

DOCTORAL (PhD) DISSERTATION

ATILLA WOHLLEBE

**HUNGARIAN UNIVERSITY OF
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HUNGARIAN UNIVERSITY OF
AGRICULTURE AND LIFE SCIENCES

FACULTY OF ECONOMIC SCIENCES

Doctoral School of Management and Organizational Science

Head of the Doctoral (PhD) School

Prof. Dr. IMRE FERTŐ D.Sc.

Supervisor

Dr. habil. SZILÁRD PODRUZSIK

CONSUMER ATTITUDE TOWARD MOBILE APPS IN
RETAIL: THE ROLE OF CUSTOMER SATISFACTION
AND PUSH NOTIFICATIONS

Created

ATILLA WOHLLEBE

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TABLE OF CONTENTS

1. GENERAL INTRODUCTION WITH BIBLIOGRAPHY	8
1.1. Practical Relevance of Mobile Apps in Retail.....	8
1.2. Technology Acceptance Model	10
1.3. Factors Influencing the Use of Apps	14
1.4. Consumer Acceptance of Push Notifications	16
1.5. Customer Satisfaction and Loyalty.....	22
2. CONCLUSIONS BASED ON THE LITERATURE.....	25
3. OBJECTIVES OF THE DISSERTATION	28
4. METHODOLOGY	31
5. PUBLICATIONS	37
5.1. Mobile Apps in Retail: Determinants of Consumer Acceptance – a Systematic Review	37
5.1.1. Introduction	38
5.1.2. Methodology.....	40
5.1.3. Results	42
5.1.4. Summary and Discussion	48
5.1.5. Conclusion.....	50
5.2 Influence of the Net Promoter Score of Retailers on the Willingness of Consumers to Install Their Mobile App.....	51
5.2.1. Introduction	51
5.2.2. Literature Review	53
5.2.3. Empirical Research.....	58

5.2.4. Results	62
5.2.5. Summary	68
5.2.6. Conclusion	69
5.3. Frequency of Generic Push Notifications From Mobile Apps in Retail and the Effect on Uninstalls and App Opens.....	72
5.3.1. Introduction.....	72
5.3.2. Literature Review.....	74
5.3.3. Method	77
5.3.4. Results.....	81
5.3.5. Discussion	86
5.3.6. Conclusion	88
5.4. Recommending a Retailer’s Mobile App – Influence of the Retailer and the Mediating Role of Push Notifications	90
5.4.1. Introduction.....	91
5.4.2. Literature review	91
5.4.3. Material and methods.....	96
5.4.4. Results.....	99
5.4.5. Discussion and implications.....	102
5.4.6. Conclusion	103
6. GENERAL DISCUSSION	105
7. CONCLUSIONS.....	109
8. NEW SCIENTIFIC RESULTS.....	111
9. SUMMARY	114

10. ACKNOWLEDGEMENTS	117
11. RELATED PUBLICATIONS OF THE AUTHOR.....	119
11.1. Papers	119
11.2. Books	120
12. OTHER PUBLICATIONS OF THE AUTHOR	120
12.1. Papers	120
12.2. Books and Book Chapters	122
13. SHORT PROFESSIONAL CV	123
REFERENCES	123

LIST OF FIGURES

Figure 1: Number of publications on “mobile apps retail” per year since 2007, based on ScienceDirect (2021).	10
Figure 2: Technology Acceptance Model as a scientific model to explain why people use a technology, e.g. apps (Davis, 1985).	11
Figure 3: Extended Technology Acceptance Model with consideration of trust and risk in the banking context by Muñoz-Leiva et al. (2017), simplified. Grey paths not significant.	12
Figure 4: Customer value, satisfaction, loyalty, and switching costs in a linear model by Lam et al. (2004). Standardized coefficients; significant coefficients bolded.	22
Figure 5: Customer value, satisfaction, and loyalty model for mobile apps by Xu et al. (2015), simplified. PR (Privacy Risk), KAQ (Knowledge of Alternative Quality), ACI (App Continuance Intention), IR (Intention to Recommend), Reco (Recommendation).	24
Figure 6: Overview of the structure of the dissertation based on the identified research problems and the derived goals as well as the included publications (own illustration).	30
Figure 7: PRISMA statement (source: (Moher et al., 2009)).....	41
Figure 8: Number of replies by age group and gender, based on collected survey data.	60
Figure 9: Recommendation and installation – average values per retailer, based on collected survey data.....	61
Figure 10: Share of consumers referring to specific retailer, based on collected survey data.	96
Figure 11: Distribution of likelihood to recommend the retailer’s app, based on collected survey data.....	99

Figure 12: Final estimated model, standardized parameters, based on statistical analysis. 100

Figure 13: Suggestion for extended TAM incorporating customer satisfaction, illustration based on original model by Davis (1985). 110

LIST OF TABLES

Table 1: Overview of the theories, models and method per included publication.....	32
Table 2: Review protocol (own elaboration).	40
Table 3: Regression results for <i>H1</i> , based on collected survey data.....	63
Table 4: NPS and likelihood to install app per merchant, based on collected survey data.	64
Table 5: Regression results for <i>H2</i> , based on collected survey data.....	65
Table 6: Regression results for <i>H3a – H3e</i> , based on collected survey data.	66
Table 7: Results of analysis regarding usage habits, based on collected survey data.	67
Table 8: Willingness to recommend by gender, based on collected survey data.	67
Table 9: Summary of the results, based on own statistical evaluation. ...	68
Table 10: Start-end-comparison of recipients, direct opens and indirect opens per frequency group, based on observed user behavior.....	80
Table 11: Start-end-comparison of direct open rate and indirect open rate per frequency group, based on observed user behavior.	80
Table 12: Uninstall rate determined by frequency – regression results, based on collected survey data.....	82
Table 13: Direct open rate determined by frequency – regression results, based on collected survey data.....	83
Table 14: Indirect open rate determined by frequency – regression results, based on collected survey data.....	84
Table 15: Comparison of regression results for direct and indirect opens, based on collected survey data.....	85

Table 16: Summary of experiment results, based on own statistical analysis.	85
Table 17: Measures, based on collected survey data.	98
Table 18: Model fit statistics, based on statistical analysis.	100
Table 19: Regression results, based on statistical analysis.	101
Table 20: Direct and indirect results, based on statistical analysis.	101
Table 21: Summary of hypotheses, based on statistical analysis.	102
Table 22: Overview of practical implications, derived from publications.	111
Table 23: Overview of new scientific results, derived from publications.	112

1. GENERAL INTRODUCTION WITH BIBLIOGRAPHY

1.1. Practical Relevance of Mobile Apps in Retail

Retail is one of the most important sectors of the economy in Germany and many other countries (Statistisches Bundesamt, 2020c). While stationary retail is coming under increasing cost pressure, partly due to declining productivity per unit area, e-commerce is steadily gaining in relevance (HDE et al., 2019). More than twelve percent of German retail sales were already generated online in 2018 (Statistisches Bundesamt, 2020a). Digitization offers new opportunities for retailers, even outside of e-commerce (Deckert & Wohllebe, 2021). In this context, the strong spread of smartphones is highly relevant (BITKOM, 2019a). In particular, **mobile apps**, which are among the most relevant smartphone functions from the user's perspective (BITKOM, 2017), are already being used in numerous sectors such as medicine and related fields (Ferretti et al., 2021; Langarizadeh et al., 2021), payment (Fontes et al., 2017; Mun et al., 2017), education (Dickinson & Bass, 2020; Papadakis et al., 2020), and tourism (McGookin et al., 2019; Prakasa et al., 2020).

The **business benefits of mobile apps in retailing** have already been investigated on several occasions. An evaluation of the usage and shopping behavior of 1,286 consumers who downloaded a retailer's app shows that app usage positively influences not only online but also offline in-store purchasing behavior (Dinner et al., 2015). Based on an evaluation of the usage and shopping behavior of 629 consumers, Heerde et al. (2019) can show that active use of a retailer's mobile app leads to more sales. At 9.5 percent, the highest increase in sales is achieved by the segment of app users who otherwise shop exclusively offline. This emphasizes the particular relevance of mobile apps in stationary retail as

the offline-only audience seems to have the biggest potential for app-driven revenue increases. The added value of apps lies in particular in the technical possibilities of being able to provide consumers with individually relevant content at the right moment (Shukla & Nigam, 2018). However, the prerequisite for achieving such commercial success is first the installation of the app by the consumer on the smartphone and then the active use of the app. In terms of building a sustainable user base, retailers need to ensure, on the one hand, that users are satisfied with the app, where satisfaction is individually determined by balancing expectations and actual experience (Rosa, 2019; Ross & Wohllebe, 2021). At the same time, satisfaction also leads to repeat purchases and a willingness to recommend the app to others, and in this respect is not only relevant ex post for evaluating an app's performance, but should also be understood ex ante as a predictor of its growth through recommendations (Luo et al., 2019; Reichheld, 2003; Siqueira et al., 2019; Xu et al., 2015). Therefore understanding the interaction between consumers and mobile apps is of great importance, especially against the background of acceptance and recommendation.

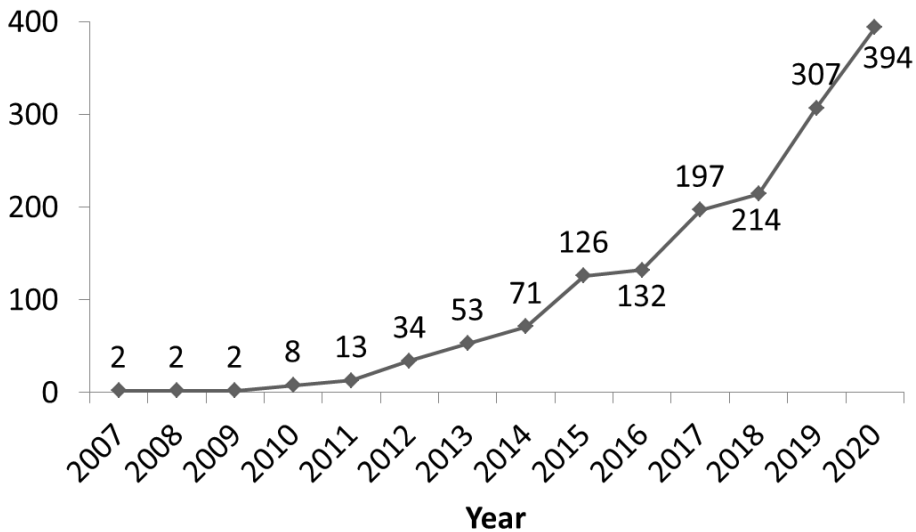


Figure 1: Number of publications on “mobile apps retail” per year since 2007, based on ScienceDirect (2021).

Researchers are focusing more and more on the topic with the emergence of mobile apps. However, data from ScienceDirect.com (2021) shows that in particular the last few years have received a great degree of attention. For example, around a quarter of all papers on "mobile apps retail" published overall since 2007 were published in 2020 (Figure 1).

1.2. Technology Acceptance Model

In scientific terms, the use of technology in general and of mobile apps in particular is discussed as consumer acceptance. Probably the most important model for consumer acceptance of technology is the **Technology Acceptance Model (TAM)** as shown in Figure 2. Previous research papers on consumer acceptance in this context preferentially use the TAM. The model was published by Davis (1985) and postulates that the use of a system depends on the behavioral intention to use the system. This behavioral intention, in turn, results from attitude toward using and perceived usefulness of the technology, with attitude toward using also

resulting from perceived usefulness as well as from perceived ease of use. The latter also influences perceived usefulness.

Important foundation of the model – and of many other models – is the Theory of Reasoned Action (TRA), according to which a reported behavioral intention is highly correlated with the actual observable behavior (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975). Thus, TRA can be considered one of the most important foundational models in behavioral research (LaCaille, 2013). Based on TRA, it can also be assumed that the acceptance and use of mobile apps in retail results from the intention to use.

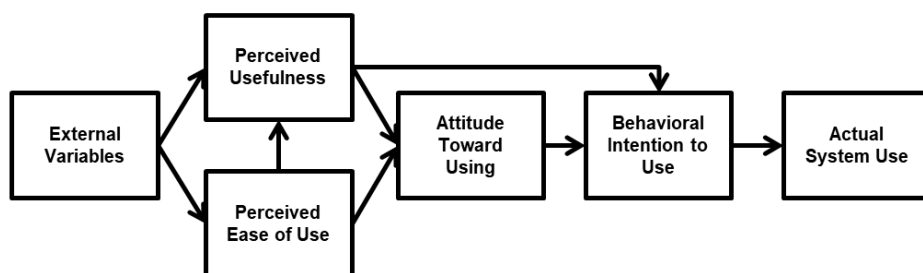


Figure 2: Technology Acceptance Model as a scientific model to explain why people use a technology, e.g. apps (Davis, 1985).

Researchers employing TAM have already confirmed perceived benefit of use and perceived ease of use being the main factors influencing consumer acceptance for many different technologies (Briz-Ponce & García-Peñalvo, 2015; Saare et al., 2019; Vahdat et al., 2020; Yoon, 2016). TAM has also been **widely applied in the context of mobile apps**. Mohamed et al. (2011) use the model to explore the acceptance of mobile health applications. The authors are able to show that the intention to use depends to a large extent on the perceived ease of use and perceived usefulness, even in the medical field. In addition, they identify

technological factors in particular, such as design, as influencing factors, as well as socio-cultural factors. Briz-Ponce and García-Peñalvo (2015) use the TAM to investigate the adoption of mobile apps in medical education. Based on a survey of students and staff members at a university, the authors can explain 46.7% of the intention to use mobile apps in medical education by applying the TAM. In the context of mobile banking apps, Muñoz-Leiva et al. (2017) extend the TAM to include the factors "perceived trust" and "perceived risk." They demonstrate a significant influence of trust on perceived ease of use ($\beta = .70$) and on attitude toward using ($\beta = .22$). It should be noted, however, that trust is surveyed exclusively via questions that refer to trust in the app, but not to the company as app publisher – in this case Banco Santander. Figure 3 shows a simplified version of the model, containing only the coefficients from significant paths and non-significant paths in grey.

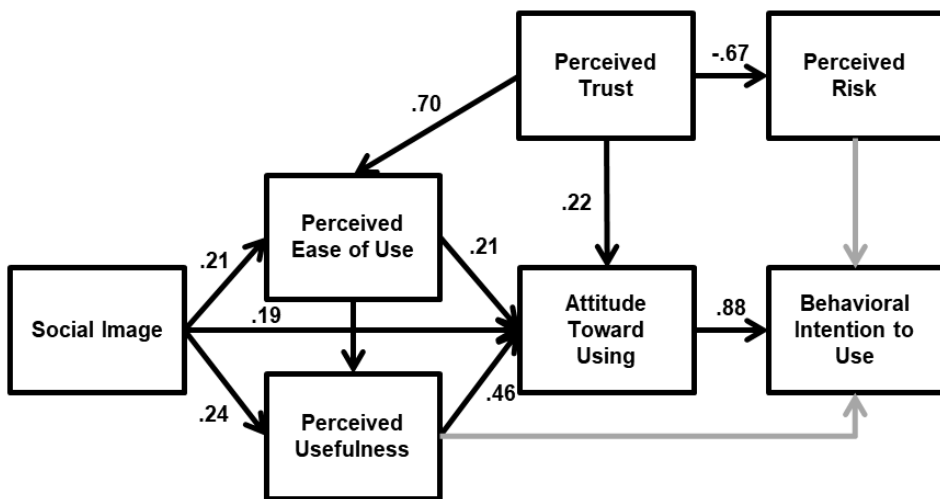


Figure 3: Extended Technology Acceptance Model with consideration of trust and risk in the banking context by Muñoz-Leiva et al. (2017), simplified. Grey paths not significant.

In addition to the TAM, Ugur and Turan (2019) integrate other theories and models to create a new model of mobile app acceptance, which they

test with a questionnaire and 1,654 students. In the new model, behavioral intention is also derived from attitude toward using. This in turn has as antecedents, as in the TAM, perceived usefulness and, in addition, subjective norms and performance expectancy. Perceived usefulness and performance expectancy are positively influenced by basic needs.

Similar to the Muñoz-Leiva et al. (2017) model, this model is therefore also primarily technology-oriented and also takes the human user into account to some extent. Cho et al. (2020) also extend the TAM when exploring mobile app adoption, in this case in the area of health and fitness. They integrate the investment model and are able to show that user satisfaction, investment size, and quality of available alternatives significantly affect the users' relationship commitment to the apps and this affects the users' continuing intention. This work also broadens the horizon of app acceptance research, especially because using an app is at the same time in some way a decision against using alternative apps. Finally, the authors draw particular attention to the fulfillment of functional requirements. In the context of e-scooters and apps that enable e-scooter rentals, Ratan et al. (2021) also propose a model that is largely based on the TAM. In doing so, they bridge the gap between the app and the actual product, the e-scooters. They can show that in addition to the e-scooter ease of use, the mobile app ease of use also has a significantly positive effect on e-scooter usefulness and e-scooter use intent. This work shows the relevance of mobile apps if they serve as a way to access a product.

