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Abstract:

Digital nudging interventions have emerged as soft-paternalistic mechanisms for reducing heuristic limitations and biases in decision-making environments. Prior research has conceptualized digital nudging interventions as subtle modifications in the decision-making environment that nudge a decision maker towards better choices without limiting other alternatives. The approach has received criticism as researchers have achieved limited consensus on its definition, categorized diverse behavior-modulation methodologies as digital nudging, and raised multiple ethical concerns about it. Such ambiguity reduces fidelity while challenging synthesis, application, and replication. In this paper, we posit the need to broaden the definition of digital nudging interventions, reconcile the inconsistencies, and present a coherent frame. Based on a systematic review of the extant literature, we propose an extended definition that is coherent with the libertarian-paternalistic principle, clarifying the intent of digital nudging interventions, and delineating the nature of the digital artifacts involved. We further present a taxonomy with standard vernacular and label its complex underlying principles and the components that can guide practitioners and researchers.

Keywords: Digital Nudging Interventions, Choice Architecture, Systematic Literature Review, Taxonomy, Information Systems Research

Torkil Clemmensen was the accepting senior editor for this paper.

1 Introduction

In the ubiquitous computing age, individuals face the need to make many decisions related to information technology artifacts, to analyze large volumes and diverse information, and to evaluate risks, benefits, and alternatives. The literature indicates that only a limited number of users possess self-reflective awareness and the ability to manage vulnerabilities associated with decision-making in an online context (Masur, 2018). Extant mechanisms to educate users about risks in their decision-making process are often disruptive, time-consuming, and cumbersome. Design interventions that leverage insights from social, behavioral, psychological, and economic theories to reshape a decision maker's choice without altering incentives, without coercion, and while preserving their freedom to choose have emerged as unobtrusive methods to influence decision makers (Tannenbaum et al., 2017; Thaler & Sunstein, 2009). One can use design interventions to provide information and simplify complex problems, and prevent decision makers from making irrational decisions due to misperceptions, biases, and heuristics. As knowledge about interventions spreads across academic disciplines, researchers and practitioners have become keen on using them to drive human behavior (Benartzi et al., 2017; Sunstein, 2013, 2016).

Thaler and Sunstein (2009) introduced "nudging" as a design intervention and described it as designing a choice environment to drive decision makers' behavior towards better choices without restricting their freedom. Among their characteristic features, nudges produce subtle changes in a choice environment that highlight optimum options without diminishing the alternatives' economic incentives. The agents (developers, solution providers, organizations) who design nudges in a choice environment, referred to as choice architects (CAs), influence a decision maker's behavior through nudging interventions such as varying the order in which choices appear, selecting an option by default (opt-in or opt-out), or altering the ease with which one can select alternatives. Nudges have become novel and innovative instruments in the governance toolbox that cost less, work better, and help people achieve their goals (Kosters & Van der Heijden, 2015). Therefore, businesses, regulators, and policymakers have become interested in leveraging nudging to shape users' behavior, test and experiment with policy interventions, and advance policy reach (Benartzi et al., 2017; Executive Office of the President National Science and Technology Council, 2016; Sunstein, 2013, 2016).

In the information systems (IS) domain, digital nudging interventions have received significant focus in practice. For example, healthcare devices (fitness bands) have been used to persuade people towards healthy behavior (Oinas-Kukkonen & Harjumaa, 2009), while framing appears to be effective at promoting user clicks on recommended news (Gena et al., 2019). A digital nudging intervention involves using digital design elements to affect a user's decision-making process and guide the user's behavior in the digital choice environment (Mirsch et al., 2018; Weinmann et al., 2016). Compared to physical contexts, digital devices are more pervasive; thus, compared to traditional nudges, digital nudging interventions have a far wider audience, one can apply them more easily, they incur lower implementation costs, and one can personalize them in addition to their broader functionalities such as data collection, monitoring, experimentation, and testing (Mirsch et al., 2018).

