Digital Nudging to Increase Usage of Charity Features on E-Commerce Platforms

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Abstract.

Using behavioral economic concepts to influence choice making in virtual environments, and more specifically to nudge participation in charitable projects, has provided fruitful opportunities for design science oriented IS research. This experimental study aims to compare two alternative nudges: an opt-in checkbox nudge and a forced-choice nudge in form of a textbox, to compare and contrast their effectivity. We assessed that the forced-choice nudge is significantly more effective in nudging participants to utilize charity features on an e-commerce platform, leading to the practical contribution of a new nudge and UI Element combination to reach targeted results. Moreover, we are able to provide new insights by putting nudging theory into practice and contributing to the overall theoretical nudging discourse in the IS research domain.

Keywords: Digital Nudging, Persuasion, Forced-Choice, Charity, E-Commerce.

1 Introduction

Organizations increasingly transition their internal and external business processes into the digital space, which naturally puts an emphasis on the architecture of such environments in both academic as well as practical endeavors. Considering such environments from the perspective of its designers is the perspective we take on in this work. Based on what is known from well-established research within social- and cognitive psychology research domains [1], we know that designers of virtual choice environments need to be mindful of their stakeholders' limited cognitive capacities. Namely to efficiently aid and guide the average user who makes irrational choices regardless of their own preferences through the online choice environments [2]. The

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designers of choice environments, called choice architects, often make use of known heuristics and biases to facilitate and improve choices in virtual environments [3]. Choice architects are defined as individuals who have "*the responsibility for organizing the context in which people make decisions*" (p. 3). Accordingly, as virtual choice environments are never neutral, choice architects should design respective environments with the decision-makers in mind to guarantee the best possible choice outcome [4]. With this line of thinking Thaler and Sunstein [4] introduce the concept of nudging to the academic discourse of Behavioral Economics, which to this day is a concept frequently adopted to the Information Systems (IS) research domain (for an overview see [50]).

The researchers Weinman et al. [5] define digital nudging in IS research and human-computer-interaction (HCI) as "*the use of user-interface design elements to guide people's behavior in digital choice environments*" ([5], p. 433). With their work, Weinman et al. [5] aimed to transfer and establish the nudging concept to the digital context, which contributes new design principles and mechanisms to the more design-oriented IS domain [5]. The e-commerce giant Amazon provides such an example as they launched an alternative sister website in 2013, called "Amazon Smile". In line with the concept of nudging, on Amazon Smile, users donate 0.5% of the purchase price of all eligible products to a non-profit organization or cause of their choice, thus allowing for small donations with virtually no costs for the customer [6]. Despite the given normative incentive of customers making donations without having extra costs themselves, users do not fully utilize the website. Therefore, designers have implemented a User Interface (UI) element, in form of a reminder, to nudge the continued use of Amazon Smile, if customers continue shopping on the regular website instead. Here, Amazon uses the UI element to bypass the decision inertia or status quo bias. The status quo bias is evident when individuals decide to stick with the status quo or prefer to maintain a decision they have previously made [7], which in this example entails shopping on the original Amazon website. While this method might be effective to remind users familiar with Amazon Smile, it does not help to inform and encourage others unfamiliar with the website, and therefore does not help to increase Amazon Smile traffic and consequent donations. This is why we implemented a similar website to assess how users can be most effectively encouraged to use charitable programs on popular E-Commerce websites similar to what Amazon tried to accomplish with Amazon Smile. Moreover, as part of the assessment in this work we identified nudging mechanisms as a promising tool to drive user engagement, which is why two different nudges will be implemented to compare their effectivity.

On the basis of this prior work and following the call from [8] to further close the gap between theory and practice, this work aims to conduct an experimental study to examine, if other approaches in addition to the reminder nudge, could be more effective in regards to traffic on a website. In an experimental setting we implement and test two default option nudges, the opt-in checkbox and the forced-choice nudge, as an alternative to the Amazon Smile reminder. Thereby, we aim to contribute new knowledge of nudging mechanisms and effects, further putting theory into practice. Moreover, in contribution to practice we aim to provide a better understanding of how

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these nudges work and if they can be implemented more effectively to incentivize customers to use charity features and thereby increase the number of donation program users.

