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DIGITAL NUDGES FOR USER ONBOARDING: TURNING VISITORS INTO USERS

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Research Paper

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Abstract

Two design recommendations (digital nudges) for decreasing user churn in mobile apps are presented. We examine commitment and personalization nudges, both of which are linked to the extant literature, in the context of a randomized online experiment with 150 participants. Our experimental study reveals that commitment and personalization cues distinctly affect consumers' intention to use a mobile app. Moreover, our study demonstrates that personalization amplifies the effect of commitment cues on users' intention to use a mobile app.

Keywords: User onboarding, commitment, personalization, intention to use, digital nudging, mobile apps.

1 Introduction

User onboarding has received much attention in information systems (IS) research and practice due to its positive influence on IT adoption in highly competitive markets, such as the app economy (Liu et al., 2017; Nielsen, 2013; Renz et al., 2014). User onboarding is the sum of methods and elements that guide new users to become familiar with a digital product and activate them to become fully registered users (Renz et al., 2014). Because less than 25% of mobile app users return to the app after their first use, user onboarding is considered to be the most critical part of the mobile user journey (Grennan, 2016). As a consequence, the need to investigate potential drivers associated with the successful implementation of user onboarding is arising in research and practice. A way to effectively guide users online is to use digital nudges, defined as design interventions that influence user behavior in digital choice environments such as websites or mobile apps (Weinmann et al., 2016). For example, Schneider et al. (2017) showed that digital nudges in the form of communication arguments can be used to nudge users into online verification. More recently, Kretzer and Maedche (2018) demonstrated how digital nudges that exploit social influence effects can be used to steer users toward reusing recommended reports in the context of enterprise recommendation agents. Jung, Erdfelder, et al. (2018), Jung and Weinhardt (2018), and Mirsch et al. (2017) showed that digital nudges can accelerate user decision-making in decision support systems. However, while many digital nudges draw on related psychological effects and theory suggests promising synergistic relationships, prior research has focused on the isolated investigation of separate digital nudges and thus has paid little attention to how related digital nudges interact (e.g., Jung and Weinhardt, 2018). Two digital nudges that are related via self-perception theory (Kressmann et al., 2006), namely, commitment nudges (i.e., users strive to be consistent with previous or reported behavior to avoid cognitive dissonance) and personalization nudges (i.e., users provide personal information that is used to

deliver a targeted user experience), are widely employed in practice and considered to be effective in user activation contexts in general and mobile user onboarding in particular (Noel, 2017). Companies such as AirBnB, Netflix, Hubspot and Duolingo draw on commitment and personalization nudges, e.g., by allowing users to immediately experience core features of their product through deferred account creation. For example, Hubspot reported a 15% increase in retention after implementing user onboarding based on such best practices (Noel, 2018). Despite the fact that commitment and personalization nudges are widely employed in combination, it remains unclear whether they complement or substitute each other. Therefore, we aim to shed light on the individual effects and the interaction effects between commitment and personalization nudges. Taken together, we address the following research questions:

RQ1: *What impact do commitment and personalization nudges have on users' intention to use a mobile app?*

RQ2: *What impact do commitment and personalization nudges in combination have on users' intention to use a mobile app?*

In this research, we cooperated with a German startup to conduct an online experiment (N = 150) with real user activation decisions. The company's social habit tracking app helps users achieve healthy behavior changes and was therefore particularly suited for an experiment related to digital nudging. The mobile app had not been released prior to the experiment and hence offered us an opportunity to test onboarding strategies without pre-experimental influences. Our findings reveal an interesting interaction of commitment and personalization nudges so that when both are employed together, personalization amplifies the positive effect of commitment on the likelihood of user activation.

Our study contributes to IS literature in two important ways. First, we investigate how two nudges that are well-established in research on offline contexts perform in a digital environment and explicate how both affect users' decision making. More broadly, albeit making valuable contributions on the effect of single and isolated digital nudges, our study is among the first to investigate the interplay of different nudges and thereby provides a more nuanced picture on how both can be used in combination. Second, following the call of Mirsch et al. (2017), we derive action and design recommendations for digital nudges, which may help firms to shape better user activation outcomes in the context of the under-researched field of user onboarding.

This work is organized as follows. In the next section, we review prior literature on user onboarding and digital nudges and summarize the theoretical foundation for our research model by drawing on literature on the principles of commitment and consistency as well as personalization. The subsequent section presents our research model and our hypotheses regarding the impact of digital nudges on consumers' intention to use decisions, including interaction effects. Furthermore, we describe the research methodology used in our experimental study, followed by our data analysis and the results of hypothesis testing. Finally, we discuss our findings, implications and directions for further research.

2 Theoretical Background

2.1 User Onboarding and Digital Nudges

User onboarding is defined as the sum of methods and elements guiding new users to become familiar with a digital product and activate them to become fully registered users (Liu et al., 2017; Renz et al., 2014). Extant research to date has investigated how onboarding can improve organizational socialization (i.e., learning and adjustment processes that enable an individual to adopt an organizational role) and digital gamification (i.e., applying gaming elements in non-gaming contexts) (T. N. Bauer and Erdogan, 2011; Liu et al., 2017; Zichermann and Cunningham, 2011).

While there have only been sparse contributions on how user onboarding can be utilized to prevent new users from churning away (Cooper et al., 2007), users' experience during the first minutes of using a new product are critical to their perceptions about the product's value. As research has shown, users have a psychological disposition to underestimate the benefits of unfamiliar products (Gourville, 2006). Among practitioners, effective user onboarding is considered to be the most important part of the customer journey due to its potential to reduce user churn by actively guiding users to better understand the value of the product as well as how to capture it (Murphy, 2016; Noel, 2018). Thus, companies deliberately design their user onboarding experience in order to optimize their conversion funnel, win new customers and thereby capture the value they create. In this context, the conversion funnel describes the transformation consumers undergo when sequentially proceeding through four stages to ultimately complete an online transaction with the firm: from being a non-visitor to becoming a visitor (also called acquisition), to becoming a registered user (also called activation) and, lastly, to becoming a converted customer (also called customer conversion) (Gallo, 2014). Considering the vastly higher cost of user acquisition (i.e., turning non-visitors to visitors), app providers increasingly shift their focus to improving user activation outcomes (i.e., turning visitors to registered users) (Hoban and Bucklin, 2015). In order to actively shape users' decision to become a registered user, i.e., to nudge users to activate, firms purposefully implement user interface (UI) design elements such as graphic design, specific content, wording or small features.

