

# The Digital Landscape of Nudging: A Systematic Literature Review of Empirical Research on Digital Nudges

Kristoffer Bergram  
University of Neuchâtel  
Neuchâtel, Switzerland  
kristoffer.bergram@unine.ch

Marija Djokovic  
University of Neuchâtel  
Neuchâtel, Switzerland  
marija.djokovic@unine.ch

Valéry Bezençon  
University of Neuchâtel  
Neuchâtel, Switzerland  
valery.bezencon@unine.ch

Adrian Holzer  
University of Neuchâtel  
Neuchâtel, Switzerland  
adrian.holzer@unine.ch

## ABSTRACT

Research output related to digital nudging has increased ten-fold over the last five years. Nudging in the digital realm differs from its analog counterpart in important ways. For instance, online, choice architectures can be interconnected and personalized using real time data. In the face of this development, it is crucial to understand the current state of the literature and to map out possible research gaps. This paper addresses this issue and provides a systematic review of empirical studies where digital nudges have been evaluated. The systematic review covers 73 peer-reviewed papers containing 109 separate studies where 231 digital nudges have been evaluated. Our results lead to nine open research questions to be addressed in the future by the research community.

## CCS CONCEPTS

• **Human-centered computing** → **HCI design and evaluation methods**.

## KEYWORDS

digital nudging, review, choice architecture, personalization, interconnectedness, nudge patterns, digital nudges

### ACM Reference Format:

Kristoffer Bergram, Marija Djokovic, Valéry Bezençon, and Adrian Holzer. 2022. The Digital Landscape of Nudging: A Systematic Literature Review of Empirical Research on Digital Nudges. In *CHI Conference on Human Factors in Computing Systems (CHI '22)*, April 29-May 5, 2022, New Orleans, LA, USA. ACM, New York, NY, USA, 16 pages. <https://doi.org/10.1145/3491102.3517638>

## 1 INTRODUCTION

The concept of *nudging* emerged in the field of behavioral economics and policy-making around 2008 with the publication of the book “Nudge” [129]. It has gained momentum since then to

become one of the most transformational trends in the public sector during 2020 [36]. Undergirding the concept of nudging is the concept of choice architecture: an environment where choices and behaviors occur. These choice architectures are omnipresent and range from natural phenomena such as the weather, to abstract concepts such as policies, or concrete objects such as furniture designs [124]. A concrete example of sensitizing people to both the opportunities and the challenges that come with the concept of choice architecture is the arrangement and display of foods in a cafeteria [129, 130]. This example shows that there is no neutral way to arrange and present the foods in a cafeteria leading the designer to inevitably guide the choices and behaviors of guests. In the literature, there is a lively debate on where to set boundaries as to what qualifies as a nudge. Definitions range from general to specific (see [48, 77, 84, 123] for a review). Among the general definitions available, a nudge could be broadly defined as an intervention that steers people in particular directions but that also allows them to go their own way [123, p. 417], or as “an intervention on the choice architecture that is predictably behavior-steering, but preserves the choice-set and is (at least) substantially non-controlling, and does not significantly change the economic incentives” [12, p. 343]. Nudges can be differentiated from changes to incentive structures or pure mandates [129]. More specific definitions start with a similar description but add some further requirements. For instance, Hansen’s definition [48, p.164] includes requirements on the underlying psychological mechanisms used and proposes that “A nudge is any aspect of the choice architecture that alters people’s behavior in a predictable way without (1) forbidding any options or (2) significantly changing incentives, whether regarded in terms of time, trouble, social sanctions, economic and so forth. (3) Nudges are called for because of cognitive boundaries, biases, routines, and habits in individual and social decision-making, and (4) work by making use of those boundaries, biases, routines, and habits as integral parts of the choice architecture.” Further definitions also include ethical criteria in their requirements, such as transparency, welfare, respect, or autonomy of the nudgee (e.g., [12, 50, 76, 77]). If these criteria are not met, the change in the choice architecture can be called a sludge or a nag instead of a nudge [128].

### 1.1 Digital nudging

With the proliferation of technology, the notion of digital nudging has started to appear with several definitions derived from

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from [permissions@acm.org](mailto:permissions@acm.org).

CHI '22, April 29-May 5, 2022, New Orleans, LA, USA

© 2022 Association for Computing Machinery.

ACM ISBN 978-1-4503-9157-3/22/04...\$15.00

<https://doi.org/10.1145/3491102.3517638>

the literature on traditional physical nudges. General definitions include adaptations of Sunstein’s definitions of nudges in the physical realm, typically specifying that the intervention is digital or happens in a digital environment such as “the use of user-interface design elements to guide people’s behavior in digital choice environments” [138, p. 433]. Specific definitions start with a similar definition and then list certain criteria (descriptive and/or normative) that a digital intervention needs to meet in order to be considered a digital nudge. For instance, Lembcke et al. [77, p.10] start their definition of the digital nudge as “...any intended and goal-oriented intervention element (e.g. design, information or interaction elements) in digital or blended environments attempting to influence people’s judgment, choice, or behavior in a predictable way”, then they further require such interventions to be made possible by, and to make use of, certain cognitive mechanisms (e.g., biases, routine), preserving full freedom of choice, being transparent, and increasing “the private welfare of the nudged individual (pro-self) or the social welfare in general (pro-social)”. In this paper, we opt for an inclusive definition of digital nudge in line with [123, 138], as the event where digital artifacts steer people in particular directions while also allowing them to go their own way.

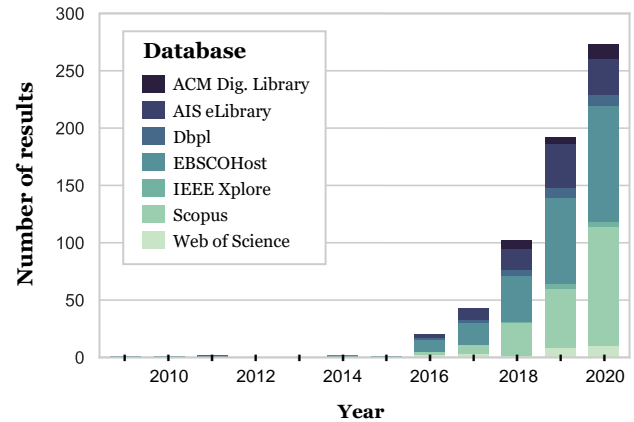
There are two characteristics to consider in relation to choice architecture that differentiate digital nudging from conventional nudging: *personalization* and *interconnectedness*. First, a combination of more personal and diverse delivery systems (mobile [69], ambient [53], wearable [104]) and the increased capacity for data analytics provides unprecedented capacity to (1) gather and use real-time data (e.g., location, user demographics, user actions) in order to (2) dynamically personalize the choice architecture of individual users. Second, the ubiquity of social media services not only presents users with personalized choice architectures, but also interconnects the choice architectures of one user with those of others. That is, (1) a choice architecture of a user can contain information from other users and (2) the actions and choices of a user can, in turn, dynamically modify the choice architecture of other users. This type of environment makes it very difficult to predict the outcome of a change to the choice architecture (i.e., a nudge), since it does not operate in a vacuum. These characteristics make it particularly important to understand the consequences of digital nudging design, as these might be unintended and far-reaching.

Returning to the cafeteria example: the cafeteria or any physical environment has certain native constraints. It is very difficult to personalize the arrangement and display of foods for different guests. Also, the choice architecture of the cafeteria is not really interconnected between guests, except in a very local sense. The choices and actions of guests will not immediately spill over into another cafeteria and modify its arrangement and display of foods. Conventional nudging is therefore mainly restricted to non-personalized and disconnected choice architectures. This contrasts with digital services which can unlock tremendous value for users with personalized and interconnected choice architectures. However, it is also these two aspects that may create very unexpected externalities that often accrue to users or society as a whole. This includes far-reaching consequences such as the algorithmic influence of democratic elections [37], the rapid spreading of fake news in online environments [136], the inadvertent radicalization of online

users [5, 102], or the tendency that a great majority of users agree to terms and data privacy policies without ever reading them [89].

## 1.2 Current knowledge

While the above problems may be far outside the normal scope of HCI designers, implementing potential solutions will inevitably fall into the lap of the HCI community. These problems are all connected to the digital choice architecture of several online services. While none of these problems have easy solutions, more systematized knowledge on the topic of digital nudging can offer more conceptual clarity to address these problems from a design perspective. Researchers have started tackling a diverse set of issues, as digital nudging has become a hot topic in academia with a ten-fold increase of the literature over the last five years (see Figure 1). Furthermore, several well-researched review articles have emerged in recent years to shed light on various aspects of nudging and digital nudging, such as effectiveness [58], categorization [23], psychological underpinning [71, 86], or analyses of their application in specific areas (e.g., privacy/security [71], recommender systems [61]).



**Figure 1: The number of search results of the term “digital nudg\*” in seven databases between the years 2010–2020**

For instance, Hummel et al. [58] conducted a quantitative review of the relative effect sizes of nudges. In their paper, they categorize nudges into ten different categories (default, simplification, social reference, change effort, disclosure, warnings/graphics, precommitment, reminders, elicit implementation intentions, feedback). Their findings suggest that, based on median effects sizes, defaults seem to be the most effective type of nudge, while commitment seems to be the least effective. It should be noted that even though Hummel et al. focused on conventional nudges, they also investigated examples of digital nudges and observed that their effects did not differ significantly compared to conventional nudges. This finding can be put in perspective with the research conducted by Caraban et al. [23]. In their study, the authors provided a review of digital nudges and synthesized them in 23 different mechanisms, grouped in six high-level patterns: facilitate, confront, deceive, social influence, fear, and reinforce. Even though they do not specifically focus on empirical studies, they still provide a rich discussion of

the evaluation results found in the literature. For instance, they observe that most (66%) nudges evaluated were effective. They also discuss several pitfalls of nudges (e.g., lack of educational effects, no long-term effects, backfiring) and argue that even though personalization has been highlighted as an important aspect of digital nudging [23, 61], it has not yet been investigated systematically and thus presents an “untapped opportunity” [23, p. 11].

### 1.3 Contribution

In summary, while the interest in digital nudging has increased and several reviews have provided valuable insights into this young field, the landscape of digital nudges has not been fully mapped. Previous literature has provided valuable insights into digital nudge mechanisms. They pointed to potential positive effects of nudging, and pitfalls, and discussed the underlying psychological mechanisms. However, there are several areas of digital nudging that warrant further systematic investigation:

- (1) Previous reviews have not mapped how the literature has investigated the specificity of digital nudges that we highlighted above: personalization and interconnectedness.
- (2) While digital nudges are increasingly employed by researchers and practitioners - the specific problems that they address have not been sufficiently mapped across the literature.
- (3) Digital nudges can be combined in a variety of ways, and evaluated using different methods and user samples. These practices have not yet been mapped out in the literature.

In this paper, we describe and synthesize empirical research contributions in the digital nudging literature across HCI and other related scientific fields. We classify these contributions across 10 established digital nudging designs, referred to as “patterns”. We then explore this design landscape by mapping these patterns across the three areas that we have highlighted above. First, we explore this design landscape by mapping these patterns across two characteristics of choice architecture, and their current delivery channels/devices. Second, we explore the problems addressed by these nudging patterns by outlining their application domains and targeted outcomes in terms of behaviors and attitudes. Third, we investigate the evaluations of digital nudging solutions by mapping their evaluation methods, sample types, and highlight whether combinations of nudging patterns have been evaluated in the literature. Finally, building on the unexplored patches in the digital nudging landscape, we contribute to the digital nudging literature by setting a future research agenda organized around nine high-level research questions to be investigated by the HCI-community.

## 2 METHODOLOGY

The methodology of this literature review will be described in four phases based on recommendations for systematic reviews [87]: literature search, screening filter, eligibility evaluation, and analysis procedure.

### 2.1 Literature search

The goal of the literature review was to survey the landscape of research that explicitly tackles digital nudging, as opposed to the

broader research that can be considered as a digital nudge but is not presented as such by the authors. To capture as many contributions as possible, we included seven major databases spanning a wide range of research fields from HCI, computer science, and information systems to economics and psychology. The following databases were searched: ACM Digital Library, AIS eLibrary, Dbpl, IEEE Xplore, EBSCOHost, Scopus, and Web of Science. We identified potential papers that authors characterize as digital nudging, using the following strings across the selected databases: “*digital nudging*” OR “*digital nudge*” OR “*digital nudges*”. All databases were accessed on 9th January 2021, yielding 638 results in total. The PRISMA flowchart in Figure 2 is adopted and modified from Liberati et al. [80]. Following the recommendations by vom Brocke et al., Figure 2 also highlights the functionalities used, and the number of identified papers from each database [19]. We filtered the publication period for all the results in this review between 2008-2020.