After the introduction, a general literature review on nudging, digital nudging, design science, and HCI will be outlined. This includes the theoretical background on the (digital) nudging theory, its delimitation to the concept of persuasion as well as psychological effects in nudging. Afterward, the research design will be presented in detail. The digital nudging design cycle [9] will be used to evaluate and design the nudges. Following that, a short description of the data collection and analysis, as well as the development of the artificial online store "spreezon" will be laid out. The results will be first described, and consequently used to calculate a logistic regression model to examine the impact on the use of the donation website. The results will be discussed in chapter five before the implications, limitations, and suggestions for further research will be presented in chapter six.

2 Theoretical Background and Relevant Literature

Before further elaborating on how digital nudges can be designed, and implemented, we will first lay out the current body of knowledge which we base our work on. We conducted our literature review across three different disciplines, namely behavioral economics, computer science, and psychology, reflecting the interdisciplinary character of the nudging concept. We gather e.g. that UI Design is part of the human-computer interaction (HCI) discipline, whereas heuristics and biases and the dual process theory are two fundamental concepts of nudging. To understand how nudgees, users who are nudged, process information in given choice environments, the nudging concept borrows from psychology and neuroscience, namely the dual process theory [10]. The theory constitutes that humans think in two different and distinct systems [11]. System I, also called the automatic system, is often described as a fast, uncontrolled, effortless and an unconscious way to solve problems using existing heuristics and biases. Contrary to that, System II, called the reflective system, is usually described as a self-aware, slow, but controlled, and rule-following way of thinking [4]. Humans would solely make rational decisions, if they only relied on their reflective system. However, in reality humans often use their low energy consuming, automatic system in everyday situations to e.g. safe time and cognitive capacities, leading to irrational decision-making [4].

In light of this, Thaler and Sunstein [12] were the first to propose a libertarian paternalist framework to assist decision-making process and provide guiding principles for the designers of nudges. Since then a more liberty-preserving understanding of the original nudging concept, understood as a soft form of paternalism has been established in both behavioral economics as well as IS research. According to the paternalistic principles of the overall nudging concept [12], nudgees should always have the freedom of choice when they are exposed to choice environments, meaning that no option should be ruled out or hidden. Additionally, the nudger is not allowed to manipulate the choice environment by using coercion,

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deception, or other manipulative strategies [13]. Nudgers can utilize heuristics and biases to trigger the reflective system or use the automatic system to counter or leverage psychological effects within the scope of libertarian paternalism [13].

One of the most frequent biases users apply in virtual environments is the status quo bias, which means that users stick to preselected choices and ignore alternatives. Samuelson and Zeckhauser [14] analyzed data on health and retirement plans, revealing that the status quo bias has a substantial impact on decision-making. This also comes into effect in the example provided above, where Amazon Smile users are reminded to shop on the website with their preselected donation feature. Here, users are not forced to make a decision, which can result in their continued use of the regular website in consequence of the status quo bias. Closely linked to this phenomenon is the decision inertia. Namely, limited time and effort lead to the decision inertia fallacy and consequently the status quo bias [12]. To overcome the status quo bias, one can either leverage the bias or counter it. When designing the choice environment nudgers can use e.g. the default option nudge, which overrides the bias by pre-selecting the option, which is most beneficial to the nudgees. The effectiveness of this method has been demonstrated in prior work by Johnson and Goldstein [15], who assessed different default option forms such as the opt-in and opt-out affect organ donation behavior and found that countries, which automatically enroll citizens in organ donation programs have a significantly higher percentage of organ donors than countries in which one has to enroll as an organ donor deliberately. Alternatively, in some situations it might make sense to use a forced-choice architecture. On the one hand, forced-choice architecture is probably the most effective method to counter the decision inertia bias, since the nudgee is forced to decide. On the other hand, choice architects have to consider that there will be a risk that customers consider this necessity to decide an inconvenience and might stop using such services or products which require a forced choice [16].