Even away from the TAM and with specific reference to retail, a few studies already deal with the **acceptance of mobile apps in retail**. Newman et al. (2018) can show in a model that app ease of use has a

positive effect on app connection. App ease of use and app connection together affect the intention to recommend the app and to purchase via the app. In a model extension, the authors further show, among other things, that the positive influence of app ease of use on app connection is moderated by frequency of use. Vahdat et al. (2020) extend the TAM to include social influence and peer influence. Both factors have a significant positive effect on attitude toward the app and confirm the authors' assumptions. The postulated influence of perceived usefulness, on the other hand, is not significant. The authors also show that the attitude toward the app has a positive effect on the purchase intention. The authors' work is particularly interesting for this thesis in two respects. On the one hand, the work shows that the TAM generally has a very high explanatory power, but – as already shown in some other studies – other factors also have an effect on acceptance. Secondly, the work builds a bridge from the use of an app to the purchase of a product and thus leaves the pure consideration of a technology.

1.3. Factors Influencing the Use of Apps

Accordingly, the question arises **which other factors** – apart from perceived ease of use and perceived usefulness and independent of the TAM – **influence the use of apps**. Papadakis et al. (2019) investigate the adoption of new apps in children's education, asking about the role of parents. Based on data from 293 Greek families, the authors show the influence of parental socio-demographic factors, i.e., age, gender, and education level, on children's adoption of apps. Thus, children of well-educated parents and of older parents are significantly more likely to use educational apps. At the same time, the parents' occupational status or income is not significant. Purchasing paid apps is more common among

young and well-educated parents, while gender or occupation do not seem to have a significant influence. These findings exemplify that socio-demographic factors can influence whether and which apps are used. Peng et al. (2014) develop a model that explains intention to use branded apps at $R^2 = 55.9$ percent. Although perceived value, which includes perceptions of quality and efficiency, is the dominant factor ($\beta = .473$), data from an online survey of 245 participants using three Taiwanese banking apps as examples also show that the company's brand is of great importance. Thus, brand attachment, i.e., the strength of the emotional connection between consumer and brand, also has a direct and significant influence ($\beta = .235$) on the intention to use a branded app. Brand identification, i.e., the extent to which a consumer identifies with the values and attributes of a brand, also influences this intention positively ($\beta = .204$) and significantly. Despite some studies on consumer acceptance of mobile apps away from the TAM, the factors of consumer acceptance of mobile apps, especially in retail, have only been sporadically researched (Wohllebe, 2021).

Although it is probably difficult to generalize the acceptance factors due to the great variety of mobile apps, the brand seems to play an important role (Ghnemat & Jaser, 2015). Peng et al. (2014) suggest a **direct influence of the brand on the acceptance of an app**. A study of 378 consumers in the tourism sector, which examined the influence of physical quality, staff behavior, ideal self-congruence, lifestyle congruence and brand identification on customer satisfaction and subsequently on brand loyalty, shows that brand identification has the strongest influence on customer satisfaction after ideal self-congruence (Nam et al., 2011). Consequently, customer satisfaction with a company

could also have an effect on the willingness to install an app – and thus on acceptance.

When accepting an app, users weigh up the costs and benefits against each other (S. Kang, 2014). In addition to rational considerations, emotions are also an important factor, with negative emotions in particular having a correspondingly negative influence on the intention to use an app and positive emotions having a positive influence on the intention to use (Ding & Chai, 2015). Based on 241 responses to an online survey, Jham (2018) shows that trust in a company also makes consumers more willing to engage with a company's mobile app. In this context, trust is not only a consequence of customer satisfaction, but at the same time can be a partial mediator of the influence of customer satisfaction on customer loyalty, as shown in a study using the example of banks from Sri Lanka (Leninkumar, 2017). This research adds to the existing literature that customer satisfaction is the most important antecedent of customer loyalty (Lam et al., 2004). A study from India based on 567 survey responses shows which factors influence consumer trust in mobile apps in retail. In addition to the familiar technological factors, i.e. how useful an app is and how easy it is to use, the results also show that the retailer's reputation and offline presence have a positive effect on trust (Kaushik et al., 2020).

1.4. Consumer Acceptance of Push Notifications

Push notifications are considered a central function of smartphone apps. The small messages are sent by a company an app published by this company and displayed to the user in the notification bar and / or on the lock screen of the smartphone. This can reach all app users who have installed the app and have actively consented (iOS) or not objected

(Android) to receiving push notifications (Ahrholdt et al., 2019, p. 166). Similar to the question about the acceptance factors of mobile apps, there is also the question **about the acceptance factors of push notifications**.

The acceptance of push notifications and mobile advertising in the broader sense has already been studied many times. **The relevance of the message received** for the individual user plays a central role. Wang et al. (2014) examine the antecedents of relevance and, based on 141 responses from consumers, find that the economic added value of a message and the topicality, i.e., the adaptation of the content to the individual consumer profile, have a particularly strong influence on perceived relevance from a receiver's perspective. The economic added value as well as the possibilities of personalization are also emphasized by Berman (2016). The author therefore suggests the inclusion of geo-location data, the reaction to local events, such as the weather, and the use of mobile couponing. Jacob and Gupta (2017) investigate for the Indian market, based on 154 answered questionnaires, which factors lead to a user opening the app later after receiving a push notification. Their research looks at three different message formats – text-based, image-based, and action button-based. While informativeness ($p < .10$) and credibility ($p < .05$) are significant for text-based notifications, only context is significant ($p < .10$) for push notifications with an image. When an action button is used, personalization ($p < .05$), entertainment value ($p < .05$), trust ($p < .10$), and gender ($p < .05$) are significant, with male users responding more strongly to the use of action buttons than female users. In particular, the content-related findings are also consistent with other publications (Kazeminia et al., 2019; Köster et al., 2015; Sahami Shirazi et al., 2014; Wohllebe, Adler, et al., 2021). A consideration of the factors topicality

and timing shows that, in contrast to other marketing channels, the right timing is also an important determinant of user response to push notifications. In fact, topicality and timing are equally important, especially for time-sensitive content or in a volatile business context (Glady, 2019).

Ahrholdt et al. (2019, pp. 301–302) emphasize the added value of personalized and location-based content, also pointing out the need to consider the situative context. At the same time, the authors also note that too many notifications can also be perceived as disruptive. User disruption is a real risk is also shown by a study of the smartphone usage behavior of 135 female undergraduate nursing students at King Saud bin Abdulaziz University for Health Sciences. The authors find that 94.8 percent of respondents carry their smartphones with them at all times, 63.0 percent have push notifications permanently turned on, and 65.9 percent always respond immediately to push notifications (Alsayed et al., 2019). With this in mind, push notifications could potentially be perceived as annoying. A 2016 study based on 10,372 notifications and 474 answered questionnaires from 20 users provides two key findings in this regard. On the one hand, the perceived disruption that a notification causes to the user depends on many factors, but especially on the type of notification, the relationship between sender and recipient, and the complexity of the activity in which the notification interrupts the user. On the other hand, it has been shown that even a notification that is perceived as important and useful is also perceived as disruptive by the user (Mehrotra et al., 2016).

The finding that **push notifications are perceived as disturbing** is largely in line with the findings of other human-computer interaction

research. McFarlane (2002) already points out the disruptive potential of notifications in the broadest sense when using computers. Iqbal and Horvitz (2007) explore the disruption of users by notifications on computers. They do this by evaluating the activity data of 27 subjects over a two-week period to determine how notifications affect subjects in completing tasks. Their results show that while users view alerts primarily as a mechanism to direct attention, the alerts also cause users to actually interrupt the actual task they are working on. Fischer et al. (2010) also point out the disruptive potential of notifications, although they do not examine push notifications from apps, but rather text messages. Sahami Shirazi et al. (2014) also point to the problem of disruption in the context of a study of 200 million push notifications and 40,000 users. They also differentiate depending on the content of the notification. Their evaluation also shows that the app WhatsApp sends the most alerts on average, with 19.9 notifications per user per day.

From the perspective of app publishers, **push notifications offer the great advantage that they can increase app usage**. Pham et al. (2016) study the behavior of 12,071 users of an English learning app. The authors find that with the number of notifications prompting to use the app, app usage actually seems to increase. However, a certain point an opposite effect could be observed. The results of a study of a self-monitoring app based on 18,000 push notifications confirm the positive effect of push notifications on app usage, with active app use having a positive effect on the likelihood of responding to a push notification (Bidargaddi et al., 2018). The case study of an app for alcoholism prevention shows that push notifications are also particularly suitable for regularly reminding users to complete tasks – in this case, for example,

documenting their own drinking behavior (Smith et al., 2017). Push notifications can also be used as regular reminders to take medication, for example against asthma (Malik et al., 2017).

The advantages of push notifications, both from the user's and the app publisher's point of view, on the one hand, but also the risk of disrupting the benefits, on the other, lead to the question of frequency, i.e., **how many messages in a certain period of time have what effect on app use**. Additionally, the question of uninstalls is also interesting (Westermann et al., 2015).

Mikulic (2016) investigates the effects of the frequency of push notifications in an experiment that combines data from questionnaires and user tracking. For this purpose, 26 users are divided into three groups, with one group receiving no notifications at all and the second receiving all notifications from all installed apps. The third group keeps their existing settings. The author looks at the behavior of the 26 test subjects over a period of 10 days in April 2016. Total daily usage (in minutes), total daily application interactions and total daily unlocks of the smartphone are considered for the evaluation. Contrary to Mikulic's expectations, the results show that there are no significant differences between the three groups in terms of overall daily usage and stress levels of the users. It is noteworthy that the first group, which does not receive notifications during the experiment period, initially shows an increase in usage behavior, but this decreases over time. The author attributes this to the subjects' fear of possibly missing something. Particularly surprising is the fact that there are hardly any differences between the first and second group. Contrary to expectations arising, for example, from McFarlane (2002), Iqbal and Horvitz (2007), and Fischer et al. (2010), frequency

does not seem to influence the behavior of app users in Mikulic's experiment. However, the small number of subjects and the short study period are major limitations of the paper and therefore require validation.

A similar picture emerges from the research of Freyne et al. (2017). Over a 24-week period, the authors investigate the impact of push notifications on users' engagement in completing self-monitoring tasks via a diet app. In qualitative evaluations, only a few of the subjects reported that the notifications were "too frequent" and "annoying after a while." Overall, the authors conclude that subjects tolerate multiple notifications per day and that these are also conducive to app use.

Also McGookin et al. (2019) point out the danger of interrupting users too often with too many notifications and thus disturbing them. On the other hand, they can also show the added value of push notifications in their study, in which 45 participants received information over a period of five days about sights on a Finnish island that matched their current location. The authors find that the test persons are already very familiar with this form of messages and like to be informed about new content and current events via this communication channel. They also confirm other research results according to which push notifications lead to increased app usage (Bidargaddi et al., 2018; Pham et al., 2016; Smith et al., 2017).

There is already some literature that provides evidence on the influence of the frequency of push notifications on app user behavior. Nevertheless, many research gaps still exist in this area (Ahrholdt et al., 2019, p. 302). Wohllebe (2020) points out various limitations of previous research. For example, research relies on user-reported behavior instead of real-observed behavior. Often, subjects know they are participating in an

experiment. Also, samples are sometimes very small and experiment periods are short. In-line with Westermann et al. (2015), research also should not only take into account the effects of push notification frequency on app usage but also on the risk of a user uninstalling the app.

1.5. Customer Satisfaction and Loyalty

In addition to acceptance, i.e., installation and use, user satisfaction and the resulting loyalty are of great importance for the success of a mobile app in the long term. A special role is played by the willingness to recommend the app to others, which is not only a diagnostic tool for satisfaction and loyalty, but can also ensure further growth in the event of actual recommendations. Lam et al. (2004) consider customer value, customer satisfaction and loyalty in a joint model using the example of a courier service provider in a B2B context. Furthermore, switching costs are included to compare the effects of customer value and customer satisfaction with the effect of switching costs. Figure 4 shows the final model of the authors including customer satisfaction and with standardized coefficients.

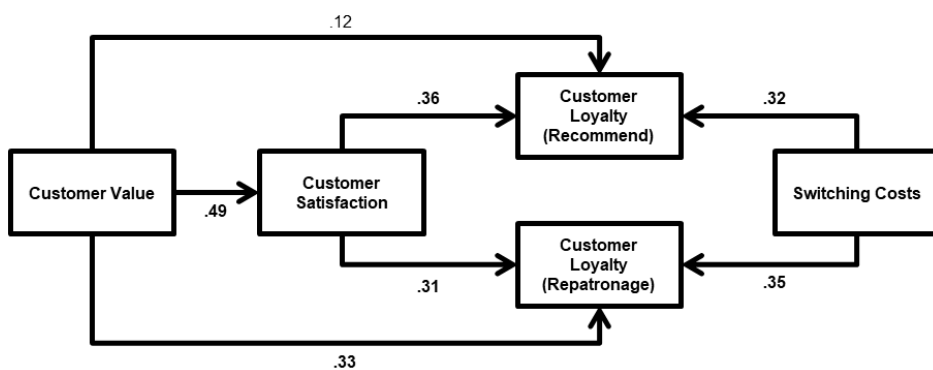


Figure 4: Customer value, satisfaction, loyalty, and switching costs in a linear model by Lam et al. (2004). Standardized coefficients; significant coefficients bolded.

The authors can show that the influence of customer value on customer loyalty in the form of repatronage is partly mediated by customer satisfaction. In the relationship between customer value and customer loyalty in the form of recommendation, customer satisfaction is fully mediating this effect and the effect of customer value on recommendation is not significant. These results show the high relevance of customer satisfaction, but at the same time point to the business value of loyalty, especially of recommendations. Apart from the topic of this thesis, it should be noted that the effect of switching costs on repatronage ($\beta = .35$) is similar to the effect of customer value ($\beta = .33$). In contrast to the (non-significant) direct effect of customer value on recommendation ($\beta = .12$, n. s.), switching costs have a significant effect on recommendation ($\beta = .32$).

Xu et al. (2015) adapt the customer value, satisfaction and loyalty perspective to mobile application recommendations. For this purpose, they survey 347 students at a US university. Their results show that satisfaction with an app has only a small direct influence on the willingness to recommend ($\beta = .11$), but that this willingness is primarily influenced by app continuance intention ($\beta = .40$). This in turn is mainly influenced by satisfaction with the app ($\beta = .49$). This paper also emphasizes the high relevance of satisfaction with a product or service, in this case an app, to the question of recommendation. Figure 5 **Error! Reference source not found.** shows the significant paths of the model developed by Xu et al. (2015).

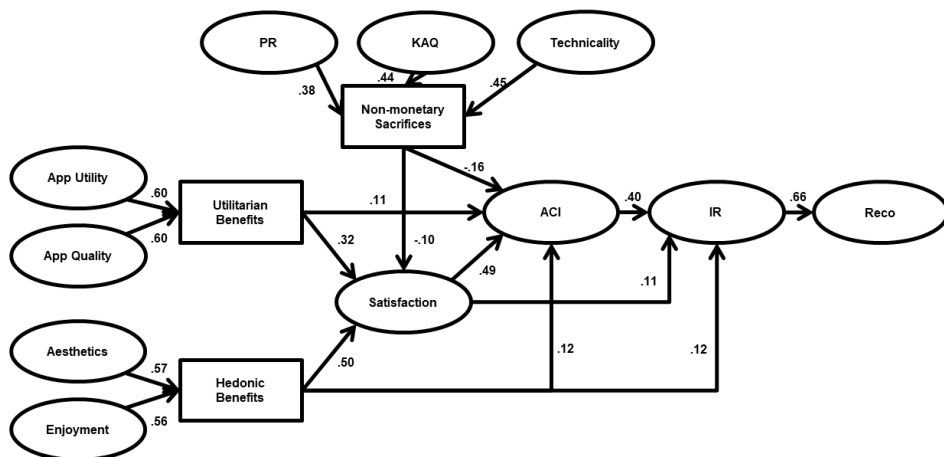


Figure 5: Customer value, satisfaction, and loyalty model for mobile apps by Xu et al. (2015), simplified. PR (Privacy Risk), KAQ (Knowledge of Alternative Quality), ACI (App Continuance Intention), IR (Intention to Recommend), Reco (Recommendation).

In both papers, Lam et al. (2004) and Xu et al. (2015) remain in one dimension each, looking exclusively at the B2B service provider and the app, respectively. Nevertheless, research in other contexts has already built **bridges between satisfaction, brand, and apps** several times. For example, Bellman et al. (2011) show that the use of a branded mobile app improves consumers' attitude toward a brand and increases purchase intention. The authors surveyed 228 subjects in the U.S., first asking them about various brands such as BMW, Gillette and Best Buy, then asking them to use their apps and finally asking them again about the brands. Conversely, Peng et al. (2014) succeed in demonstrating an immediate and significant influence of brand attachment and brand identification on app usage.

The relevance of push notifications as a key tool in the app environment has already been discussed (Malik et al., 2017; Smith et al., 2017). It could also be shown that sending push notifications influences the consumer perception of the app on the one hand and is related to the

consumer perception of the app publisher on the other hand. The comparison of the use of a web and app stress management intervention with 381 web users and 261 app users shows that the regular sending of push notifications leads to a higher app interaction, app users consume more content and are thus likely to be more satisfied with the app (Morrison et al., 2018). Effects on the willingness to recommend the app can be assumed (Xu et al., 2015). Also, an already high app usage seems to increase the probability of a reaction to a push notification (Bidargaddi et al., 2018).

2. CONCLUSIONS BASED ON THE LITERATURE

Based on the introductory literature review, the findings of previous research are summarized. From this summary, several research questions are derived, which are the basis of the dissertation's objectives.

