BUSINESS PERSPECTIVES

Atilla Wohllebe, Ph.D. Student, Doctoral School in Management and Organizational Science, MATE Hungarian University of Agriculture and Life Sciences – Kaposvár Campus, Kaposvár, Hungary. (Corresponding author)

Dirk-Siegfried Hübner, Ph.D. Student, Doctoral School in Management and Organizational Science, MATE Hungarian University of Agriculture and Life Sciences – Kaposvár Campus, Kaposvár, Hungary.

Uwe Radtke, Ph.D. Student, Doctoral School in Management and Organizational Science, MATE Hungarian University of Agriculture and Life Sciences – Kaposvár Campus, Kaposvár, Hungary.

Szilárd Podruzsik, Ph.D., Centre for Economic and Regional Studies, Institute of Economics, Budapest, Hungary.

Atilla Wohllebe (Hungary), Dirk-Siegfried Hübner (Hungary), Uwe Radtke (Hungary), Szilárd Podruzsik (Hungary)

MOBILE APPS IN RETAIL: EFFECT OF PUSH NOTIFICATION FREQUENCY ON APP USER BEHAVIOR

Abstract

Push notifications are a core functionality of mobile apps and allow app publishers to interact with existing app users and send promotional content. Since every push notification can also interrupt or annoy app users, the frequency of push notifications is a critical success factor. This study investigates how different frequencies of push notifications affect the behavior of app users of mobile apps in retail. In an experiment with 17,500 app users, five different frequencies are tested over seven weeks, and the effects on real observed app user behavior are analyzed. The results show that as the frequency of the non-personalized push notifications increases, uninstalls increase, and the direct open rate of push notifications decreases. A significant influence on indirect opens cannot be proven. The results provide practitioners with important insights into the potential harm that a too high frequency of push notifications can cause. Furthermore, the results support the importance of relevant content tailored to the respective user.

Keywords	app user engagement, Germany, linear regression, digital marketing, mobile CRM
JEL Classification	M31, M37, L81

INTRODUCTION

With the spread of the smartphone, the mobile share of Internet traffic has increased strongly in recent years. Around 90 percent of Europeans are connected to the Internet (Eurostat, 2018), with mobile devices accounting for more than half of global Internet traffic (StatCounter, 2019). At the same time, digitization is becoming increasingly relevant in many areas (Deckert, 2019; Deckert & Wohllebe, 2021; Diez, 2020). In this context, the importance of mobile apps has also increased massively. The small applications from different categories like communication, organization, games, education, or retail are among the most relevant functionalities of smartphones (Ross, 2020; VuMA, 2017; Wohllebe et al., 2020).

From a company's point of view, push notifications are the central function of smartphone apps: The small messages can be sent via installed apps and appear on the lock screen or in the notification bar of a smartphone user. The user does not need to open the respective app to see the notification. Typically, companies or app publishers inform their existing app users about new content in the app in order to encourage them to open the app and – e.g., in retail or e-commerce – make a purchase.

Earlier research suggests that notifications of software applications in a broader sense can also be perceived as interrupting and therefore annoying (Fischer et al., 2010; Iqbal & Horvitz, 2007; McFarlane, 2002).

Furthermore, push notifications may change the user's perception of the advertiser and the corresponding mobile app in the long run (Bellman et al., 2013; Peng et al., 2014).

Although push notifications have been studied scientifically several times, the scientific findings regarding the frequency of push notifications are limited (Freyne et al., 2017). It is unknown how different frequencies of push notifications affect app user behavior in reality, especially user engagement (opening a push notification) and app uninstalls.

Against this background, this paper examines how the frequency of push notifications sent from mobile retail apps influences app user behavior. After reviewing the existing literature, hypotheses on the effect of frequency on uninstalls and app opens will be derived. These hypotheses are then statistically tested using data from an experiment with an app of a German retailer. In the experiment, generic push notifications, which are not personalized or sent based on user behavior, are employed. The frequency impact on app open rates und app uninstalls is quantified.