The majority of literature on nudging, digital nudging, and design science strives to present theoretical findings supported by real-life examples [5], [8], [17], [51], whereas other studies focus on analyzing qualitative or quantitative data [18], [19]. However, most of the work outlines how nudges can be utilized, not which UI elements (e.g. radio buttons, sliders, textboxes) have the most significant impact on user behavior. Schneider et al. [9] created an overview of the most effective combinations of heuristics and biases with UI elements and matched them to the corresponding choice they influenced. More precisely, they focused on three heuristics and biases, the “decoy effect” [20], “scarcity effect” [21] and the “middle-option bias” [22].

As mentioned in the introduction, the concept of nudging is applicable to digital choice architectures, mainly due to an information overload and individuals making quick and automated decisions, which in turn can lead to flawed decisions [23]. Therefore, Weinmann et al. [5] coined and defined the term “digital nudging” and have since been reinforcing the visibility and necessity for further nudging research within the IS research community. Regarding the applications of digital nudging in IS, Weinmann et al. [5] laid out a diverse range of use cases digital nudging can be applied to, ranging from e.g. e-commerce and e-business to e-health, and social media. Within the e-commerce domain, research has assessed many studies concerning various aspects of the online shopping experience. Hou [24] conducted a field study on food-ordering websites to examine if user interfaces showing how much a person consumes can influence their food intake. Meanwhile, in a lab experiment, Esposito et al. [25] used emotive warning messages and showing incompatibility information throughout the customer journey, finding that to prevent the purchase of incompatible goods, according information must be shown during the checkout process. Likewise, Djurica and Figl [26] assessed the impact of nudging techniques on customers product choice processes, whereas Cave and Cave [27] assessed the positive impact of nudging mechanisms such as providing energy efficiency information to online shoppers. Weinmann et al. [5] rightfully predicted that digital nudging research would eventually evolve into an essential area of design science, given the emergence of digital choice environments of new devices and applications on the horizon.

3 Research Design

3.1 Digital Nudging Life Cycle

The IS research discipline offers some unique opportunities and methods for utilizing psychological nudging effects. Web and mobile technologies such as e.g. real-time tracking, personalization of user interfaces, or the analysis of user behavior allow quick testing and optimization of digital nudges [9]. In recent years, IS scholars proposed guidelines tailored towards IS research, such as the DINU-Model [13] or the digital nudge design method [28]. Our study builds on the digital nudging design cycle framework by Schneider et al. [9], who based their work on knowledge derived from Ly et al. [29] and Datta and Mullainathan [30], to design, implement, and test two digital nudges. The digital nudging design cycle framework consists of four iterative steps, namely: (1) defining the goal, (2) understanding the users, (3) designing the nudge, and (4) testing the nudge. Particularly relevant according to Schneider et al. [9] is the type of choice that is to be made by users, such as binary, continuous, or discrete choices. Moreover, ethical aspects of the nudge should also be considered to avoid nudging users against their own preferences [9]. While analyzing the target group, nudgers should identify heuristics and biases, which might influence the choice selection, and assess psychological effects, which can be used to increase the impact. By means of these two steps, the nudger can begin the design process by selecting appropriate nudging mechanisms to guide users through the choice environment. As designers of information systems operate in virtual environments, they have a plethora of utilities and methods for implementing nudges at their disposal.

While implementing nudges, designers should remember to follow the generally accepted design guidelines of the specific platform they are developing, to ensure conformity and intuitive design. After the design process, the nudge can be tested through online experiments or field studies. Due to the nature of digital environments, this can be accomplished comparatively easily and at low costs. The effectiveness of a

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nudge varies depending on the goal and context of the choice environment. There it is important to identify reasons for deviations during the testing phase. The collected data and knowledge during the testing phase allow to iteratively revisit previous steps and re-evaluate the set of goals, identified heuristics and biases, and design of the nudge. The designer may repeat this procedure until the nudge shows the desired features and is both effective and efficient.

3.2 Experimental Case Study

The overall goal of the two nudges designed for this experimental case study was to nudge participants to use the charity website of a (fictitious) e-commerce store called “spreezon”. The nudges are presented during the sign-in process. Users on e-commerce platforms usually have limited time and limited cognitive capacities when it comes to the sign-in process, therefore it is crucial to display information as succinctly as possible. Additionally, there should be as little distraction as possible in order to keep the user's attention to the most important UI elements. The nudges have been designed with the mentioned considerations and goals in mind.