The multiple ways in which researchers have recently conceptualized digital nudging interventions have resulted in duplicate classifications and undermined the potential to accumulate a standardized core for the concept. Prior research has also found that researchers have largely provided these classifications as unstructured lists or developed structured categories for specific behavioral domains (privacy and security-related behavior, e-commerce and product recommendations, crowdfunding, etc.). While some researchers have attempted to synthesize the different types into thematic categories (e.g., Caraban et al., 2019; Meske & Potthoff, 2017), the resultant taxonomies have either not considered the type of information system element and the role they play or have merely clustered the types of digital nudging interventions into a behavioral categorization. We also observe that most existing taxonomies pertain to specific contexts, primarily focus on psychological biases, and do not uniquely apply to the online environment. Such taxonomies do not address the challenges that CAs face in anticipating the effects of digital nudging interventions.

While researchers (especially in the behavioral economics domain) have established the nudging concept and its roots well, nudging as digital nudging interventions in the IS domain remain relatively new and quite heterogeneous (Meske & Amojo, 2020). By exhaustively reviewing digital nudging interventions (both conceptually and empirically) and developing a precise definition, one could integrate the literature and help develop a bridge between disciplines that examine the concept. In this work, we (re)define digital nudging interventions and characterize their various tenets via reviewing the extant literature and empirical studies.

We believe redefining digital nudging interventions would add significant value to the literature given the current approaches adopted by CAs. In particular, CAs have increasingly designed digital nudging interventions that not only limit decision makers' control over how they evaluate choices but also seemingly manipulate users. In doing so, CAs inadvertently (or purposely) disrespect decision makers' value systems.

In this study, we focus on two research objectives: 1) identifying ways in which researchers have conceptualized digital nudging interventions and to distinguish them from nudging in the offline context and 2) based on extant research, establishing a comprehensive yet generic definition for digital nudging that incorporates ethical dimensions (while keeping in mind the above concerns) and acts as a guide for designing digital nudging interventions. By incorporating a two-layered classification mechanism, we develop a taxonomy that incorporates the purpose of digital nudging interventions and the information systems design aspects while taking cognizance of the ethical issues.

This paper proceeds as follows: In Section 2, we describe behaviorally informed design, revisit the literature on nudging, and highlight the need to treat digital nudging interventions differently from offline nudging. In Section 3, we present the method that we used to conduct our systematic literature review. In Section 4, we present our analysis and findings from the structured literature review as the three key aspects: 1) archetypes that digital nudging interventions use, 2) the types of information systems elements that they use, and 3) the psychological biases and heuristics that underlie digital nudging interventions. In Section 5, we discuss our taxonomy. In Section 6, we revisit the definition of digital nudging interventions and broaden it to reconcile inconsistencies, present a coherent frame, and address ethical concerns. Finally, in Section 7, we discuss the implications and possible future extensions as well as conclude the paper.

2 Background

2.1 Dual-process Theory

Kahneman and Tversky (1979) opened up avenues for developing analytical concepts, tools, and investigatory techniques related to behavioral decision-making by cataloging systematic mistakes and non-logical patterns in people's choices. Their work on the dual-process theory states that people rely on two systems—System 1 (automatic) and System 2 (reflective)—to process information, which affects the thought process. Researchers also sometimes refer to these two systems as Type 1 and Type 2 processes (Stanovich, 2010). While System 2 (also known as "the planner") bases decisions on long-term gains and traditional economic theory, System 1 (also known as "the doer") "lives for the moment" and relies on mental models, shortcuts, heuristics, and biases (Tversky & Kahneman, 1974). System 1 decision processes rely on psychological or cognitive heuristics in the decision-making frame to reduce cognitive load and make decisions more quickly. One can understand heuristics as mental shortcuts or rule-of-thumb strategies in the decision-making process. While people can find heuristics helpful and they often result in sound outcomes, they are subject to several biases. For example, people perceive loss as more severe when compared to an equivalent gain (called the loss aversion bias) (Mirsch et al. 2017). The dual-process theory contends that, if a strong persuasive message adequately motivates a decision maker (i.e., the message affects both systems), the context's auxiliary features will have little effect on the decision maker. Models based on dual process theory, such as the elaboration likelihood model, abstract this aspect in positing a process whereby individuals receive a message that changes their attitude based on which they potentially change their behavior (Petty & Cacioppo, 1986).