1. LITERATURE REVIEW AND HYPOTHESES

Push notifications are a key feature of mobile apps. Looking at both notifications and mobile apps in general, the literature repeatedly emphasizes the importance of personalized, time-sensitive, and relevant content (Ahrholdt et al., 2019; Kazeminia et al., 2019; Mehrotra et al., 2016; Wang et al., 2014). As a result, app users react positively to push notifications by tapping on them and thus opening the app (Berman, 2016; Glay, 2019).

However, literature also emphasizes that notifications from software in general, but also from smartphone apps in particular, can be perceived as annoying. App users do appreciate a certain amount of entertainment value (Jacob & Gupta, 2017) and react very quickly to received notifications (Alsayed et al., 2019). However, the busier they are at the moment of receiving a notification, the more annoying they find these (Mehrotra et al., 2016). Push notifications are perceived as both, informative and annoying at the same time (Sahami Shirazi et al., 2014). Therefore, the literature suggests that any notification received by a user should be seen as an interruption and therefore as a form of cost to that user (Fischer et al., 2010). That is why, besides interactions with push notifications, app uninstalls have also to be taken into account to determine the success or failure of a push notification (Westermann et al., 2015).

Due to this ambivalent perception of app users on push notifications, investigating the impact of frequency on app user behavior is required. This is particularly relevant given that smartphone users are likely to receive up to 100 notifications per day on average (Mehrotra et al., 2016).

It has already been shown that a high frequency of notifications can have a positive effect on the frequency of app use, for example in the environment of mobile learning apps (Pham et al., 2016). Based on a survey of 381 web and 261 app users, it can be shown that, in addition to easy access to app features, the regular sending of push notifications leads to users perceiving more content of an app (Morrison et al., 2018).

These results have been confirmed by observing the user behavior in the context of a diet app, considering qualitative as well as quantitative app usage. A frequency of three messages per day is identified as the limit of user tolerance (Freyne et al., 2017). Other research in medical and medical-related contexts also confirm the added value of regular push notifications for app users (Hsu & Tang, 2020; Malik et al., 2017; Smith et al., 2017).

Regular notifications can play a decisive role, especially when activating app users who are still not very active. A study of 18,000 push notifications and about 1,400 app users shows that the activity of app users and response rates to push notifications correlate positively. This emphasizes the importance of regular push notifications as a tool to activate newly acquired app users (Bidargaddi et al., 2018).

Despite the perception of push notifications as an interruption (Fischer et al., 2010; Sahami Shirazi et al., 2014), a survey of 159 app users shows that too frequent notifications cannot be considered a central driver for app uninstalls (Vagrani et al., 2017). In fact, the frequency of push notifications tolerated by users seems to increase with the frequency of app usage, as a cluster analysis across multiple smartphone apps in the mobile health segment shows (Chen, 2017).

If frequency is perceived by app users as too high, content relevancy can compensate this. This is shown in a five-day survey of 45 app users in the tourist industry. The study asks app users about their perception of the frequency of notifications after a stay on an island in Finland using a corresponding app (McGookin et al., 2019).

To avoid disturbances, some studies suggest mechanisms to detect when a user switches between two tasks. Sending notifications right in such a moment can reduce the mental effort (Adamczyk & Bailey, 2004; Okoshi et al., 2015). There are corresponding programming libraries that use activity, location, daytime, emotions, and engagement to detect such moments (Pejovic & Musolesi, 2014).

The frequency of advertising messages in general and of push notifications in particular has often been the subject of scientific work already. However, there is a lack of quantifying the effect of the frequency of push notifications on app uninstalls and app opens. Both metrics can provide concrete information about the business consequences of a potentially too high frequency. In particular, experimental papers investigating real observed user behavior are missing (Wohllebe, 2020). Existing work either explores effects other than uninstall (Freyne et al., 2017; Pham et al., 2016) or is based on survey data instead of observed user behavior (Vagrani et al., 2017).

The aim of this study is to find out what influence different frequencies of generic, non-personalized push notifications of a mobile app in retail have on app user behavior. In line with the reviewed literature and the identified research gaps, the focus will be on app uninstalls and app opens.