Because users increasingly make decisions on screens, the concept of nudging is gaining relevance in the digital sphere. This trend is not limited to the decision to use a particular mobile app but ranges from the choice of a travel destination to the right life partner, insurance, or investment (Mirsch et al., 2017). However, due to the vast amount of information available online, individuals often fail to process all the relevant details to reach an optimal choice. Instead, individuals often make decisions on screens in a hasty and automated manner (Benartzi and Lehrer, 2015). In this context, digital nudging, which is defined as the practice of using visual UI elements to influence consumer behavior in digital choice environments, has proven be an effective tool to guide users' decision making (Weinmann et al., 2016). For example, the usage of pull vs. push mechanisms in requesting information from users may influence their privacy concerns and thereby activation likelihood (Xu et al., 2009). Compared to physical contexts, digital environments provide several advantages for designing nudges: the implementation of digital nudges is easier, faster and cheaper; furthermore, IT provides specific functionalities, such as user tracking, which allows the personalization of nudges presented to users, making them potentially more effective (Weinmann et al., 2016). Most research on nudging has occurred in the offline context, and digital nudging is still fairly young. Yet, Weinmann et al. (2016) allude to the fact that this research stream is likely to converge with design research. Hence, the differential design of user experience journeys, which deals with how to design and sequence parts of a user interaction for a better user experience, may become an additional way to influence user decisions in digital choice environments, beyond the use of visual UI elements (Cyr, 2014; Lemon and Verhoef, 2016). However, as reflected in Mirsch et al. (2017)'s call for further research, little attention has been paid to the design and evaluation of digital nudges. Schneider et al. (2017), who were among the first to investigate digital nudges, showed that digital nudges in the form of communication arguments can be used to nudge users into online verification. More recently, Kretzer and Maedche (2018) demonstrated how digital nudges that exploit social influences can be used to steer users toward reusing recommended reports in the context of enterprise recommendation agents. Huang et al. (2018) investigated the effectiveness of digital nudging for users' social sharing behavior regarding online platform content. They report that nudging messages with monetary incentives as well as relational and cognitive capital framings lead to an increase in social sharing, while nudging messages with simple requests decrease social sharing, compared to the control group without nudges.
Although many nudges draw on related psychological effects, and therefore, theory suggests promising synergistic relationships, prior literature is focused on the isolated investigation of separate digital nudges, and little attention has been paid to how digital nudges interact. Two related digital nudges are commitment (i.e., users strive to be consistent with previous or reported behavior to avoid cognitive dissonance) and

personalization (i.e., users provide personal information that is used to deliver a targeted user experience). Both nudges are widely implemented together in practice and considered to be effective in user activation contexts in general and mobile user onboarding in particular (Balboni, 2016). For instance, companies such as AirBnB, Slack, Netflix and Duolingo draw on commitment and personalization nudges, e.g., by allowing users to immediately experience core features of their products through deferred account creation. Although there have been substantial contributions on the effect of commitment nudges in offline contexts, little attention has been paid to the design and evaluation of those nudges in the context of IS adoption in general and mobile devices in particular (Mirsch et al., 2017). Personalization has been studied for its interdisciplinary characteristics in various academic fields, such as economics, management, marketing, information systems, and computer science, and has proven to be an effective strategy to improve user activation on websites (Kwon and Kim, 2012). Tam and Ho (2006) found consumers to be receptive to personalized content and find it useful as a decision aid. Therefore, we recommend evaluating the effectiveness of personalized content in the user onboarding experience, which aims to help new users become familiar with a digital product. Most importantly, it remains unclear whether commitment and personalization nudges complement or substitute each other. The underlying psychological effects, personalization and commitment-consistency, are related via self-perception theory. For instance, by providing personal information, users may perceive themselves as co-creators of the user experience and hence be more committed to using a mobile app (Schlosser et al., 2006; Surprenant and Solomon, 1987). Theoretically, this coherence of commitment and personalization nudges suggests promising yet unexplored synergies. From a practical perspective, understanding the potential interaction between both nudges is critical because personalization and commitment nudges are often employed together. Against this backdrop, we focus on how commitment and personalization nudges, which are ubiquitously applied both alone and in combination, can be designed and evaluated in order to actively shape activation outcomes in mobile user onboarding journeys.

2.2 Commitment

Commitment is defined as a state of mind that holds people in a line of behavior (Newman and Sabherwal, 1996; Staw et al., 1981). The underlying rationale is a desire for consistency within one's attitudes, beliefs, and actions, which has been unveiled as a central motivator of human conduct in numerous studies (Festinger, 1957; Heider, 2013; Newcomb, 1953). After studying six technology-mediated persuasion strategies, Orji et al. (2015) found commitment to be the most persuasive. Practitioners leverage the principles of commitment and consistency in their user onboarding experiences, where it is essential to persuade users of the value the product can generate for them. According to Noel (2017), user commitment is a fundamental pattern in the user onboarding best practices applied in successful digital products such as Netflix, Slack and Duolingo. Language-learning app Duolingo, for example, draws on deferred account creation and drives users to commit to a specific language and learning goal. Before even signing up, users can then complete their first mini-lesson and immediately experience how the core product features look and feel.

According to Cialdini (2001), commitment-consistency theory provides a comprehensive overview of the phenomenon of influence through small commitments. As a compliance technique, small commitments can be used effectively by convincing subjects to perform a seemingly insignificant task to which they are likely to agree without giving it much thought. Once subjects agree to perform a small task, they also end up agreeing to the next bigger task in order to remain consistent in their behavior. People's need to be consistent is driven by a variety of related underlying processes (Burger 1999). The process most commonly used to explain why commitment-consistency theory works is drawn from self-perception theory (Bem, 1972). Following this rationale, individuals generally hold only weak attitudes and use self-observation of their behavior to infer their attitudes. Thus, in complying with an initial request, people infer that they must feel favorably about the issue and are more likely to comply with related future requests as a result of this inference. In particular, previous commitments, e.g., through an action or statement,

shape users' self-perception (i.e., beliefs about their own identities, values, lifestyles, preferences, and habits) (Kressmann et al., 2006). Thus, a need for self-consistency motivates people to behave in ways consistent with how they see themselves. In particular, previous marketing research has found strong empirical evidence that users' need for self-consistency motivates purchase behavior (Ericksen and Srigy, 1989; Malhotra, 1981; Mangleburg et al., 1998; Sirgy and Coskun Samli, 1985). To understand why commitment is such a powerful motivator, it is also important to recognize that in most circumstances, consistency is socially valued. High consistency is normally associated with personal and intellectual strength Cialdini and Garde (1987). Therefore, individuals have a strong desire to appear and be consistent in their behaviors. Thus, performing a behavior pressures them to perform future behaviors that are consistent with the initial behavior.