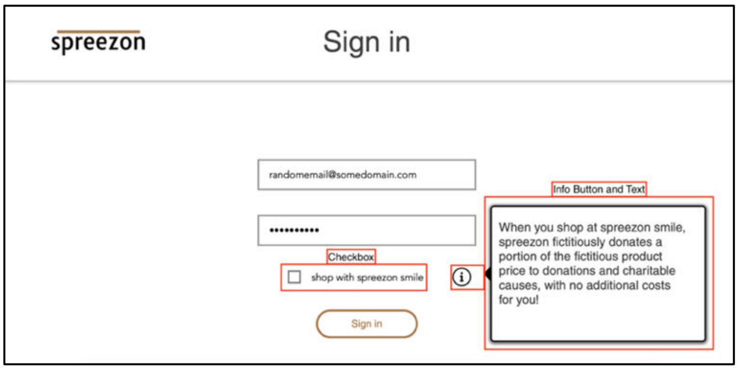

Figure 1. Opt-In Default Value Nudge via checkbox (N1)

The first nudge (N1) is a default value option nudge, implemented through an opt-in UI element (Figure 1). Opt-in in this context means that the participant or user has to manually select the option in question (here: whether or not they want to shop using the charity sister website). To achieve this, a checkbox labeled “shop with spreezon smile” and an info button right next to it has been designed. These elements were placed beneath the input fields for the email address and password. The user could click on the info button to learn more about the donation program. The information provided about the "Smile program" was identical for both nudges and kept rather concise to increase the likeliness of users reading it. The wording was inspired by Amazon's description for their Smile program. The other nudge, a forced-choice nudge (N2), was implemented utilizing a textbox (Figure 2). The group N2 sign-in page did not contain the checkbox and the info button. However, after clicking the sign-in button, users were confronted with a textbox containing the information about the “Smile program”, while all other interactions were disabled. The goal of this nudge is to force the user to actively select whether or not they want to shop via the charity sister website. To achieve this, two buttons labeled “Use Smile” and “Continue without Smile” were placed in the textbox, right beneath the provided information.

Figure 2. Forced Choice Nudge via textbox (N2)

It is to be expected that the forced-choice nudge will be more effective in nudging participants to use the charity feature of the e-commerce site since it forces users to make a choice and actively reflect on the charity program. Therefore, by using the two nudges in the experimental design as outlined above, we hypothesize that: *Participants who are exposed to the forced-choice nudge (N2) are significantly more likely to use the charity sister website than participants exposed to the opt-in default value option nudge (N1).*

3.3 Data Collection and Analysis

The participants were acquired by word of mouth as well as through the online recruitment platform prolific.ac. According to Berinsky et al. [31], recruitment platforms offer a valid alternative to obtaining random- and reliable samples of the population (instead of convenience samples) [32], [33]. Participants recruited via prolific.ac were at least 18 years old, the subjects mean age was thirty-two years, of which 48,24 % were women. They were able to conduct the study in German or English. Altogether, 255 participants were recruited, 171 through prolific and 84 through word of mouth, and they received the equivalence of 7.20 £/hour for participating. An artificial e-commerce store was designed (home page, check-out, etc.) to reconstruct a real shopping experiment within the constraints of an experimental study research design. The online store was constructed and coded on a website editor. Implemented UI elements like buttons, or grid display of items used standard features to ensure the least possible distraction for the participants who were informed about the e-commerce experimental setting, and asked to act as they usually do. They were given a fictitious budget of 100 € to shop in the online store. Participants were randomly assigned and equally distributed to the two groups,

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depending on how many participants were already assigned to each group. The assigned group determined, which corresponding nudge they were shown. Group one was exposed to the default value option nudge as an opt-in UI element (N1), while group two was subject to the forced-choice nudge (N2). Afterward, participants were asked to provide basic demographic information.