### 2.2 Screening filter

Two of the co-authors deleted duplicate records which resulted in a dataset containing 361 unique results. Very incomplete entries were removed, e.g., papers lacking a title, publication year, and publication venue. Entries with titles that were not written in the English language were removed. As in other reviews on similar topics - entries that were not published in a peer-reviewed conference proceeding or journal were removed as a proxy for quality control [23, 47, 71]. This last step removed entries such as proceeding adjuncts, workshops, dissertations, student consortiums, or talk papers, leaving 289 full-text articles.

### 2.3 Eligibility evaluation

During the third stage of the review, the papers were distributed among three of the co-authors to ensure that each paper had a full-text assessment by at least two reviewers. The following two criteria were specified to include appropriate articles for the review: the paper had to (1) mention “*digital nudge*”, “*digital nudges*”, or “*digital nudging*” in the full-text, excluding the references, and (2) the outcomes of the digital nudge had to be observed or tested to some context, i.e., empirically demonstrated/evaluated. Conflicting assessments on the criteria were noted and resolved by at least two reviewers.<sup>1</sup> Three papers were excluded because they relied on the same empirical studies as two other included papers. In these cases, we included the most recent iteration of the papers in the final analysis. Following the example of Connolly et al., a random sub-sample of 59 articles (20 %) was assessed by an independent reviewer and compared to one of the co-authors to gauge inter-rater reliability [29]. All eligibility criteria between these two assessments showed good agreement overall (*Cohen’s Kappa* = 0.74). Finally, 73 papers met the eligibility criteria and were included in the analysis. Figure 2 provides an overview of the process.

### 2.4 Analysis procedure

To synthesize and analyze the included literature, a concept-centric approach was used in accordance with Webster and Watson [137].

<sup>1</sup>The following papers were included though they only referenced “digital nudg\*” without explicitly mentioning it in the full text: [1, 67, 69, 73, 98, 121, 131, 132]

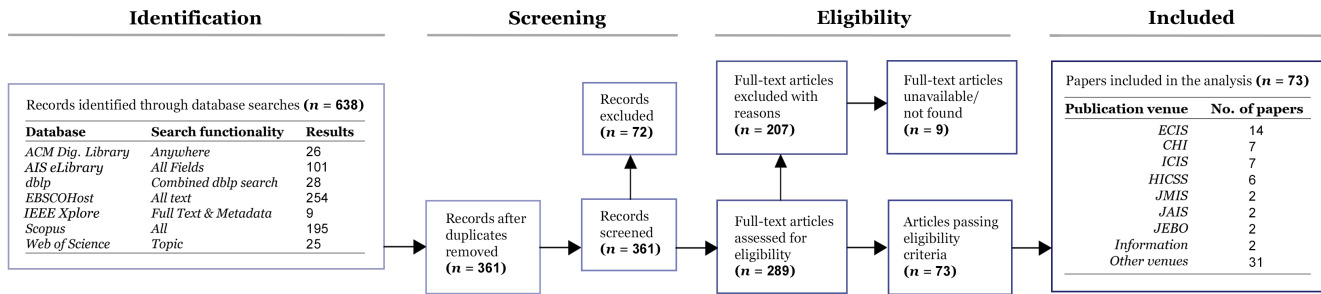


Figure 2: Overview of review methodology (adapted and modified PRISMA flowchart [80])

A concept matrix was compiled in an iterative fashion while the included papers were read by the co-authors. Primarily, two of the co-authors coded and classified the selected articles with the assistance of a third. When codes or classifications were difficult to infer for a specific paper, we discussed these issues until we reached agreement. First, highly accessible and descriptive information was extracted, such as publication year, authors, publication venue, number of participants, and application context. Next, we coded detailed information about the digital nudges being investigated in the papers along the following dimensions: type of outcome, nudge pattern, choice architecture, delivery devices, delivery channels, study’s sample type, and evaluation methods. Depending on the coded dimension, the unit of analysis varied between papers, studies, and digital nudges. Indeed, one paper may contain several studies investigating different nudge patterns, outcomes, or different evaluation methods.

### 3 DIGITAL NUDGING LANDSCAPE

The analysis of the digital nudging landscape is based on a diverse sample of 73 peer-reviewed papers. While Figure 2 shows that the majority of included papers are clustered in well-known publication outlets within information systems and computer science, the whole sample of papers extends across 38 unique conference and journal venues spanning several scientific fields. The included papers contained 109 discrete studies in total. The number of observations in all these studies ranged from 10 to over 1 million (*median* = 183). Across these studies, we identified 231 separate digital nudging interventions that were demonstrated and evaluated. Table 1 provides an overview of all papers and their codes included in the literature review.

#### 3.1 Design of digital nudges

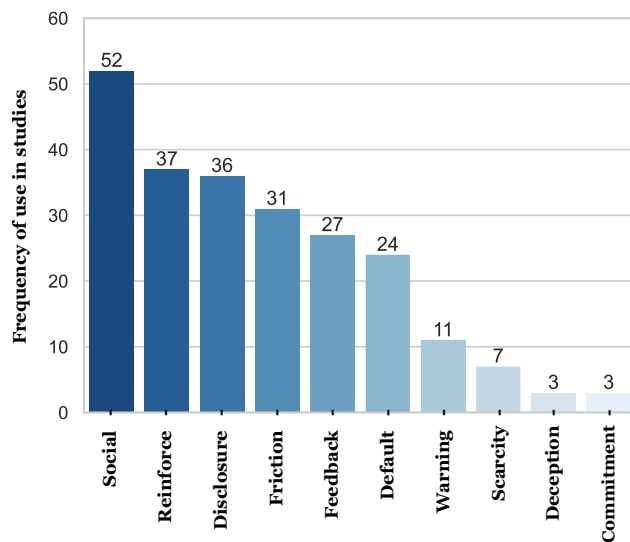
We analyzed the design aspect of digital nudges in the literature from the perspective of the nudge patterns, the characteristics of the surrounding choice architecture, and the delivery channels/devices.

**3.1.1 Digital nudge patterns.** To steer users in a certain direction, different nudge patterns can be chosen. These patterns, or design solutions to a recurring problem [38], are sometimes referred to simply as nudges [122], nudge categories [58], or nudging mechanisms [23]. We drew on previous literature [23, 58, 122] to assemble

a list of the ten main nudge patterns: social, reinforce, disclosure, friction, feedback, default, warning, scarcity, deception, and commitment. We settled on these patterns after recursively labeling and comparing our corpus of papers with patterns in the literature. More specifically, we derived seven patterns from the list of ten nudge patterns presented by Hummel et al. [58], and Sunstein [122], grouping together certain categories into a single pattern (e.g., change effort and simplification into friction) because they were difficult to differentiate during coding. To these we added three patterns derived from Caraban et al. [23], who categorized technology-mediated nudges specifically, and which were difficult to classify as other patterns: reinforce, scarcity, and deception. Figure 3 gives an overview of the digital nudge patterns among the analyzed papers. Below, we provide a brief summary of each pattern with concrete examples of its application from the literature.

**Social nudges.** This nudge guides the user’s behavior by providing references to how other users behave, thereby creating a social norm [122]. In a classical example, researchers investigate the influence of a social nudge for towel reuse in a hotel [46]. In the hotel room, a sign tells a group of guests they can reuse their towels if they wish to help the environment. Another group in the social nudge condition sees a similar sign with a text mentioning that almost 75% of guests participate in the programme [122]. The researchers show that towel reuse is significantly increased in the latter group [46]. In the reviewed literature, these social nudges are often used to make it appear as if the choice architecture is interconnected without it actually being so. To illustrate: Kretzer and Maedche investigated how social nudges can be used in the context of business information systems to encourage employees to reuse reports [73]. More specifically, they evaluated if employees would tend to reuse a report more if there was a mention next to it indicating that someone else with similar characteristics liked the report, e.g., “Ian, a project leader from the accounting department in France, liked this report.” They found that users were more inclined to reuse a report if it was liked by someone from a similar rank (inter vs director), belonging to the same department or coming from the same location. In an online experiment, DiCosola and Neff showed how different forms of social comparisons could nudge users to reduce the number of calories contained in their shopping baskets in an e-commerce scenario [32]. By conducting their study on a sample of healthy-weight adults, out-group comparisons were

achieved by providing calorie benchmarks for overweight adults. Surprisingly, out-group comparisons seemed to work just as well if not better than in-group comparisons for eliciting more healthy choices.



**Figure 3: Number of empirically evaluated digital nudges in the papers, across the ten patterns (unit of analysis: nudges)**

*Reinforcement nudges.* These nudges reinforce behaviors and choices by increasing their salience in the mind of the user [23]. This entails practices that rely solely on persistent or frequent exposure, or some underlying psychological mechanism such as priming, where a stimulus is associated with a desired behavior (when asked to complete the word “so\_p”, participants previously primed with a picture of a shower tend to say “soap”, whereas participants primed with a picture of food, tend to say “soup” [133]), or anchoring where potentially unrelated information influences the outcome (telling someone Mark Twain’s birth year can influence their estimate of the length of the Mississippi river [91, 133]). These nudging patterns are perhaps the broadest in this literature review. As an illustration, Dennis et al. conducted seven lab experiments to investigate how both numeric and semantic priming could be used to sway users’ willingness to pay in e-commerce/marketing contexts [31]. In their paper, priming meant that users were exposed to a stimulus (a product and its price) that was meant to later affect their intention to make certain purchases. Their experiments highlight that both kinds of priming seem to work better in online auction settings than in normal e-commerce shops. In the former, it is possible to sway users to pay more for products through priming since the value of auction products is often uncertain. Reinforcement nudges can also be applied to problems in education. On a large sample of university students, Brown et al. showed how a combination of reinforcement and social nudges in a web-enabled coaching system could increase students’ proactivity to get started on their homework [21].

*Disclosure nudges.* As a nudge, disclosure entails adding information that is accessible, clear, and relevant to the choice that the user is about to make [122]. Product labels indicating energy efficiency are typical examples of disclosure nudges (e.g., [8]). In the reviewed articles, Gimpel et al. investigate how a disclosure nudge can increase the ability of social media users to identify fake news [44]. In their experiment they show participants a series of articles posted by news providers (some truthful, some not). In the nudge condition they disclose related articles below the main article to provide additional knowledge to users. They find that this nudge works best if the related articles are a mix of truthful and fake news articles. Indeed, if the related articles are only truthful, the authors find no increase in fake news detection. Also, various kinds of disclosure nudges can sometimes have harmful consequences. In the UI of ridesharing platforms, Abramova demonstrated through an online experiment how different disclosures (such as a Middle Eastern male name in the profile of the driver) decreased West European users’ willingness to pay for a ride [1].

*Friction nudges.* A behavior can be encouraged or discouraged by removing or adding friction respectively. Sunstein [122, p. 4] refers to this nudge as “increases in ease and convenience”, Hummel et al. [58, p. 52] uses the label “change effort”, and Caraban et al. [23, p. 6] identified a mechanism they called “creating friction”. We have adopted the one-word descriptor above to convey that this digital nudge pattern can be used in two ways: by removing or by adding friction to the user experience. Furthermore, while simplification is sometimes thought of as its own type of nudge – we see it as a means of removing friction for the user. Kim et al. showed in a field experiment how a lockout task with zero to very small workloads could limit smartphone usage [69]. Their paper demonstrated how the simple friction of an app arbitrarily asking users to input 0-30 random numbers helped users to self-regulate their smartphone app use over time. Friction nudges can also provide valuable solutions in the context of policy-making. In an extensive analysis of field data, Fox et al. evaluated digital nudges targeting the friction of accessing healthcare in the US [40]. Online features such as receiving real-time eligibility decisions, or opting in for presumptive eligibility had considerable effects on enrollments over time. This was especially true for children since these nudges remove the administrative friction that accrues to parents.

*Feedback nudges.* Whereas a disclosure nudge provides information about an upcoming choice of a user, a feedback nudge provides information about a past or a current behavior of a user. An example of such a pattern in the reviewed papers include a field experiment where Hoffmann et al. applied feedback nudges to a fleet of truck drivers [53]. They increased truck-drivers’ eco-efficient driving behavior by using an eco-score shown on the truck’s telematics system. Okeke et al. designed and evaluated a mobile app that delivered haptic feedback in the form of continuous vibration if users exceeded their daily Facebook limits [90].

*Default nudges.* Defaults are perhaps the most well-known and most effective pattern for nudging [58, 122]. The idea of a default nudge is to design the choice architecture in such a way that the default behavior is the desired behavior [20]. The classical example for this nudge pattern is organ donation enrollment policy. The

policy can dramatically increase the percentage of people consenting to being donors by changing from a default set to non-donor with a possibility to explicitly opt in, to a default set to donor with a possibility to opt out [62]. While also investigating two specific personality dimensions and their relationship to nudging in an online experiment, Ingendahl et al. changed the preselection of various product categories in an e-commerce scenario [60]. While the measured personality dimensions showed little to no detectable relationship to nudging, the default nudge was successful in altering product choices among users. This was especially true when the default was combined with a social nudge. In a later section we will look at how frequently different nudging patterns were combined and investigated together in the literature.