The success of commitment nudges in computer-mediated contexts suggests that nudges could potentially be used to influence user behavior in the early stages of the user journey (Aggarwal et al., 2007). Given that the decision processes underlying the commitment-consistency effect have already been extensively examined, we focus instead on the effectiveness of this theory for influencing usage intentions in the context of digital user journeys. Thereby, we seek to shed light on how commitment nudges can be employed to improve user activation outcomes and to derive corresponding design recommendations for design-oriented researchers and practitioners alike.

2.3 Personalization

Personalization is defined as using a user's information to deliver targeted solutions to that user (Peppers and Rogers, 1997). Firms draw on personalization strategies to tailor offers and information services for users' specific needs (Cox III et al., 1974; Petrison et al., 1997). Information and communication technologies reduce the effort required to employ personalization strategies in order to deliver customized solutions (Thorbjørnsen et al., 2002).

Research on personalization has focused predominantly on three aspects. The first include the implementation aspects of personalization that deal with how information can be ascertained about users (i.e., explicit or implicit collection) and how to employ this information to tailor communications and offerings (Dahan and Hauser, 2002; Mobasher et al., 2000; Montgomery and Smith, 2009; Rossi et al., 1996). The literature differs in terms of three forms of personalization, namely, transaction-, context-, and user-driven personalization (Wessel and Thies 2015). Transaction-driven personalization draws on previous transactions to derive personalized suggestions for users. Context-driven personalization refers to dynamic content selection based on live clickstream data. User-driven personalization refers to mechanisms that allow users to explicitly customize their experiences. The literature has shown that explicit personalization is not only as representative of users' preferences as implicit personalization (i.e., context- and transaction-driven) but also makes users feel more invested, by making them co-creators of value (Schlosser et al., 2006; Surprenant and Solomon, 1987). Second, the literature has unveiled the positive impact of personalization on cognitive or affective user reactions, such as perceived usefulness, user satisfaction (Liang et al., 2009), information processing (e.g., Tam and Ho, 2006), and stickiness to a website (e.g., Benlian, 2015; Thies et al., 2016). Third, the literature has dealt with the underlying psychological mechanisms of personalization. Among this stream of research, personalization has been highlighted as a strategy to decrease information overload and thereby create greater goal-specificity (Liang et al., 2009; Tam and Ho, 2006). Thereby, personalization enables app providers to guide users to the information they are seeking.

Although personalization has been extensively researched in many contexts, few researchers have addressed the problem of how personalization may drive better activation outcomes in the context of digital user journeys. Benlian (2015) is among the first to examine how personalization affects website stickiness. Therefore, our study aims to shed light on how personalizing user onboarding journeys affects consumers' usage intention.

3   Research Model and Hypothesis Development

As depicted in Figure 1, our research model investigates the (main and direct) effects of commitment and personalization on intention to use (H1/H2), as well as the role of personalization in moderating the effect of commitment on intention to use (H3).
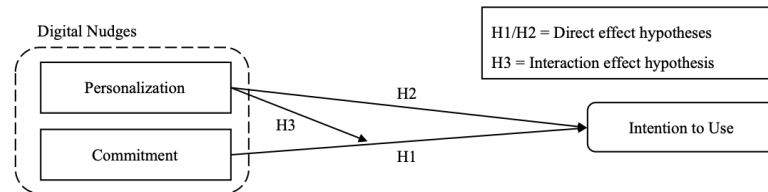

Figure 1: Research model

3.1   The Effect of Commitment on Intention to Use

By obtaining small, active commitments from users during their onboarding experience, firms try to trigger consistent behavior when users make decisions about whether to use the firms' products. The mechanics underlying this commitment-consistency phenomenon are described by the theory of self-perception (Bem, 1972). According to this theory, individuals use self-observation of their behavior as a heuristic for inferring their attitudes. That is, on complying with an initial request, people infer that they feel favorably about the issue and are more likely to comply with related future requests as a result of this inference (Aggarwal et al., 2007). Moreover, because consistency is valued in society, they have a strong desire to appear and be consistent in their behaviors (Cialdini, 2001). Thus, performing a behavior pressures consumers to perform future behaviors that are consistent with the initial behavior (Vaidyanathan and Aggarwal, 2005). In sum, self-perception, i.e., beliefs about their own identities, values, lifestyles, preferences, and habits are formed by previous actions, and they drive consumers' need for consistent behavior in the future. In line with this theory, we put forward that embedding commitment nudges in the user journey of mobile apps affects users' self-image enough to trigger a desire for consistent behavior. In the context of information processing, commitment through previous actions or statements has been found to trigger consistent behavior, particularly when users' product involvement is low (Aggarwal et al., 2007). In these situations, users may act first and then form their beliefs and attitudes based on their action (Clow, 2004). In other words, when the consequences of making a mistake are relatively low, users may readily agree to statements in support of a particular topic. Once they have acted, they will use their observation of these actions to infer that they have a favorable attitude towards that cause, which in turn affects their future behavior regarding a product linked to that topic. Because users' product involvement is typically low in the early stages of the user journey, we put forward that self-perception drives users' need for consistent behavior, especially in the user onboarding experience. On this basis, we argue that by obtaining a small, active commitment that alters users' self-image such that it triggers a desire for consistent behavior during the user's onboarding journey, users' intention to use a mobile app will increase. Accordingly, we hypothesize that

H1: *Users will have a higher intention to use a mobile app after undergoing an onboarding experience with commitment nudges compared to an onboarding experience without commitment nudges.*