Researchers have used dual process theory to explain the human decision-making process quite convincingly; however, it too has its limitations. Grayot (2020) critically reviewed dual-process theories and argued that they often do not explicitly state what distinguishes different mental processes from one another and that neither system can singularly sufficiently explain how decision makers make decisions. In other words, opportunity, which refers to external factors enabling or prompting a behavior (Michie et al., 2011), is a key determinant in decision-making. These factors include one's surroundings, antecedent state, temporal perspective, emotions, and the task itself. In other words, "opportunity" can impact a decision maker's "capability"—the "psychological and physical capacity to engage in [an] activity" (Michie et al., 2011, p. 4). Empathy, for instance, can alter the nature of a decision as compared to reasoned action in an ethically complex situation. Researchers have recognized that, while dual-process theories challenge the belief that people rely on rationality in normative decision-making, the transition from System 1 to System 2 (especially when ethical and moral dimensions arise) places significant demands on a decision maker's cognition (Hagendorff, 2022). Hence, researchers have examined intertemporal and intrapersonal choices to understand how dualistic structures result in diverse choice behavior (Grayot, 2020).

Nevertheless, dual-process theories form the basis for the nudging and, thereby, digital nudging interventions. Nudging interventions have been used to counter psychological biases or to facilitate the use of heuristics by presenting a conducive choice environment (Weinmann et al., 2016). Such interventions also add to decision makers' capability by strengthening their intentions and increasing the consistency between their reasoning and intended behavior (Crano & Prislin, 2006). Thus, nudging interventions attempt to improve System 2 and facilitate the decision-making process for System 1. In Section 2.2, we discuss the ways in which researchers have recently conceptualized nudging and digital nudging interventions and their relationship with dual-process theories.

2.2 Nudging and Digital Nudging Interventions

Thaler and Sunstein (2009) popularized nudging as a concept in their book *Nudge: Improving Decisions about Health, Wealth, and Happiness*. As an intervention based on inferences that attempt to alter the choice environment, nudging has received significant research attention in behavioral economics and decision-making (for a detailed review, see Beshears & Kosowsky, 2020). Nudges often comprise a subtle intervention with the potential to steer decision makers towards the desired choice, which increases the likelihood that they will perform a specific behavior but without forbidding options available to them or significantly changing the different options' economic incentives. As an intervention tool, nudging and its implications have received research attention from myriad disciplines such as policymaking (Benartzi et al., 2017), healthcare (King et al., 2013), pro-environmental behavior (Byerly et al., 2018), administrative law and regulations (Alemanno & Spina, 2014), education (Damgaard & Nielsen, 2018) and in thematic areas such as consumer behavior (Petit et al., 2018). Behavioral interventions, particularly in policy and public administration, have also faced many challenges and resulted in many concerns such as repeated exposure effects, long-term impact, unintended consequences, and cultural variation while continuing to present opportunities for scaling and social diffusion (Sanders et al, 2018). Researchers have also taken critical perspectives primarily centered around issues of volitional autonomy, undermined rationality, lack of transparency, and the dominating control exercised by those in power (Schmidt & Engelen, 2020).