*Warning nudges.* Different kinds of warnings and graphics assist users by grabbing their attention to various risks or consequences [122]. This is important because digital choice environments tend to abstract real-world outcomes for the user. In a lab experiment designed to investigate decision inertia with financial planning tools, Jung et al. demonstrated how warning nudges from a robo-adviser can mitigate this problem even when controlling for financial literacy among users [63]. Yet their study also suggested that default nudges were more effective in this context. Another study demonstrated how warning nudges could help protect user privacy by raising potential unwanted data disclosure on social media [135]. To illustrate, when a user is about to post about himself and his wife Yvette having dinner at Brotzeit despite a headache, a warning message would point to sensitive information that the system could gather from this post, e.g., “potential sensitive topic found (health), potential identifier found (Yvette), potential location found (Brotzeit)” [135, p. 4431].

*Scarcity nudges.* Scarcity nudges work on the assumption that people assign more value to something that is going to be more difficult to acquire in the future [27]. Typical examples of scarcity nudges found online include the indication that there is “only one room left” on hotel booking platforms [127]. Similarly, in the reviewed papers, Schneider et al. use a scarcity nudge to increase the selection of a crowdfunding option by placing the indication “only five left” next to it [111]. Their results show that there is a reversal in preference towards the option with the scarcity nudge. Another example is provided by Wessel et al. who examined how a scarcity nudge in the form of sold-out early birds influenced users’ behavior in crowdfunding campaigns [139]. Early bird reward options are often at a discount to encourage early backers of crowdfunding campaigns. Yet, even when they were unavailable as a choice but still visible to the user, they nudged users to choose the comparable but undiscounted reward options more often.

*Deception nudges.* This pattern uses mechanisms that covertly affect how choice alternatives are perceived by users [23]. A typical example of a deception nudge is adding a decoy option to the choice architecture. A decoy option is an option that will not be selected by the user, but that steers their choice to one specific alternative. Schneider et al. [111] provide a good illustration of this nudge pattern. In the context of a crowdfunding platform, they offer two options to users: (A) pay \$10 get the eBook, (B) pay \$20 get the eBook and the hardcopy of the book. In this setting, it is not easy to

compare the option. In the end 69% of participants choose A. Add the decoy option (C): pay \$20 get the hardcopy of the book – and the result is the reverse: 68% of participants choose B. Predictably almost no one (1% of participants) chooses C as it is objectively worse than B, but the fact that it allows to set B as objectively better than one option increases its appeal.

*Commitment nudges.* The idea of this pattern is that when commitments are elicited from the user, they will motivate the user to behave in a way that is consistent with those previous commitments [28]. In a small online experiment, Kroll et al. used commitment and social nudges in a mockup UI of a smart home app to encourage users to save more energy [74]. The researchers elicited a commitment from users by letting them preselect from what household devices (e.g., dishwasher, lightbulbs etc.) they wanted to save energy. They detected no impact on energy consumption attitudes among users when these digital nudges were used on their own. However, a combination of commitment and social nudges led to more energy-saving choices. In a later section we will highlight how frequently such combinations of nudging patterns were investigated in the literature.

*3.1.2 Choice architecture characteristics.* We coded each nudge investigated in the literature based on the characteristics of their choice architecture in terms of interconnectedness and personalization.

*Interconnectedness.* The interconnectedness dimension has three levels: Level 0 none, Level 1 partial, Level 2 full. Partial interconnectedness is met when a study investigates how information from other users affects user behavior in a choice architecture. Full interconnectedness is met when the study also investigates how actions of one user, in turn dynamically modify the choice architecture of other users. A rare example of a study that reaches the second level of interconnectedness is a paper by Antinyan et al. that examines the effect of a social nudge, which additionally includes either a disclosure nudge or an incentive (a tax), to decrease the consumption of positional goods (e.g., luxuries) compared to private goods (e.g., necessities) [10].

The study takes the form of a game played over 30 rounds by four interconnected participants. At every round participants can spend a certain amount of virtual money on either private goods or more expensive positional goods. Before making their decision they receive information about how much the others consumed during the previous round. As such, their choice architectures are fully interconnected, as (1) they receive information about the behaviors of others (a social nudge) and (2) their behavior, in turn, will influence the choice architecture of others in the following round. The game rules are set so that everyone would benefit if the consumption of positioning goods was low, but the rules also push individuals to consume more positional goods than the others, which results in excessive positional goods consumption and substantial welfare loss. In the disclosure nudge condition, participants receive information about the negative consequences of excessive positional consumption, whereas in the tax condition, a 25% consumption tax is introduced after a certain level of positional goods consumption. The results show that both interventions work well only when the choice architecture is interconnected and all participants are

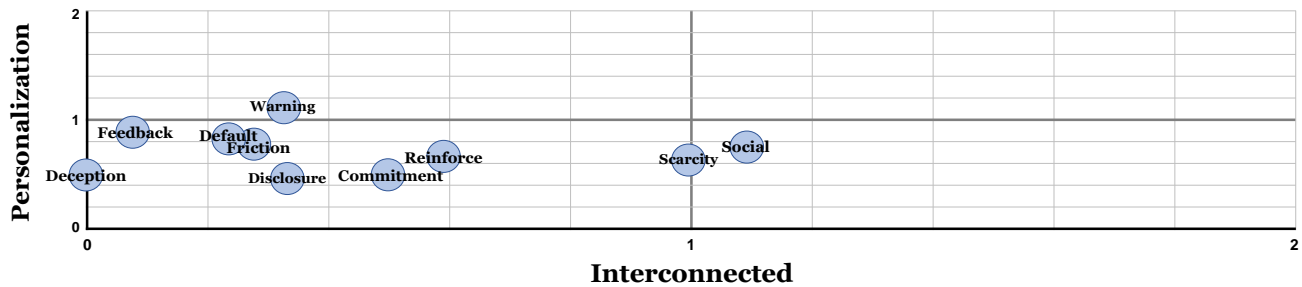


Figure 4: Mean level of interconnectedness & mean level of personalization per digital nudge pattern (unit of analysis: studies)

aware of each other’s behaviors. Studies that reach the first level of interconnectedness are more common. Indeed, studies examining social nudges do by definition integrate information from other users in the choice architecture. Schneider et al. provide a representative example of such studies. They used a social nudge to encourage adoption of an electronic identification (eID) by showing participants that 77% of previous users had opted for it too [112]. However, the behavior of the participant does not in turn spill over to change the choice architecture and potentially the behavior of others.

*Personalization.* The personalization dimension also has three levels: Level 0 none, Level 1 partial, Level 2 full. The first level is met when a study gathers user data (e.g., location, user demographics, user actions) in order to infer the potential influence of the nudge on user behavior. The second level is met when such information is used to dynamically personalize the choice architecture of individual users. A rare study that reaches full personalization used the smartphone’s vibration feature as a feedback nudge for users to spend less time in the Facebook app [90]. For one of the study’s conditions, the trigger for this vibration was personalized, based on users’ past daily visits and their time spent in the Facebook app. If users in this condition reached 50% of their past daily visits or time spent (this threshold was derived from a baseline week) then their phone started vibrating every five seconds. As one might expect, users in this condition spent significantly less time on Facebook.

As with interconnectedness, studies that reach the first level of personalization are more common and a typical example can be found in Buck et al. [22]. In a series of experiments using an outcome measure called the app information privacy concern (AIPC), they show how privacy attitudes of users are sensitive to various patterns of nudges, and associated to the user’s gender or the operating system (OS) of the user’s smartphone. While examples can be found on both interconnected and personalized choice architecture, most research on digital nudging is conducted with the user’s choice architecture being disconnected and non-personalized. This result is shown in Figure 4 where most of the nudge patterns end up in the bottom left quadrant.

*3.1.3 Delivery channels and devices.* We also investigated the delivery channels (visual, audio, haptic) and delivery devices (e.g., desktop, mobile, wearable, ambient) of nudges. Our results show that the delivery channel for these digital nudges is almost exclusively visual, that is, via a screen. The reviewed literature only contains two exceptions, which are haptic [59, 90]. The first haptic

study examines how feedback can be provided through nerve stimulations [59]. In that study, the goal was to help pedestrians with navigation. As participants would approach a crossroad where they needed to turn left, the system would deliver a nerve stimulation through a wearable electrode placed on the left arm causing the arm to move. The other example comes from the previously mentioned study by Okeke et al., where the continuous vibration of a smart-phone would be triggered if users exceeded their daily time limits on Facebook [90]. As for devices, we found only two instances of wearables [59, 117] and two instances of ambient objects [13, 53]. In addition to the wearable electrode discussed above, the other example of a wearable device is in a paper by Sengupta et al. that used a smartwatch to measure steps, in order to provide a feedback nudge to hospital patients to increase their mobility [117]. The first example of an ambient object is from Hoffmann et al. with their connected dashboard in a truck [53]. Here, 104 truck-drivers received feedback on their driving style to increase their eco-efficient driving behavior [53]. The other example is a connected bottle that overflows to give feedback to users who do not drink enough water [13].

## 3.2 Digital nudge context

To code the problem contexts of digital nudges, we focused on application domains on the one hand and desired outcomes on the other hand.

*3.2.1 Application domains.* To code application domains, we relied on categories identified in previous literature (i.e., [23, 58]) and adapted them to offer additional granularity. The following list of domains was established: privacy/security, e-commerce/marketing, social media, sustainability, recommender systems, crowdfunding, policy-making, education, innovation, work, education, health, and miscellaneous. The heat-map in Figure 5 shows the application domains in which each digital nudging pattern is studied. The application domains in which digital nudges are used to influence choices or behaviors most frequently is privacy/security. Various papers in this context have focused on designing UIs to make privacy policies more accessible to users [15], facilitating user privacy interactions by modifying cookie consent notices [132], or nudging users into adopting electronic identification (eID) features [112].

However, e-commerce/marketing and various forms of sustainability behaviors are also common problem contexts. Furthermore, we found very few examples of otherwise well-known patterns of digital nudges (e.g. friction, feedback, or warnings/graphics) being

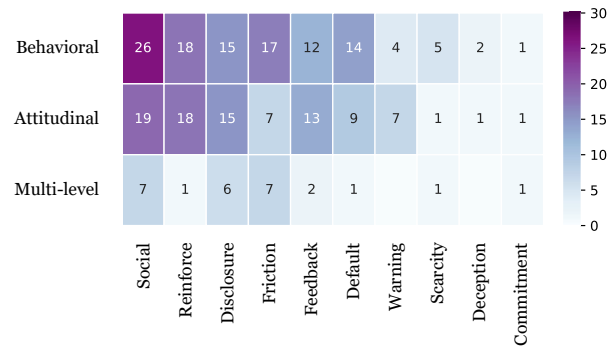


**Figure 5: Frequency of digital nudges per pattern and application domains (unit of analysis: nudges)**

applied to any of the problem contexts in the bottom of Figure 5. A rare example of a study targeting the infrequent context of health came from the previously mentioned paper by Sengupta et al. where eight hospital patients were being evaluated over 91 days [117].

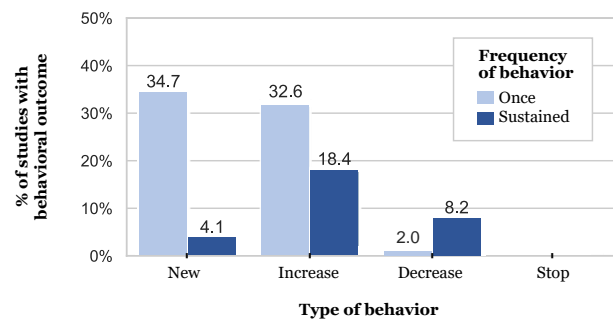
**3.2.2 Outcomes.** To code the outcomes of the studies, we used a more abstract level and looked at whether the objective was centered on changes in behavior or attitude. When studies investigated both of these higher-level outcomes or incorporated other levels such as physiological outcomes, we coded them as multi-level. The heat-map in Figure 6 shows that digital nudges are most frequently used to change behavioral outcomes. An example of nudges targeting behavioral outcomes can be found in van Oldenbeek et al. [134]. They showed how a simple feedback nudge in the form of a personalized email on students’ online lecture viewing progress had an impact on the behavior of the students. In short, this simple feedback made the students watch more of the online course content.