3.2   The Effect of Personalization on Intention to Use

App providers often draw on personalization nudges to increase their information system's value for an individual user by customizing it to the user's personal needs. Personalization has been found to affect

cognitive processes and may be used to shape consumers' decision making (Greer and Murtaza, 2003; Shalley, 1991). These cognitive processes are stimulated by suggesting to users that they are addressed with benevolence when personalization is employed, which is a great motivator for intention to use (McAdams and J. J. Bauer, 2004). In particular, explicit (i.e., user-driven) personalization as opposed to implicit (i.e., transaction- and context-driven) personalization makes users feel more invested because when they actively provide their personal information, they become co-creators of value (Schlosser et al., 2006). The provision of personal information further leads users to perceive greater goal specificity (i.e., the degree to which the target of a goal is defined) and hence augments their motivation to continue using the app. Thus, we posit that the usage of personalization nudges within the context of the onboarding experience of mobile apps increases consumers' intention to use. The argument is that personalizing the onboarding experience leads users to feel more invested in a mobile app because they are likely to perceive themselves as co-creators of value (Schlosser et al., 2006; Surprenant and Solomon, 1987). This investment, in turn, increases goal specificity for users and makes them perceive greater motivation to continue using the app. Thus, we suggest that personalization nudges increase consumers' intention to use. Based on the preceding argumentation, we derive the following hypothesis:

H2: *Users will have a higher intention to use a mobile app after undergoing an onboarding experience with personalization compared to an onboarding experience without personalization.*

4 Research Methodology

4.1 Experimental Design and Treatments

We cooperated with a nascent German startup to conduct a randomized online experiment. The startup provides a social habit tracking app in which users can track their progress when pursuing a goal together. Consistent with previous research on sampling strategies (e.g., Keith et al., 2013), we acquired subjects through email campaigns and social media groups and randomly assigned them to our treatments (Jung, Erdfelder, et al., 2018). Subjects were motivated to participate in exchange for a small fee of €2. The experiment was conducted over the course of two weeks. Subjects participated with their own mobile devices to increase ecological validity. We employed a 2 (commitment: presence vs. absence) x 2 (personalization: presence vs. absence) between-subjects, full-factorial design. All treatments of commitment were combined with the personalization treatments on the main campaign landing page, resulting in a total of four experimental conditions (see Figure 2).
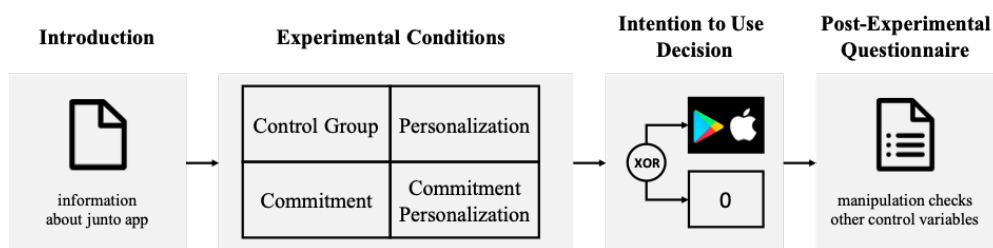

Figure 2: Experimental procedure and conditions

The experiment proceeded in the following manner: First, participants were introduced to how the app helps to cultivate habits. Participants were randomly assigned to one of the four experimental conditions. Second, subjects in a commitment condition were asked to either commit to a first mini-challenge (drink a glass of water after waking up three days in a row) by clicking on a button labeled "I accept the challenge" or refuse and press a button labeled "I'd rather not" (see Figure 3). Participants in a non-commitment condition simply passed through to the next screen. For our analysis, we considered only the participants
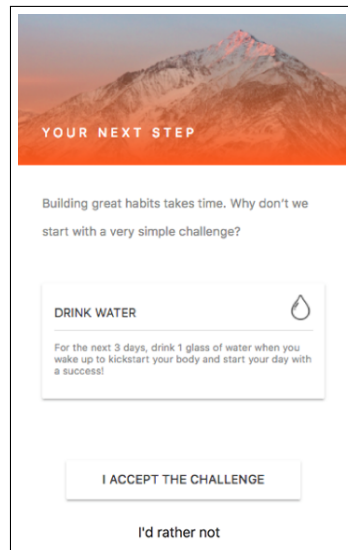
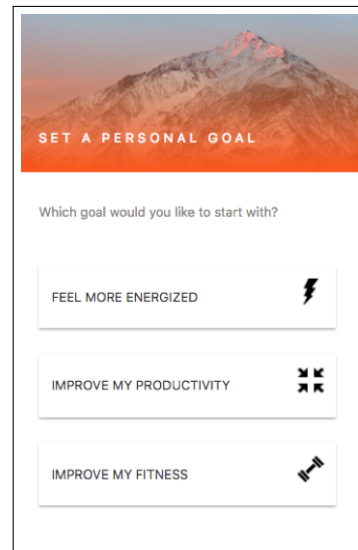Figure 3: Implementation of the commitment condition

Figure 4: Implementation of the personalization condition

that accepted the mini-challenge. Third, depending on the experimental condition to which a subject was assigned, participants in a personalized condition could choose between three presented goals that they wanted to pursue, while in a non-personalization condition, they had no options to specify their goal (see Figure 4). Fourth, all participants were presented a screen that showed hyperlinks for the most popular app stores (i.e., Apple App Store and Google Play Store), as it is common practice to guide users to install an app. They also had the choice to opt out via a third button, which recorded our dependent binary variable "intention to use". Hereafter, a post-experimental questionnaire captured participants' responses to questions measuring perceived usefulness, control variables, manipulation checks, and several other variables (see Variables Measured and Measurement Validation). Finally, participants were debriefed and thanked for their participation at the end of the survey.

4.2 Measured Variables and Measurement Validation

We recorded our dichotomous dependent variable, intention to use, in line with Ramaseshan and Stein (2014) based on actual intentional behavior collected via a clickstream analysis. Therefore, we presented subjects two options on a designated page. They could either choose to install the app by clicking on a button to continue to their operating app store (as is common practice among practitioners) or refuse to install the app by clicking on a button that was labeled "No thanks, proceed". After clicking either option, the subjects' choices were captured, and they were redirected to the post-experimental questionnaire.

Then, we recorded several control variables that have been identified as the most salient drivers of behavioral intention in prior literature (i.e., perceived disorientation, personal innovativeness, education, and gender). Perceived disorientation was measured using three items adapted from Webster and Ahuja (2006) on a 7-point scale ranging from (1) never to (7) always. Further, we adopted three items from Agarwal and Prasad (1998) to record personal innovativeness, measured on a 7-point Likert scale ranging from (1) strongly disagree to (7) strongly agree. Lastly, we recorded participants' highest education level and gender.