Despite these challenges, increasing data availability and growth in choice engines that interpret the data in large volumes (Thaler & Tucker, 2013) have given rise to numerous opportunities for digital nudging. One can describe digital nudging simply as using digital design artifacts to influence decision makers towards making better choices. While one can find several references to digital nudging interventions in the literature, the earliest instance we found comes from 2016 (Meske & Potthoff, 2017; Weinmann et al., 2016). Like nudging, digital nudging must also preserve autonomy and not inhibit other choices. Among their noticeable features, nudging interventions feature a middle ground between paternalism[1] and libertarianism[2] regimes; that is, they adopt a libertarian-paternalistic methodology towards modulating behavior. Thaler and Sunstein (2009) argued that nudges should ideally guide decision makers without burdening them and while preserving their ability to choose; in other words, nudges should maintain decision makers' authority, ownership, and control. Policymakers and organizations function as the CAs that design the context, process, and environment in which people make decisions. With these guiding principles, researchers have further defined digital nudging interventions, and we list the many definitions they have provided in Table 1.

[1] Paternalism is a political philosophy which believes that bounded rationality and limited cognitive ability render the human decision-making a flawed process; hence other actors like the government need to act on decision makers' behalf to guide them towards the optimal choice. The guidance/influence should be such that evaluation of the outcome should come from the decision maker.
[2] Libertarianism is a philosophy that believes in freedom of choice, without any intervention, with the belief that people are the best judges about what is right for them.

Table 1. Pivotal Definitions of Nudging and Digital Nudging Interventions

Source	Definition
Nudging	
Thaler & Sunstein (2009)	"Any aspects of choice architecture that alter people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives" (p. 6)
Hausman & Welch (2010)	"Nudges are ways of influencing choice without limiting the choice set or making alternatives appreciably more costly in terms of time, trouble, social sanctions, and so forth." (p. 126)
Selinger & Whyte (2011)	"Nudges are changes in the decision-making context that work with cognitive biases, and help prompt us, in subtle ways that often function below the level of our awareness, to make decisions that leave us and usually our society better off." (pg. 925)
Sunstein (2014)	"Liberty-preserving approaches that steer people in particular directions, but that also allow them to go their way" (p. 1)
Digital nudging	
Weinmann et al. (2016)	"Digital nudging is the use of user-interface design elements to guide people's behavior in digital choice environments." (p. 433)
Meske & Potthoff (2017)	"A subtle form of using design, information, and interaction elements to guide user behavior in digital environments, without restricting the individual's freedom of choice" (pg. 2589)
Mirsch et al. (2018)	"Attempt to influence decision-making, judgment, or behavior in a predictable way by counteracting the cognitive boundaries, biases, routines, and habits that hinder individuals from acting to their own benefit in the digital sphere" (p. 3)
Lembcke et al. (2019)	"Digital nudge is 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" (p. 10)

Many authors have categorized nudges and suggested alternatives for choice architectures based on different dimensions. Thaler and Sunstein (2009) presented six principles for designing choice architectures (incentives, mappings, defaults, feedback, expecting errors, and structuring complex choices), which have since then also become a nudge typology. Beshears and Gino (2015) aggregated different nudge types into three broad levers that can use choice architectures to improve organizational decision-making: trigger System 1, engage System 2, or bypass both systems. Hansen and Jespersen (2013) introduced a more intricate classification based on two dimensions: the mode of thinking engaged (System 1 or System 2) and the transparency of the intervention (see Figure 1). The 'mode of thinking' dimension draws from Kahneman's (2011) dual process theory that distinguishes between intuitive-automatic thinking and reflective-rational thinking. Hansen and Jespersen (2013) employed the dual-process model to classify nudging interventions based on the mode of thinking involved. They distinguished interventions that influence behavior through automatic thinking, devoid of deliberation (Type 1), and interventions rooted in reflective thinking that impact judgment and, consequently, induce change through deliberation (Type 2). The 'transparency' dimension captures an essential feature of digital nudging interventions. A transparent nudge is presented in such a way that "the intention behind it, as well as the means by which behavioral change is pursued, could reasonably be expected to be transparent to the agent being nudged as a result of the intervention" (Hansen & Jespersen, 2013, p.17). Hence, when a nudge is transparent, the intention and the means of pursuing behavioral change are reasonably explicit to the individual being nudged.