An example for attitudinal outcomes can be found in Schöbel et al. [114]. With an online survey they studied Slack user preferences towards several digital nudging patterns (defaults, social, feedback etc.) in the context of privacy. By showing users a variety of nudging patterns and simply asking for their most vs. least preferred option they showed that users preferred to be nudged in the direction of privacy by defaults and red/green warning graphics. Multi-level outcomes are rarely examined in a single study. Note however that



**Figure 6: Frequency of digital nudges per pattern and type of outcomes (unit of analysis: nudges)**

some papers employ several studies with different objectives that together gauge attitudinal and behavioral outcomes and are labeled as multi-level in Table 1, see for example [41, 43, 132]. Furthermore, since most nudges belong to studies with behavioral outcomes, we deepened our analysis by coding the type of behavior that was targeted with the nudge. Using a simplified version of Fogg’s behavior grid [39] we coded whether digital nudges that were focused on behavioral outcomes were used to investigate single or sustained occurrences of behavior, and whether the objective was to instigate a new behavior, increase/decrease a familiar behavior, or stop a behavior from occurring. As Figure 7 illustrates, most behavioral studies were focused on one-time outcomes aimed at increasing the intensity of a familiar behavior or on instigating a new behavior for the user. In other words, these studies measured the outcome of their digital nudge once. What is far rarer is studies where the outcomes of digital nudges are measured over a sustained period. The previously mentioned field experiment involving the driving behaviors of truck drivers was conducted over a 30-week period [53], while Kim et al. decreased app usage with their lockout task in a 3-week field experiment [69]. Another example was the combination of reinforcement and feedback nudges aimed at increasing the physical activity of hospital patients over a 3-month period [117].

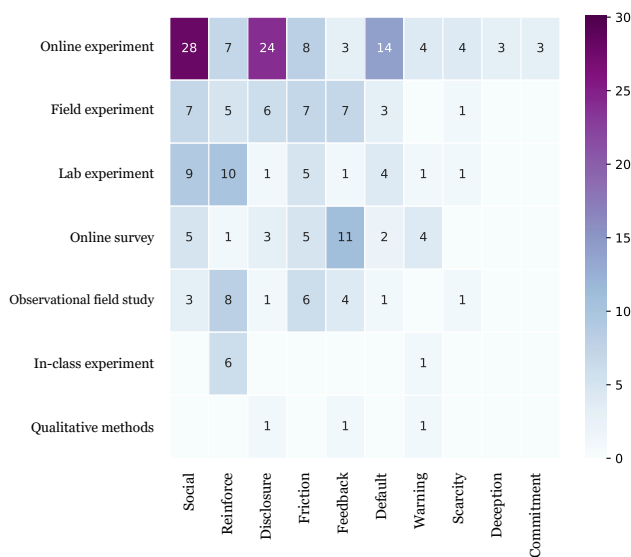


**Figure 7: Percentage of behavioral outcome studies across targeted behavior types (unit of analysis: studies)**

### 3.3 Evaluation of digital nudges

To assess the types of empirical evaluations that were used in the literature, we coded the type of method and the type of sample, and we also assessed whether a different combinations of nudges were investigated.

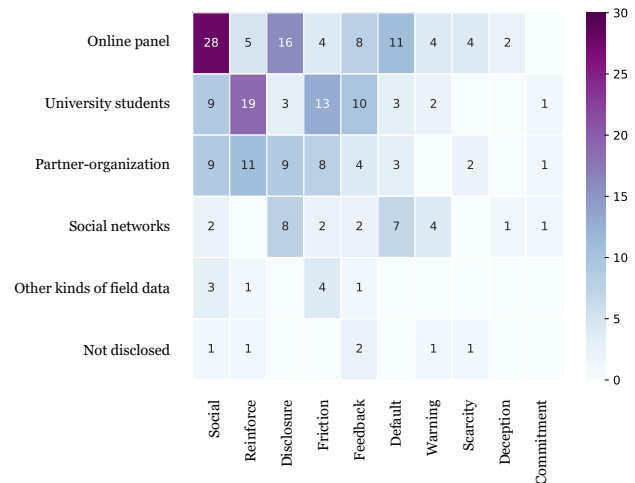
**3.3.1 Evaluation methods.** We grouped studies according to their evaluation methods (e.g., online experiment, field experiment, online surveys, observational field study etc.). Figure 8 reveals that the most frequent methods for evaluating digital nudges were online experiments. Just as in the previous section, we still only found a few examples of digital nudges (e.g., feedback and warnings) being demonstrated or evaluated in field settings. Furthermore, qualitative evaluation methods are very rare in the domain of digital nudging. Some examples can be found in Kim et al., where they also conducted user interviews after a field experiment [69]. Another study elicited expert feedback [135], and Schilling et al. used both expert feedback and focus groups as evaluation methods [110].



**Figure 8: Frequency of digital nudges per pattern and evaluation method (unit of analysis: nudges)**

**3.3.2 Sample type.** We investigated what type of sample was used for each evaluation (e.g. online panels, university students, partner-organizations). The heat-map in Figure 9 shows that when digital nudges were evaluated, a variety of sample types were used. Our analysis suggests that the use of online panels is now more common than reaching out to local university students. The most frequently used online panels in the literature were Mturk, Prolific, and Qualtrics. We also observe that several field studies or experiments are conducted with user data from a partner-organization (see for instance [121], [15], and [139]). Figure 9 echoes the point that several patterns of nudges are not evaluated based on samples from various field settings. As for sample geography, around 69% of all studies sourced participants from either Europe or North America. Four studies were conducted in Asia, one study might

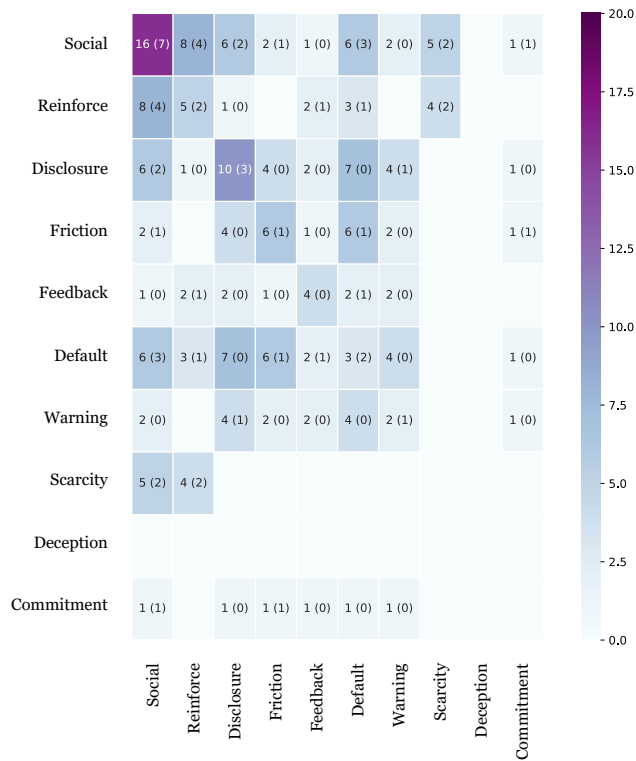
have been conducted on a sample from South America [94], and no studies were explicitly sourced from the African continent. Roughly 27% of all studies did not explicitly disclose the geographical location from which their users were sampled. Evaluation methods and sample types also overlap in important ways. For example, online experiments are often conducted with participants from an online panel, and field experiments often require a partner-organization.



**Figure 9: Frequency of digital nudges per pattern and sample type (unit of analysis: nudges)**

**3.3.3 Nudge combination evaluation.** We assessed whether evaluations covered more than one nudge and whether their interaction effects were measured. The heat-map in Figure 10 highlights the number of times that digital nudge patterns were evaluated together in the same study. Depending on the design of such a study, this provides an opportunity to measure if the effect of one nudge pattern is dependent on the presence of another (i.e., statistical interaction). While a measurement of interacting nudge patterns depends on the evaluation method that is being employed it should be stated that when digital nudges are studied together, only in about a quarter of cases are statistical interactions measured and evaluated. The results in Figure 10 are obviously correlated to the number of times specific nudge patterns have been investigated in the literature. However, these results illuminate quite significant knowledge gaps around how different combinations of nudge patterns might impact user choices and behaviors. Good examples of studies where nudge patterns are used together and where statistical interactions are examined can be found in the previously mentioned papers from Ingendahl et al. [60], Kim and Dennis [67], and Sengupta et al. [117].

**3.3.4 Summary of the digital nudging landscape.** Table 1 provides an overview of the digital nudging landscape by showing the most relevant information that was coded from the selected papers in this review. The unit of analysis for this table is papers. For each paper, the table presents the nudge patterns that were investigated, the types of outcomes that were measured, the context, and the types of evaluation that were conducted. The table indicates whether the paper also investigated a partial or fully personalized and/or



**Figure 10: The first number is the frequency of digital nudge patterns that were evaluated together, and the second number in brackets is the number of times statistical interactions were measured (unit of analysis: studies)**

interconnected choice architecture. Further, it highlights the instances where a paper investigated particular delivery devices (i.e., wearable or ambient) or delivery channels (i.e., haptic). Finally, it indicates the number of studies conducted in each paper.

## 4 DISCUSSION

The present paper presented a landscape of empirical research contributions on the growing topic of digital nudging through a systematic literature review. After an initial count of 638 papers related to “digital nudging”, we conducted a thorough screening and eligibility process which led to the inclusion of 73 papers that were analyzed in detail along four dimensions: patterns of nudges, types of outcomes, types of contexts, and types of evaluations. Overall, the results of this review point to a highly heterogeneous research domain. While the most common publication venues are associated with information systems and computer science, digital nudging is now being applied to a varied set of contexts, ranging from policy interventions [40] to the design of hydration-encouraging water bottles [13]. Strikingly, our results show that some common online nudges are hardly investigated. The most prominent example is scarcity, which is used by many service providers to nudge users to quickly purchase a service or product (e.g. “three seats left at this price” or “two rooms left for these dates”). Our results further show that field experiments are relatively rare, as they represent less

than 16% of studies. This is again surprising given the ubiquity with which experimentation occurs online. In the industry, hundreds of experiments are being run daily to determine the efficacy of small visual changes in design features at various tech companies such as LinkedIn [108], Facebook [72], and Google with their infamous 50 shades of blue experiments, where the color of advertising links was live tested on users and reportedly led to USD 200 million a year worth of extra clicks [52].

This points to a possible gap between the digital nudges that are implemented in practice and the digital nudges that are actually researched. The imbalance or lack of research on certain nudges (e.g. deceive), types of behavior (e.g., decrease or stop), delivery channels (e.g. haptic), or device (e.g. wearable) and the lack of certain evaluation methods (field experiments) could also show a focus on what is convenient to measure rather than on what is relevant to measure (i.e., implemented in practice or forward looking). Prominent researchers have observed a similar phenomenon in the field of consumer behavior and asked to avoid a too narrow framing on most obvious or easy-to-measure behaviors (e.g., [95]). Below, we discuss our results structured along six key topics that emerged from our analysis. We also lay out research questions that could be addressed to fill important knowledge gaps and open new research avenues.

### 4.1 Context and culture

Previous research on digital nudges focused on three problem contexts that take up almost half of the research effort (i.e., privacy/security, e-commerce/marketing, and social media). Research in the other contexts is much less prominent. The original conceptualization and applications of nudging by the authors of the book “Nudge” were deeply anchored in policy-making. It is thus surprising that only 7% of research on digital nudging is applied to this context. A similar observation can be made about the context of health. These disparities raise the following research question:

**RQ1:** Can the outcomes of a digital nudging be transposed to different classes of problems?

Geographic sample diversity is also lacking, as only five studies in the included papers have been conducted outside of Europe and North America. This should be a research priority if we want to understand whether the effects we study entail some forms of universalism, or whether digital nudges are bounded by cultural conditions. For instance, given that nudging has a specific political ideology (libertarian paternalism), could the effect of digital nudges be dependent on cultural aspects such as power distance beliefs (accepting and expecting power inequalities, [54, 92]) or cultural tightness (vs. looseness, [42]). More broadly, this raises the following future research question:

**RQ2:** Are the effects of digital nudges moderated by cultural contexts?

### 4.2 Choice architecture externalities

The results highlight that the majority of digital nudges have been researched in contexts that we call disconnected and non-personalized. This means that nudges are employed in situations where choice

architectures are independent of one another and the choice architecture is not investigated in a context where personal data from the user is taken into account (i.e., non-personalized). While this increases effectiveness of evaluating the impact of various nudging patterns, it does not accurately reflect the digital sphere that users find themselves in every day and leaves open the following research question:

**RQ3:** How can the impact on users from interconnected and personalized choice architectures be better quantified and understood?

Indeed, Google's search results, Facebook's newsfeed, or video recommendations from YouTube are all highly personalized and interconnected choice environments and are likely capable of nudging users in one direction or another. In this context, several studies have been investigating how potential positive feedback loops leading to filter bubbles can be reduced [33]. On social media timelines, personalized nudges, which display relevant information more prominently, lead users to interact with it more. The increased interaction leads the algorithm to display more similar content and so on. In the end, a so-called filter bubble is created. In some cases, where the filter bubbles become problematic in terms of disinformation, social media platforms might use a warning nudge to break the user out of the vicious circle [33]. Another example, for the same purpose, is to present a feedback nudge to a user showing the balance of opinion on their timeline to raise awareness [101]. While this particular context has been under increased scrutiny over the past five years owing to the fake news phenomenon, research is still ongoing and calls for a better understanding on how platform design and individual choices combine to influence outcomes [70].