Previous research on consumer acceptance of technologies is primarily based on the TAM according to Davis (1985). The importance of perceived benefit of use and perceived ease of use is highlighted (Saare et al., 2019; Vahdat et al., 2020; Yoon, 2016). Research in the specific context of mobile apps can confirm these factors in health, education, and banking, among others (Briz-Ponce & García-Peñalvo, 2015; Mohamed et al., 2011; Muñoz-Leiva et al., 2017). In some cases, the work extends the TAM to other factors, such as socio-cultural (Mohamed et al., 2011) or trust and risk perception (Muñoz-Leiva et al., 2017). In the retail context, consumer acceptance of mobile apps also appears to be influenced by social influence and peer influence (Vahdat et al., 2020). Research in the retail context also uses TAM factors as antecedents of recommendation and purchase intention (Newman et al., 2018). In

summary, studies particularly focus on the TAM or build on the model. At the same time, there is very little evidence on specific requirements of app users in retail, especially away from the TAM. There is a particular lack of a structured summary that reflects the current state of research. This leads to the first research question - **Q1: What are the drivers of consumer acceptance of mobile apps in retail?**

A review of further literature in the context of app acceptance reveals a large number of other factors. Of particular note is the connection between app adoption and the company in a broad sense and the company's brand in particular (Ghnemat & Jaser, 2015; Peng et al., 2014). The bridge between trust in a company and willingness to engage with a company's mobile app is also of great importance because it broadens the view of the overall context in which a consumer perceives an app (Jham, 2018). Based on these findings, customer satisfaction with a company could also be an important driver of willingness to install an app in the retail sector and at the same time be understood as an expression of customer loyalty. In this respect, the question of the influence of customer satisfaction on the willingness to install an app is of great importance not only from a scientific but also from a theoretical point of view. This leads to the second research question - **Q2: What influence does customer satisfaction with a retailer have on the willingness to accept its app?**

With regard to the acceptance of push notifications, research primarily emphasizes the importance of relevance, added value, and information content of the message for the user (Berman, 2016; Jacob & Gupta, 2017; Wang et al., 2014). Then, the short messages can help users to use the app more (Bidargaddi et al., 2018; Pham et al., 2016). At the same time, people point out the risk that push notifications can disturb the user and

therefore every time they receive a notification, they also risk uninstalling it (Ahrholdt et al., 2019, pp. 301–302; Alsayed et al., 2019; Mehrotra et al., 2016; Sahami Shirazi et al., 2014). This evidence can be confirmed by several research papers around the frequency of push notifications (Freyne et al., 2017; McGookin et al., 2019; Mikulić, 2016). With regard to the goal of this thesis to better understand consumer attitudes towards apps in retail, it is important to note in particular that the issue of the frequency of push notifications from mobile apps in retail has not been researched in this way before. In this respect, the influence of advertising pressure through push notifications on consumer acceptance of mobile apps in retail is thus unknown. The research question **Q3 – How does variation in advertising pressure from different frequencies of push notifications affect consumer rejection of mobile apps in retail?**

Regarding the importance of satisfaction and loyalty, research shows that loyalty in the form of recommendation is a direct consequence of customer satisfaction - also in the context of mobile apps (Lam et al., 2004; Xu et al., 2015). A good app experience also has a positive effect on attitudes toward the brand and purchase intentions (Bellman et al., 2011; Peng et al., 2014). Overall, previous research suggests a relationship between consumer perception of the retailer, consumer perception of push notifications from a retailer's app, and willingness to recommend the app. However, the question of the effect of consumer attitude toward the retailer on consumer acceptance and ultimately on the recommendation of the mobile app must be considered as a research gap in the retail context. Against this background, the overarching research question arises **RQ – What is the role of the retailer as a company in**

consumer acceptance and recommendation of its mobile app and how is this relationship influenced by push notifications?

3. OBJECTIVES OF THE DISSERTATION

To answer these research questions, consumer acceptance and recommendation of mobile apps in retail must not be viewed solely as a result of technological performance in terms of meeting perceived benefit expectations and ease of use expectations. Rather, research on consumer acceptance and recommendation of a retailer's mobile app must also consider the retailer itself in its role as the app publisher. A bridge between a retailer's app as a technology and the retailer as the company publishing the app is needed. Thus, this thesis **shifts the focus from the app as a technology to the retailer as a company** and brand when examining consumer adoption and recommendation of the retailer's app. Additionally the thesis incorporates the role of push notifications in this context as a central feature of mobile apps.

Based on the research questions and the underlying research gap, this thesis integrates four research avenues: the factors of consumer acceptance in the specific case of retail, quantifying the influence of customer satisfaction with a retailer on the acceptance of its mobile app, the role of push notifications as a central feature of mobile apps and in particular the influence of the frequency of notifications on consumer rejection, and finally the perception of a retailer and its push notifications as **factors influencing the willingness to recommend the app** and in this respect indirectly on satisfaction with the app. This allows for a **comprehensive look at**, in particular, **the role of customer satisfaction**

with a retailer in relation to acceptance and, ultimately, recommendation of the retailer's app.

Therefore, the overall objective is to gain an understanding of how **consumer attitude toward mobile apps in retail is affected by customer satisfaction with the retailer and how this relationship is influenced by push notifications**. Recommendation is understood to be the most important indicator of satisfaction, in line with the literature considered. This leads to the overarching research question:

RQ: What is the role of the retailer as a company in consumer acceptance and recommendation of its mobile app and how is this relationship influenced by push notifications? (cf. Wohllebe et al. (2022a))

The overarching research question requires taking multiple perspectives, so initially there are three partially interrelated questions which answers finally lead to answering the overarching research question:

Q1: What are the drivers of consumer acceptance of mobile apps in retail? (cf. Wohllebe et al. (2020))

Q2: What influence does customer satisfaction with a retailer have on the willingness to accept its app? (cf. Wohllebe et al. (2020))

Q3: How does variation in advertising pressure from different frequencies of push notifications affect consumer rejection of mobile apps in retail? (cf. Wohllebe et al. (2021))

The research approaches the overarching goal and the research questions in **four publications**, which, taking into account further own and external papers, partly build on each other. Figure 6 summarizes the research

problems identified, the objectives derived from the research problems and the published papers included to achieve these objectives.

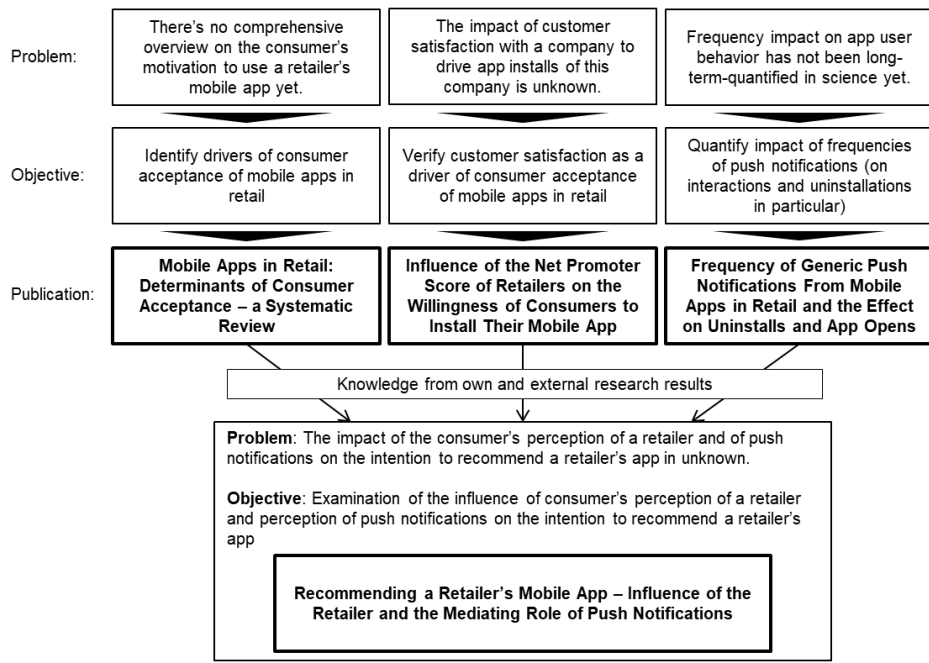


Figure 6: Overview of the structure of the dissertation based on the identified research problems and the derived goals as well as the included publications (own illustration).

A review is first used to provide a comprehensive overview of the **drivers of consumer acceptance of mobile apps in retail** (cf. Wohllebe et al. (2020)). As a results, this paper shows, among other things, that consumer's perception of the retailer itself (in terms of the brand and in terms of the service provided) plays an important role (Iyer et al., 2018; Kaushik et al., 2020; Rosa, 2019). However, the **influence of customer satisfaction with a retailer as a driver for app installations** is still rather unknown and in particular not quantified. Therefore, the extent to which customer satisfaction with a retailer being a driver of consumer acceptance of mobile apps in retail will be examined (cf. Wohllebe et al. (2020)).

To achieve the overall objective, the role of push notifications is also to be elaborated. To this end, the factors that influence consumer perception of push notifications in the retail sector are to be identified. In addition to other factors, which will be developed in the fourth publication, the **effect of the frequency of push notifications on app opens and app uninstalls** will be examined in particular (cf. Wohllebe et al. (2021)). This influence on app user behavior in the context of mobile apps in retail has not yet been quantified in the long term.

In the final publication, the model for achieving the overall goal of the dissertation will be developed (cf. Wohllebe et al. (2022a)). This model aims to investigate the **influence of the consumer's perception of a retailer and of push notifications the retailer sends via its app on the consumer's willingness to recommend the retailer's app**. In addition to the factors that influence the perception of push notifications, the factors that can be used to summarize the consumer's perception of a retailer will be elaborated as well.

The model will understand mobile apps in retail not only as a technological product, but also in the context of the retailer publishing the app and the push notifications sent via the app. As such, the model will simultaneously provide an initial impetus to understand mobile apps more holistically and provide a new, complementary view on factors beyond the well-established Technology Acceptance Model approach, which is primarily narrowed to technology.

4. METHODOLOGY

The methodological summary discusses the main theories, models and statistical methods of this thesis. The starting point is the publications.

Table 1 shows an overview per paper, which theories and models underlie them and which (mainly statistical) methods are used. Theories, models and methods that are used but not explained in the methodology part are marked in italics.

Table 1: Overview of the theories, models and method per included publication.

Paper	Theories, models and methods
Mobile Apps in Retail: Determinants of Consumer Acceptance – a Systematic Review (Wohllebe, Dirrler, et al., 2020)	<ul style="list-style-type: none"> • Systematic review (PRISMA)
Influence of the Net Promoter Score of Retailers on the Willingness of Consumers to Install Their Mobile App (Wohllebe, Ross, et al., 2020)	<ul style="list-style-type: none"> • Linear regression • <i>Levene test</i> • <i>Two-sample t-test</i>
Frequency of Generic Push Notifications From Mobile Apps in Retail and the Effect on Uninstalls and App Opens (Wohllebe, Hübner, et al., 2021)	<ul style="list-style-type: none"> • Linear regression
Recommending A Retailer’s Mobile App – Influence Of The Retailer And The Mediating Role Of Push Notifications (cf. Wohllebe et al. (2022a))	<ul style="list-style-type: none"> • Structural Equation Modeling

As the determinants of consumer acceptance of mobile apps in retail have already been investigated in various scientific publications, the corresponding paper summarizes these findings (cf. Wohllebe et al., 2020a). To ensure that the results are reproducible and to allow the investigation to be repeated in the future to conclude about the developments over time, the paper employs a **systematic review** based on the PRISMA statement (Moher et al., 2009). The PRISMA statement is an approach to identify, screen, select and finally include relevant research work in a literature review as shown in Figure 7. Also the criteria to find potentially relevant literature are defined in a structured way as Table 2 shows. The limitation of the considered sources to the first 100 search results is based on systematic reviews from other disciplines, which in many cases limit their evaluation to the first five pages / 50

results (Haddaway, Burden, et al., 2014; Haddaway, Styles, et al., 2014; Roe et al., 2014; Savilaakso et al., 2014; Sciberras et al., 2013).

Regarding the influence of the Net Promoter Score of retailer on the willingness of consumers to install their mobile app, a quantitative approach is used (cf. Wohllebe et al., 2020b). As the different hypotheses in this paper assume one or more different variables to influence the willingness of consumers to install a retailer's mobile app in a linear way manner, **linear regressions** are employed (Frost, 2017, p. 1).

A linear regression is a statistical evaluation of how the change in one or more independent variables affects a dependent variable (Frost, 2017, p. 1). Linear regression, along with logistic regression and Cox regression, is the simplest but probably the most widely used form of regression (Frost, 2017, p. 1). Linear regression assumes a linear relationship between two variables, where the dependent variable must be continuous and the independent variable can be continuous, binary, or categorical.

In the application of linear regression, a function $Y = a + b * X$ is estimated, where a is the intersect and b the slope (Frost, 2017, p. 6). In estimation, the ordinary least squares method is often used, trying to find a regression function for which the difference between the observed and calculated data should be minimal (Schneider et al., 2010).

Linear regression makes various assumptions about the data. For example, there must be a linear relationship, there must be no outliers, the residuals should be independent, there must be no multicollinearity, there must be homoscedasticity and normal distribution of the residuals (Hemmerich, 2021). Various tests and procedures exist to verify the assumptions, which will not be discussed further here.

Once the linear regression function has been estimated, the model quality must be evaluated. For this purpose, the R-square and the F-test are to be used. The null hypothesis of the F-test (H_0 : All regression coefficients are 0) should be rejected. The R-square describes the proportion of variance explained by the regression function. Additionally, the adjusted R-square can be used, which penalizes a higher number of explanatory variables. For the R-square, a value of .26 or more is considered high (Cohen, 1977).

When interpreting the regression coefficients, they must be significant ($p < .05$). The value of the coefficient (b) indicates how much Y increases when X increases by 1. The constant a shows value of Y when $X = 0$.

A linear relationship is also assumed in the case of observing (increasing) uninstalls and (decreasing) app opens as a consequence of the (higher) frequency of sending generic push notifications from a retailer's mobile app (cf. Wohllebe et al., 2021). Therefore, three **linear regression** models are postulated and calculated using a linear regression. Formula 1 is an example for one of the linear regression models.

$$\textit{Uninstall Rate} = a + b * \textit{Frequency}$$

Formula 1: Uninstall rate as a function of push notification frequency

A linear **structural equation model** (SEM) is used to answer the question of the influence of consumer perception of the retailer on the recommendation of its mobile app and how this relationship is influenced by consumer perception of push notifications (cf. Wohllebe et al. (2022a)).

A SEM is a model representing a part of complex reality and is used to test hypotheses – usually derived from the literature – about relationships between variables (Steinmetz et al., 2015, pp. 4–5). The models use correlations, which follow from causalities (Steinmetz et al., 2015, p. 6); however, correlation does not mean causality (Matthews, 2000).

SEM combine the ideas of regression analysis, factor analysis and path model. In a simple model, where X acts on Y, both variables can be indicators or observables, i.e., they are measured directly. Alternatively, X and/or Y can also be latent variables, which are composed of several indicators or observables, similar to the factors in a factor analysis (Steinmetz et al., 2015, pp. 33–35).

Using a SEM typically takes three steps (Steinmetz et al., 2015, p. 61). In the first step, model specification, latent variables are defined, often validated in advance e.g. via factor analysis, and the interrelationships of the variables are defined (Steinmetz et al., 2015, pp. 52–53). In the second step, the model is estimated on the basis of the data. For this purpose, with multivariate normal distribution as a prerequisite, the maximum likelihood estimation method can be used. If the precondition is not fulfilled, the Chi-square value is too high and the standard errors of the parameters are estimated too low (Finney & DiStefano, 2013; Steinmetz et al., 2015, p. 66). In practice, the multivariate normal distribution is sometimes not given (Steinmetz et al., 2015, p. 28), therefore SEM can be calculated directly with robust standard errors (Steinmetz et al., 2015, pp. 66–67). For final testing of the model, five different fit indices, among others, can be checked (Hu & Bentler, 1999; Kline, 2015). The Chi-square test is less important because of the problems described above

(Steinmetz et al., 2015, p. 28). Of central importance are CFI and TLI as well as RMSEA and SRMR (Hu & Bentler, 1999; Kline, 2015).

According to the literature, the results of the fit indices can be interpreted as follows:

- Chi-square:
Value should be low (Gatignon, 2010)
- p(Chi-square):
Should be above .05 (Gatignon, 2010)
- CFI:
Minimum: .90; Good: .95 (Hu & Bentler, 1999)
- TLI:
Minimum: .90; Good: .95 (Hu & Bentler, 1999)
- RMSEA:
Good: <.05; Okay: <.06; Bad: >.08 (Hu & Bentler, 1999)
- p(RMSEA):
Should be above .05 (Hu & Bentler, 1999)
- SRMR:
Acceptable: <.08 (Hu & Bentler, 1999)

Beyond the described possibilities of SEM, the method offers the possibility to perform mediation analyses. It is examined whether the effect of a variable X on a variable can be explained completely or partially by a third variable M, the mediator. If the effect of X on Y is completely explained by adding the mediator M via this path, complete mediation is present. If the effect is at least partially explained by the mediator M, it is called partial mediation (Baron & Kenny, 1986).

5. PUBLICATIONS

5.1. Mobile Apps in Retail: Determinants of Consumer Acceptance – a Systematic Review

This paper was originally published as

Wohllebe, A., Dirrler, P., & Podrutzsik, S. (2020). Mobile Apps in Retail: Determinants of Consumer Acceptance – a Systematic Review. *International Journal of Interactive Mobile Technologies (iJIM)*, 14(20), 153–164. <https://doi.org/10.3991/ijim.v14i20.18273>.