We conducted a confirmatory factor analysis (CFA) revealing that all scales exhibited satisfactory levels of convergent validity, and each scale's average variance extracted exceeded multiple squared correlations indicating that all discriminant validity requirements were met (see Table 1) (Awad and Krishnan, 2006; Fornell and Larcker, 1981). In addition to that, we recorded perceived personalization ("Junto delivers a

personalized onboarding experience by asking me for my personal preferences") and commitment ("I am strongly committed to tracking how often I drink water each day in Junto") as manipulation checks on a 7-point Likert scale.

Variables	Items (7-point scales)
Personal Innovativeness Agarwal and Prasad (1998) (CA=0.83; CR=0.85; AVE=0.64)	Among my peers, I am usually the first to try out new online platforms or web services
	I have confidence in my ability to solve problems creatively
	I feel that I am good at generating novel ideas
Perceived Disorientation Webster and Ahuja (2006) (CA=0.80; CR=0.88; AVE=0.72)	While I was in the onboarding process, I felt lost
	While I was in the onboarding process, I did not know how to get to my desired location
	While I was in the onboarding process, I felt disoriented
Note: CA = Cronbach's Alpha; CR = Composite Reliability; AVE = Average Variance Extracted	

Table 1: Results of Confirmatory Factor Analysis for Core Variables

5 Results

5.1 Sample Description, Controls and Manipulation Checks

Of 1,000 potential subjects, 178 accepted our invitation (18% response rate). We eliminated 21 incomplete surveys. Additionally, 7 subjects failed to complete our attention questions. As a result, we had a sample size of 150 subjects, of which 69% were males with an average age of 32, ranging from 17 to 52 (see Table 2).

Dependent Variable	Mean	StD
Intention to Use (in %)	39%	.49
Controls & Mediators	**Mean**	**StD**
Personalization	.56	.50
Commitment	.30	.46
Education	3.82	.93
Perceived Disorientation	3.88	2.03
Personal Innovativeness	5.19	1.33
Gender (male in %)	69%	.47
Age	31.97	6.90
Note: means and standard deviations; N = 150		

Table 2: Descriptive statistics

In order to confirm the randomized assignment of our participants to the experimental conditions, we conducted several one-way ANOVAs. We found no statistically significant difference in perceived disorientation ($F=1.030$; $p > 0.05$), gender ($F=1.303$; $p > 0.05$), education ($F=0.460$; $p > 0.05$), and personal innovativeness ($F=1.408$; $p > 0.05$) between all experimental groups, which confirmed that the randomization was successful. Based on a clickstream analysis, we were able to verify when users triggered an installment button that recorded our binary dependent variable (intention to use).

The manipulation check results indicated that subjects in personalization conditions ($M=5.28$; $SD=1.221$) rated perceived personalization to be significantly higher than those in conditions with no personalization ($M=4.58$; $SD=1.608$; $F(1,149)=18.549$; $p < 0.01$). Additionally, participants in commitment conditions

rated the commitment (*M*=5.37; *SD*=1.306) to be consistently higher than in conditions without commitment (*M*=4.54; *SD*=1.532; $F(1,149)$=10.155; $p < 0.01$).

5.2 Main Effect Analysis for Commitment and Personalization

We conducted a three-stage hierarchical logistic regression on our dependent variable, intention to use, to test H1 and H2. In the first stage, we entered all control variables. Subsequently, we added our independent variables – commitment and personalization – in the second stage. Lastly, we added the interaction term of commitment and personalization in the third stage. To analyze our model's significance, we computed Nagelkerke's R^2 and χ^2-Statistics for all stages. Our results demonstrated statistically significant positive effects of commitment (*p < 0.001*) and personalization (*p < 0.01*) on users' intention to use (see Table 3).

	Stage 1		Stage 2		Stage 3	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Intercept	-1.253	1.049	-3.393**	1.272	-3.457**	1.317
Commitment			2.191***	0.439	1.249*	0.620
Personalization			1.416**	0.430	0.818	0.494
Interaction Term					1.941*	0.967
Education	-0.052	0.199	-0.032	0.234	-0.009	0.244
Perceived Disorientation	0.030	0.085	0.066	0.100	0.085	0.101
Personal Innovativeness	0.132	0.150	0.164	0.172	0.190	0.180
Gender	0.267	0.369	0.547	0.445	0.757	0.483
Nagelkerke's R^2	0.015		0.337		0.366	
Log-Likelihood	198.551		157.337		152.981	
Omnibus-Tests	1.619		42.833		47.189	
*Note: N = 150; * p <0.05; ** p <0.01; *** p <0.001; SE = Standard Error*						

Table 3: Main Effect Analysis

In support of hypotheses H1 and H2, the logistical regression demonstrated a statistically significant main effect for commitment (*b = 2.191; Wald statistic (1) = 24.963; p < 0.001*) and personalization (*b = 1.416; Wald statistic (1) = 10.844; p < 0.01*). Furthermore, our results demonstrated a statistically significant positive interaction effect of commitment and personalization on intention to use (*b =1.941; Wald statistic (1) = 4.024; p < 0.05*), indicating support for H3. We will examine the interaction effect of commitment and personalization in the following section.

5.3 Interaction Effect Analysis for Personalization and Commitment

In H3, we suggested that personalization will moderate the effect of commitment on intention to use. In the previous section, we observed a preliminary indication of an interaction between commitment and personalization. Thus, to facilitate the interpretation of the moderated effect, we conducted a simple slope analysis (Aiken et al., 1991). Additionally, we tested how personalization moderates the effect of commitment on intention to use by conducting a bootstrap moderation analysis with 10,000 samples and a 95% bias-corrected confidence interval (Hayes, 2017).
As shown in Figure 5, the effect of commitment on intention to use in absence of personalization is higher (39.82%) than the effect of personalization on intention to use in absence of commitment (30.07%). On

the other hand, the separate effects are each outperformed when both treatments are employed together (91.26%).
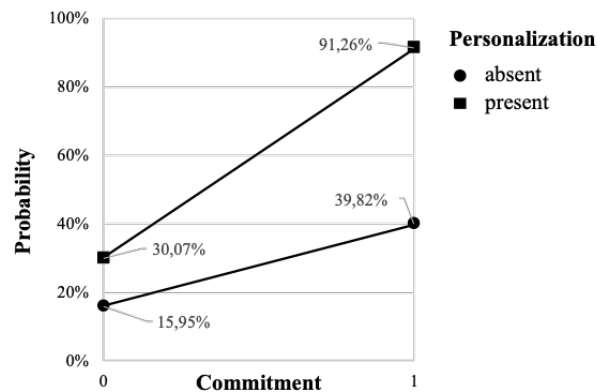