### 4.3 Personalization tools

Our review shows that personalized choice architectures are a promising research avenue, as researchers have started to investigate how different personal and psychological traits influence the effectiveness of nudges. However, the reviewed articles align with Caraban et al.'s observation that personalized nudging remains understudied [23]. This leaves open the following research question:

**RQ4:** How can effective personalized nudges be designed using minimal real-time contextual data?

The trade-off between large scale data collection to design highly personalized nudges and privacy-by-design one-size-fits-all nudging is an important aspect to consider. Technically, personalization can be achieved at a crude and transparent level by asking users about preferences. More advanced personalization can be achieved by (1) understanding which user characteristics (e.g., demographic data, psychological data) or contexts (e.g., location, current behavior, or time [100]) predict the efficacy of different nudges and (2) use adequate tools to identify when a user fits these characteristics or finds themselves in a particular context. With digital technology, it becomes increasingly feasible to infer some of a user's behaviors online (e.g., is the user reading an article? [16]) and offline (e.g., is the user going home? [26]), but it remains a very difficult task, which requires creative solutions for many behaviors (e.g., researchers have suggested detecting whether a user is smoking by using acoustic properties of a smoking breath recorded through

wearable devices [35]). Even contexts such as the current transportation mode of a user (e.g., car, bus, train, bike) are difficult problems, where effective solutions require creative combinations of different sensors (e.g., motion, sound, and vision [103]). Promising examples of such approaches have been successfully used in similar areas of research. For instance, in their work, Anagnostopoulou et al. used a transportation mode detection system to personalize interventions to support sustainable behaviors of a user [6]. Future research could further take advantage of novel devices and sensors to improve context and behaviour detection. This avenue of research by definition raises questions about privacy and data tracking. It also raises a broader ethical question. Nudging in general has been called into question and labeled manipulative [49]. Personalized digital nudging would go a step further, increasing their power to influence users to choose what the designer decided. Also, this is happening in a context where personal data is being proactively collected about users. Thus, even if digital nudges are, by definition, letting users have the final choice, one may argue on the one hand that artifacts that steer users in a specific direction with an ever-increasing probability (such as could be achieved by personalized digital nudges) constrain users' autonomy and even limit their freedom of choice. However, it could also be argued that if a nudge is in the interest of a user (as perceived by her or him), it would be unethical not to increase the probability of steering a user in a certain direction [93]. These considerations lead to the following broader question:

**RQ5:** What are the emergent ethical boundaries of personalized nudging?

### 4.4 Pervasive delivery

In our review we found only a very few instances of nudges using delivery systems other than visual interfaces on mobiles or desktops. This leaves open the following research question:

**RQ6:** Are the effects of digital nudges moderated by the delivery device or channel?

Typical examples of such innovative delivery channels include wearable devices or ambient objects, and could offer interactions through visual, haptic, audio, or olfactory cues. At this stage, it is not clear to what extent these novel delivery channels could help design more effective nudges, even though there are some promising avenues for some of them. For instance, the good vibration study found that a haptic feedback nudge could reduce the time spent on social media by up to 20% in the short term [90]. If used well they can offer more subtle, but more visible and targeted, interactions than mobile or desktop interventions in certain contexts. Examples include an artistic digital screen to display electrical consumption directly on the kitchen counter [105], a teddy bear with a connected Raspberry Pi that tells its owner when to take their asthma medication [45], a virtual aquarium that visualizes user contributions to a knowledge management system in a shared office [55], or a connected smart mirror, which could not only serve as an ambient feedback object, but also include augmented reality features [85].

## 4.5 Symmetric effects

Only about half of the outcomes of the digital nudges related to actual behaviors (vs non-behaviors, which we broadly categorized as attitudes). This is a small proportion, given that behavior change is inherent to the original definition of a nudge. Also, almost 90 percent of behavioral studies were focused on instilling a new behavior or increasing an existing one. Only about ten percent focused on decreasing behaviors and not one on stopping behaviors. Interventions to decrease or stop behaviors are, however, common (for instance in public health). Future work could restore balance:

**RQ7:** Is a given digital nudge as effective at stopping or decreasing a behavior as it is at initiating or increasing a behavior?

In a similar vein, most research evaluated the effect of nudges on one-time behavior changes. However, the long-term effects of digital nudging are not yet well understood [23]. Simplicity can again partially explain this narrow focus on one-time behaviors: it requires more resources and more complex designs to monitor and analyze long-term behavior change, while it also poses several ethical hurdles to research. However, this longer-term perspective is important if we want to understand real phenomena, as behaviors online are often repeated over time. Also, in many contexts, users are exposed to the same nudge several times.

**RQ8:** Is a given digital nudge as effective at changing repeated behaviors as it is at changing one-time behaviors?

These two questions (i.e., RQ7 and RQ8) raise the issue of symmetry of effects of digital nudges on different outcomes. Current knowledge cannot provide clear answers given the imbalance of research output on the different types of outcome. Overall, future research could focus on investigating different types of behavior change as well as longer-term behavior change. This would more accurately reflect the phenomena actually occurring, despite providing a more challenging problem to solve for researchers.

## 4.6 Combined effects

As nudging gains traction in the private and public sphere, users become more likely to be exposed to several nudges at the same time [107]. However, our results show that the formal study of the interaction effect of digital nudges is not yet mature. Some nudging practitioners have attempted to evaluate how interventions interact, see for instance [18]. Also, a recent study showed that a combination of defaults and social influence nudges led to a stronger impact on compliance for the user than each nudge individually [60]. However, the study of the potential interaction effects due to the combination of different digital nudges is only at the beginning and still requires further empirical investigation. For instance, in the context of social media, are the effects of adding two types of frictions on the same social media platform simply cumulative or does one friction feature moderate the effect of the other? Also, more formal investigations of the underlying mechanisms related to potential interaction effects of nudges are yet to be made. This leaves open the following broader research avenue:

**RQ9:** How do digital nudges interact and through which mechanisms?

## 4.7 Limitations

Even though we followed the guidelines for systematic reviews carefully, the present paper is not without limitations. As is inherent in a systematic literature review, its scope is limited to the search results of the initial query and the database selection. The keywords used for searching the databases without snowballing could potentially leave out otherwise relevant results. We recognize that there are other papers (e.g. [37, 102, 118]) that would be relevant to the digital landscape of nudging. Yet, the mentioned papers have not been included in this literature review as they never mention or reference digital nudging by name. We could have aimed for more exhaustivity by using search terms specific to nudge patterns whose authors did not call digital nudges (e.g. online commitment). However, for this approach, we would have needed to identify an exhaustive list of search terms, which is hard to attain and risked biasing our results by putting too much emphasis on one pattern over another. Our approach is more restrictive, limiting the results to research labeled as digital nudging, but this ensures exhaustivity within that label, which is our objective. Since the exact definition of what digital nudges entail remains blurry, our research describes the landscape of what authors generally call digital nudging. Our approach may support future efforts that seek to further converge towards a unified definition of digital nudging, that would describe what digital nudging entails and what it does not, as the boundaries are not always consistent throughout the literature. Over the years, various definitions of nudging have grown more specific, yet more complex – see [77] for a discussion on this topic. Since the number of articles explicitly related to digital nudging had grown very steeply over the last five years, we judged that it was the right time to capture the evolution of digital nudging literature and map it for future researchers.

## 5 CONCLUSION

This paper presented a systematic review of the literature on digital nudges. We provided a detailed analysis of 73 papers, based on 109 studies containing 231 digital nudges that had been demonstrated and evaluated by previous scholars. Our results show that while research on the topic has been very active, there seems to be a concentration of investigations in several specific areas of the landscape. For instance, almost half of the research on digital nudging focuses on three contexts: privacy/security, e-commerce/marketing, and social media. Furthermore, several patterns of nudges seem to be hardly investigated, even though they seem to be widely used online, such as scarcity nudges (e.g., only one room left), deception nudges (e.g., a decoy option), or commitment nudges. The type of behavioral outcome is very rarely a decrease or a complete cessation of a behavior when nudges are applied in the literature. Moreover, while few single studies measure both attitudinal and behavioral outcomes, more papers conduct several studies to better triangulate outcomes. Finally, while both interconnected and personalized choice architectures can differentiate digital from conventional nudges, most of the research is conducted in what we call disconnected and non-personalized choice environments. Based on these observations, we laid out nine future research questions to illuminate several unexplored patches in the digital nudging landscape that future researchers might want to explore.

**Table 1: Digital nudge literature overview containing: Nudge pattern. Outcome. Context. Evaluation. Sample type. Personalization: partial (★), full (★★). Interconnected: partial (★), full (★★). Delivery other than visual through a mobile or computer screen (Delivery): Haptic delivery channel (Haptic), Wearable delivery device (Wearable), Ambient delivery device (Ambient)**