Abstract — With the increasing relevance of smartphones, more and more companies are trying to use mobile apps for their business purposes. At the same time, the digital transformation and online trade are putting increasing pressure on the stationary retail trade. Many retailers are therefore looking for ways to use mobile apps to attract new customers or retain existing ones. With the growing number of mobile apps in the app marketplaces, the sustainable loyalty of app users is becoming an increasing challenge. For retailers, the question arises as to which determinants influence consumer acceptance of mobile apps in retail. From an initial 44,800 search results at Google Scholar, 18 scientific papers are analyzed in a qualitative synthesis by means of a systematic review based on the PRISMA schema. In general, perceived value, practical benefits and user-friendliness are identified as determinants. In addition, the importance of linking the mobile app to the stationary POS and the function of mobile apps in retail more as digital shopping assistants and less as online stores is highlighted. The retailer who

publishes the app itself also plays an important role in the consumer acceptance of the app.

5.1.1. Introduction

The spread of mobile devices or smartphones and the importance of these devices for accessing the Internet has been growing steadily for many years since the first smartphone was sold (IDC, 2020; StatCounter, 2019). At the same time, the importance of mobile applications, or mobile apps for short, is also growing: Apps now exist for practically all areas of life and are used by consumers (PwC, 2020), for example for vacations, education or in the health sector (BITKOM, 2020; Kalogiannakis & Papadakis, 2019; H.-J. Kim & Rha, 2018; Papadakis & Kalogiannakis, 2020; Saare et al., 2019).

As a result, more and more companies are looking for ways to use mobile apps commercially (AppBrain, 2020). Because mobile apps can also help to retain existing customers (Allurwar et al., 2016; Verma & Verma, 2013; Wohllebe, 2020), commercial hopes are correspondingly high (BITKOM, 2011).

Parallel to these developments, stationary retail is under increasing pressure. Available retail space is still rising (HDE, 2019), while rents remain constant (BulwienGesa et al., 2019). Following the in some cases significant declines in sales in the past (Statistisches Bundesamt, 2020b), sales productivity in terms of sales per square meter of sales space is recovering slowly (HDE et al., 2019). At the same time, the relevance of online retailing as a share of total retail sales is steadily growing steadily (Statistisches Bundesamt, 2020a).

For the design of their local shopping experience, customers therefore increasingly expect technological innovation, such as self-scanning options, digital advertising for local offers or virtual opportunities to try on clothing based on augmented reality technologies (HDE, 2018). Mobile apps could play a decisive role, particularly in payment processing or by checking the availability of goods online (IfH Köln, 2019; PwC, 2020). At the same time, however, research from other contexts also shows that the development of mobile apps does not always match the expectations of potential users (Papadakis et al., 2018).

Scientific research has already frequently examined and demonstrated the use of mobile apps in the retail industry. Customers of a retailer who have installed the app generate more sales on average (Heerde et al., 2019). The actual use of the app plays an important role here, because customers who enjoy using a retailer's app are more likely to recommend it to others (Stocchi et al., 2018).

Previous research in the app context in general has already comprehensively investigated the factors that determine consumer acceptance of mobile apps. In addition to consumer loyalty to a brand (Bellman et al., 2013; Peng et al., 2014), a functional, attractive design also plays an important role (K. Kang et al., 2020). Further research results indicate that the perception mobile apps also seems to be determined by socio-economic background of people (Papadakis et al., 2019). Furthermore, with regard to mobile apps, it is generally emphasized that actual added value, such as time savings, drives consumer acceptance (Rojas-Osorio & Alvarez-Risco, 2019).

This raises the question of what is causing consumers to adopt and actually use mobile apps in retail in particular. Using a systematic review this paper therefore investigates the determinants of consumer acceptance of mobile apps in retail.

5.1.2. Methodology

For the systematic review, the authors use the scientific database Google Scholar on August 12, 2020. The systematic review is methodically structured according to the PRISMA scheme (Moher et al., 2009).

Table 2 shows the procedure for searching and selecting literature as a review protocol.

Table 2: Review protocol (own elaboration).

Review Question	„What drives consumer acceptance of mobile app in retail?“
Literature Search	Source: <i>Google Scholar</i>
	Search term: „mobile apps retail“
Sorting	<i>By relevance</i>
Filtering	<i>Exclusion of patents and citations</i> <i>Years: 2016 – 2020</i>
Exclusions	<i>By position in list: Only first 10 pages / 100 results</i>
	<i>By title: Thematic reference given in the title in the broadest sense, excluding e.g. entries focusing on mobile banking or gastronomy as well as mainly technological concepts</i>
	<i>By abstract: Exclusion of entries with no reference to mobile apps in retail or with no recognizable reference to consumers and customers</i>
Evaluation	<i>Full-text assessment: Inclusion of only those articles with specific references to the consumer acceptance of mobile apps in retail</i>

The total of 44,800 search results for "mobile apps retail" will be reduced to 38,500 after exclusion of patents and citations. The subsequent restriction to results since 2016 or later reduces the results to a total of 23,200. The restriction to the last five calendar years is made because the research field of mobile apps is still relatively new and technological developments are fast.

Sorted by relevance (at Google Scholar's discretion), the first 100 search results are then screened. The search results, which have probably been updated again and again in the meantime, can be called up at Google Scholar (2020).

Figure 7 shows the subsequent procedure according to the PRISMA statement (Moher et al., 2009).

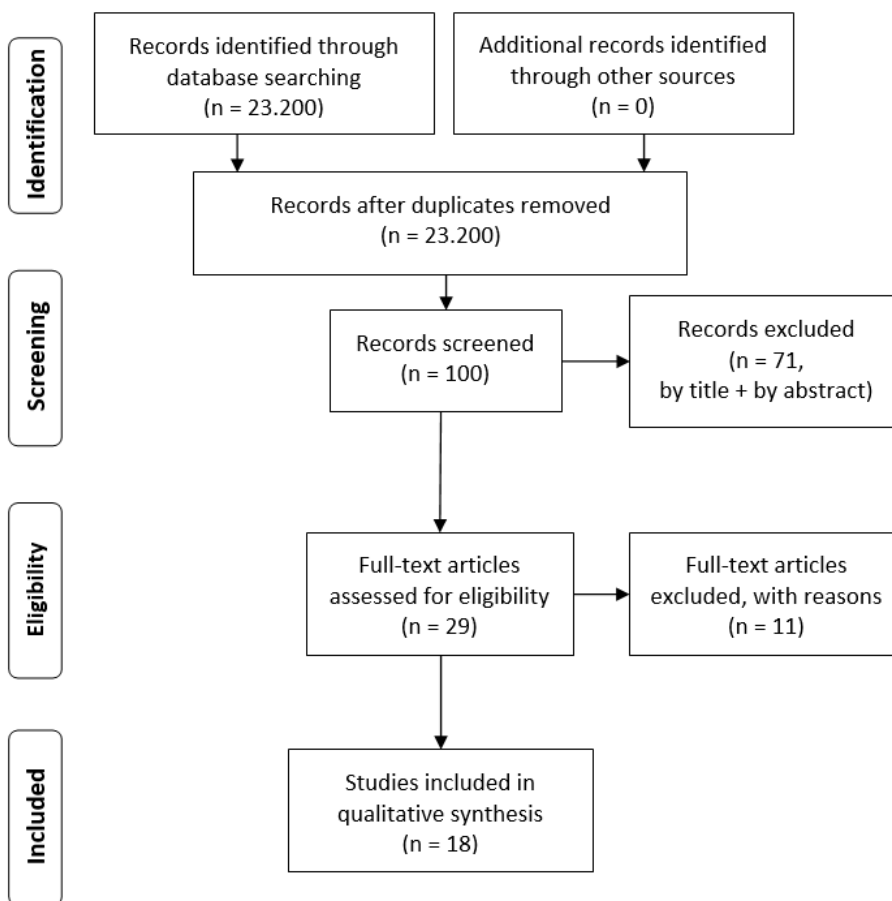


Figure 7: PRISMA statement (source: (Moher et al., 2009)).

In the first screening, only those items that have a clear link to the retail trade are included in the next step, the full-text assessment for eligibility.

This does not include articles on mobile banking (Thusi & Maduku, 2020) and purely technological concepts in the broadest sense (Moorhouse et al., 2018). Also articles from other business areas such as gastronomy have not been included (Kapoor & Vij, 2018).

In the subsequent full-text assessment, a further 11 of 29 articles are excluded. Examples of excluded articles are:

- an article that examines how a retailer in China can use the WeChat app as a mobile instant messaging application to build customer relationships. As this is not the retailer's own app, but the WeChat app is used as a third-party provider, the article is excluded (Vazquez et al., 2017).
- an article that examines web and app as access routes to the retail market in India. Because it is only a two-page case study, this article is also excluded (Vashisht et al., 2016).
- an article on mobile payment technologies in retail is also excluded: The article focuses on mobile payment and not on retail (Taylor, 2016).

After the full-text assessment and dropping eleven articles, 18 journal articles, books, book chapters and articles from conference proceedings are included in the qualitative synthesis.

5.1.3. Results

In the following, the articles are summarized in the context of the qualitative synthesis and references to the question of consumer acceptance factors are established. The review increases in chronological

order from year to year. Papers published in the same year increase in alphabetical order, according to the surname of the first author.

A study comparing technological innovations in retail via apps or via stationary installed devices comes to the conclusion, that previously piloted technical solutions have experienced rather moderate acceptance. Based on an online survey of consumers, the authors emphasize the importance of emotions. Also the importance of joy trying out new solutions is pointed out. At the same time, they also leave open what could drive consumer acceptance of mobile apps in retail in the long term beyond the mere joy of innovation (Kheiravar & Richter, 2016).

In a qualitative research with 29 consumers, Pantano & Priporas (2016) investigates the willingness of consumers to change their shopping behavior using mobile technologies. The authors consider this question for Italy and in particular against the background of click and collect procedures or so-called pick-up boutiques. They come to the conclusion that consumers would like to see more use of mobile apps as shopping aids. The stronger connection of mobile technologies with the physical store on site plays a strong role for consumer acceptance and thus for the long-term success of mobile apps in retail.

Parker & Wang (2016) investigate the motivation for app engagement in the context of a fashion retail app by means of 18 qualitative interviews within the framework of explorative research. They distinguish between hedonic and utilitarian motivations. As a result, they conclude that efficiency and convenience are the most important utilitarian motivators. They also stress the importance of personalized service and convenient operation processes. Their statement is important for the long-term

consumer acceptance of mobile apps in retail: The authors clearly distinguish themselves from the industry's usual focus on experiential interactions in this context.

Using a quantitative analysis of 272 shopping apps and a survey, Dacko (2017) investigates how the use of mobile augmented reality apps in retail can create added value for customers. The author finds that augmented reality technologies basically have the potential to improve the retail shopping experience and thus contribute to consumer acceptance.

By surveying 630 U.S. consumers and processing a SEM and an ANOVA, Kang (2017) investigates augmented reality apps in fashion retail in the USA. In particular, the impact of trust in AR applications on the use of these applications and visiting a retail store is investigated. As a result, it is concluded that novelty is positively related to trust and trust is positively related to the intention to visit a retail store. With this research, the author shows an important connection how mobile apps can help retailers to increase store visits. Therefore they emphasize engaging with existing app users. Consequently, trust in an app not only contributes to app usage but also to the increase of store visits.

A survey of 146 consumers using smartphones in retail stores was conducted to find differences by product category and gender. In particular, the authors find that high involvement product categories and young men are particularly affine to using smartphones and mobile apps in retail stores. This means that consumer acceptance of mobile apps in retail stores also depends on the context in which they are used (Eriksson et al., 2018).

Iyer et al. (2018) investigate the impact of mobile apps in retail and their impact on customer satisfaction in the multichannel environment. On the basis of collected user data they find out that hedonic and functional aspects have a positive effect on customer satisfaction. They also point out that the congruence between retailer image and mobile app leads to higher customer satisfaction. With regard to the long-term acceptance of mobile apps in retail by consumers, the importance of the image of a retailer is to be emphasized. Besides, hedonic and functional aspects play an important role.

Investigating the antecedents and consequences of mobile app engagement, the authors of Kim & Baek (2018) find that time convenience, interactivity and compatibility have a positive influence on mobile app engagement and can lead to a strengthening of self-branded connections. They confirm the importance of time convenience and practical benefits for long-term app usage by consumers.

A similar conclusion was reached by the authors of Newman et al. (2018): The authors examine the influence of consumer experiences with mobile retail apps on the intentions of use and recommendation. They also take into account channel preferences and purchasing behavior. They refer to retailers who sell via an app as well as via a store. They show that the perceived ease of use in particular has an effect on channel preferences and purchasing behavior as well as on future purchasing intentions. Their results underline the importance of a user-friendly implementation on consumer acceptance.

Trust, privacy, learning and relaxation features also play an important role. This can be derived from the work of Olaleye et al. (2018): The

authors compare models for the use and continuous use of mobile apps in retail and use the unified theory of acceptance and use of technology.

Examining mobile technologies as drivers of digital change in retail, a review of existing scientific literature and other popular sources conclude that digital channels such as mobile apps should not be understood as a mere distribution channel. Rather, the authors emphasize the importance of embedding them in a holistically thought-out multichannel strategy. In this respect, consumer expectations of mobile apps in retail should not only be considered from the perspective of a distribution channel. This might not be sufficient for long-term consumer acceptance (Shukla & Nigam, 2018).

Using eye tracking and scan path visualizations, the authors of Tupikovskaja-Omovie & Tyler (2018) capture consumer shopping behavior on smartphones in fashion retail. They identify various usability issues. Their work also emphasizes the importance of a user-friendly application and a development that is strongly oriented towards the needs and habits of the users. This can ensure the user acceptance.

Understanding the intention to reuse as an expression of long-term consumer acceptance, Lee & Kim (2019) demonstrates the importance of mobile app atmospherics. The authors develop and test a model to define the relationships between hedonic shopping orientation, consumer need for mobile apps atmospherics, entertainment gratification, mobile irritation and the intention to reuse mobile apps. In the context of apparel shopping, they develop a model, which they test with 216 US mobile shoppers between 18 and 34: The mobile app atmospherics plays a central role in the intention to reuse mobile apps.

In the context of the disruption of traditional retail through mobile technologies, Bodmeier et al. (2019) present various building blocks for the use of mobile in retail. They state that the exclusive adaptation of known e-commerce systems and functionalities is not sufficient to meet the needs of mobile digitization of stationary retail from the customer's perspective. Their results are decisive for the question of consumer acceptance of mobile apps in retail, since a mobile app of a retailer must offer more than just a shopping functionality.

A similar conclusion can be reached on the basis of a study that uses a cross-section survey to examine the impact of e-service quality on customer loyalty, using Zara and Mango as examples. The authors emphasize the importance of mobile app design, but also show that return handling policies and price offerings are important for customer loyalty. Their work is interesting for consumer acceptance in so far as, in addition to the app itself, the services of a retailer are also important to strengthen the long-term use of mobile apps by retailers (Rosa, 2019).

With a view to food retailing, Beeck et al. (2020) examine how mobile apps affect customer loyalty in this area. The authors work out that the perceived value of an app by users positively contributes to cognitive and conative loyalty. With a view to long-term user acceptance, this finding is central in that it emphasizes the importance of actual added value for the customer.

In a grocery store with the example of fresh salmon, the use of mobile apps as a tool to support the purchase decision is examined. The study uses a conjoint experiment with 90 participants. The authors find out that quality indicators of other customers as well as individual offers in

particular contribute to the usefulness of an app and thus contribute to a higher consumer acceptance (Fagerstrøm et al., 2020).

The last paper considered here shows the antecedents and consequences of consumer confidence in mobile retails apps in India. Using a SEM and data from a survey of 567 participants, the authors show that previous consumer experience, the usefulness of an app, the ease of use and quality of the app, and the reputation and offline presence of an organization have a positive impact on consumer trust in mobile apps. They emphasize the central role of trust in the adoption of apps in retail. At the same time, they emphasize that the app alone is not enough, but that the retailer also contributes significantly to consumer acceptance of mobile apps in retail (Kaushik et al., 2020).

5.1.4. Summary and Discussion

For this systematic review on the question, which determinants affect the consumer acceptance of mobile apps in retail, a total of 18 were filtered out and analyzed for the qualitative synthesis on the basis of initial 44,800 papers.

First of all, it should be emphasized that the acceptance of a mobile app in retail always depends on the specific context in which it is used - product categories with a high level of involvement are particularly suitable for the use of mobile apps (Eriksson et al., 2018).

In summary, the acceptance of mobile apps in retail is primarily determined by expected efficiency gains, practical benefits and user-friendliness (S. Kim & Baek, 2018; Parker & Wang, 2016; Tupikovskaja-Omovie & Tyler, 2018). The perceived value of an app plays a major role, especially for long-term consumer acceptance (Beeck et al., 2020).

The role of trust and respect for privacy are also described as determinants (J.-Y. M. Kang, 2017; Kaushik et al., 2020; Olaleye et al., 2018) and can even contribute to increasing store visits (J.-Y. M. Kang, 2017). These results do not particularly differ from previous findings on consumer acceptance of mobile apps in general.

From a functional point of view, mobile apps in retail should not only represent a distribution channel (in the sense of m-commerce), but should rather be understood and developed as digital shopping assistants for in-store shopping. A mobile app as a pure online shopping tool without any reference to the stationary point of sale is not sufficient for long-term consumer acceptance (Bodmeier et al., 2019; Pantano & Priporas, 2016; Shukla & Nigam, 2018).