Accordingly, the following four hypotheses are to be investigated:

H1: *With increasing frequency of push notifications, the probability of an app uninstall increases.*

H2: *With increasing frequency of push notifications, the probability of a direct open decreases.*

H3: *With increasing frequency of push notifications, the probability of an indirect open decreases.*

H4: *The negative effect of frequency on direct opens is stronger than the effect on indirect opens.*

2. METHOD

To test the hypotheses stated, an experiment is conducted with the mobile app of a German retailing company. In total, 17,500 app users are randomly divided into five groups of 3,500 users each. To exclude other factors than frequency, all groups are treated the same during the experiment. The groups are furthermore excluded from any other messaging activities. The experiment is conducted over a period of seven weeks in June – July 2020. In total, 16 generic non-personalized push notifications are sent, each drawing attention to products, special discounts or current promotions. The notifications are always sent at the same day of a week (Saturday) and at the same time of the day (5:30 pm). For the group receiving two notifications per week, the second day to send the message is also always a fixed one (Wednesday) at the same time. For technical reasons, notifications can only be sent to users that have not opted out from receiving notifications.

As the notifications do not contain personalized content, all look the same for all users receiving them. As the retailer's app is available only in

Germany and the app is in German, all push notifications are in German as well. In the following, a couple of notifications are translated and shown.

- "Trend: Timeless products in black & white"
- "Make your rooms cozier"
- "20% discount on the most expensive product of your next order"
- "Just today and tomorrow: Many products with free shipping!"
- "Don't forget: Discover our most current offers now!"

The frequency is experimented with

- two messages per week,
- one message per week,
- one message every two weeks,
- one message per month,
- no message during the experiment period.

To determine the effect of the frequency over the test period, all groups receive a message at the beginning and end of the experiment period. This first and last message are then compared in terms of uninstalls (during the experiment period) and direct as well as indirect app opens (at the beginning and end of the period). Although interesting to examine as well, the data set provided by the company does not contain data about how time or money spent per frequency group changes over time.

Table 1 compares the number of receivers, direct opens and indirect opens per frequency group at the beginning and end of the experiment period. In this experiment, an indirect open is defined as an app open of a user receiving a push notification without directly tapping the notification. As the mobile engagement platform Airship is used to send the notifications, Airship's definition of an indirect app open is used. Accordingly, a time window of 12 hours after receiving the notification is employed to measure indirect app opens (Airship Inc., 2020). As all app users in the experiment do receive a maximum of two messages per week, no user will receive two notifications within twelve hours. If an app user opens the app two or more times within the time frame of twelve hours, it will be counted as just one indirect open anyway.

Table 1. Start-end-comparison of recipients, direct opens and indirect opens per frequency group

Frequency group	Recipients		Direct opens		Indirect opens	
Frequency	Start	End	Start	End	Start	End
Two per week	3500	3274	478	358	734	477
One per week	3500	3322	479	390	753	492
One every two weeks	3500	3389	480	435	725	550
One per month	3500	3411	495	460	714	551
None	3500	3452	500	530	721	619

To better compare direct and indirect opens, Table 2 shows direct and indirect open rates based on the number of the recipients of the respective notifications. For all groups, all open rates are lower at the end of the experiment. Interestingly, the exception is the direct open rate of users who did not receive any notifications during the experiment.

Table 2. Start-end-comparison of direct open rate and indirect open rate per frequency group

Frequency group	Direct open rate		Indirect open rate	
Frequency	Start	End	Start	End
Two per week	13.66%	10.93%	20.97%	14.57%
One per week	13.69%	11.74%	21.51%	14.81%
One every two weeks	13.71%	12.84%	20.71%	16.23%
One per month	14.14%	13.49%	20.40%	16.15%
None	14.29%	15.35%	20.60%	17.93%

To test the four previously stated hypotheses, three regression analyses are calculated, whereby the frequency is interpreted as the number of messages per week and used as an independent variable. The dependent variable is chosen accordingly for each regression.