Paper	Nudge pattern	Outcome	Context <sub>1</sub>	Evaluation <sub>2</sub>	Sample type <sub>3</sub>	Personalized	Interconnected	Delivery	Studies
[1]	Social, Disclosure	Attitudinal	Miscellaneous	Online Exp.	Online panel		★		1
[2]	Social	Attitudinal	E-comm. /Marketing	Online Exp.	Online panel	★★	★		1
[3]	Reinforce	Attitudinal	Recommender Systems	Online Exp.	Online panel	★★			1
[4]	Reinforce, Scarcity	Behavioral	Crowdfunding	Online Exp.	Online panel	★	★		1
[7]	Social	Attitudinal	Social media	Online Exp.	Online panel	★	★		1
[9]	Social	Behavioral	E-comm. /Marketing	Online Exp.	Other field data		★★		1
[10]	Disclosure	Multi-level	Policy-making	Lab Exp.	Online panel		★★		1
[11]	Social, Default, Feedback Warning, Commitment, Disclosure	Behavioral	Work	Online Exp.	Social networks				1
[13]	Feedback	Behavioral	Health	Field Study	Uni. students			Ambient	2
[14]	Social, Friction, Default	Behavioral	Sustainability	Field Exp.	Social networks	★★			1
[15]	Friction	Multi-level	Privacy/Security	Online Exp., Field Study	Online panel, Partner-organ.				2
[17]	Friction	Attitudinal	Innovation	Lab Exp.	Uni. students	★★			1
[21]	Social, Reinforce	Multi-level	Education	Online Exp., Field Exp.	Uni. students, Online panel	★★	★★		2
[22]	Reinforce, Warning, Deception	Attitudinal	Privacy/Security	In-class Exp., Online Exp.	Uni. students, Social networks	★			6
[24]	Disclosure, Friction, Default	Behavioral	Crowdfunding	Field Study	Partner-organ.				1
[25]	Reinforce, Social	Behavioral	Policy-making	Field Study	Partner-organ.		★		1
[30]	Disclosure	Attitudinal	E-comm. /Marketing	Online Exp.	Uni. students				1
[31]	Reinforce	Attitudinal	E-comm. /Marketing	Lab Exp.	Uni. students		★		7
[34]	Feedback	Attitudinal	Privacy/Security	Online Survey	Online panel	★			1
[32]	Social	Behavioral	Health	Online Exp.	Online panel	★			1
[40]	Friction	Behavioral	Policy-making	Field Study	Other field data		★		1
[41]	Feedback	Multi-level	Recommender Systems	Field Study, Online Survey	Uni. students				4
[43]	Social, Reinforce	Multi-level	Recommender Systems	Field Exp., Online Survey	Partner-organ.				3
[44]	Disclosure	Behavioral	Social media	Online Exp.	Social networks				1
[51]	Reinforce, Default	Behavioral	Sustainability	Lab Exp.	Uni. students	★			1
[53]	Feedback	Behavioral	Sustainability	Field Exp.	Partner-organ.	★		Ambient	1
[56]	Disclosure	Behavioral	Social media	Field Exp.	Partner-organ.				1
[57]	Disclosure	Behavioral	Sustainability	Online Exp.	Social networks				1
[59]	Feedback	Behavioral	Miscellaneous	Field Exp.	Not disclosed			Haptic, Wearable	2
[60]	Social, Default	Behavioral	E-comm. /Marketing	Online Exp.	Online panel	★	★		2
[63]	Default, Warning	Behavioral	E-comm. /Marketing	Lab Exp.	Online panel	★★			1
[64]	Social, Disclosure, Default, Warning	Attitudinal	Privacy/Security	Online Exp.	Online panel				1
[65]	Disclosure	Attitudinal	Sustainability	Online Exp.	Uni. students	★★			1
[66]	Social, Reinforce, Scarcity	Behavioral	E-comm. /Marketing	Online Exp.	Not disclosed				1
[68]	Social	Multi-level	Social media	Online Exp.	Online panel		★		2
[69]	Friction	Multi-level	Miscellaneous	Field Exp., Qual. methods	Uni. students	★★			2
[67]	Social, Disclosure	Multi-level	Social media	Online Exp.	Online panel	★★	★		2
[73]	Social	Multi-level	Recommender Systems	Lab Exp.	Uni. students	★	★		1
[75]	Friction, Warning	Attitudinal	Privacy/Security	Online Survey	Social networks	★	★		1
[74]	Social, Commitment	Attitudinal	Sustainability	Online Exp.	Uni. students		★		1
[78]	Feedback	Behavioral	E-comm. /Marketing	Lab Exp.	Uni. students	★★			1
[79]	Reinforce	Behavioral	Crowdfunding	Field Study	Partner-organ.				1
[81]	Friction, Default	Behavioral	E-comm. /Marketing	Lab Exp.	Uni. students				1
[82]	Social, Disclosure, Reinforce	Attitudinal	Sustainability	Online Exp.	Uni. students				1
[83]	Friction, Default	Behavioral	E-comm. /Marketing	Online Exp.	Online panel	★			1
[88]	Disclosure, Default	Multi-level	Crowdfunding	Online Exp., Field Study	Online panel, Other field data	★★			3
[90]	Feedback	Behavioral	Social media	Online Exp.	Online panel	★★		Haptic	1
[94]	Default	Attitudinal	Policy-making	Online Exp.	Social networks	★			1
[96]	Reinforce	Behavioral	Education	In-class Exp.	Uni. students				1
[97]	Friction	Behavioral	Miscellaneous	Online Exp.	Online panel	★			1
[98]	Friction, Feedback, Warning	Attitudinal	Health	Online Survey	Uni. students	★			1
[99]	Friction	Attitudinal	Social media	Online Survey	Uni. students, Partner-organ.		★		2
[106]	Feedback	Behavioral	Education	Field Study	Uni. students	★★			1
[109]	Social, Friction	Multi-level	Innovation	Online Exp.	Uni. students	★	★		1
[110]	Disclosure, Feedback	Attitudinal	Work	Qualit. methods	Partner-organ.				2
[113]	Disclosure	Behavioral	Privacy/Security	Online Exp.	Online panel	★			1
[111]	Scarcity, Deception	Behavioral	Crowdfunding	Online Exp.	Online panel				3
[112]	Social, Default	Behavioral	Privacy/Security	Online Exp.	Online panel	★	★		1
[114]	Social, Disclosure, Feedback, Default, Warning	Attitudinal	Privacy/Security	Online Survey	Social networks				1
[115]	Friction	Behavioral	Privacy/Security	Online Exp.	Uni. students	★			1
[116]	Disclosure	Attitudinal	Sustainability	Online Exp.	Online panel	★★			1
[117]	Reinforce, Feedback	Behavioral	Health	Field Exp.	Other field data	★★		Wearable	1
[120]	Reinforce, Default	Attitudinal	Innovation	Lab Exp.	Uni. students				1
[119]	Reinforce, Feedback, Default	Behavioral	Innovation	Field Exp.	Online panel	★			1
[121]	Social, Scarcity	Multi-level	Social media	Field Exp., Lab Exp.	Online panel, Partner-organ.		★★		3
[125]	Default	Attitudinal	Sustainability	Online Exp.	Online panel	★			1
[126]	Friction, Commitment	Multi-level	Miscellaneous	Online Exp.	Partner-organ.	★★			1
[131]	Feedback	Multi-level	Work	Field Exp.	Partner-organ.	★★			1
[132]	Disclosure, Friction, Default	Multi-level	Privacy/security	Field Exp., Online Survey	Partner-organ.				4
[134]	Feedback	Behavioral	Education	Online Exp.	Uni. students	★★	★		1
[135]	Warning	Attitudinal	Social media	Qual. methods	Not disclosed	★★	★		1
[139]	Social, Reinforce, Scarcity	Multi-level	Crowdfunding	Online Exp., Field Study	Online panel, Partner-organ.	★	★		2
[140]	Friction	Multi-level	Innovation	Lab Exp.	Uni. students	★			1

1: E-commerce / Marketing (E-comm. / Marketing)  
 2: Experiment (Exp.), Qualitative Methods (Qual. methods)  
 3: Partner-organization (Partner-organ.), University (Uni.)

## REFERENCES

- [1] Olga Abramova. 2020. What's in a name: Examining discrimination on sharing platforms and its possible remedies. In *Proceedings of ECIS'20*. AIS, Marrakech, Morocco, 1–17.
- [2] Martin Adam and Mario Pecorelli. 2018. Recommendations in augmented reality applications – The effect of customer reviews and seller recommendations on purchase intention and product selection. In *Proceedings of ECIS'18*. AIS, Portsmouth, UK, 1–19.
- [3] Martin Adam, Jonas Toutaoui, Nicolas Pfeuffer, and Oliver Hinz. 2019. Investment decisions with robo-advisors: the role of anthropomorphism and personalized anchors in recommendations. In *Proceedings of ECIS'19*. AIS, Stockholm & Uppsala, Sweden, 1–18.
- [4] Martin Adam, Michael Wessel, and Alexander Benlian. 2019. Of early birds and phantoms: how sold-out discounts impact entrepreneurial success in reward-based crowdfunding. *Review of Managerial Science* 13, 3 (2019), 545–560.
- [5] Mark Alfano, Amir Ebrahimi Fard, J Adam Carter, Peter Clutton, and Colin Klein. 2021. Technologically scaffolded atypical cognition: The case of YouTube's recommender system. *Synthese* 199, (2021), 835–858.
- [6] Evangelia Anagnostopoulou, Jasna Urbančić, Efthimios Bothos, Babis Magoutas, Luka Bradesko, Johann Schrammel, and Gregoris Mentzas. 2020. From mobility patterns to behavioural change: leveraging travel behaviour and personality profiles to nudge for sustainable transportation. *Journal of Intelligent Information Systems* 54, (2020), 1–22.
- [7] Simge Andi and Jesper Akesson. 2020. Nudging Away False News: Evidence from a Social Norms Experiment. *Digital Journalism* 9:1 (2020), 106–125.
- [8] Mark A Andor, Andreas Gerster, and Stephan Sommer. 2020. Consumer inattention, heuristic thinking and the role of energy labels. *The Energy Journal* 41, 1 (2020), 83–112.
- [9] Marzia Antenore, Giovanna Leone, Alessandro Panconesi, and Erisa Terolli. 2018. Together we buy, alone I quit: some experimental studies of online persuaders. In *Proceedings of DTUC'18*. ACM, Paris, France, 1–4.
- [10] Armenak Antinyan, Gergely Horváth, and Mofei Jia. 2020. Curbing the consumption of positional goods: Behavioral interventions versus taxation. *Journal of Economic Behavior & Organization* 179 (2020), 1–21.
- [11] Sandra Bammert, Ulrich Matthias König, Maximilian Roegliger, and Tabitha Wruck. 2020. Exploring potentials of digital nudging for business processes. *Business Process Management Journal* 26 (2020), 1329–1347.
- [12] Adrien Barton and Till Grüne-Yanoff. 2015. From libertarian paternalism to nudging—and beyond. *Review of Philosophy and psychology* 6, 3 (2015), 341–359.
- [13] Adam Beddoe, Romana Burgess, Lucian Carp, James Foster, Adam Fox, Leechay Moran, Peter Bennett, and Daniel Bennett. 2020. Disruptabottle: Encouraging Hydration with an Overflowing Bottle. In *Proceedings of CHI'20 Extended Abstracts*. ACM, Honolulu, HI, USA, 1–7.
- [14] Michelle Berger, Chiara Müller, and Niclas Nüske. 2020. Digital Nudging in Online Grocery Stores—Towards Ecologically Sustainable Nutrition. In *Proceedings of ICIS'20*. AIS, Hyderabad, India, 1–17.
- [15] Kristoffer Bergam, Valéry Bezençon, Paul Maingot, Tony Gjerlufsen, and Adrian Holzer. 2020. Digital Nudges for Privacy Awareness: From consent to informed consent?. In *Proceedings of ECIS'20*. AIS, Marrakech, Morocco, 1–16.
- [16] Robert Bixler and Sidney D'Mello. 2016. Automatic gaze-based user-independent detection of mind wandering during computerized reading. *User Modeling and User-Adapted Interaction* 26, 1 (2016), 33–68.
- [17] Ivan Boskovic-Pavkovic, Isabella Seiber, and Ronald Maier. 2019. How Digital Nudges Affect Consideration Set Size and Perceived Cognitive Effort in Idea Convergence of Open Innovation Contests. In *Proceedings of HICSS'19*. ScholarSpace, Maui, HI, USA, 4415–4424.
- [18] Guglielmo Briscese and Cameron Tan. 2018. *Applying Behavioural Insights to Labour Markets*. Report. The Behavioural Insights Team.
- [19] Jan vom Brocke, Alexander Simons, Bjoern Niehaves, Bjorn Niehaves, Kai Reimer, Ralf Plattfaut, and Anne Cleven. 2009. Reconstructing the giant: On the importance of rigour in documenting the literature search process. In *Proceedings of ECIS'09*. AIS, Verona, Italy, 1–12.
- [20] Christina L Brown and Aradhna Krishna. 2004. The skeptical shopper: A metacognitive account for the effects of default options on choice. *Journal of consumer research* 31, 3 (2004), 529–539.
- [21] Michael G Brown, James J Schiltz, Holly Derry, and Caitlin Holman. 2019. Implementing online personalized social comparison nudges in a web-enabled coaching system. *The Internet and Higher Education* 43, 1 (2019), 100691.
- [22] Christoph Buck, Simone Burster, and Torsten Eymann. 2018. An Experiment Series on App Information Privacy Concerns. In *Proceedings of ECIS'18*. AIS, Portsmouth, UK, 1–18.
- [23] Ana Caraban, Evangelos Karapanos, Daniel Gonçalves, and Pedro Campos. 2019. 23 Ways to Nudge: A Review of Technology-Mediated Nudging in Human-Computer Interaction. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. ACM, Glasgow, Scotland, UK, 1–15.
- [24] Abhijnan Chakraborty, Nuno Mota, Asia J Biega, Krishna P Gummedi, and Hoda Heidari. 2019. On the impact of choice architectures on inequality in online donation platforms. In *Proceedings of WWW '19*. ACM, San Francisco, CA, USA, 2623–2629.
- [25] Yan Chen, Shuyuan Deng, Dong-Heon Kwak, Ahmed Elnoshokaty, and Jiao Wu. 2019. A multi-appeal model of persuasion for online petition success: A linguistic cue-based approach. *Journal of the Association for Information Systems* 20, 2 (2019), 105–131.
- [26] Yohan Chon, Elmurod Talipov, Hyejeong Shin, and Hojung Cha. 2011. Mobility prediction-based smartphone energy optimization for everyday location monitoring. In *Proceedings of SenSys '11*. ACM, Seattle, WA, USA, 82–95.
- [27] Robert B Cialdini. 2001. *Influence*. Pearson Education, Boston, MA, USA.
- [28] Robert B Cialdini and Noah J Goldstein. 2004. Social influence: Compliance and conformity. *Annu. Rev. Psychol.* 55 (2004), 591–621.
- [29] Thomas M Connolly, Elizabeth A Boyle, Ewan MacArthur, Thomas Hainey, and James M Boyle. 2012. A systematic literature review of empirical evidence on computer games and serious games. *Computers & education* 59, 2 (2012), 661–686.
- [30] Francis Joseph Costello, Jin Ho Yun, and Kun Chang Lee. 2020. A NeuroIS Investigation of the Effects of a Digital Dark Nudge. In *NeuroIS Retreat*. Springer Nature, Cham, Switzerland, 64–70.
- [31] Alan R Dennis, Lingyao Yuan, Xuan Feng, Eric Webb, and Christine J Hsieh. 2020. Digital Nudging: Numeric and Semantic Priming in E-Commerce. *Journal of Management Information Systems* 37, 1 (2020), 39–65.
- [32] Blake M DiCosola and Gina Neff. 2020. Using Social Comparisons to Facilitate Healthier Choices in Online Grocery Shopping Contexts. In *Proceedings of CHI'20 Extended Abstracts*. ACM, Honolulu, HI, USA, 1–8.
- [33] Dominic DiFranzo and Kristine Gloria-Garcia. 2017. Filter bubbles and fake news. *XRDS: Crossroads, The ACM Magazine for Students* 23, 3 (2017), 32–35.
- [34] Nicolás E Diaz Ferreyra, Tobias Kroll, Esma Aïmeur, Stefan Stieglitz, and Maritta Heisel. 2020. Preventative Nudges: Introducing Risk Cues for Supporting Online Self-Disclosure Decisions. *Information(Switzerland)* 11, 8 (2020), 399.
- [35] Íñigo Torres Uribe Echebarria, Syed Anas Intiaz, Mingxu Peng, and Esther Rodriguez-Villegas. 2017. Monitoring smoking behaviour using a wearable acoustic sensor. In *39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, Jeju, South Korea, 4459–4462.
- [36] William Eggers, Mike Turley, Bruce Chew, Rae Jeneanne, Jason Manstorf, and Stine Degnegaard. 2020. *Government Trends 2020 report*. Technical Report. Deloitte.
- [37] Robert Epstein and Ronald E Robertson. 2015. The search engine manipulation effect (SEME) and its possible impact on the outcomes of elections. *Proceedings of the National Academy of Sciences* 112, 33 (2015), E4512–E4521.
- [38] Sally Fincher, Janet Finlay, Sharon Greene, Lauretta Jones, Paul Matchen, John Thomas, and Pedro J Molina. 2003. Perspectives on HCI patterns: concepts and tools. In *Proceedings of CHI'03 Extended Abstracts*. ACM, Fort Lauderdale, FL, USA, 1044–1045.
- [39] Brian J Fogg and Jason Hreha. 2010. Behavior wizard: A method for matching target behaviors with solutions. In *Proceedings of PERSUASIVE'10*. Springer, Copenhagen, Denmark, 117–131.
- [40] Ashley M Fox, Edmund C Stazyk, and Wenhui Feng. 2020. Administrative easing: Rule reduction and medicaid enrollment. *Public Administration Review* 80, 1 (2020), 104–117.
- [41] Marko Gasparic and Francesco Ricci. 2020. IDE Interaction Support With Command Recommender Systems. *IEEE Access* 8 (2020), 19256–19270.
- [42] Michele J Gelfand, Lisa H Nishii, and Jana L Raver. 2006. On the nature and importance of cultural tightness-looseness. *Journal of applied psychology* 91, 6 (2006), 1225–1244.
- [43] Cristina Gena, Pierluigi Grillo, Antonio Lieto, Claudio Mattutino, and Fabiana Vernerio. 2019. When Personalization Is Not an Option: An In-The-Wild Study on Persuasive News Recommendation. *Information (Switzerland)* 10, 10 (2019), 300.
- [44] Henner Gimpel, Sebastian Heger, Julia Kasper, and Ricarda Schäfer. 2020. The Power of Related Articles—Improving Fake News Detection on Social Media Platforms. In *Proceedings of HICSS'20*. ScholarSpace, Maui, HI, USA, 6063–6072.
- [45] Aleksander Gisvold and Esben Aarseth. 2014. *Using Gamification and Tangible User Interfaces to Treat Asthmatic Children*. Technical Report. Institutt for datateknikk og informasjonsvitenskap.
- [46] Noah J Goldstein, Robert B Cialdini, and Vlaslas Griskevicius. 2008. A room with a viewpoint: Using social norms to motivate environmental conservation in hotels. *Journal of consumer Research* 35, 3 (2008), 472–482.
- [47] Juho Hamari, Jonna Koivisto, and Harri Sarsa. 2014. Does gamification work?—A literature review of empirical studies on gamification. In *Proceedings of HICSS'14*. IEEE, Waikoloa, HI, USA, 3025–3034.
- [48] Pelle Guldberg Hansen. 2016. The definition of nudge and libertarian paternalism: Does the hand fit the glove? *European Journal of Risk Regulation* 7, 1 (2016), 155–174.
- [49] Pelle Guldberg Hansen and Andreas Maaløe Jespersen. 2013. Nudge and the manipulation of choice: A framework for the responsible use of the nudge approach to behaviour change in public policy. *European Journal of Risk Regulation* 4, 1 (2013), 3–28.