It is also noteworthy that the retailer itself, as a brand and with the services it offers, apparently also has a major influence on consumer acceptance of the mobile app it offers, as is repeatedly emphasized (Iyer et al., 2018; Kaushik et al., 2020; Rosa, 2019).

Regarding the limitation it is to be noted that Google Scholar is a comprehensive, but also quite broad database. In particular when sorting the search results by relevance, Google Scholar's definition was used. The search engine's understanding of relevance is not necessarily consistent with other bibliographic methods and is not completely transparent.

Regarding the remaining research gaps, two aspects in particular are identified. First, there seem to be different user typologies in the use of mobile apps in retail, as a certain joy of trying new innovations identified by Kheiravar & Richter (2016) or the use of an app as an online store or digital shopping assistant outlined by Bodmeier et al. (2019) and Shukla

& Nigam (2018) suggest. Secondly, the question arises as to what specific functionality retailers are trying to use to meet this consumer demand.

5.1.5. Conclusion

The aim of this paper was to present current scientific findings on the determinants of consumer acceptance of mobile apps in retail by means of a systematic review. Using the scientific database Google Scholar a total of 18 current journal articles, articles from conference proceedings and book chapters were identified in a qualitative synthesis.

It can be stated that many determinants in the case of mobile apps in retail are similar to those of mobile apps in general: User friendliness, added value for the user and user trust in the app play essential role. In addition, the retailer offering the mobile app is particularly important for mobile apps in retail. The strength of their brand, a positive image and the service offered also have a positive impact on the acceptance of the mobile app.

The functionality of the mobile app should be emphasized in particular: Consumers expect less of a sales channel in the sense of a mobile online store, but rather a digital shopping assistant that helps them with their local retail purchases.

At the same time, the results shown also raise the question of different user typologies of mobile apps in retail and the question of the concrete answer to the expectation of a digital shopping assistant in terms of concrete features.

5.2 Influence of the Net Promoter Score of Retailers on the Willingness of Consumers to Install Their Mobile App

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Abstract — Mobile apps have become increasingly important in the retail sector in recent years. A central challenge for retailers is the acquisition of new users for their mobile apps. A potentially interesting target group for this can be a company's existing, satisfied customer base, whereby customer satisfaction is often measured by the willingness to recommend the app or the Net Promoter Score. This paper investigates the influence of the willingness to recommend a retailer by consumers on their willingness to install a mobile app from this retailer. The influence of usage habits is also examined. The analysis of a survey of 105 consumers on a total of five retailers can confirm the hypotheses regarding the willingness to recommend a retailer and the Net Promoter Score (NPS) in particular: With the willingness to recommend, the willingness to install a retailer's app also increases.

5.2.1. Introduction

In recent years, the worldwide distribution of smartphones and consequently the distribution of mobile apps has increased significantly (Eurostat, 2016). Apart from access to the Internet, apps are among the

most frequently used and most important functionalities of smartphones (VuMA, 2017). Meanwhile they are used in many areas of life, some health, vacation, education or retail (BITKOM, 2020; gfs.bern, 2020; Kalogiannakis & Papadakis, 2017). Accordingly, many companies have high expectations of increasing customer loyalty through their own mobile apps, so more and more companies are publishing their own mobile apps (BITKOM, 2011). In 2019, the number of mobile apps available in the Google Play Store for the Android operating system was around 2.46 million (Appfigures, 2019).

This wide range of mobile apps means correspondingly high competitive pressure, which makes it increasingly difficult to acquire new app users via the usual stores of the operating system providers, while companies' expectations of the release of a mobile app continue to rise (BITKOM, 2019b). In the retail sector in particular, mobile apps offer numerous opportunities for sales activities due to their ability to address customers location-based (Allurwar et al., 2016; Verma & Verma, 2013). Active application users are also expected to generate higher sales in stationary retail (Dinner et al., 2015), which makes an app an interesting additional offer for stationary retailers to their customers.

Especially for companies that offer a mobile app for smartphones as a supplement to other access and distribution channels, it may therefore make sense to consider ways of generating users that go beyond presenting the app in an app marketplace. It would be conceivable here, for example, to distribute paid advertising via channels such as display advertising or to address the company's own existing customer or user base via other channels. For retailers with an associated distance selling business, the catalogue or, in e-commerce, especially the web shop would

be conceivable as a channel. The selection of the right target group is one of the challenges. Existing research suggests that users are more willing to adopt an app if they have a strong relationship with the brand behind the mobile app (Peng et al., 2014). Because mobile apps are used by a wide variety of people, it is difficult to generalize about the factors that contribute to the adoption of companies and services (Ghnemat & Jaser, 2015). In addition, in the area of education, for example, the acceptance of apps is also influenced by people's socioeconomic backgrounds (Papadakis et al., 2019).

Against this background, this paper examines in the specific context of retail how consumer satisfaction with a retailer affects the willingness to install a mobile app offered by the retailer. Customer satisfaction is measured with the Net Promoter Score (NPS), which is widely used in practice (Fisher & Kordupleski, 2019; Reichheld, 2003). On the basis of the existing literature, hypotheses are formulated, especially after critical evaluation of the NPS, and checked by means of several regression analyses. The usage habits of smartphone users in general and in the specific context of retail are also taken into account.

5.2.2. Literature Review

The literature review first considers existing findings on the consumer adoption and usage of mobile apps. This is followed by a review of the literature on the Net Promoter Score, which is also critically evaluated here. Finally, hypotheses for the later investigation are formed.

Consumer Adoption and Usage of Mobile Apps

The adoption of a mobile app by consumers and its active use is mainly highlighted in the literature as a trade-off between effort and benefit or

expected added value. Potential app users weigh up the costs and benefits against each other to determine whether they want to use an app continuously (S. Kang, 2014). The benefits of an app can lie, for example, in time convenience and interactivity, which both have a positive influence on consumer engagement with the application (S. Kim & Baek, 2018). The attitude of consumers towards a particular app has a direct effect on their intention to actually use it. In contrast to this are negative emotions related to an app, which have a correspondingly negative effect on their intention to use it on a long-term basis (Ding & Chai, 2015). In return, the benefits that a branded app offers pay off positively on the willingness of app users to recommend the app to others (Stocchi et al., 2018).

Overall, the brand of a company with all its facets, such as the brand attachment and the consumer's brand identification, is of great importance in connection with consumer adoption and the use of mobile apps. The use of a mobile app pays off positively on the brand attitude and product category involvement of app users (Bellman et al., 2013). A study on the impact of brand attachment and brand identification in the financial sector in Taiwan also shows, that they have a positive effect on mobile app adoption (Peng et al., 2014). Wu (2015) also emphasizes that in addition to effort and performance expectancy, brand identification also has an effect on the active use of mobile apps.

Particularly noteworthy is the work of Jham (2018) regarding to the question of the overall effect of satisfaction with a company on the willingness to install its app. The authors find that the trust, users generally place in a company helps to create trust for the mobile app published by the company (Jham, 2018). In addition to this, it can be

noted that respect for the privacy of app users, for example, can be seen as a confidence-building factor that is conducive to adoption (Belkhamza & Niasin, 2017; Wang et al., 2014).

Measuring Customer Satisfaction using the Net Promoter Score

Although many factors related to user satisfaction with mobile apps are known, it is not possible to generalize across different industries or countries without restriction. The reason therefore is, that mobile apps are now published practically worldwide and for a wide variety of purposes (Ghnemat & Jaser, 2015). In this respect, app development adapted to the customers of the respective company that wants to publish an app is an important component to increase the satisfaction of existing users (Hussain et al., 2019). However, it is unclear how customer satisfaction with the company can affect the acquisition of new app users when acquiring them from the existing customer base of a company. This requires a simple method for measuring customer satisfaction.

The Net Promoter Score (NPS) was introduced in 2003 as "The One Number You Need to Grow" for measuring customer satisfaction. At its core is the question to customers, how probability they would recommend a company, a brand or a service to a friend or colleague. The respondents give their answer on a scale of 0 (unlikely) to 10 (very likely), where those who answer with 9 or 10 are called promoters. Those who answer with 0 to 6 are called detractors, and those who answer with 7 or 8 are called indifferent. Finally, the NPS is calculated as the difference between the proportion of promoters and detractors and can thus lie between +100 (promoters only) and -100 (detractors only) percent (Reichheld, 2003).

The basically simple method of the NPS (cf. Korneta (2018)) is also critically discussed in science - especially against the background of its application for measuring customer satisfaction. The NPS, for example, does not live up to its claim as the only necessary metric for measuring customer satisfaction (Fisher & Kordupleski, 2019) and is also not suitable as a method for measuring customer loyalty (Kristensen & Eskildsen, 2014). In particular, the NPS can only be one of several methods for measuring customer satisfaction (Korneta, 2018; Laitinen, 2018; Leisen Pollack & Alexandrov, 2013; Mandal, 2014), especially since the NPS alone does not provide any insights into concrete improvement potentials (Laitinen, 2018). It is also noteworthy that, for example, the survey method, i.e. the channel on which customers are asked to rate seems to have an influence on the NPS (Temple et al., 2020). Similar observations were also made for gender (Eskildsen & Kristensen, 2011).

Despite all the criticisms, NPS has been used several times from the beginning, not only in practice but also in research (Eger & Mičik, 2017; Inal, 2018; Korneta, 2018; Kristensen & Eskildsen, 2014; Laitinen, 2018; Leisen Pollack & Alexandrov, 2013; Mandal, 2014). Originally developed by Reichheld (2003) as a measure correlating with company growth, satisfaction the NPS is repeatedly used as a method for measuring customer, here expressed by the intention to recommend it as the highest form of customer satisfaction (Dvořáková & Faltejsová, 2016; Inal, 2018; Kristensen & Eskildsen, 2014). In this respect, the NPS may be regarded as one of the most popular methods in business practice for measuring customer satisfaction.

Hypothesis

Based on existing findings on the adoption and use of mobile applications, a number of hypotheses are derived below. The formulated hypotheses are tested empirically in our research.

The basis are the research results, which emphasize the importance of the brand and consumers' attachment to the brand and the trust of consumers in a company for mobile app adoption. Accordingly, the hypothesis is derived that the willingness to recommend a company increases the willingness to install an app of this company (Bellman et al., 2013; Jham, 2018; Peng et al., 2014; Wu, 2015):

H1: The willingness of consumers to recommend a company increases the willingness of consumers to install an app from that company.

Similarly, it is assumed that the NPS calculated by Reichheld (2003) from the willingness to recommend a company, increases the willingness to install its app, since a high NPS can be considered as an indication of highly satisfied customers (Dvořáková & Faltejisková, 2016; Reichheld, 2003):

H2: With the NPS related to a company, the willingness to install an app of this company increases.

The activity of app users also increases the turnover generated in online and stationary retail trade (Dinner et al., 2015) and those users who have a particular affinity for the internet and shopping are likely to benefit from installing a mobile app for this purpose (S. Kang, 2014). Regarding to that, the following hypotheses are also put forward on how people's

internet usage and online shopping habits affect their willingness to install a mobile app from a stationary retailer (Dinner et al., 2015):

- *H3a: The willingness to install an app from a retailer increases with the frequency of Internet use.*
- *H3b: The willingness to install an app from a retailer increases with the frequency of smartphone use.*
- *H3c: The willingness to install an app from a retailer increases with frequency of mobile internet use.*
- *H3d: The willingness to install an app from a retailer increases with online shopping frequency.*
- *H3e: The willingness to install an app from a retailer increases with mobile online shopping frequency.*

In addition, the phenomenon found by Eskildsen & Kristensen (2011) that the NPS differs according to gender will be examined. Accordingly, a gender-specific hypothesis will be formulated:

H4: There is a significant difference in the willingness to recommend the NPS depending on the gender of the respondents.

5.2.3. Empirical Research

In the following, first the study design and data collection are described, followed by a description of the statistical methods used to analyze the data.

Survey Design and Data Collection

Using an online questionnaire conducted between January and May 2020 in Germany, we examined the formulated hypotheses.

For this purpose, consumers in Germany were first identified by gender and age.

Subsequently, they will be asked about the frequency of use of a) the internet, b) the smartphone, c) the internet on the smartphone, d) online shopping, e) mobile online shopping. The respondents are asked to rate the frequency of use on a scale of 1 (very rarely) to 6 (very often).

In the next step, respondents are asked to indicate, for a total of five retailers in Germany, the extent to which they are willing to recommend them to friends or colleagues. In the style of the NPS, the information is given on a scale of 1 (very unlikely) to 10 (very likely).

For the same five retailers, the final step is to ask to what extent respondents are willing to install an application from these retailers. This question is asked for each retailer, with the answers being given on a scale of 1 (very unlikely) to 6 (very likely). In addition, the respondent may indicate that the application has already been installed (which is rated 7 in the later statistical evaluation and analysis).

The questionnaire was answered a total of 113 times, leaving 105 valid responses with incomplete questionnaires. Figure 8 shows the distribution of answers by gender and age group. It should be noted that the group of 20 to 29 year olds is particularly strongly represented. In contrast, the age groups over 40 years of age are hardly represented.

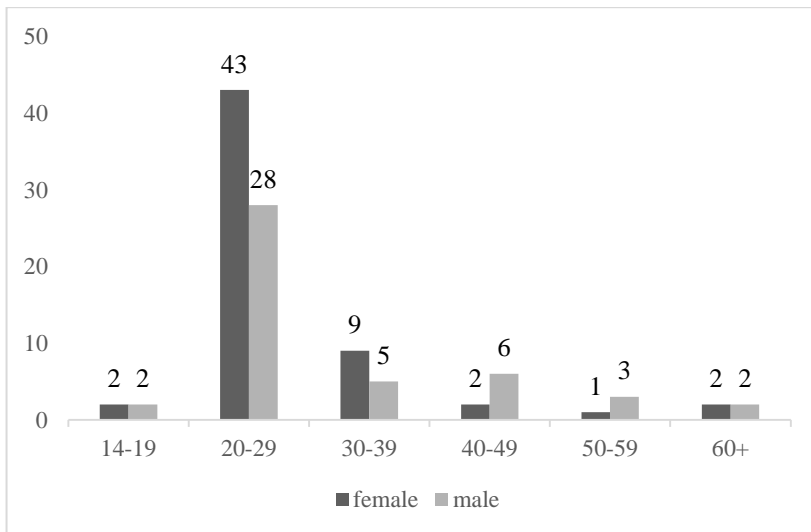


Figure 8: Number of replies by age group and gender, based on collected survey data.

In addition, Figure 9 shows the average recommendation probability or the average installation probability of an app by retailers. Here it is particularly noteworthy that for all retailers on average the willingness to recommend is higher than the willingness to install an app from the particular retailer.

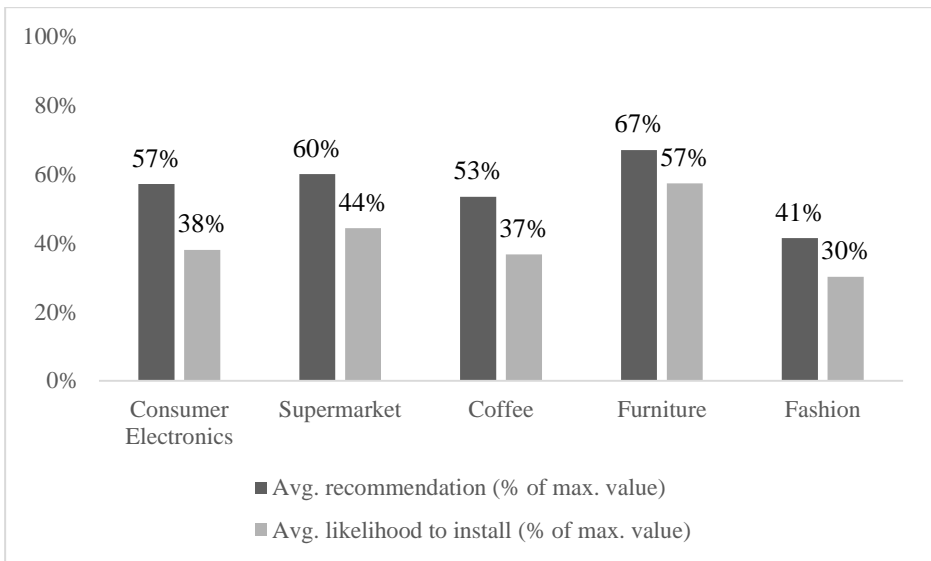


Figure 9: Recommendation and installation – average values per retailer, based on collected survey data.

For better comparability, the values in Figure 9 are given as a percentage of the maximum achievable value (recommendation: 10; app installation: 6).

Methodology

In order to test the hypotheses *H1*, *H2* and *H3a-H3e*, regression analyses are carried out, whereby a linear relationship is assumed between the willingness to recommend or the NPS or the variables on usage habits and the willingness to install an app. The latter represents the respective dependent variable.

Using simple linear regression analysis, we investigate how the independent variable (i.e. the willingness to recommend or variables on usage habits) affects the dependent variable of the willingness to install an app (Freedman, 2009). Using the ordinary least squares method (OLS), an attempt is made to show the relationship between the two variables under

investigation in a linear relationship. The deviations of the calculated regression line from the values actually observed should be as small as possible.