After the login page with varying UIs dependent on group affiliation, the artificial "shopping experiences" were identical for both groups regarding budget and offered products. After checking out via the shopping cart, users were directed to a "purchase confirmed" site, where they had to answer a few more questions concerning their “attitude towards donating”, “helping”, the artificial e-commerce store, and their shopping experience. The dependent variable "usedSmile" was either set to false or true, depending on the user's decision during the sign in process. In line with the hypothesis, we primarily assessed the impact of the binominal variable “group” affiliation (group 1 or 2), on the binominal, dependent variable “used Smile”. Apart from these variables, several control variables were collected. Literature and studies on donation behavior suggest that various demographic characteristics influence donation behavior [34], [35]. Five demographic variables which might have an influence on the participant's donation behavior were collected: age [36], gender [37], [38], [39], and income, educational years and number of children [34].

Additionally, participants were presented with ten statements on a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), which aimed to estimate their attitude towards donations, generosity, and charity, by using an adapted version of the helping attitude scale (HAS) by Nickell [40]. In our study, a score of thirty is considered to be neutral [41], to assess whether individuals with a higher score and thus a more positive attitude towards donating were more likely to shop via the charity sister website. Moreover, participants were asked to take a stand on four statements on a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) estimating how appealing, pleasant, and satisfactory the shopping experience was, and determine their overall satisfaction with the online store. The individual scores of these measurements were collected to analyze whether or not the charitable behavior of the artificial e-commerce platform provider had an impact on the participant's attitude towards the store, which allows for measuring if the fictitious corporate image changed due to the offer of charity features.

4 Results

The analysis is conducted utilizing the statistical software package R by using the integrated developer environment RStudio[1]. The data has been prepared by deleting unneeded metadata and filtering out all missing values. There was only one instance

[1] The data has been visualized using the packages “stargazer” for tables [42], “ggplot2” for plots [43] and

"lmtest" for log-likelihood ratios [44].

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of a participant who selected the gender level “diverse” and on further inspection it was revealed that this level of the variable had no significant impact on the model. Accordingly, gender allocation is binary with: 0 representing male and 1 representing female participants. Following these preparations, the data from the study will now be described, which subsequently allows for a detailed analysis of the data, including t-tests, logistic regressions and the comparison of the logistic regression models by using log-likelihood ratios.

4.1 Descriptive Data

Table 1 shows the descriptive statistics of most of the control variables collected during the study. The documented statistic metrics are reasonably consistent among each group.

Table 1. Descriptive Statistics

	Group1				*Group2*			
Variable	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
Gender (Female=1)	0.5	0.5	0	1	0.5	0.5	0	1
Age	31.4	10.5	18	61	32.7	12.8	18	72
Years of Education	13.9	5.1	1	34	12.6	5.4	1	30
Number of Children	0.6	1.0	0	4	0.8	1.3	0	8
HAS Scale	40.6	4.8	27	50	40.0	5.5	24	50
Appealing Scale	3.6	1.0	1	5	3.7	1.0	1	5
Quality Scale	3.5	1.1	1	5	3.5	1.0	1	5
Pleasant Scale	3.8	0.9	2	5	4.0	0.8	1	5
Satisfaction Scale	3.5	1.1	1	5	3.6	1.0	1	5

The distribution of the income levels among each group is relatively balanced. The slight income differences between both groups did not significantly impact the results. Figure 3 shows a stacked bar plot comparing the number of participants choosing to use the smile program in green and those who chose not to in red. About 76.19% of the participants from the N2 group used the smile program, as compared to only 32.56% in the N1 group. This result provides support for our hypothesis that N2 participants were more likely to use the charity feature.

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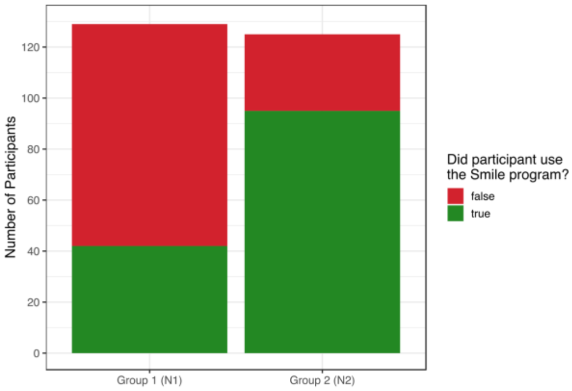

Figure 3. Opt-In Default Value Nudge via checkbox (N1)