Figure 5: Interaction Effect between Commitment and Personalization

As our main effect analysis indicated, our main effects of commitment and personalization on intention to use were qualified by a significant two-way interaction (*b = 1.941, standard error = 0.967; p < 0.05*). Moreover, the results of our moderation analysis demonstrate that the effect of commitment on intention to use is moderated by personalization such that the effect is amplified when personalization is present (*effect = 3.1895, standard error = 0.7333, 95% bias-corrected confidence interval (CI) = [1.7522, 4.6269]*) compared to when personalization is absent (*effect = 1.2489, standard error = 0.6204, 95% bias-corrected confidence interval (CI) = [0.0330, 2.4648]*).

6   Discussion

The app economy has experienced dramatic growth over the past decade. As a result, users are deluged with offers and information, which has led to increased churn rates. Therefore, app providers attach great importance to their user onboarding strategy in order to actively guide users to recognize their products' value as well as how to capture it. This study illuminates how firms can apply digital nudges in the user onboarding experience to positively affect users' intention to use a product and thereby actively shape user activation outcomes. In particular, we analyzed how commitment and personalization nudges employed in the user onboarding experience of a mobile app affect users' intention to use the app.

Our results support the premise that embedding commitment and personalization nudges in the user onboarding experience positively influence users' intention to use a mobile app. In particular, we found that obtaining small, active commitments during user onboarding triggers a consistent decision about their intention to use. The underlying reasoning is that users strive to be consistent with a previous commitment, formed by a behavior that slightly alters their self-perception, to avoid cognitive dissonance. User-driven personalization nudges, on the other hand, make users feel more invested in the app as they perceive themselves as co-creators of value and thus affects their intention to use the app because they actively generate higher goal specificity. Furthermore, we explicated that the effect of commitment on intention to use is moderated by personalization so that when personalization is present, it amplifies the effect of commitment on intention to use. The underlying rationale is that users experience intrinsic motivation when they become co-creators of value by providing their personal information. Additionally, when commitment nudges are combined with explicit personalization, consumers feel a greater benevolence and are more likely to be invested in the product.

Thus, our study has two important theoretical contributions to IS research: First, extending prior contributions on how single and isolated digital nudges affect user behavior (Mirsch et al., 2017; Weinmann et al., 2016), our study is among the first to investigate the interplay of multiple digital nudges. Our results

demonstrate that the joint effect of commitment and personalization nudges is much more effective in increasing the intention to use compared to both effects separately. Hence, extending the literature on personalization and commitment, our study gives a much more detailed picture of how digital nudges can be combined and thus lead to better activation outcomes in the nascent context of user onboarding (Benlian, 2015; Cialdini, 2001). Second, we empirically evaluated the effectiveness of two digital nudges, namely, personalization and commitment, in the context of the under-researched field of user onboarding by drawing on a randomized online experiment with real users' intention to use (Liu et al., 2017). Thus, we demonstrated how digital nudges can be used in user onboarding to shape better activation outcomes. Thereby, Mirsch et al. (2017)'s call, our study contributes to IS research by giving actionable and design-oriented insights on digital nudges.

Beyond these theoretical contributions, this study provides valuable insights for app providers in the form of two actionable strategies to increase users' intention to use. We demonstrated how commitment and personalization nudges can be used and designed to drive better activation outcomes during user onboarding. In particular, we showed that obtaining a small, active commitment during the user onboarding experience significantly increases users' intention to use a mobile app. By employing personalization tactics during the user onboarding experience, app providers can draw on personal information to tailor their information and offers to user needs and thereby actively guide users to recognize the apps' value, as well as how to capture it. Most importantly, we shed light on the interaction effect of personalization and commitment nudges and showed that combining both nudges, e.g., allowing users to commit to personal goals for using the product during the onboarding experience, promises even higher activation outcomes.

7   Limitations, Future Research and Conclusion

Our findings should be interpreted in view of three noteworthy limitations. First, although we recorded actual intention to use behavior, we were unable to provide insights about actual usage behavior. Thus, we recommend that scholars complement our findings by studying the impact of commitment and personalization strategies on actual usage behavior in an empirical investigation. This avenue promises sound findings about how firms may use commitment and personalization to actively shape activation outcomes. Second, we explicated how commitment tactics in user onboarding may be used to drive intentional behavior. However, our results indicate that commitment nudges need to be employed carefully and should always be kept within a realistic margin. Thus, we encourage future studies to examine the threshold of how much commitment can be demanded from users before the effect changes. Third, future studies should investigate how our findings translate to other app contexts. While our findings show that user onboarding is effective in guiding new and unaware users to a mobile app's value in the context of a habit-cultivating app, future research could corroborate our findings in different mobile app contexts. Further, it appears promising to consider different user characteristics in the implicit personalization of the user onboarding experience. The results may allow for tailoring digital nudges to individual users based on their characteristics and current usage context. Lastly, design-oriented researchers could investigate other digital nudges, such as social proof, saliency or reciprocity, including their interaction effect with commitment and personalization nudges.

In summary, our study illuminates the effect of commitment and personalization nudges in mobile user onboarding experiences in order to improve user activation outcomes. The results of this research may be beneficial for design-oriented researchers as well as organizations considering the use of commitment and personalization nudges in their user onboarding. We hope that it provides an impetus for future research on user onboarding that may be applied by practitioners designing mobile user onboarding experiences.

References

Agarwal, R. and J. Prasad (1998). "A conceptual and operational definition of personal innovativeness in the domain of information technology." *Information systems research* 9 (2), 204–215. ISSN: 1047-7047.

Aggarwal, P., R. Vaidyanathan, and L. Rochford (2007). "The wretched refuse of a teeming shore? A critical examination of the quality of undergraduate marketing students." *Journal of Marketing Education* 29 (3), 223–233. ISSN: 0273-4753.

Aiken, L. S., S. G. West, and R. R. Reno (1991). *Multiple regression: Testing and interpreting interactions*. Sage. ISBN: 0761907122.