The results of each regression analysis are evaluated and interpreted in several steps: An F-test is used to check the overall quality of the model (null hypothesis: all coefficients are equal to 0). The empirical coefficient of determination R^2 checks the extent to which the model with its independent variables explains the variance of the dependent variable. The individual regression coefficients give magnitude over the strength of the relationship, with the p-value of the t-statistic of the regression coefficient indicating whether the individual regression coefficient has a significant influence on the dependent variable (Schneider et al., 2010).

In order to test hypothesis $H4$, we will first examine the extent to which both groups (male, female) show equal variances. To test the equality of the variances, a Levene test for homoscedasticity is performed (null hypothesis: the variances of the samples are equal) (Levene, 1960). Then, if the variance in the populations is equal, a two-sample t-test is performed, or if the variance is unequal, a Welch test is performed (null hypothesis in each case: the mean values of the populations are equal (Student, 1908; Welch, 1947)). As a result, a statement can be made as to the extent to which $H4$ that the NPS differs depending on gender, is to be accepted or rejected.

5.2.4. Results

The results of the statistical evaluation for the individual hypotheses are presented below.

Willingness to Recommend and to Install

First of all it is checked to what extent the willingness to recommend has an effect on the willingness to install an app.

H1: The willingness of consumers to recommend a company increases the willingness of consumers to install an app from that company.

Table 3 shows the results of the linear, simple regression analysis. The model explains the influence of the willingness to recommend an app installation significantly ($F = 258.26, p = .0000$). The model explains one third of the variance of the dependent variable ($R^2 = .3306$).

Table 3: Regression results for *H1*, based on collected survey data.

Source	SS	df	MS	Number of obs	525
Model	535.85	1	535.85	F (1, 523)	258.26
Residual	1085.15	523	2.07	Prob > F	.0000
Total	1621.00	524	3.09	R-squared	.3306
				Adj R-squared	.3293

Like_AppInst	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]
Like-Recommend	.3749	.0233	16.07	.000	.3291 .4208
_cons	.3856	.1446	2.67	.008	.1016 .6696

The result shows that with the readiness of a recommendation the readiness of an app installation increases significantly ($\beta = .3749, t = 16.07, p = .000$). When interpreting these results, it is important to note that the willingness to install an app was measured on a scale of 1 to 6.

NPS and Willingness to Install

To test the second hypothesis, which examines the connection between (company-related) NPS and the willingness to install apps, the NPS is calculated for each company.

H2: With the NPS related to a company, the willingness to install an app of this company increases.

For the purpose to test the connection between NPS and willingness to install apps, the share of detractors is deducted from the share of promoters. At the same time the average willingness to install an app is calculated for each company. Then a simple regression analysis is calculated.

Table 4 shows the number of detractors, indifferents and promoters as well as the NPS and the average likelihood to install an app from that company.

Table 4: NPS and likelihood to install app per merchant, based on collected survey data.

	M1	M2	M3	M4	M5
Detractors	61	47	64	44	82
Indifferent	35	48	25	28	17
Promoter	9	10	16	33	6
NPS	-49.5238	-35.2381	-45.7143	-10.4762	-72.3810
Avg. Likelihood to install	2.2762	2.6667	2.2000	3.4381	1.8095

The subsequent regression examines the influence of the NPS on the average willingness to install an app of this merchant.

Although the number of cases is very low at 5 for a linear regression and well below the value of 20 recommended for a regression analysis with an independent variable, the results can be interpreted due to the good F-test ($F = 67.46$, $p = .0038$), the high R^2 ($R^2 = .9574$) and significant result of the independent variable ($t = 8.21$, $p = .004$) (cf. Schneider et al. (2010)).

Table 5: Regression results for *H2*, based on collected survey data.

Source	SS	df	MS	Number of obs	5
Model	1.45	1	1.46	F (1, 3)	67.46
Residual	.06	3	.02	Prob > F	.0038
Total	1.52	4	.38	R-squared	.9574
				Adj R-squared	.9432

Like_AppInst	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]
NPS	.0268	.0033	8.21	.004	.0164 .0372
_cons	3.6211	.1539	23.53	.000	3.1313 4.1110

The results show a significantly positive influence of NPS on the willingness to install a retailer's app ($\beta = .0268$, $t = 8.21$, $p = .004$). It should be noted here that the NPS is measured on a scale of -100 to +100, while the readiness to install the app is measured on a scale of 1 to 6 (cf. Table 5).

For example, if it were possible to convert 10 detractors to indifferent customers for M1, the NPS would increase from -49.5238 to -40.0014. As a result, the willingness to install an app for this retailer would increase by about 0.2679 points - an increase of more than 10 percent measured by the respondents' current willingness to install the retailer's app (see Table 4).

Habits of Use

A multiple linear regression is used to investigate possible correlations between the respondents' usage habits and the willingness of the retailers mentioned to install the app. Table 6 shows the results of this regression analysis.

The model can be regarded as significant overall ($F = 15.32, p = .0000$), but has a lower explanatory power compared to the willingness to recommend or NPS models ($R^2 = .1286$).

Table 6: Regression results for $H3a - H3e$, based on collected survey data.

Source	SS	df	MS	Number of obs	525
Model	208.50	5	41.70	F (5, 519)	15.32
Residual	1412.49	519	2.72	Prob > F	.0000
Total	1621.00	524	2.09	R-squared	.1286
				Adj R-squared	.1202

Like_AppInst	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]	
Freq_IntUse	-.3890	.0939	-4.14	.000	-.5734	-.2046
Freq_PhoneUse	-.0578	.1151	-0.50	.616	-.2838	.1683
Freq_IntPhoneUse	.0729	.0893	0.82	.415	-.1025	.2483
Freq_IntShop	-.1164	.0788	-1.48	.140	-.2713	.0384
Freq_PhoneShop	.4191	.0694	6.04	.000	.2828	.5554
_cons	3.7126	.4226	8.79	.000	2.8824	4.5427

Only the frequency of shopping with the mobile phone explains the willingness to install an app significantly and in the sense of the hypotheses ($\beta = .4191, t = 6.04, p = .000$).

The frequency of Internet use has a significant influence on the willingness to install an app, but contrary to the hypothesis $H3a$, this is even negative ($\beta = -.3890, t = -4.14, p = .000$).

Table 7: Results of analysis regarding usage habits, based on collected survey data.

Hypothesis	Result
<i>H3a: Internet usage</i>	Rejected – Negative influence
<i>H3b: Smartphone usage</i>	Rejected
<i>H3c: Mobile internet usage</i>	Rejected
<i>H3d: Online shopping frequency</i>	Rejected
<i>H3e: Mobile online shopping frequency</i>	Accepted

Gender-Dependent Differences

The fourth hypothesis, derived from the work of Eskildsen & Kristensen (2011), postulates differences in the willingness to recommend the study depending on the gender of the respondents:

H4: There is a significant difference in willingness to recommend depending on the gender of the respondents.

To test the hypothesis, a two-sample t-test is performed assuming equal variances. For this purpose, the mean values of the willingness to recommend the test depending on gender are formed and compared with each other.

Table 8 shows the number of observations, mean value of willingness to recommend and variance of the same for both groups.

Table 8: Willingness to recommend by gender, based on collected survey data.

	Male	Female
Number of observations	230	295
Mean	5.0043	6.0305
Variance	7.2009	6.8936

Using the Levene test, the condition of equal variances of the two groups, male and female, is first checked. The null hypothesis that the variances of the groups are equal is not rejected ($F=.649$, $p=.421$).

In the subsequent t-test, the null hypothesis that the mean values of the two groups are equal is rejected ($t=4,404$, $p=.0000$).

The hypothesis *H4* that there is a significant difference in the willingness to recommend is considered confirmed.

5.2.5. Summary

Altogether, the study examined hypotheses from four areas on the influence on the willingness to install an app by a retailer.

In particular, the hypotheses at the core of this study, that the willingness to recommend (*H1*) and the NPS (*H2*) have a positive effect on the willingness to install an app, can be confirmed.

Also the result of the work of Eskildsen & Kristensen (2011) that there are gender dependent differences in NPS (*H4*) could be confirmed.

Table 9: Summary of the results, based on own statistical evaluation.

Hypothesis	Result
H1: Recommendation	Confirmed
H2: NPS	Confirmed
H3a: Internet usage	Rejected – Negative influence
H3b: Smartphone usage	Rejected
H3c: Mobile internet usage	Rejected
H3d: Online shopping frequency	Rejected
H3e: Mobile online shopping frequency	Confirmed
H4: Gender-dependent differences	Confirmed

The results are less clear with regard to usage habits: Here, only the positive influence of the frequency of online shopping via mobile phone on the willingness to install the app could be confirmed (*H3e*). Smartphone usage frequency, mobile Internet usage frequency and online shopping frequency, on the other hand, have no significant influence (*H3b - H3d*). Internet usage frequency even has a negative effect on the

willingness to install a retailer's mobile app (*H3a*). Table 9 summarizes the results of the analysis for all hypotheses.

With regard to the limitations of this elaboration, the thematic and geographical focus and the survey method are to be named in particular. Thus, the survey conducted here asks for the willingness to recommend or install an app by means of a questionnaire and asks the interviewees to give their own assessment when assessing their usage habits. As is usual with such surveys, however, the actual recommendation or installation or the actual usage habits observed in a quantifiable manner are not collected.

With regard to the thematic and geographical focus, it should be noted that the data collected was collected exclusively in Germany and exclusively for the retail trade. In this respect, the transferability of the results to other sectors or countries is not possible without further examination.

Methodologically, the hypothesis *H2*, which examines a correlation between NPS and app installation readiness at the retailer level, should be tested: Since the survey asked for the values of only five retailers, the corresponding regression analysis is carried out with a very small number of cases. Although the evaluations on the quality of the model are consistently positive, these results cannot be transferred without restrictions either.

5.2.6. Conclusion

The aim of the elaboration is to investigate the connection between the willingness to recommend a retailer and the willingness to install an app of this retailer.

After an introductory explanation of the relevance of mobile apps in the corporate context and in the retail sector in particular, a review of the existing literature shows that up to now, the willingness to recommend a company or to recommend an app as a target variable has been investigated. However, how the willingness to recommend a retailer affects the willingness of consumers has not been investigated so far. In particular the elaboration of Jham (2018) suggests, however, that - analogous to the trust that is transferred from companies to apps - the willingness to recommend or the NPS could have a positive effect here.

The data collected in the course of the study and evaluated by means of statistical methods can confirm this assumption and thus make a valuable contribution to the business practice of acquiring new App users: Especially the existing, satisfied customer base of a company is a promising target group if new App users are to be acquired with limited resources.

The investigation of the willingness to install apps in relation to usage habits shows in most cases that the hypotheses put forward have to be rejected. Only those customers of a company who have a particularly high affinity for shopping via the smartphone represent a potentially attractive target group for advertising campaigns for the marketing of a retailer's mobile app.

Three things can be regarded as interesting for further research projects: Firstly, the examination of the extent to which the results can be transferred to sectors other than retail or to countries other than Germany; secondly, with regard to the NPS per retailer, a renewed, more comprehensive investigation with more retail companies; thirdly, the

validation of the results determined here in the context of a case study in applied business practice.

5.3. Frequency of Generic Push Notifications From Mobile Apps in Retail and the Effect on Uninstalls and App Opens

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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.

5.3.1. 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, Dirrler, et al., 2020).

A central function of smartphone apps from a company's point of view are push notifications: 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 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 and app uninstalls is quantified.

5.3.2. Literature Review

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).

Nevertheless, literature also emphasizes that notifications from software in general, but also from smartphone apps in particular, have the potential to 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 more busy 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). Literature therefore 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's 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). Corresponding programming libraries exist which 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's 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.*

5.3.3. 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 then the 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 (5:30pm). 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. Due to technical reason, notifications can only be sent to users which 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 more cozy”
- “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 10 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 10: Start-end-comparison of recipients, direct opens and indirect opens per frequency group, based on observed user behavior.

Frequency	Recipients		Direct Opens		Indirect Opens	
	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 11 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, an exception is the direct open rate of users how haven't received any notifications during the experiment.

Table 11: Start-end-comparison of direct open rate and indirect open rate per frequency group, based on observed user behavior.

Frequency	Direct Open Rate		Indirect Open Rate	
	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 ($X^2 (1, N = 7,000) = .4342, p = .5099$).

5.3.4. 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 uninstall increases.

Table 12 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 ($R^2 = .9436$).

Table 12: Uninstall rate determined by frequency – regression results, based on collected survey data.

Source	SS	df	MS	Number of obs	
Model	.0016	1	.0016	F (1, 3)	50.17
Residual	.0001	3	.0000	Prob > F	.0058
Total	.0017	4	.0004	R-squared	.9436
				Adj R-squared	.9248

UninstallRate	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]	
MsgPerWeek	.025	.0035	7.08	.006	.0138	.0362
_cons	.0185	.0036	5.09	.015	.0069	.0301

According to the results of the regression analysis, one additional message per week increases the uninstall rate by 2.50 percentage points over the experiment period ($\beta = .0250, t = 7.08, p = .006$). Without a single message, the uninstall rate during the experiment period is 1.85 percent ($\beta = .0185, t = 5.09, p = .015$) 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 13 shows the results of the regression analysis. 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 ($R^2 = .8178$).

Table 13: Direct open rate determined by frequency – regression results, based on collected survey data.

Source	SS	df	MS	Number of obs	5
Model	.0401	1	.0401	F (1, 3)	13.46
Residual	.0090	3	.0030	Prob > F	.0350
Total	.0491	4	.0123	R-squared	.8178
				Adj R-squared	.7570

DirectOpenRate	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]
MsgPerWeek	-.1267	.0345	-3.67	.035	-.2366 - .0168
_cons	.9332	.0356	26.22	.000	.8200 1.0466

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, an interpretation of the constant is only of limited use.

The effect of frequency on the direct open rate decreases as assumed in *H2* ($\beta = -.1267$, $t = -3.678$, $p = .035$). One notification more per week

decreases the direct open rate by 12.67 percent, comparing the beginning and the end of the experiment.

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 14, $F = 8.65$, $p = .0605$). Nevertheless, the explained variance of the dependent variable by the model is still to be considered relatively high ($R^2 = .7425$).

Table 14: Indirect open rate determined by frequency – regression results, based on collected survey data.

Source	SS	df	MS	Number of obs	5
Model	.0167	1	.0167	F (1, 3)	8.65
Residual	.0058	3	.0019	Prob > F	.0605
Total	.0225	4	.0056	R-squared	.7425
				Adj R-squared	.6566

IndirectOpenRate	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]
MsgPerWeek	-.0818	.0279	-2.94	.060	-.1704 .0067
_cons	.9502	.0287	33.13	.000	.8590 1.0415

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, 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 15).

Table 15: Comparison of regression results for direct and indirect opens, based on collected survey data.

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 16: Summary of experiment results, based on own statistical analysis.

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

Table 16 summarizes the results of the hypothesis tests. Apart from *H3*, the experiment shows evidence to confirm all hypotheses stated.

5.3.5. Discussion

In the following, the contribution to scientific theory and the practical implications are summarized. Subsequently, the limitations of this paper are pointed out and suggestions for further research needs are made.

The existing literature has already examined the 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 the best knowledge of the authors this is the first time in research examining this question 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 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. In further investigations, those metrics should be taken into account as well in order to create an 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 researched 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.

5.3.6. Conclusion

This paper investigates the impact of the frequency of push notifications 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 our 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.

Secondly, 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.

Thirdly, the results for *H3* indicate no negative effect of a 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, app publisher may be able to reach out to their app users more frequently without negative implications here.

5.4. Recommending a Retailer's Mobile App – Influence of the Retailer and the Mediating Role of Push Notifications

This paper is forthcoming and will be originally published as

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Abstract — Against the backdrop of increasing digitization, many retailers are trying to better reach their existing customers with the help of mobile apps. For the growth of an app and the satisfaction with it, the willingness to recommend this app by existing users is of great importance. This paper develops a structural equation model that relates the willingness to recommend a retailer's mobile app to consumer perceptions of that retailer, including the role of push notifications as a mediator. The collected data show a significant relevance of the perception of the retailer on the willingness to recommend the app to others. It can be shown that this relationship is partially mediated by the perception of the retailer's app push notifications. In this respect, all hypotheses stated can be confirmed. Further research questions are proposed and include in particular a validation of the model in other socio-demographic compositions as well as in the context of a field study and the expansion of the model.

5.4.1. Introduction

With the digitalization in retail, not only e-commerce is growing but also consumers expect retailers to offer both online and offline sales channels and to network them with each other (Adler & Wohllebe, 2020; Ewerhard et al., 2019). Mobile devices are fundamentally changing consumers' shopping behavior, making mobile shopping the new standard of shopping (Pantano & Gandini, 2017). Accordingly, the relevance of mobile apps is growing not only in retail but also in many other sectors (Papadakis et al., 2018; Ross, 2020; Wohllebe, Dirrler, et al., 2020). Studies show a positive impact on customer sales (Heerde et al., 2019). Push notifications to reach app users with advertising draw customers' attention to exclusive promotions or discounted products, for example (Ahrholdt et al., 2019, p. 161). At the same time, however, retailers risk disturbing their users with the notifications and thus harming their business (Wohllebe, 2020).

In order to meet high expectations of retailers for mobile applications, user acquisition is a key challenge. As customers being satisfied with a company are more likely to recommend it to others, it is conceivable that satisfaction with a retailer may lead existing users to recommend that retailer's app to others. Thus, satisfied customers of a retailer who use the retailer's app can contribute to its growth.

This study therefore investigates how the perception of a retailer and the perception of its push notifications affect consumer's willingness to recommend that retailer's app.