4.2 Data Analysis

After finding supporting evidence for the hypothesis during the description of the data, these assumptions were tested with a regression analysis. Since the dependent variable is binary scaled, a logistic regression model is applied. At first, only the primary explanatory variable "group" is added to the model. Then, the control variables are gradually added to the model to examine a possible relationship with the dependent variable. The results from this approach can be seen in Table 2. From our analysis we gathered, that the group assignment significantly impacts whether a participant uses the smile program. This finding persists throughout all model specifications and shows high statistical significance ($p< 0.01$). Meanwhile, none of the applied control variables have a significant impact on the outcome. To verify these insights, log likelihood ratios have been calculated since the models are nested within each other. Hereby, we compared nested model pairs with one another by calculating their chi-square values, only to find that none of the chi-square values are significant. We conclude that the outcome of the logistic regression model does not change significantly when adding the applied control variables (Table 2).

	Dependent variable:						
	Used Smile (=True)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Group (2)	6.56***	6.58***	6.55***	6.57***	6.76***	6.81***	7.11***
	(1.32)	(1.33)	(1.33)	(1.33)	(1.34)	(1.34)	(1.35)
Gender (female = 1)		0.93	0.89	0.89	0.91	0.94	0.87
		(1.32)	(1.33)	(1.33)	(1.35)	(1.37)	(1.37)
Age			1.02	1.02	1.02	1.03	1.03
			(1.01)	(1.01)	(1.01)	(1.02)	(1.02)
Educational Years				1.00	0.99	0.99	0.99
				(1.03)	(1.03)	(1.03)	(1.03)
Income (1000-1999)					1.09	1.09	1.06

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					(1.44)	(1.44)	(1.44)
Income (2000-2999)					0.45	0.45	0.47
					(1.54)	(1.54)	(1.54)
Income (3000-3999)					1.48	1.48	1.42
					(1.82)	(1.82)	(1.83)
Income (4000-4999)					1.14	1.19	1.28
					(2.25)	(2.28)	(2.28)
Income (> 5000)					0.71	0.73	0.71
					(1.97)	(1.97)	(1.98)
Number of Children						0.95	0.92
						(1.16)	(1.17)
HAS Scale							1.04
							(1.03)
Constant	0.48	0.50	0.29	0.28	0.29	0.28	0.07
	(1.21)	(1.26)	(1.57)	(1.73)	(1.76)	(1.82)	(3.66)
Observations	255	255	255	255	255	255	255
Log Likelihood	-150.28	-150.25	-149.17	-149.17	-146.13	-146.08	-145.39
Akaike Inf. Crit.	304.57	306.49	306.34	308.34	312.25	314.15	314.78
Notes: Standard errors are in parentheses, estimates are odds-ratios.					$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		

Table. 2. Logistic Regression Results

Additionally, a possible relation between the participant's attitude towards helping and donating (HAS Scale) and using the smile program is examined. For this purpose, a Welch two-sample t-test is conducted, which does not indicate any impact of the HAS Scale towards the usedSmile variable (t=-0.81, p=0.42, DF=246.97). The attractiveness or image of the online store could also be influenced by offering a charity program. Therefore, the four attributes “appealing”, “quality”, “pleasant”, and “satisfaction”, all scaled from 1 (strongly disagree) to 5 (strongly agree) are analyzed. Initially, a Welch two sample t-test examining the impact of each scale on the variable “usedSmile” is conducted. It was found that no p-value is lower than the chosen significance level of 0.05. However, the p-value of the Welch t-test analyzing the relation between the satisfaction scale and “usedSmile” has a p-value of 0,06 (t=-1.89, DF=228.42), making it significant on a level of $p<0.1$. Multiple linear regression models are conducted to further investigate these insights. Initially, only the influence of the “usedSmile” variable on the appealing scale is examined. Then, other control variables are added. The significant impact of the variable “usedSmile” on the dependent variable “appealingScale” stays reasonably consistent among each model ($p<0.1$ for models 1-4, 7 and $p<0.05$ for models 5-6). Besides, other control variables like gender ($p<0.01$ for models 1-5, $p<0.05$ for models 5-7), and income level <999 ($p<0.1$) also have a significant impact on the dependent variable appealingScale.