Awad, N. F. and M. S. Krishnan (2006). "The personalization privacy paradox: an empirical evaluation of information transparency and the willingness to be profiled online for personalization." *MIS quarterly*, 13–28. ISSN: 0276-7783.

Balboni, K. (2016). *500 User Onboarding Experiences categorized into 8 UI/UX Patterns*. URL: `https://www.appcues.com/blog/user-onboarding-ui-ux-patterns`.

Bauer, T. N. and B. Erdogan (2011). "Organizational socialization: The effective onboarding of new employees." *APA handbook of industrial and organizational psychology* 3, 51–64.

Bem, D. J. (1972). "Self-perception theory." *Advances in experimental social psychology* 6, 1–62. ISSN: 0065-2601.

Benartzi, S. and J. Lehrer (2015). *The smarter screen: Surprising ways to influence and improve online behavior*. Portfolio. ISBN: 1591847869.

Benlian, A. (2015). "Web personalization cues and their differential effects on user assessments of website value." *Journal of Management Information Systems* 32 (1), 225–260. ISSN: 0742-1222.

Cialdini, R. B. (2001). "Harnessing the science of persuasion." *Harvard Business Review* 79 (9), 72–81. ISSN: 0017-8012.

Cialdini, R. B. and N. Garde (1987). *Influence*. Vol. 3. A. Michel.

Clow, K. E. (2004). *Integrated advertising, promotion, and marketing communications*. Pearson Education India. ISBN: 8131763293.

Cooper, A., R. Reimann, and D. Cronin (2007). *About face 3: the essentials of interaction design*. John Wiley & Sons.

Cox III, E. P., W. T. Anderson Jr, and D. G. Fulcher (1974). "Reappraising mail survey response rates." *Journal of Marketing Research*, 413–417. ISSN: 0022-2437.

Cyr, D. (2014). "Return visits: a review of how Web site design can engender visitor loyalty." *Journal of Information Technology* 29 (1), 1–26. DOI: `10.1057/jit.2013.25`. URL: `https://link.springer.com/article/10.1057%2Fjit.2013.25#citeas`.

Dahan, E. and J. R. Hauser (2002). "The virtual customer." *Journal of Product Innovation Management* 19 (5), 332–353. ISSN: 1540-5885.

Ericksen, M. K. and M. J. Srigy (1989). "Achievement motivation and clothing behaviour: A self-image congruence analysis." *Journal of Social Behavior and Personality* 4 (4), 307. ISSN: 0886-1641.

Festinger, L. (1957). "A theory of cognitive dissonance Evanston." *IL: Row, Peterson* 1.

Fornell, C. and D. F. Larcker (1981). "Structural equation models with unobservable variables and measurement error: Algebra and statistics." *Journal of marketing research*, 382–388. ISSN: 0022-2437.

Gallo, A. (2014). "The value of keeping the right customers." *Harvard Business Review* (October), 29.

Gourville, J. T. (2006). "Eager sellers & stony buyers." *Harvard Business Review* 84 (6), 98–106.

Greer, T. H. and M. B. Murtaza (2003). "Web personalization: The impact of perceived innovation characteristics on the intention to use personalization." *Journal of Computer Information Systems* 43 (3), 50–55. ISSN: 0887-4417.

Grennan, T. (2016). *Spring 2016 mobile customer retention report: an analysis of retention by day*. Tech. rep. Tech. rep., Appboy.

Hayes, A. F. (2017). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. Guilford Publications. ISBN: 146253466X.

Heider, F. (2013). *The psychology of interpersonal relations*. URL: https://books.google.de/books?hl=en&lr=&id=tVFmY0xvn-wC&oi=fnd&pg=PP1&dq=1958.+The+Psychology+of+Interpersonal+Relation&ots=UIDEqobkvX&sig=bgJLRMN_sVVjmGJ48mb_vGpYbDs.

Hoban, P. R. and R. E. Bucklin (2015). "Effects of internet display advertising in the purchase funnel: Model-based insights from a randomized field experiment." *Journal of Marketing Research* 52 (3), 375–393.

Huang, N., P. Chen, Y. Hong, and S. Wu (2018). "Digital Nudging for Online Social Sharing: Evidence from A Randomized Field Experiment." In: *Proceedings of the 51st Hawaii International Conference on System Sciences*. ISBN: 0998133116.

Jung, D., E. Erdfelder, and F. Glaser (2018). "Nudged to win-Designing robo-advisory to overcome decision inertia." In: *Proceedings of the 26th European Conference on Information Systems (ECIS 2018)*.

Jung, D. and C. Weinhardt (2018). "Robo-Advisors and Financial Decision Inertia: How Choice Architecture Helps to Reduce Inertia in Financial Planning Tools."

Keith, M. J., S. C. Thompson, J. Hale, P. B. Lowry, and C. Greer (2013). "Information disclosure on mobile devices: Re-examining privacy calculus with actual user behavior." *International Journal of Human-Computer Studies* 71 (12), 1163–1173. ISSN: 1071-5819.

Kressmann, F., M. J. Sirgy, A. Herrmann, F. Huber, S. Huber, and D.-J. Lee (2006). "Direct and indirect effects of self-image congruence on brand loyalty." *Journal of Business Research* 59 (9), 955–964. ISSN: 0148-2963.

Kretzer, M. and A. Maedche (2018). "Designing Social Nudges for Enterprise Recommendation Agents: An Investigation in the Business Intelligence Systems Context."

Kwon, K. and C. Kim (2012). "How to design personalization in a context of customer retention: Who personalizes what and to what extent?" *Electronic Commerce Research and Applications* 11 (2), 101–116. ISSN: 1567-4223. DOI: https://doi.org/10.1016/j.elerap.2011.05.002. URL: http://www.sciencedirect.com/science/article/pii/S1567422311000238.

Lemon, K. N. and P. C. Verhoef (2016). "Understanding Customer Experience Throughout the Customer Journey." *http://dx.doi.org/10.1509/jm.15.0420*. DOI: 10.1509/jm.15.0420. URL: http://journals.ama.org/doi/abs/10.1509/jm.15.0420?code=amma-site.

Liang, T.-P., H.-Y. Chen, and E. Turban (2009). "Effect of personalization on the perceived usefulness of online customer services: A dual-core theory." In: *Proceedings of the 11th International Conference on Electronic Commerce*. ACM, pp. 279–288. ISBN: 1605585866.