Investigating frequency and uninstalls, the uninstall rate is calculated as the quotient of the difference between the receivers at the beginning and end of the experiment and the number of receivers at the beginning of the experiment. For example, for two notifications per week an uninstall rate of 1 – (3274/3500) *100% = 6.457% is calculated. Due to technical restrictions, the exact time of the uninstall event is unknown. It is only known that an uninstall has happened between two push notifications. However, the experimental setup looks at isolated groups completely treated the same during the experiment. It is therefore assumed that the differences in uninstalls must be due to the differences in frequency.

In the case of the hypotheses for the direct and indirect opening rate, the open rate of the group "None" at the end of the experiment serves as the starting point. The difference between the open rate of "None" and the respective test group at this time is calculated as a percentage value. For example, for the group "Two per week" it is calculated that the direct open rate at the end of the experiment is 1 − (10.93%/15.35%)*100% = 28.79% lower than in the control group. Since the groups were randomly divided, it can be assumed that the minimal differences in open rates at the starting point across the different groups were caused randomly. This is verified by comparing the groups with the highest and the lowest number of opens. A chi square test does not indicate significant differences ($X1$)^2, N = 7,000) = .4342, p = .5099).

3. RESULTS

First, the influence of push notification frequency on app uninstalls is investigated.

H1: *With increasing frequency of push notifications, the probability of an app uninstalls increases.*

Table 3 shows the results of the regression analysis with the uninstall rate depending on the number of messages per week. Although the number of cases is quite small (n = 5) due to the consideration per frequency group, the overall model is significant (F = 50.17, p = .0058). It explains a large part of the variance of the dependent variable (R^2 = .9436).

According to the regression analysis results, one additional message per week increases the uninstall rate by 2.50 percentage points over the experi-

ment period (β = .0250, t = 7.08, p = .006). Without a single message, the uninstall rate during the experiment period is 1.85 percent (β = .0185, t = 5.09, p = .015) according to the model. The actually observed value was 1.37 percent during the experiment. *H1* can therefore be confirmed: With increasing frequency of push notifications, the probability that a user will uninstall the corresponding app increases.

With regard to app opens, firstly direct app opens by tapping the notification are investigated. After that, indirect app opens by opening the app within a period of twelve hours after receiving a push notification (without directly tapping it) are examined.

H2: *With increasing frequency of push notifications, the probability of a direct open decreases.*

Table 4 shows the regression analysis results. The overall model can be regarded as significant (F = *13.46, p = .0350*) and explains a large part of the variance of the direct open rate (R^2 = *.8178*).

When evaluating the regression coefficient and the constant, it has to be taken into account that the direct open rate in this regression per frequency was expressed as a percentage difference to the group of app users who did not receive a push notification. In this respect, the interpretation of the constant is only of limited use.

The effect of frequency on the direct open rate decreases as assumed in *H2* (β = −.1267, t = −3.678, p = .035). One notification more per week decreases the direct open rate by 12.67 percent, comparing the beginning and the end of the experiment.

Table 3. Uninstall rate determined by frequency – regression results

Source	SS	df	MS	Number of obs	=	5
				F (1, 3)	=	50.17
Model	.0015625	1	.0015625	Prob > F	=	0.0058
Residual	.000093435	3	.000031145	*R*-squared	=	0.9436
				Adj *R*-squared	=	0.9248
Total	.001655935	4	.000413984	Root MSE	=	.00558
Uninstall R~e	**Coef.**	**Std. Err.**	**t**	**P > |t|**	**[95% Conf. Interval]**	
MsgPerWeek	.025	.0035296	7.08	0.006	.0137673	.0362327
_cons	.0185071	.0036382	5.09	0.015	.0069287	.0300856

Table 4. Direct open rate determined by frequency – regression results

Source	SS	df	MS	Number of obs	=	5
				F(1, 3)	=	13.46
Model	.040138756	1	.040138756	Prob > F	=	0.0350
Residual	.008945283	3	.002981761	*R*-squared	=	0.8178
				Adj *R*-squared	=	0.7570
Total	.049084039	4	.01227101	Root MSE	=	.05461
D~IndirectO~d	**Coef.**	**Std. Err.**	**t**	**P > |t|**	**[95% Conf. Interval]**	
MsgPerWeek	−.1267103	.0345356	−3.67	0.035	−.2366178	−.0168028
_cons	.9332747	.0355984	26.22	0.000	.8199846	1.046565

With regard to the indirect open rate, a decreasing probability of an indirect open was stated.