We adapt Hansen and Jespersen's (2013) classification (see Section 5) to categorize nudge archetypes given the increasing importance accorded to transparency in digital applications, which extant digital nudging studies have often ignored. Also, unlike some other frameworks, Hansen and Jespersen's (2013) classification allows one to map archetypes across multiple categories (see Section 5). The four categories include:

1) Type 1 transparent interventions, which influence behavior by activating the automatic system to take precedence and guide decision-making. Reflective thinking occurs as a byproduct and not by the design of the interventions.
2) Type 1 non-transparent interventions, which achieve their outcome by covertly activating the automatic system.

3) Type 2 and non-transparent interventions, which manipulate choice. Specifically, they target the reflective mind (System 2); however, due to their covert nature, the reflective mind does not engage in the manner that decision makers intend.
4) Type 2 transparent interventions, which align with the libertarian-paternalistic school of thought. Decision makers possess the faculty to acknowledge these interventions and their mechanism(s). If decision-makers so desire, they can skip these interventions and maintain their freedom to make the choice.

		Transparency	
		Transparent	**Non-Transparent**
Type	**Type 1**	1 Influence behavior	2 Manipulate behavior
	Type 2	4 Facilitate consistent choice	3 Manipulate choice

Figure 1. Intervention Types Based on Hansen and Jespersen (2013)

2.3 Systemic Differences between Online vs. Offline Nudging

Thaler and Sunstein (2009) argued that we need to nudge decision makers in situations where “choices have delayed effects; [that] are difficult, infrequent, and offer poor feedback; and where the relation between choice and experience is ambiguous” (p. 76-77). While these situations warrant the need for interventions, they primarily pertain to the offline context. In the form we know now, the Internet and the Web, particularly the social Web, represent relatively new phenomena and, therefore, characteristically differ from offline decision-making environments. Online environments can provide more choices and promote greater efficiencies than offline environments (Dennis et al., 2020), although both online and offline market environments feature product and seller uncertainty. While the characteristics and nature of the digital social Web affect decision makers and the decisions they make in ways similar to offline contexts, they pose some entirely new virtual environment challenges. Unlimited content, a higher number of connections, limitless space, and timeless storage alongside technology’s rapidly changing nature and adaptability (Kozyreva et al., 2020) pose significant challenges to decision makers. Furthermore, online media fosters dissociative anonymity, asynchronicity, invisibility, solipsistic imagination, dissociative imagination, and status and authority minimization, which, in turn, create online disinhibition effects (both benign and/or toxic) (Suler, 2005). The cumulative effect of these characteristics in an online environment leads individuals to behave in widely different ways with limited control over the consequences of their actions, which renders various implications, particularly for online businesses. For instance, Dennis et al. (2020) found that numeric and semantic priming is often used in offline retail and will need to be used differently in online retail, especially for products with a clear value.

In Section 3, we present a systematic review of the literature on digital nudging interventions to develop a resulting taxonomy and provide a comprehensive definition of the concept of digital nudging interventions.

3 Systematic Literature Review: Method

We drew on Webster and Watson’s (2002) recommendations for conducting structured literature reviews. We chose to use Webster and Watson’s guidelines, given that they have found strong acceptance in the IS literature and given the nascency of digital nudging as a research theme. Moreover, their guidelines allow for both backward and forward snowballing through citations, which we found important given that some papers may not have directly referred to their intervention as a digital nudge. For instance, we found over 400 citations to Weinmann et al. (2016), and, while many did not directly pertain to our analysis, some did. Webster and Watson (2002) also provide directions for theory, which befits the taxonomy we wished to create and the resulting (re)definition of digital nudging interventions.

In line with our overarching research objectives, we included studies that we believed would help our efforts to identify, describe, examine, and classify digital nudging interventions. We conducted a search for literature reviews and research papers using the term “digital nudg*” in the title, keywords, and abstract.

Given the interdisciplinary nature of nudging as a theme, especially digital nudging, we decided to cast a wide net and conduct the search in five databases: the ACM's digital library, AIS e-Library, EBSCO Host, Elsevier's ScienceDirect, and Scopus. The initial search resulted in 208 papers.