Liu, D., R. Santhanam, and J. Webster (2017). "Toward Meaningful Engagement: A Framework for Design and Research of Gamified Information Systems." *MIS quarterly* 41 (4).

Malhotra, N. K. (1981). "A scale to measure self-concepts, person concepts, and product concepts." *Journal of marketing research*, 456–464. ISSN: 0022-2437.

Mangleburg, T. F., M. J. Sirgy, D. Grewal, D. Axsom, M. Hatzios, C. Claiborne, and T. Bogle (1998). "The moderating effect of prior experience in consumers' use of user-image based versus utilitarian cues in brand attitude." *Journal of Business and Psychology* 13 (1), 101–113. ISSN: 0889-3268.

McAdams, D. P. and J. J. Bauer (2004). "Gratitude in modern life: Its manifestations and development." *The psychology of gratitude*, 81–99.

Mirsch, T., C. Lehrer, and R. Jung (2017). "Digital Nudging: Altering User Behavior in Digital Environments."

Mobasher, B., R. Cooley, and J. Srivastava (2000). "Automatic personalization based on web usage mining." *Communications of the ACM* 43 (8), 142–151. ISSN: 0001-0782.

Montgomery, A. L. and M. D. Smith (2009). "Prospects for Personalization on the Internet." *Journal of Interactive Marketing*. URL: http://www.sciencedirect.com/science/article/pii/S1094996809000322.

Murphy (2016). *The Secret to Successful Customer Onboarding*. URL: http://sixteenventures.com/customer-onboarding.

Newcomb, T. M. (1953). "An approach to the study of communicative acts." *Psychological review* 60 (6), 393. ISSN: 1939-1471.

Newman, M. and R. Sabherwal (1996). "Determinants of commitment to information systems development: a longitudinal investigation." *MIS quarterly*, 23–54. ISSN: 0276-7783.

Nielsen (2013). "The Mobile Consumer: A Global Snapshot." *Nueva York, Estados*.

Noel, J. (2017). *Leveraging User Psychology for User Onboarding*. URL: https://www.appcues.com/blog/consistency-principal.

— (2018). *Why User Onboarding is the Most Important Part of the Customer Journey by 2.6x Jackson*. URL: https://www.appcues.com/blog/why-user-onboarding-is-the-most-important-part-of-the-customer-journey-by-2-6x.

Orji, R., R. L. Mandryk, and J. Vassileva (2015). "Gender, age, and responsiveness to Cialdini's persuasion strategies." In: *International Conference on Persuasive Technology*. Springer, pp. 147–159.

Peppers, D. and M. Rogers (1997). "Enterprise 1–2–1: Tools for building unbreakable customer relationships in the Interactive Age." *Piatkus, London*.

Petrison, L., R. C. Blattberg, and P. Wang (1997). "Database Marketing–Past." *Present and*.

Ramaseshan, B. and A. Stein (2014). "Connecting the dots between brand experience and brand loyalty: The mediating role of brand personality and brand relationships." *Journal of Brand Management* 21 (7-8), 664–683. ISSN: 1350-231X.

Renz, J., T. Staubitz, J. Pollack, and C. Meinel (2014). "Improving the Onboarding User Experience in MOOCs." *Proceedings EduLearn*.

Rossi, P. E., R. E. McCulloch, and G. M. Allenby (1996). "The value of purchase history data in target marketing." *Marketing Science* 15 (4), 321–340. ISSN: 0732-2399.

Schlosser, A. E., T. B. White, and S. M. Lloyd (2006). "Converting web site visitors into buyers: how web site investment increases consumer trusting beliefs and online purchase intentions." *Journal of Marketing* 70 (2), 133–148. ISSN: 0022-2429.

Schneider, D., S. Lins, T. Grupp, A. Benlian, and A. Sunyaev (2017). "Nudging Users Into Online Verification: The Case of Carsharing Platforms."

Shalley, C. E. (1991). "Effects of productivity goals, creativity goals, and personal discretion on individual creativity." *Journal of Applied psychology* 76 (2), 179. ISSN: 1939-1854.

Sirgy, M. J. and A. Coskun Samli (1985). "A path analytic model of store loyalty involving self-concept, store image, geographic loyalty, and socioeconomic status." *Journal of the Academy of Marketing Science* 13 (3), 265–291. ISSN: 0092-0703.

Staw, B. M., L. E. Sandelands, and J. E. Dutton (1981). "Threat rigidity effects in organizational behavior: A multilevel analysis." *Administrative science quarterly*, 501–524. ISSN: 0001-8392.

Surprenant, C. F. and M. R. Solomon (1987). "Predictability and personalization in the service encounter." *The Journal of Marketing*, 86–96. ISSN: 0022-2429.

Tam, K. Y. and S. Y. Ho (2006). "Understanding the impact of web personalization on user information processing and decision outcomes." *MIS quarterly*, 865–890. ISSN: 0276-7783.

Thies, F., M. Wessel, and A. Benlian (2016). "Effects of Social Interaction Dynamics on Platforms." *Journal of Management Information Systems* 33 (3), 843–873. ISSN: 0742-1222.

Thorbjørnsen, H., M. Supphellen, H. Nysveen, and P. E. Pedersen (2002). "Building brand relationships online: A comparison of two interactive applications." *Journal of interactive marketing* 16 (3), 17–34. ISSN: 1094-9968.

Vaidyanathan, R. and P. Aggarwal (2005). "Using commitments to drive consistency: enhancing the effectiveness of cause-related marketing communications." *Journal of Marketing Communications* 11 (4), 231–246. ISSN: 1352-7266.

Webster, J. and J. S. Ahuja (2006). "Enhancing the design of web navigation systems: The influence of user disorientation on engagement and performance." *Mis Quarterly*, 661–678. ISSN: 0276-7783.

Weinmann, M., C. Schneider, and J. v. Brocke (2016). "Digital Nudging." *Business and Information Systems Engineering* 58, 433–436. DOI: 10.1007/s12599-016-0453-1.

Xu, H., H.-H. Teo, B. C. Tan, and R. Agarwal (2009). "The role of push-pull technology in privacy calculus: the case of location-based services." *Journal of Management Information Systems* 26 (3), 135–174. ISSN: 0742-1222.

Zichermann, G. and C. Cunningham (2011). *Gamification by design: Implementing game mechanics in web and mobile apps*. " O'Reilly Media, Inc."