- [50] Daniel M Hausman and Brynn Welch. 2010. Debate: To nudge or not to nudge. *Journal of Political Philosophy* 18, 1 (2010), 123–136.
- [51] Christopher Henkel, Anna-Raissa Seidler, Johann Kranz, and Marina Fiedler. 2019. How to nudge pro-environmental behaviour: An experimental study. In *Proceedings of ECIS'19*. AIS, Stockholm and Uppsala, Sweden.
- [52] Alex Hern. (February 2014). Why Google has 200m reasons to put engineers over designers. Website. Retrieved April 5, 2021 from: <https://www.theguardian.com/technology/2014/feb/05/why-google-engineers-designers>.
- [53] Christin Hoffmann and Kirsten Thommes. 2020. Can digital feedback increase employee performance and energy efficiency in firms? Evidence from a field experiment. *Journal of Economic Behavior & Organization* 180 (2020), 49–65.
- [54] Geert Hofstede. 2001. *Culture's consequences: Comparing values, behaviors, institutions and organizations across nations*. Sage publications, Thousand Oaks, CA, USA.
- [55] Adrian Holzer, Bruno Kocher, Samuel Bendahan, Isabelle Vonèche Cardia, Jorge Mazuze, and Denis Gillet. 2020. Gamifying knowledge sharing in humanitarian organisations: a design science journey. *European Journal of Information Systems* 29, 2 (2020), 153–171.
- [56] Ni Huang, Peiyu Chen, Yili Hong, and Shinyi Wu. 2018. Digital nudging for on-line social sharing: Evidence from a randomized field experiment. In *Proceedings of HICSS'18*. AIS, Waikoloa Village, HI, USA, 1483–1491.
- [57] Julian Huber, Dominik Jung, Elisabeth Schaule, and Christof Weinhardt. 2019. Goal framing in smart charging-increasing BEV users' charging flexibility with digital nudges. In *Proceedings of ECIS'19*. AIS, Stockholm and Uppsala, Sweden, 1–16.
- [58] Dennis Hummel and Alexander Maedche. 2019. How effective is nudging? A quantitative review on the effect sizes and limits of empirical nudging studies. *Journal of Behavioral and Experimental Economics* 80 (2019), 47–58.
- [59] Rohan Hundia, Aditya Vijayvargiya, and Aaron Quigley. 2020. Closed loop feedback nudges using nerve stimulation. In *Proceedings of SIGCHI on EICS'20*. ACM, Honolulu, HI, USA, 1–6.
- [60] Moritz Ingendahl, Dennis Hummel, Alexander Maedche, and Tobias Vogel. 2020. Who can be nudged? Examining nudging effectiveness in the context of need for cognition and need for uniqueness. *Journal of Consumer Behaviour* 20 (2020), 324–336.
- [61] Mathias Jesse and Dietmar Jannach. 2021. Digital nudging with recommender systems: Survey and future directions. *Computers in Human Behavior Reports* 3 (2021), 1–14.
- [62] Eric J Johnson and Daniel Goldstein. 2003. Do defaults save lives? *Science* 302, 5649 (2003), 1338–1339.
- [63] Dominik Jung and Christof Weinhardt. 2018. Robo-advisors and financial decision inertia: How choice architecture helps to reduce inertia in financial planning tools. In *Proceedings of ICIS'18*. AIS, San Francisco, CA, USA.
- [64] Shipi Kankane, Carlina DiRusso, and Christen Buckley. 2018. Can We Nudge Users Toward Better Password Management? An Initial Study. In *Proceedings of CHI'18 Extended Abstracts*. ACM, Montreal, QC, Canada, 1–6.
- [65] Indrani Karmakar and Jane Webster. 2018. Personalization of an Environmental Message: Developing a Measure. In *Proceedings of ICIS'18*. AIS, San Francisco, CA, USA, 1–9.
- [66] Katarzyna Katner and Radu Jianu. 2019. The Effectiveness of Nudging in Commercial Settings and Impact on User Trust. In *Proceedings of CHI'19 Extended Abstracts*. ACM, Glasgow, Scotland, UK, 1–6.
- [67] Antino Kim and Alan R Dennis. 2019. Says who? The effects of presentation format and source rating on fake news in social media. *MIS Quarterly* 43, 3 (2019).
- [68] Antino Kim, Patricia L Moravec, and Alan R Dennis. 2019. Combating fake news on social media with source ratings: the effects of user and expert reputation ratings. *Journal of Management Information Systems* 36, 3 (2019), 931–968.
- [69] Jaejeung Kim, Joonyoung Park, Hyunsoo Lee, Minsam Ko, and Uichin Lee. 2019. LocknType: Lockout task intervention for discouraging smartphone app use. In *Proceedings of the 2019 CHI conference on human factors in computing systems*. ACM, Glasgow, Scotland, UK, 1–12.
- [70] Brent Kitchens, Steven L Johnson, and Peter Gray. 2020. Understanding Echo Chambers and Filter Bubbles: The Impact of Social Media on Diversification and Partisan Shifts in News Consumption. *MIS Quarterly* 44, 4 (2020), 1619–1650.
- [71] Agnieszka Kitkowska, Yefim Shulman, Leonardo A Martucci, and Erik Wästlund. 2020. Psychological effects and their role in online privacy interactions: A review. *IEEE Access* 8 (2020), 21236–21260.
- [72] Adam DI Kramer, Jamie E Guillory, and Jeffrey T Hancock. 2014. Experimental evidence of massive-scale emotional contagion through social networks. *Proceedings of the National Academy of Sciences* 111, 24 (2014), 8788–8790.
- [73] Martin Kretzer and Alexander Maedche. 2018. Designing social nudges for enterprise recommendation agents: An investigation in the business intelligence systems context. *Journal of the Association for Information Systems* 19, 12 (2018), 1145–1186.
- [74] Tobias Kroll, Ute Paukstadt, Kseniya Kreidermann, and Milad Mirbabaie. 2019. Nudging people to save energy in smart homes with social norms and self-commitment. In *Proceedings of ECIS'19*. AIS, Stockholm and Uppsala, Sweden, 1–10.
- [75] Tobias Kroll and Stefan Stieglitz. 2019. Digital nudging and privacy: improving decisions about self-disclosure in social networks. *Behaviour & Information Technology* 40:1 (2019), 1–19.
- [76] Leonhard K Lades and Liam Delaney. 2020. Nudge FORGOOD. *Behavioural Public Policy* 6, 1 (2020), 75–94.
- [77] Tim-Benjamin Lembecke, Nils Engelbrecht, Alfred Benedikt Brendel, Bernd Herrenkind, and Lutz M Kolbe. 2019. Towards a Unified Understanding of Digital Nudging by Addressing its Analog Roots. In *Proceedings of PACIS'19*. AIS, Xi'an, China, 1–14.
- [78] Tim-Benjamin Lembecke, Nils Engelbrecht, Mathias Willnat, and Sascha Lichtenberg. 2020. Behavioral Design in Online Supermarkets: How Virtual Shopping Cart Functions Impact Sustainable Consumption. In *Proceedings of AMCIS'20*. AIS, Salt Lake City, UT, USA, 1–10.
- [79] Yijing Li, Wenjie Fan, Fei Liu, Eric TK Lim, Yong Liu, and Chee-Wee Tan. 2018. Exploring the Nudging and Counter-Nudging Effects of Campaign Updates in Crowdfunding. In *Proceedings of PACIS'18*. AIS, Yokohama, Japan, 1–8.
- [80] Alessandro Liberati, Douglas G Altman, Jennifer Tetzlaff, Cynthia Mulrow, Peter C Gøtzsche, John PA Ioannidis, Mike Clarke, Philip J Devereaux, Jos Kleijnen, and David Moher. 2009. The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration. *Journal of clinical epidemiology* 62, 10 (2009), e1–e34.
- [81] Shouwang Lu, Gong Gordon Chen, and Kanliang Wang. 2020. Overt or covert? Effect of different digital nudging on consumers' customization choices. *Nankai Business Review International* 12, 1 (2020), 56–74.
- [82] Thomas Mejtoft, Charlotte Ristinieni, Ulrik Söderström, and Eva Mårell-Olsson. 2019. User experience design and digital nudging in a decision making process. In *Proceedings of Bled eConference'19*. University of Maribor Press, AIS, Bled, Slovenia, 427–442.
- [83] Christian Meske, Ireti Amojó, and Peter Mohr. 2020. Digital Nudging to Increase Usage of Charity Features on E-Commerce Platforms. In *Proceedings of International Conference on Wirtschaftsinformatik*. AIS, Potsdam, Germany, 1203–1218.
- [84] Christian Meske and Tobias Potthoff. 2017. The DINU-model—a process model for the design of nudges. In *Proceedings of ECIS'17*. AIS, Guimarães, Portugal, 1–11.
- [85] Riccardo Miotto, Matteo Danieletto, Jerome R Scelza, Brian A Kidd, and Joel T Dudley. 2018. Reflecting health: smart mirrors for personalized medicine. *NPJ digital medicine* 1, 1 (2018), 1–7.
- [86] T. Mirsch, C. Lehrer, and R. Jung. 2017. Digital nudging: Altering user behavior in digital environments. In *Proceedings of International Conference on Wirtschaftsinformatik*. AIS, St.Gallen, Switzerland, 634–648.
- [87] David Moher, Alessandro Liberati, Jennifer Tetzlaff, Douglas G Altman, Prisma Group, et al. 2009. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *PLoS Medicine* 6, 7 (2009), e1000097.
- [88] Nuno Mota, Abhijnan Chakraborty, Asia J Biega, Krishna P Gummadi, and Hoda Heidari. 2020. On the Desiderata for Online Altruism: Nudging for Equitable Donations. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW2 (2020), 1–21.
- [89] Jonathan A Obar and Anne Oeldorf-Hirsch. 2020. The biggest lie on the internet: Ignoring the privacy policies and terms of service policies of social networking services. *Information, Communication & Society* 23, 1 (2020), 128–147.
- [90] Fabian Okeke, Michael Sobolev, Nicola Dell, and Deborah Estrin. 2018. Good vibrations: can a digital nudge reduce digital overload?. In *Proceedings of MobileHCI'18*. ACM, Barcelona, Spain, 1–12.
- [91] Daniel M Oppenheimer, Robyn A LeBoeuf, and Noel T Brewer. 2008. Anchors aweigh: A demonstration of cross-modality anchoring and magnitude priming. *Cognition* 106, 1 (2008), 13–26.
- [92] Daphna Oyserman. 2006. High power, low power, and equality: Culture beyond individualism and collectivism. *Journal of Consumer Psychology* 16, 4 (2006), 352–356.
- [93] Eyal Peer, Serge Egelman, Marian Harbach, Nathan Malkin, Arunesh Mathur, and Alisa Frik. 2020. Nudge me right: Personalizing online security nudges to people's decision-making styles. *Computers in Human Behavior* 109 (2020), 106347.
- [94] Antonio Gualberto Pereira and Luís Eduardo Afonso. 2019. Automatic enrollment and employer match: an experiment with the choice of pension plans. *Revista de Gestão* 27, 3 (2019), 281–299.
- [95] Michel Tuan Pham. 2013. The seven sins of consumer psychology. *Journal of Consumer Psychology* 23, 4 (2013), 411–423.
- [96] Gabriele Piccoli, Marcin Łukasz Bartosiak, Biagio Palese, and Joaquin Rodriguez. 2020. Designing scalability in required in-class introductory college courses. *Information & Management* 57, 8 (2020), 103263.
- [97] Martin Poniatowski and Jürgen Neumann. 2020. Getting Personal with Review Systems—Analyzing the Influence of Personality Traits on the Relationship between Review Templates and Reviewing Behavior. In *Proceedings of ECIS'20 Research-in-Progress Papers*. AIS, Marrakech, Morocco, 1–11.