5.4.2. Literature review

Recommendation of mobile apps

The role of recommendation of products, brands and companies is interesting in several ways. In a direct way, recommendation is a form of word-of-mouth and leads to more people being aware of what is being recommended. In addition, there are - quite controversial - approaches that proclaim the management of an entire company based on the willingness to recommend (Reichheld, 2003). Furthermore, recommendation is an indirect expression of customer satisfaction; recommendation and satisfaction are closely related (Luo et al., 2019; Siqueira et al., 2019).

Recommendation as a dependent variable is repeatedly investigated in the context of mobile apps. Factors such as respect for privacy and the added value can be named as indirect influencing factors on recommendation (Xu et al., 2015). In particular, however, customers who are particularly satisfied with an app are more likely to recommend it to others (Peng et al., 2014; Xu et al., 2015). Iyer et al. (2018) demonstrate congruence between a retailer image and a retailer mobile app.

H1: The app user's perception of a retailer positively influences the probability of the app to be recommended.

Perception of retailers

The retailer's brand is of central importance in determining how consumers perceive a retailer. A strong brand or a positive attitude of the consumer towards the retailer's brand promotes the purchase intentions of the consumer. (Park et al., 2015). Customer satisfaction is of great importance in this context (Pappu & Quester, 2006). Also there is a congruence between retailer image and mobile app of a retailer (Iyer et

al., 2018). Customer satisfaction manifests itself in the question of whether a consumer likes to buy from a retailer.

Another key factor in the perception of a retailer is the extent to which customers have had good experiences with it. Good experiences are not only important for customer satisfaction (Vakulenko et al., 2019). Furthermore, good experiences lead to brand attachment and can thus increase the intention to continuously use a retailer's mobile app (Li & Fang, 2019). Customer satisfaction is a mediator of the influence of the corporate image on the behavioral intention to repurchase. (Yu & Ramanathan, 2012). In the long term, good experiences and thus trust built up over time lead to loyalty (Mainardes & Cardoso, 2019).

Particularly in connection with customer satisfaction, the willingness to recommend is repeatedly emphasized. Recommendation is a consequence of customer satisfaction (Eger & Mičák, 2017). Perceived retail service quality impacts the intention to recommend a company to others (Yu & Ramanathan, 2012). In addition, the recommendation of a retailer is considered an important driver of purchase intention (Beneke et al., 2016). Customer satisfaction and loyalty have a positive long-term effect on consumer acceptance of apps (Bellman et al., 2013; Peng et al., 2014).

Derived from the literature, the items enjoyment, recommendation and experiences are identified as dimensions for determining the perception of a retailer (cf. tbl. 1, 1.1 - 1.3).

Perception of push notifications

In the context of push notifications, the importance of the relevance of the content for the perception of push notifications is emphasized. For

example, customized content of push notifications tailored to the app user increases the relevance and subsequently the probability of interaction (Bidargaddi et al., 2018). Relevance is important in connection with research on the effects of frequency in that the frequencies tolerated by users increase with the relevance of content (McGookin et al., 2019). The use of location data in the sense of location-based marketing increases the relevance of the notifications because a reference to the context of the respective user is established (Banerjee et al., 2020).

The relevance of notifications can be achieved both by using personal data of app users and by incorporating the individual context. Users are more likely to perceive content as relevant or helpful accordingly (E. Kim et al., 2013). Notifications are perceived as helpful if they refer to current events. For news and social media in particular, the topicality of the content is especially important so that users find it helpful (Sahami Shirazi et al., 2014).

In the context of shopping apps and mobile apps in retail, monetary incentives play an important role in the positive perception of push notifications. Incentives, such as coupons and discounts, have a positive influence on the basic attitude toward push notifications (Shankar et al., 2010). In online auctions, push notifications lead to an increase in the bidders' chances of winning the auction (März et al., 2021).

The frequency with which app users receive push notifications appears to play an important role. On the one hand, push notifications with higher frequency can generate higher user engagement in the short term (Pham et al., 2016). On the other hand, depending on the use case, target group and content, different frequencies are perceived as too high (Freyne et al.,

2017). In general, especially with regard to the long-term perception of push notifications, the frequency should not be too high (Wohllebe, 2020), as they can always be perceived as a disturbance (Fischer et al., 2010; McGookin et al., 2019).

After reviewing the relevant literature, usefulness, offers, relevance and frequency are defined as items for the perception of previous push notifications (cf. tbl. 1, 2.1 - 2.4).

Push notifications are an essential functionality of mobile apps. The content communicated via push notifications therefore has a high influence on how the push notifications themselves and the app that sends them are perceived (Shankar et al., 2010; Stocchi et al., 2018). Consequently, push notifications have an effect on the satisfaction with an app and correspondingly on the likelihood of recommendations (Bellman et al., 2013; Peng et al., 2014; Xu et al., 2015).

H2: The app user's perception of push notifications from a retailer's app positively influences the probability of the app to be recommended.

Furthermore, it can be assumed that push notifications are perceived more positively if the sender is perceived positively. This assumption corresponds with the assumption that the sender (here: a retailer) has a positive effect on the perception of the app itself (Iyer et al., 2018; Newman et al., 2018; Wohllebe, Ross, et al., 2020).

H3: The app user's perception of the retailer positively influences the app user's perception of push notifications from the retailer's app.

Accordingly, it can be assumed that:

H4: The effect of the perception of the retailer on the probability of the retailer's app to be recommended is partly mediated by the perception of push notifications.

5.4.3. Material and methods

Sampling and data collection

A quantitative research approach is used for this study. Consumers are interviewed via an anonymous online survey. Consumers are first informed that a prerequisite for participating in the survey is that they have installed the mobile app of at least one retailer. The respondents had to indicate which mobile application of which retailer they will refer to. Figure 10 shows how often each retailer was mentioned. Most consumers referred to their experiences with Amazon and the corresponding app.

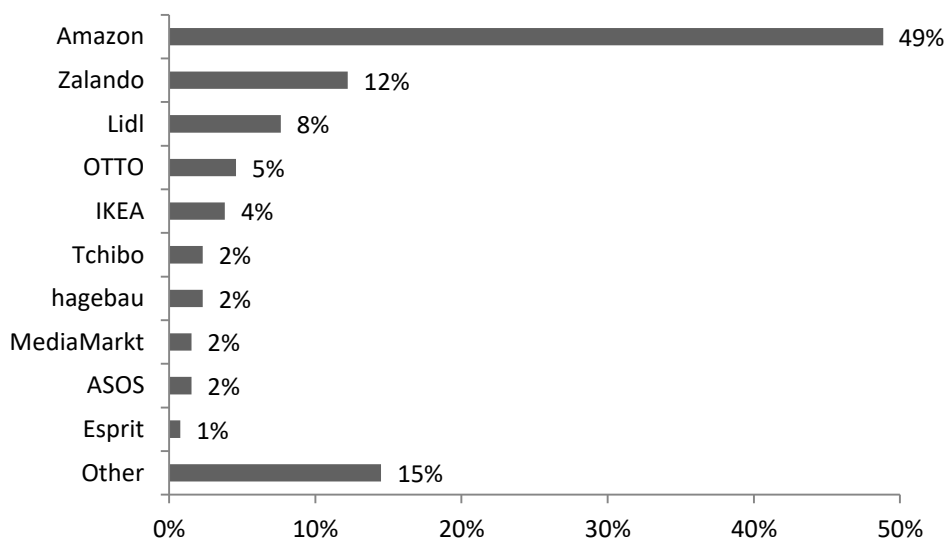


Figure 10: Share of consumers referring to specific retailer, based on collected survey data.

The survey is distributed in German-speaking countries and is conducted in German. A total of 131 people take part in the survey.

Measures

The questionnaire consists of three sections. First, consumers are informed about the survey and asked to define which retailer they will be referring to for their answers. In the second section, consumers are asked to provide information about their perception of the retailer and the push notifications they have received from the app so far. In the third part, consumers are asked to indicate whether they would recommend the app of the retailer to friends or colleagues. All items are measured from 1 (completely disagree) to 5 (completely agree) using a Likert scale.

Table 17 lists the questionnaire items corresponding to the perception of the retailer and the perception of push notifications. Furthermore, it shows the rotated factor loadings and uniqueness of each item as well as Cronbach's Alpha for each factor.

Based on Cronbach's Alpha, the reliability testing of the measured variables shows good and excellent levels of internal consistency (Schmitt, 1996; Vakulenko et al., 2019).

Table 17: Measures, based on collected survey data.

	Factor Loading	Uniqueness	Cronbach's Alpha
Perception of Retailer			
1.1 Enjoyment	.7838	.3531	.88
1.2 Recommendation	.7951	.3182	
1.3 Experience	.7994	.3519	
Perception of Push Notifications			
2.1 Usefulness	.8171	.3218	.73
2.2 Offers	.6919	.4728	
2.3 Relevance	.8141	.2925	
2.4 Frequency	.1962	.9610	

The factor loadings indicate a high relevance of all items for the respective factors. Only frequency plays a separate role; the factor loading is relatively low in comparison. However, the item remains as part of the factor, as the relevance in the context of push notifications has been emphasized as critical by researchers in the past (Freyne et al., 2017; Wohllebe, 2020).

In addition, also on a Likert scale of 1 to 5, respondents were asked how likely they would be to recommend the retailer's app to others (cf. Figure 11).

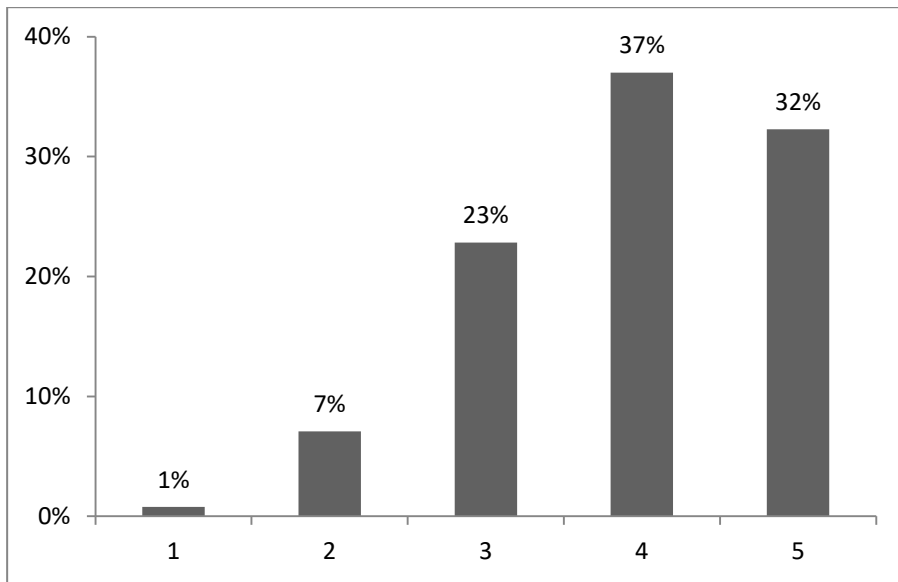


Figure 11: Distribution of likelihood to recommend the retailer's app, based on collected survey data.

When looking at the distribution, it should be noted that consumers who would not recommend a retailer's app to others would probably be dissatisfied with it. In this respect, they would probably uninstall it and would therefore not be able to refer to it in the survey.

5.4.4. Results

The hypotheses are tested using a structural equation model. For this purpose, the "lavaan" package in R is used. In addition to testing the individual hypotheses, the direct and indirect effects are calculated. Thus, the role of the perception of push notifications as a mediator can be discussed. The model is estimated using a robust maximum likelihood with Yuan-Bentler correction of the Chi Square statistics and Huber-White standard error estimation (Steinmetz et al., 2015, pp. 66–67). Figure 12 shows the final estimated model.

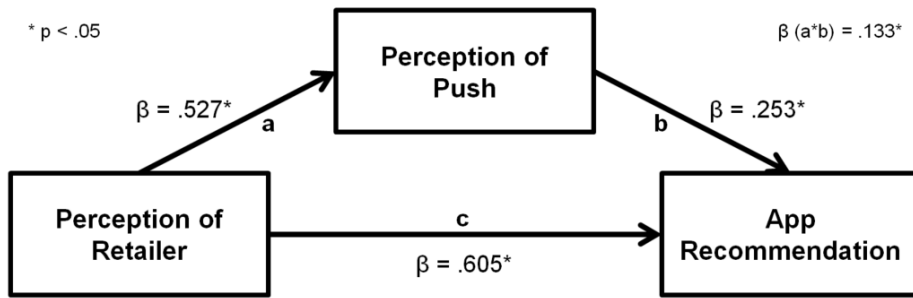


Figure 12: Final estimated model, standardized parameters, based on statistical analysis. The model fit is determined on the basis of the common goodness of fit indices, such as those proposed by Kline (2015) and Hu & Bentler (1999) (cf. Table 18). The Chi Square test shows that the proposed model is better than the baseline model. The values for CFI, TLI, RMSEA and SRMR are all in the very good range (Hu & Bentler, 1999).

Table 18: Model fit statistics, based on statistical analysis.

Index	Value
Chi Square	21.515
p(Chi Square)	.254
CFI	.990
TLI	.985
RMSEA	.038
P(RMSEA)	.569
SRMR	.044

All previously assumed effects can be confirmed as significant on the basis of the data (cf. Table 19). The positive perception of push notifications has a significant effect on the willingness to recommend the app to others (cf. effect *b*), however significantly weaker than the positive perception of the retailer (cf. effect *c*). The effect of the retailer's

perception on the app recommend (cf. effect *c*) is similar in size to the effect on positive perception of push notifications (cf. effect *a*).

Table 19: Regression results, based on statistical analysis.

Effect	Estimate	Standard Error	z-Value	p
a	.527	.107	4.937	.000
b	.253	.106	2.397	.017
c	.605	.121	4.985	.000

Since the indirect effect (*ab*) and the direct effect (*c*) are significant, partial mediation is present. Mediation analysis results are display in Table 20.

Table 20: Direct and indirect results, based on statistical analysis.

Effect	Estimate	Standard Error	z-Value	p
Indirect (<i>ab</i>)	.133	.058	2.305	.021
Direct (<i>c</i>)	.605	.121	4.985	.000
Total	.738	.103	7.195	.000

According to the results of the structural equation model analysis, the results of the hypotheses to be tested are summarized in Table 21. All four hypotheses can be confirmed.

Table 21: Summary of hypotheses, based on statistical analysis.

Hypothesis	Effect	Interpretation
H1: The app user's perception of a retailer positively influences the probability of the app to be recommended.	c	Confirmed
H2: The app user's perception of push notifications from a retailer's app positively influences the probability of the app to be recommended.	b	Confirmed
H3: The app user's perception of the retailer positively influences the app user's perception of push notifications from the retailer's app.	a	Confirmed
H4: The effect of the perception of the retailer on the probability of the retailer's app to be recommended is partly mediated by the perception of push notifications.	ab, c	Confirmed

5.4.5. Discussion and implications

The model proposed in this paper puts the retailer and its mobile app into one context and additionally considers the role of push notifications for the first time. The study provides a supplement to the existing findings on the antecedents of the willingness to recommend. With regard to the perception of retailers, previous studies have considered the sub-aspects used here separately from one another or as a consequence of one another. Although the retailer perception factor is much broader than retailer image, the confirmation of H1 is unsurprising in light of prior work finding congruence between retailer image and mobile app of a retailer (Iyer et al., 2018). The mediating role of push notifications on app recommendation confirms previous research results connecting push notification and mobile app user behavior (Freyne et al., 2017; März et al., 2021; Pham et al., 2016). The model shows that consumers seem to be generally more positive about push notifications when they are associated with a retailer that consumers perceive positively.

From a managerial perspective, mobile app marketing in retail should not just focus on the app as a technology. Obviously, the retailer itself and how it is perceived plays a major role in marketing: If a customer has a positive perception of a retailer, the probability to recommend the retailer's app to others increases. In addition, the positive perception affects how customers perceive the push notifications. These are additionally relevant for the app recommendation probability. The study therefore contributes to a better understanding of mobile apps in retail.

At the same time, it is not without limitations, which can be seen as possible further research questions. Firstly, the model of the study is based on data from a survey. There may be differences in the survey of willingness to recommend between behavior that respondents report and behavior that respondents would actually exhibit in a field study. This has already been criticized, particularly in the context of recommendations (Fisher & Kordupleski, 2019). The survey data comes from a clearly defined geographical region (Germany). For other regions, the statistical analyses could turn out differently in the result (Fisher & Kordupleski, 2019). Shifts in the gender composition of respondents can lead to changes in (Eskildsen & Kristensen, 2011). In this respect, it is suggested that the model be validated by further surveys. In addition, the model presented here is reduced to two latent variables and the target variable. Among other things, more complex relationships are conceivable, especially of the variables that are considered exogenous and equivalent within the framework of the model proposed here.

5.4.6. Conclusion

The goal of this paper is to develop a model that relates the willingness to recommend a retailer's mobile app to consumer perceptions of that

retailer, including the role of push notifications as a mediator. The literature review shows that previous research rarely combines the retailer and mobile app perspectives. In particular, mobile applications have so far been considered primarily in an encapsulated way as technological platforms. The context to the company publishing the app is rarely established. In this respect, the proposed model represents a simple but much more context-rich approach compared to existing literature. The collected data show a significant relevance of the perception of the retailer on the willingness to recommend the app to others. Also, it can be shown that this relationship is partially mediated by the perception of the retailer's app push notifications. In this respect, all hypotheses stated can be confirmed. Further research questions include in particular a validation of the model in other socio-demographic compositions as well as in the context of a field study and the expansion of the model.