H3: With increasing frequency of push notifications, the probability of an indirect open decreases.

Assuming a significance level of $\alpha = 0.05$, the corresponding overall model must be rejected or at least interpreted with great caution (cf. Table 5, $F = 8.65$, $p = .0605$). Nevertheless, the explained variance of the dependent variable by the model is still to be considered relatively high ($R^2 = .7425$).

When interpreting the influence of frequency, it is negative ($\beta = -.0818$), but overall it is not significant ($t = -2.94$, $p = .060$) and within a confidence interval that cannot be interpreted clearly ($-.1704 < \beta < .0067$). In this respect, *H3* stating a negative effect of frequency on indirect app open rate is rejected. As a higher frequency on the one hand leads to a lower direct open rate (cf. results for *H2*), the results for *H3* may show that users still remain interested in the content at a higher notification frequency.

Based on the results of the regressions (cf. Table 4 and Table 5), the hypothesis is tested that a higher frequency has a stronger negative effect on direct open rate than on indirect open rate.

H4: The negative effect of frequency on direct opens is stronger than the effect on indirect opens.

Even when assuming significance of the regression model and the coefficients for *H3*, the effect of the frequency on direct open rate is stronger than on indirect open rate (cf. Table 6).

Table 6. Comparison of regression results for direct and indirect opens

Regression	β	t	p	Confidence interval
Direct open	−1.267	−3.67	.035	$-.2366 < \beta < .-.0168$
Indirect open	−.0818	−2.94	.060	$-.1704 < \beta < .0067$

In this respect, *H4* is confirmed regardless of whether the coefficient for the indirect open rate was significant.

Table 7. Summary of experiment results

Hypothesis	Result
H1: Increasing frequency → Increasing uninstall rate	Accepted
H2: Increasing frequency → Decreasing direct open rate	Accepted
H3: Increasing frequency → Decreasing indirect open rate	Rejected
H4: Negative effect of frequency higher on direct than on indirect rate	Accepted

Table 5. Indirect open rate determined by frequency – regression results

Source	SS	df	MS	Number of obs	=	5
				F (1, 3)	=	8.65
Model	.016741826	1	.016741826	Prob > F	=	0.0605
Residual	.005807414	3	.001935805	*R*-squared	=	0.7425
				Adj *R*-squared	=	0.6566
Total	.022549239	4	.00563731	Root MSE	=	.044
D~Indirect~d	**Coef.**	**Std. Err.**	**t**	**P > |t|**	**[95% Conf. Interval]**	
MsgPerWeek	−.0818336	.0278266	−2.94	0.060	−.1703903	.0067232
_cons	.9502392	.028683	33.13	0.000	.8589569	1.041521

Table 7 summarizes the results of hypothesis testing. Apart from *H3*, the experiment shows evidence to confirm all of the hypotheses stated.

4. DISCUSSION

Contributions to scientific theory and practical implications are summarized below. Subsequently, the limitations of this paper are pointed out and suggestions for further research are made.

The existing literature has already examined user behavior and acceptance of smartphone apps, and the influence of push notifications, in particular, frequently and in many different facets. In particular, the positive effect of push notifications on the activation of app users is emphasized again and again (Bidargaddi et al., 2018; Hsu & Tang, 2020; Malik et al., 2017; Morrison et al., 2018; Pham et al., 2016; Smith et al., 2017). Nevertheless, many research results also indicate that push notifications have a certain potential for disruption for the user (Chen, 2017; McGookin et al., 2019; Sahami Shirazi et al., 2014). In this respect, an unlimited benefit of frequent push notifications for app users and companies cannot be assumed. In particular, the question of frequency affecting uninstalls and app open rate is still largely unexplored, especially using experimental data (Wohllebe, 2020).