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5 Discussion

In our experimental case study, we assess, that the forced-choice nudge (N2), presented in the form of a textbox, is significantly more effective than the default value option nudge, presented in the form of an opt-in checkbox, to nudge the use of charity features. More specifically, N2 group participants averaged a constant odds-ratio, which is 6.56 times higher than with the N1 group participants. We therefore argue, that the way of charity feature presentation matters to successfully nudge user participation. Practitioners have to be aware, that an ineffective combination of UI elements and nudges can lead to undesirable results. For instance, we show that N2 is effective in a neutral virtual environment rather than a flashy user interface with special effects (e.g. shadows, blurr effects) that may distract from nudge interventions. Other control variables (e.g. participant's age, gender, income) did not have any significant impact on the decision. This information decreases the necessary considerations designers have to be mindful of and therefore simplifies interventions considerably. It also means that our work provides important arguments in favor of future implementations.

Furthermore, even the participant's attitude towards “helping” or “donating” did not have a significant impact on the dependent variable, “useSmile”. This in turn supports our argument that charitable nudge interventions attract the users’ normative incentive to participate in public welfare as a motivation to use charitable features. In addition to being more effective than the opt-in default option, the forced-choice nudge also helps overcome the decision inertia bias by forcing the nudgees to engage with the decision they have to make, and thereby informing them about the existence of charity features. Given the qualification as a non-monetary nudge intervention, nudging users to make a conscious decision while at the same time not forcing the use of charitable features, ensures libertarian paternalist ideals. This means that users who, upon critical reflection, distrust the charity program always have the opportunity to opt-out. We contribute that it is crucial to overcome the decision inertia or the status quo bias in digital environments, which can be done with the forced-choice nudge to i.e. nudge the use of charity features. Accordingly, our results inform digital nudging research in non-profit and welfare-oriented IS contexts.

In addition to providing more empirical evidence to the existing body of research, our work does so by producing hands on results applicable in the real world. We established the forced-choice nudge as a tool for future charity driven research questions in online contexts. These insights fall in line with similar studies, such as e.g. a study by Lau and Kennedy [45], who found that forcing active choice-making provides more accurate data than providing select-all-that-apply options. Likewise, practitioners can utilize our findings to design more effective nudging mechanisms to comply e.g. with their corporate social responsibility and achieve set goals. These insights on the benefits of the forced-choice nudge could be transferred to other online applications where choice architectures consist of a simple yes/no questions [46].

Apart from the advantages of forced choice architectures, some considerations remain. Platform users experience information- and task-overloaded during online shopping experiences, leading to higher exit rates for e-commerce websites [46].

Therefore, nudgers have to be mindful of the quick and uninformed decisions they influence, when there is either too much or too little information [47], [48]. We suggest the highest amount of simplicity in the wording of a forced-choice architecture, while the remaining UI should be unobtrusive and straightforward [17]. However, it is essential to consider ethical aspects of forcing an individual to consciously reflect choice-making [49]. Despite the rather technical perspective applied in this work, we emphasize that considering the ethical aspects of forced-choice architectures also lies within the responsibility of choice architects.

6 Conclusion

By outlining essential theories and concepts behind nudging, and distinguishing nudging from persuasion, we laid out important groundwork for our experimental case study. Based on the identification of the forced-choice nudge as the most efficient way to nudge charity program participation, we conclude that careful consideration for the design and purpose of nudging mechanisms on e-commerce platforms significantly influences their impact.

Overall, there are some limitations as experimental studies naturally do not entirely reflect real world phenomena. The artificial online store was designed to limit the influence of external factors (e.g. no real shopping expenses). Likewise, exploring the insignificance of the control groups might also provide interesting insights in future work. Moreover, participants could only donate to fictitious charity organizations and our sample of participants may not be fully representative. Further research could also address how timing (e.g. nudge exposure during the log-in versus the checkout processes) as well as the presentation (pop-up window versus no pop-up window) could further influence decision making. Additionally, other iterations of the default option (e.g. active choice; opt-out default value) and other nudging approaches (e.g. framing; social norms) could be tested in the future. Even combinations of above-mentioned nudges could be tested to assess synergy effects. Lastly, future research should also address how the tested effects put theory into practice to further inform and possibly extend nudging theory.

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