6. GENERAL DISCUSSION

The aim of the discussion is to explain the results of the dissertation, to establish references to the existing literature, to discuss limitations and to address further research. The general discussion is derived from the individual publications.

The overview of **consumers' motivation to use a retailer's mobile app** (cf. Wohllebe et al. (2020a)) shows similarities with other industries. The importance of (perceived) added value and ease of use should be emphasized (S. Kang, 2014; S. Kim & Baek, 2018; Yang, 2013). These factors correspond to the findings of the widely used TAM (Davis, 1985). Trust in the app or the company and respect for privacy are also important factors for consumers (J.-Y. M. Kang, 2017; Kaushik et al., 2020; Olaleye et al., 2018). **Consumer expectations** of a high functional relationship with stationary retail are worth highlighting: Consumers expect mobile apps in retail to offer functions that enhance the stationary shopping experience. As a stationary retailer, it is not sufficient to simply add an online shopping function to the mobile app (Bodmeier et al., 2019; Olaleye et al., 2018; Pantano & Priporas, 2016). Furthermore, research shows that - in addition to the technological-functional aspects - the retailer itself and the consumer's attachment to its **brand** play an important role (Iyer et al., 2018; Kaushik et al., 2020; Rosa, 2019). **Limitations** of the study are in particular the criteria of the literature used, especially with regard to the period of publication. Also, some of the literature considered is not explicitly related to the retail sector, but to other industries or to mobile apps in general (S. Kang, 2014; S. Kim & Baek, 2018; Yang, 2013). Further research should address, among other things, the question of concrete functions to fulfill consumer expectations.

With regard to the **influence of customer satisfaction** with a retailer on the willingness to install apps (cf. Wohllebe et al. (2020b)), the results are largely **in line with expectations**. The willingness to recommend a retailer (as an indicator of satisfaction) has a positive effect on the willingness to install an app. The mobile online shopping frequency indicated by respondents also has a positive effect. **Contrary to expectations**, mobile internet usage and online shopping frequency do not have a significant positive effect on the willingness to install apps. This may be explained by the fact that the main driver among the variables considered is probably satisfaction with the retailer. The results add to the existing literature, as according to Iyer et al. (2018), retailer brand image and mobile app must fit together for positive impact on customer satisfaction. Also, according to Jham (2018), trust in a company makes consumers more likely to participate in mobile marketing measures, such as installing an app. It should be noted that the data collected relates exclusively to the German-speaking region. Furthermore, respondents are asked about their willingness to recommend or install the product. Although theory postulates a high correlation between reported intention and actual behavior, it is not possible to draw complete **conclusions from intention to actual behavior** (Fishbein & Ajzen, 1975). In particular, it is proposed to extend the model to include more influencing factors than the willingness to recommend the retailer and to validate the results with the help of observed behavior in the field.

When it comes to the **influence of frequency** on app user behavior (cf. Wohllebe et al. (2021)) in the retail sector, the results are largely in line with expectations. Increasing frequency leads to more uninstalls and lower open rates. The results are **in line with the existing findings**,

which see the risk of disruption in notifications and therefore assume that users are disturbed and annoyed (Fischer et al., 2010; Iqbal & Horvitz, 2007; Pham et al., 2016). At the same time, the results **contradict** a study from Kim (2014) that found more notifications also results in more usage. Research in the area of a diet app by Freyne et al. (2017) sees the optimal frequency at 3 messages per day. Although the push notifications in the frequency test are not personalized and come from a retail context rather than medicine, the data suggest a completely different tolerance level for frequency than that identified by Freyne et al. (2017). The sending of standardized, non-personalized push notifications is a **major limitation**, since only generic push notifications are sent in the study. For example, in an experiment using location-based push notifications to deliver tourism information, McGooking et al. (2019) emphasize the importance of content that is tailored to each user and their situation. In this respect, a validation with messages that are perceived as relevant by users would be a further research project (McGookin et al., 2019; Rigollet & Kumlin, 2015). Also, repeating the experiment in other contexts, such as social media, messaging, or gaming, could yield different results.

Research findings on how consumer perceptions of retailers and push notifications **influence app recommendation intention** (cf. Wohllebe et al. (2022a)) largely match expectations.. Both the relevance of the perception of the retailer and the perception of push notifications can be **confirmed**. In particular, the role of the perception of retailer can be shown - in line with the literature - to be (Iyer et al., 2018). The perception of push notifications is a partial mediator, as was also assumed on the basis of the mobile marketing literature (Merisavo et al., 2007; Smutkrup et al., 2011). The composition of the perception of a retailer

corresponds with the literature with regard to brand (Park et al., 2015), satisfaction (Pappu & Quester, 2006), and good shopping experiences (Vakulenko et al., 2019). This is largely also valid for the composition of the perception of push notifications (Fischer et al., 2010; E. Kim et al., 2013; S. Kim et al., 2016; Smutkrup et al., 2011; Wang et al., 2014). The influence of frequency, however, is **less evident than was assumed** on the basis of the literature (M. Kim, 2014; Pham et al., 2016). The reason for this could be that the relevance of notifications - which was also queried - is significantly more important to app users than the frequency, as discussed previously (McGookin et al., 2019; Rigollet & Kumlin, 2015). With regard to the **limitations**, however, the geographical scope of the data collection in German-speaking countries must be noted once again. Together with the dependence of the results on the socio-demographic composition of the sample (Eskildsen & Kristensen, 2011) and the question of the suitability of surveys in the context of inquiring about recommendation (Fisher & Kordupleski, 2019) this results in further research suggestions. For example, observing real behavior, extending the model and larger samples would be conceivable.

In summary, the present work contributes to a better understanding of the **consumer's attitude towards mobile apps in retail**. Despite the geographical limitations, the results largely confirm the existing findings of related questions and disciplines and provide new insights on how consumers adopt mobile apps from retailers. In particular, the results provide the impetus for research to focus even more on the role of the retailer – in addition to the already intensively discussed issue of apps as technology.

7. CONCLUSIONS

This research addresses the question of how customer satisfaction and push notifications influence consumer attitude toward mobile apps in retail. The findings show that customer satisfaction with the **retailer** and perception of **push notifications** that can be sent by mobile apps have a **strong influence on consumer attitude**. Customer satisfaction or positive perceptions of a retailer have a significant positive effect on willingness to install and recommend apps. Recommendation of mobile apps in retail is affected by the positive perception of push notifications. The frequency of push notifications has a strong negative effect and leads to an increase in uninstalls. In summary, the main limitations of the papers are the geographical focus on the German-speaking region and – apart from the study on the frequency of push notifications – the use of reported (rather than actually observed) behavior by using questionnaires.

The results of the research and its limitations mean **several theoretical implications** and give good approaches for further research projects. In this context, the discussed limitations represent a significant starting point for further research projects. In the case of consumer motivation to use a retailer's mobile app, the selection criteria of the literature were mentioned as a limitation. Accordingly, a further research direction could be to expand the literature databases considered, broaden the keyword focus, or include exclusively retailing-related results. Regarding the influence of customer satisfaction on the willingness to install a retailer's mobile app, the findings may provide a starting point to incorporate customer satisfaction into the TAM, for example, as another antecedent of the consumer's attitude toward an ad besides perceived benefit of use and perceived ease of use (Figure 13).

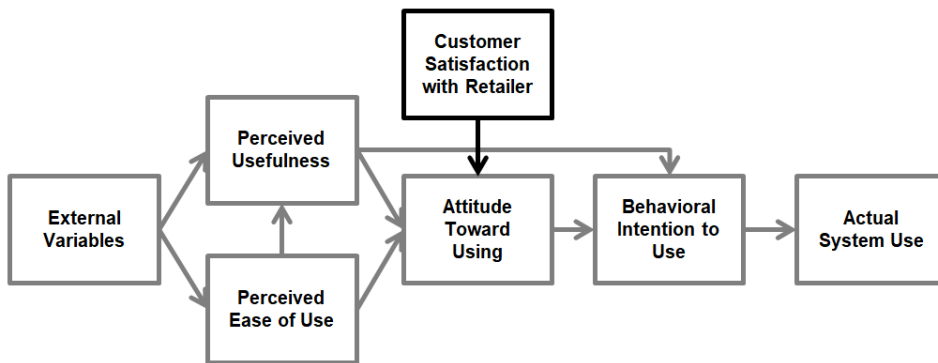


Figure 13: Suggestion for extended TAM incorporating customer satisfaction, illustration based on original model by Davis (1985).

For research on the frequency of push notifications, the findings can also be integrated into existing models, where either the frequency or the overall perception of push notifications should also be integrated as a component, for example in an extended TAM model focusing on app acceptance. Additionally, this should also take into account that the tolerated frequency could vary depending on the message relevance for the individual user. This also implies that an extended app-related TAM model in this sense should be calculated for different types of mobile apps and the results should be compared with each other. Finally, the fourth publication relates consumer perceptions of retailer and of push notifications to app recommendation intention. The significance of the results can be aligned with research on branded apps and clearly shows that future research on technology acceptance should increasingly pursue a broader focus than just the technology as such. Specifically, future models that examine satisfaction with or recommendation of mobile apps in retail must also consider the app publisher, i.e., the retailer, as well as interactions with push notifications. **More comprehensive models and considerations** are needed to gain a holistic understanding of the drivers of consumer attitude.

Table 22: Overview of practical implications, derived from publications.

Implication	Reference(s)
Mobile apps in retail must first and foremost enhance the brick-and-mortar shopping experience and be functionally designed as a digital shopping assistant.	Wohllebe et al. (2020a)
When acquiring new app users, retailers should increasingly include their overall business and showcase their brand.	Wohllebe et al. (2020a), Wohllebe et al. (2020b), Wohllebe et al. (2022a)
Satisfied and loyal customers are particularly suitable as a target group in app install marketing to increase the number of app installs.	Wohllebe et al. (2020b)
For app user satisfaction and app referral, retailers need to focus not only on the app as such, but on the overall customer experience.	Wohllebe et al. (2022a)
For long-term satisfaction and mobile app referral, push notifications should communicate relevant content, such as special offers.	Wohllebe et al. (2022a), Wohllebe et al. (2021)
When sending push notifications, retailers need to ensure appropriate frequency so as not to disturb app users.	Wohllebe et al. (2021)

The findings of the dissertation offer a **variety of practical implications** for using mobile apps in retail. The implications arise on the individual publications. Table 22 lists a selection of the most significant practical implications with reference to the respective publication.

8. NEW SCIENTIFIC RESULTS

The new scientific results are based on objectives of the dissertation. They are based on the research gaps identified in the literature review. The individual papers provide a variety of new insights. Table 23 gives a brief overview of the new scientific findings.

Table 23: Overview of new scientific results, derived from publications.

No.	Result	Novelty	Reference(s)
1	Retail consumers expect features from mobile apps that enhance the in-store shopping experience.	First time summary of customer expectations of mobile apps specifically in retail by systematic review of multiple studies	Wohllebe et al. (2020a)
2	Retailers as app publishers, companies and brands have a high impact on consumer adoption of mobile apps in retail.	First time summary of customer expectations of mobile apps specifically in retail by systematic review of multiple studies	Wohllebe et al. (2020a)
3	Customer satisfaction with a retailer has a significant positive impact on app installation readiness.	First time investigation of impact of customer satisfaction, expressed in Net Promoter Score, on app installation willingness in retail sector	Wohllebe et al. (2020b)
4	Consumer perception of retailer as app publisher has a strong positive impact on app recommendation.	First time to prove influence of retailer's overall perception as determinant in app context	Wohllebe et al. (2022a)
5	Increased frequency of push notifications significantly increases app uninstalls.	First time to prove influence of frequency on app uninstalls in experiment based on real observed data in retail	Wohllebe et al. (2021)

It was found that there's a lack of insights into what motivates consumers to use a retailer's mobile app. For a positive consumer attitude towards mobile apps in retail, the added value offered is of high importance. The systematic review shows that this added value is manifested in the fact that a retailer's mobile app **must enhance the in-store shopping experience**. In particular, it is not enough to merely offer an online shopping function with the app (cf. Wohllebe et al. (2020a)).

Also, the influence of customer satisfaction on the willingness to install a mobile app in retail was unknown until then. The systematic review

suggests that the **retailer as a company and brand** is very important for consumer adoption in this regard (cf. Wohllebe et al. (2020a

)). The study of the influence of customer satisfaction with the retailer on the willingness to install an app shows, especially taking into account the Net Promoter Score, for the first time a significant **positive impact of customer satisfaction** on the willingness to install an app in the retail context (cf. Wohllebe et al. (2020b)). Positive consumer perception of the retailer is a decisive factor in the willingness to recommend an app, whereby willingness to recommend can be seen as a measure for satisfaction. The research results show for the first time very clearly that a **mobile app in retail benefits strongly from the retailer as its app publisher** apart from its characteristics as a technical software product (cf. Wohllebe et al. (2022a)).

The role of push notifications in the context of mobile apps in retail has also hardly been researched so far. Especially regarding the frequency of push notifications, there are hardly any reliable results from practical research – also from other research fields; the frequency impact on app user behavior has not been long-term quantified in science yet. On the one hand, the results show a significant impact of consumer perception of push notifications on app recommendation in retail (cf. Wohllebe et al. (2022a)). On the other hand, and to the author's knowledge **these results are unique in science so far, real observed app user data** from an experiment show for the first time the massive negative impact of (too) high frequencies over a longer period of time on consumer attitudes in the form of quantifiable app uninstalls (cf. Wohllebe et al. (2021)).

9. SUMMARY

The overall objective of this cumulative dissertation is to gain an understanding of the consumer attitude toward mobile apps in retail focusing on the impacts of customer satisfaction with the retailer and how this relationship is influenced by push notifications.

To this end, the first step is to identify the drivers of consumer acceptance of mobile apps in retail. The results emphasize, in addition to the factors on the Technology Acceptance Model, in particular the **functional requirements** of the stationary shopping experience and the importance of a **company's brand**.

Subsequently, the influence of customer satisfaction with a retailer as a driver for app installations is examined and quantified. The willingness to recommend is used as an indicator for customer satisfaction. The result shows a **strong connection of the retailer brand and the behavioral intention to install the retailer's mobile app**.

In the third step, as a contribution to the understanding of the perception of push notifications, the effect of the frequency of push notifications on app opens and app uninstalls is examined. Based on a field experiment, the results are an important contribution to the controversial debate regarding the effects of frequency. The results show that a **higher frequency** of non-personalized push notifications over a period of several weeks **clearly has a negative impact** on app opens and increases the uninstall rate.

Finally, the influence of the consumer's perception of a retailer and of push notifications the retailer sends via its app on the consumer's willingness to recommend the retailer's app is investigated. The results

show that the **consumer's perception of a retailer** has a positive effect on the consumer's perception of push notifications and on the intention to recommend the app. Also, it can be shown that the perception of push notifications partly mediates the influence of the retailer's perception on app referral.

Overall the retailer takes a critical role in consumer acceptance and adoption of retailer mobile apps. Push notifications are also important in this case. Previous literature primarily focuses on apps as a technology. The entirety of the elaboration shows that this focus is not sufficient: **the app publisher and the marketing actions controlled through the app must also be considered.**

This knowledge contributes to a better understanding of mobile apps in retail and the theoretical implications provide new impulses for further research. In particular, the sampling of individual papers, which was identified as a limitation, should be used to replicate the findings in broader contexts. Also, the results show that the TAM model, which is the starting point of many research papers in the context of mobile app adoption, does not go far enough in the case of branded apps, especially in retail. Future research using the TAM and similar models to explore consumer acceptance of mobile apps in retail should include the consumer perception of the overall context, i.e., both the retailer as app publisher and push notifications as a central function of apps.

In particular, the results support the demand that research on mobile apps in retail in particular, but also on human-computer interaction in general, needs models that take a broader scope. Thus, not only the technology as such should be considered, but also the context from which the

technology originates - in the case of this thesis **the retailer as the app publisher - should be given more scientific attention.**

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Hamburg, Germany, April 2022

11. RELATED PUBLICATIONS OF THE AUTHOR

11.1. Papers

Wohllebe, A. (2020). Consumer Acceptance of App Push Notifications: Systematic Review on the Influence of Frequency. *International Journal of Interactive Mobile Technologies (iJIM)*, 14(13), 36–47. <https://doi.org/10.3991/ijim.v14i13.14563>

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Innovative Marketing, 17(2), 102–111.
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Wohllebe, A. (2021). Scrum as an Agile Method for Strategic Organizational Learning in Digital Enterprise Transformation: Applying the Four Elements of Organizational Learning. In K. Sandhu (Ed.), Disruptive Technology and Digital Transformation for Business and Government (pp. 24–42). IGI Global. <http://doi.org/10.4018/978-1-7998-8583-2.ch002>

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13. SHORT PROFESSIONAL CV

Time	Company	Position
since 10/2021	University of Applied Sciences Wedel	Freelance Lecturer for Multi-Channel Retailing (B. Sc. E-Commerce)
since 05/2020	Wohllebe & Ross Publishing	Managing Partner
since 02/2019	hagebau connect	Senior App Marketing Manager
since 06/2012	Freelance	Digital Marketing Consultant
07/2017 – 01/2019	OTTO	Marketing Manager (Digital Push)
10/2016 – 05/2017	netnomics	CRM Consultant & Project Manager
01/2015 – 09/2016	netnomics	Junior Consultant
10/2011 – 09/2014	OTTO	Corporate Degree Student

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