We limited our search results from 2016 when Weinmann et al.'s (2016) paper appeared as it seemed to propose among the earliest recognized digital nudging interventions in the IS literature until May 2021. We excluded duplicates, papers that did not appear in conferences or academic journals, and papers in the natural sciences since they fell outside our purview for this study. Through this screening process, we narrowed the initial 208 papers we identified to 71. We then snowballed through backward and forward processes (Webster & Watson, 2002) by reviewing citations and papers that cited the papers in our list. From this process, we added another 9 papers, which brought our relevant paper list to 80.

We then examined the 80 papers more closely to assess their relevance and rigor. We applied three criteria for the assessment. First, we included publications that investigated one or more behavioral interventions in the digital domain, used a digital artifact, or related to digital choice architecture. Second, we excluded papers that did not clearly describe their interventions and the digital artifacts they used to design and deliver them or did not provide sufficient details about their interventions because we could not clearly categorize them. Third, unlike many existing literature reviews that have focused more on experimental studies, we also added descriptive and case-based studies. Applying the selection criteria and appraisal criteria mentioned above, we chose 64 publications (39 journal papers and 25 conference papers) for the detailed review and analysis. While we were primarily interested in papers in the IS area (49 out of 64), we did not exclude papers published in non-IS (15) journals and conferences because these papers described a digital artifact and behavioral intervention. Table 2 summarizes our results from the search and selection process.

We carefully perused each paper in our list to identify and understand the digital nudging intervention, the description of the intervention, the underlying psychological effects of the intervention, the biases exploited, and the heuristics deployed (if any). We performed this identification process in an iterative manner, and, through it, we adapted the way in which Mirsch et al. (2017) described each psychological effect, heuristic, and bias for behavioral change (see Appendix A). We adapted the descriptions to help ourselves classify papers while then revisiting earlier ones as we made changes to the descriptions. Via carefully reading each paper in conjunction with these descriptions, we further classified each intervention's type, subtype, and standard archetype (such as subtype: decoy effect, archetype: deceptive visualizations; subtype: scarcity-effect, archetype: deceptive visualizations). We note that, without a standardized vernacular, researchers have used varying terminologies to refer to or describe the interventions they apply. Thus, wherever available, we used the terminology that authors used to refer to a nudge but sought to more appropriately classify it based on the description they provided. For instance, when referring to scarcity (subtype) in deceptive visualizations (archetype), Caraban et al. (2019) denominated it as 'making resources scarce' (p. 8) which refers to limiting the inventory of the chosen alternative to elevate its value by signaling that other users are also interested in the choice, while Johnson et al. (2012) referred to it as "limited time window" (p. 489) and described it as placing a temporal limitation on the availability of a choice alternative to create an urgency to act, which makes the limited alternative more attractive. Appendix B presents representative extracts from the analysis.

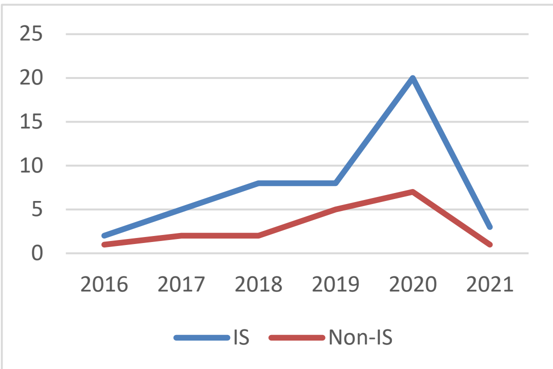
Using Hansen and Jespersen's (2013) framework (see Figure 1), we also placed each intervention into one of the four categories: manipulate choice, manipulate behavior, facilitate consistent choice, and facilitate influence behavior (along the two dimensions of transparency and type of nudge). By doing so, we could further cluster the different interventions, especially when authors did not explicitly state the type of nudge they used. Finally, the artifact that the authors used to operationalize the digital nudging intervention could be focused on informational, structural, and interaction elements.