This paper provides concrete information by quantifying the impact of frequency on uninstalls and app opens. Among other things, the results of Freyne et al., who identify a frequency of three messages per day as the limit of user tolerance, are supplemented (Freyne et al., 2017). This paper therefore provides important information on the concrete effects of too high frequencies.

Furthermore, the research results confirm the necessity of approaches to find appropriate moments to send push notifications to app users (Adamczyk & Bailey, 2004; Okoshi et al., 2015; Pejovic & Musolesi, 2014).

To authors' knowledge, this is the first study to examine this issue for a retailer's app in a setup with real observed data.

Within the framework of this elaboration, first of all current research results were summarized in a literature review. Hypotheses were derived based on these research results. The results of the experiment provide concrete evidence of how the frequency of push notifications affects uninstalls as well as direct and indirect app opens.

Nevertheless, some limitations have to be made, especially considering the experimental setup. For the experiment, the app users were chosen randomly but all come from the same app of a retailer. The research results may therefore not be transferred to other retailers or other kinds of apps without further verification. In particular, results may be different when repeating the experiment with social media, gaming, or messaging apps.

Furthermore, the effects on uninstall and open rates were gathered from an experiment with non-personalized, broadly sent push notifications. Based on the existing literature, notifications tailored to individual users, e.g. based on socio-demographic or behavioral data, may produce different results. The practical implications are nevertheless considered valuable. After all, app publishers also send such generic push notifications as here in the experiment.

Lastly, a limitation of the research is the dataset. It was provided by a retailing company and does not contain data regarding time or money spent in app per frequency group. Different frequencies may influence these metrics as well. Further research should also take these metrics into account to gain even better understanding.

The limitations give rise to two areas, in particular for further research. On the one hand, the topic is still largely unexplored for other sectors like social media, gaming, or messaging apps. On the other hand, it should be explored to what extent employing user attributes and user behavior for sending notifications changes the acceptance of higher frequencies.

The data set used here covers a period of about two months. It could therefore also be interesting to take an even longer-term view.

CONCLUSION

This paper investigates the impact of push notification frequency in the context of mobile apps in retail on app user behavior. The focus is on the question of the impact on uninstalls and open rates. Based on the existing literature, four hypotheses are derived, three of which can be confirmed. To the best of the authors' knowledge, this is the first time that the effects of push notification frequency on app user behavior have been studied in an experiment with real app users.

Especially for practitioners who use push notifications as a marketing tool, three important implications arise.

First, the probability of an uninstall increases with the frequency of notifications sent. In this respect, every message sent, especially standardized, non-personalized, should be checked to see if the content is actually relevant enough and if it adds value for the app users.

Second, this work provides a concrete indication of the "costs" of a push notification, in particular in the form of uninstalls. For marketers, the increasing uninstall rate depending on the frequency can be an important basis to calculate the costs of a push notification. In practice, knowledge of the acquisition costs or the costs for an app install is necessary to do so.

Third, the *H3* results indicate no negative effect of higher frequency on indirect app opens. Consequently, app publishing companies should also look at indirect app opens when evaluating the effects of push notifications. As a higher frequency does not lower indirect app opens significantly, an app publisher can reach out to their app users more frequently without any negative implications.

AUTHOR CONTRIBUTIONS

Conceptualization: Atilla Wohllebe.
Data curation: Atilla Wohllebe, Uwe Radtke.
Formal analysis: Atilla Wohllebe.
Investigation: Atilla Wohllebe, Dirk-Siegfried Hübner.
Methodology: Atilla Wohllebe.
Project administration: Uwe Radtke, Dirk-Siegfried Hübner.
Supervision: Szilárd Podruzsik.
Validation: Uwe Radtke, Szilárd Podruzsik.
Visualization: Dirk-Siegfried Hübner.
Writing – original draft: Atilla Wohllebe, Szilárd Podruzsik.
Writing – review & editing: Uwe Radtke, Dirk-Siegfried Hübner, Szilárd Podruzsik.

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