- [98] Aarathi Prasad and Asia Quinones. 2020. Digital Overload Warnings—“The Right Amount of Shame”? In *Proceedings of International Conference on Human-Computer Interaction*. Springer, Copenhagen, Denmark, 117–134.
- [99] Aditya Kumar Purohit, Louis Barclay, and Adrian Holzer. 2020. Designing for Digital Detox: Making Social Media Less Addictive with Digital Nudges. In *Proceedings of CHI'20 Extended Abstracts*. ACM, Honolulu, HI, USA, 1–9.
- [100] Aditya Kumar Purohit and Adrian Holzer. 2019. Functional digital nudges: Identifying optimal timing for effective behavior change. In *Proceedings of CHI'19 Extended Abstracts*. ACM, Glasgow, Scotland, UK, 1–6.
- [101] Paul Resnick, R Kelly Garrett, Travis Kriplean, Sean A Munson, and Natalie Jomini Stroud. 2013. Bursting your (filter) bubble: strategies for promoting diverse exposure. In *Proceedings of CSCW'13*. ACM, San Antonio, TX, USA, 95–100.
- [102] Manoel Horta Ribeiro, Raphael Ottoni, Robert West, Virgílio AF Almeida, and Wagner Meira Jr. 2020. Auditing radicalization pathways on YouTube. In *Proceedings of FAT\* '20*. ACM, Barcelona, Spain, 131–141.
- [103] Sebastien Richoz, Lin Wang, Philip Birch, and Daniel Roggen. 2020. Transportation mode recognition fusing wearable motion, sound, and vision sensors. *IEEE Sensors Journal* 20, 16 (2020), 9314–9328.
- [104] Annamina Rieder, U Yeliz Eseryel, Christiane Lehrer, and Reinhard Jung. 2021. Why Users Comply with Wearables: The Role of Contextual Self-Efficacy in Behavioral Change. *International Journal of Human-Computer Interaction* 37, 3 (2021), 281–294.
- [105] Johnny Rodgers and Lyn Bartram. 2011. Exploring ambient and artistic visualization for residential energy use feedback. *IEEE transactions on visualization and computer graphics* 17, 12 (2011), 2489–2497.
- [106] Joaquin Rodriguez, Gabriele Piccoli, and Marcin Bartosiak. 2019. Nudging the classroom: Designing a socio-technical artifact to reduce academic procrastination. In *Proceedings of HICSS'19*. ScholarSpace, Maui, HI, USA, 4405–4414.
- [107] Arden Rowell. 2017. Once and Future Nudges. *Missouri Law Review* 82 (2017), 1–18.
- [108] Guillaume Saint-Jacques, Amir Sepehri, Nicole Li, and Igor Perisic. (March 2020). Building inclusive products through A/B testing. Website. Retrieved March 9, 2021 from: <https://engineering.linkedin.com/blog/2020/building-inclusive-products-through-a-b-testing>.
- [109] Renata Santiago Walser, Isabella Seeber, and Ronald Maier. 2019. Designing a Digital Nudge for Convergence: The Role of Decomposition of Information Load for Decision Making and Choice Accuracy. *AIS Transactions on Human-Computer Interaction* 11, 3 (2019), 179–207.
- [110] Raphael Schilling, Stephan Aier, and Robert Winter. 2019. Designing an Artifact for Informal Control in Enterprise Architecture Management. In *Proceedings of ICIS'19*. AIS, Munich, Germany, 1–17.
- [111] Christoph Schneider, Markus Weinmann, and Jan Vom Brocke. 2018. Digital nudging: guiding online user choices through interface design. *Commun. ACM* 61, 7 (2018), 67–73.
- [112] David Schneider, Johannes Klumpe, Martin Adam, and Alexander Benlian. 2019. Nudging users into digital service solutions. *Electronic Markets* 30, 4 (2019), 863–881.
- [113] David Schneider, Sebastian Lins, Tillmann Grupp, Alexander Benlian, and Ali Sunyaev. 2017. Nudging users into online verification: the case of carsharing platforms. In *Proceedings of ICIS'17*. AIS, Seoul, South Korea, 1–20.
- [114] Sofia Schöbel, Torben Bavev, Andreas Janson, Felix Hupfeld, and Jan Marco Leimeister. 2020. Understanding User Preferences of Digital Privacy Nudges—A Best-Worst Scaling Approach. In *Proceedings of HICSS'20*. ScholarSpace, Maui, HI, USA, 3918–3927.
- [115] Charlotte Schöning, Christian Matt, and Thomas Hess. 2019. Personalised nudging for more data disclosure? On the adaption of data usage policies format to cognitive styles. In *Proceedings of HICSS'19*. ScholarSpace, Maui, HI, USA, 4395–4404.
- [116] Tim Schrolls, Mourad Zoubir, Jacob Stahl, Katharina Drozniak, and Thomas Franke. 2020. Good Boy Here or Bad Boy Far Away?. In *Proceedings of International Conference on Human-Computer Interaction*. Springer, Copenhagen, Denmark, 398–411.
- [117] Avijit Sengupta, Anol Bhattacharjee, and Kaushik Dutta. 2020. Information Technology Interventions in Cardiac Rehabilitation: A Theory Driven Approach. In *Proceedings of ICIS'20*. AIS, Hyderabad, India, 1–17.
- [118] Alexander J Stewart, Mohsen Mosleh, Marina Diakonova, Antonio A Arechar, David G Rand, and Joshua B Plotkin. 2019. Information gerrymandering and undemocratic decisions. *Nature* 573, 7772 (2019), 117–121.
- [119] Carola Stryja and Gerhard Satzger. 2019. Digital nudging to overcome cognitive resistance in innovation adoption decisions. *The Service Industries Journal* 39, 15–16 (2019), 1123–1139.
- [120] Carola Stryja, Gerhard Satzger, and Verena Dörner. 2017. A decision support system design to overcome resistance towards sustainable innovations. In *Proceedings of ECIS'17 Research-in-Progress Papers*. AIS, Guimarães, Portugal, 2885–2895.
- [121] Tianshu Sun, Siva Viswanathan, Ni Huang, and Elena Zheleva. 2019. Designing Promotional Incentive to Embrace Social Sharing: Evidence from Field and Lab Experiments. In *Proceedings of ICIS'19*. AIS, Munich, Germany, 1–17.
- [122] Cass R Sunstein. 2014. Nudging: a very short guide. *Journal of Consumer Policy* 37, 4 (2014), 583–588.
- [123] Cass R Sunstein. 2015. The ethics of nudging. *Yale Journal on Regulation* 32, 2 (2015), 413–450.
- [124] Cass R Sunstein. 2015. Nudges, agency, and abstraction: A reply to critics. *Review of Philosophy and Psychology* 6, 3 (2015), 511–529.
- [125] Nadine Székely, Markus Weinmann, and Jan vom Brocke. 2016. Nudging People To Pay Co2 Offsets—The Effect of Anchors in Flight Booking Processes. In *Proceedings of ECIS'16 Research-in-Progress Papers*. AIS, Istanbul, Turkey, 1–10.
- [126] Philipp Terres, Johannes Klumpe, Dominik Jung, and Oliver Koch. 2019. Digital Nudges for User Onboarding: Turning Visitors into Users. In *Proceedings of ECIS'19*. AIS, Stockholm and Uppsala, Sweden, 1–16.
- [127] Timm Teubner and Antje Graul. 2020. Only one room left! How scarcity cues affect booking intentions on hospitality platforms. *Electronic Commerce Research and Applications* 39 (2020), 100910.
- [128] Richard H. Thaler. 2018. Nudge, not sludge. *Science* 631, 6401 (2018), 431.
- [129] Richard H Thaler and Cass R Sunstein. 2008. *Nudge: Improving decisions about health, wealth, and happiness*. Yale University Press, New Haven, CT, USA.
- [130] Richard H Thaler, Cass R Sunstein, and John P Balz. 2013. Choice architecture. In *The behavioral foundations of public policy*. Princeton University Press, Princeton, NJ, USA, 428–439.
- [131] Vincent W-S Tseng, Matthew L Lee, Laurent Denoue, and Daniel Avrahami. 2019. Overcoming distractions during transitions from break to work using a conversational website-blocking system. In *Proceedings of CHI'19*. ACM, Glasgow, Scotland, UK, 1–13.
- [132] Christine Utz, Martin Degeling, Sascha Fahl, Florian Schaub, and Thorsten Holz. 2019. (Un)informed consent: Studying gdpr consent notices in the field. In *Proceedings of CCS'19*. ACM, London, UK, 973–990.
- [133] Andre Calero Valdez, Martina Ziefle, and Michael Sedlmair. 2017. Priming and anchoring effects in visualization. *IEEE transactions on visualization and computer graphics* 24, 1 (2017), 584–594.
- [134] Maxim van Oldenbeek, Till J Winkler, Julie Buhl-Wiggers, and Daniel Hardt. 2019. Nudging in Blended Learning: Evaluation of Email-based progress feedback in a Flipped-Classroom Information Systems Course. In *Proceedings of ECIS'19*. AIS, Stockholm and Uppsala, Sweden, 1–15.
- [135] Christian von der Weth, Ashraf Abdul, Shaojing Fan, and Mohan Kankanhalli. 2020. Helping Users Tackle Algorithmic Threats on Social Media: A Multimedia Research Agenda. In *Proceedings of MM'20*. ACM, Seattle, WA, USA, 4425–4434.
- [136] Soroush Vosoughi, Deb Roy, and Sinan Aral. 2018. The spread of true and false news online. *Science* 359, 6380 (2018), 1146–1151.
- [137] Jane Webster and Richard T Watson. 2002. Analyzing the past to prepare for the future: Writing a literature review. *MIS quarterly* 26, 2 (2002), 13–23.
- [138] Markus Weinmann, Christoph Schneider, and Jan vom Brocke. 2016. Digital nudging. *Business & Information Systems Engineering* 58, 6 (2016), 433–436.
- [139] Michael Wessel, Martin Adam, and Alexander Benlian. 2019. The impact of sold-out early birds on option selection in reward-based crowdfunding. *Decision Support Systems* 117 (2019), 48–61.
- [140] Arnold Wibmer, Frederik M Wiedmann, Isabella Seeber, and Ronald Maier. 2019. Why less is more: An eye tracking study on idea presentation and attribute attendance in idea selection. In *Proceedings of ECIS'19*. AIS, Stockholm and Uppsala, Sweden, 1–14.