Our analysis also revealed several interesting overall insights across the papers we reviewed. First, researchers have explored digital nudging interventions in several decision domains and through various applications, but they seldom explicitly described their fundamental design principles. Second, the sample sizes varied widely across the papers in the sample, and some that used smaller samples often mentioned it as a key limitation. Third, we also observed that authors often transferred definitions for nudging that pertain to offline contexts with little or no modification to the digital context and that they often cited literature that has defined nudging for the offline context.

Table 2. Databases and Number of Publications

Database	Number of results from the preliminary search	Number of publications selected for review
ACM Digital Library	34	6
AIS e-Library	34	8
EBSCO Host	40	16
Science Direct	15	3
SCOPUS	76	22
L-R Search		9
Unified results from the databases		64

2(a): Distribution of papers



2(b): Dominant methodology used

Survey	8.1%
Experiments (online, field and laboratory)	45.9%
Descriptive and case studies	31.1%
Mixed methods	4.9%
Reviews	9.8%

2(c): Dominant application domains

E-commerce	21%
Healthcare	5%
Managerial decision making and policy	26%
Mobile apps	2%
Privacy and cyber security	9%
Recommendation systems	9%
Behavior on social networking sites	16%
Sustainable environmental behavior	12%

2 (d): Pivotal dependent variables

Pro-environmental behavior	16%
Health behavior	13%
Information sharing	10%
Compliance	6%
Digital consumption	6%
Innovation	6%
Privacy	6%
Willingness to pay	6%

Note: for Figure 2a, we considered papers up until May, 2021.

Figure 2. Descriptive Statistics

Figure 2 presents the descriptive statistics of the papers we reviewed. From the trend in the graph, one can clearly see rising interest in digital nudging interventions in IS research over time (see Figure 2a). Around 40% of the papers employed qualitative research methods such as vignettes based on ethnography, case studies, structured literature reviews, and so on. We intentionally included these papers to broaden our review's scope since they presented ethical concerns and characterized digital nudging interventions in other ways in more detail in contrast to the survey or experiment papers provide.

4 Results: Taxonomy

One can find three approaches for developing a taxonomy in the literature: inductive, deductive, and intuitive (Nickerson et al., 2013). While the inductive approach begins with anecdotal evidence and moves towards delineating characteristics, the deductive approach uses a contextual definition from theory as the starting point and moves towards empirical results. In contrast, the less formal intuitive approach uses a researcher's experience and perception to drive efforts to develop a taxonomy. We combined these approaches given research on digital nudging interventions remains in its nascence. We began by examining the different toolsets that the CAs used along with the goals, the decisions that decision makers needed to make, and, where available, the underlying heuristics in each selected paper. Second, we employed a deductive approach to draw from extant theories in academic literature to categorize the nudges. Finally, we used an intuitive approach to help demonstrate the different clusters of digital nudging interventions.

Researchers have made prior attempts to develop digital nudging intervention taxonomies (Caraban et al., 2019; Hummel & Maedche, 2019). We observe that these studies focus on specific contexts (Jesse & Jannach, 2021), base how they characterize interventions on their purposes (Caraban et al., 2019; Johnson et al., 2012; Münscher et al., 2016), focus only on the underlying psychological biases (Datta & Mullainathan, 2014; Dolan et al., 2012; Mirsch et al., 2017), or do not apply specifically to the online environment (Münscher et al., 2016). Our work differs from these approaches in that it incorporates a two-layered classification mechanism. First, we clustered nudge subtypes into different archetypes based on the commonalities in their approaches. Drawing from Hansen and Jespersen (2013), we classified the archetypes based on whether the digital nudging intervention targeted System 1 or System 2 along with transparency criteria. Subsequently, we specified the information systems element as manifested in the digital artifact that the interventions used. With this two-layered classification scheme, we could develop a comprehensive (11 archetypes and three IS elements) but also parsimonious (mapped to Hansen and Jespersen's (2013) four quadrants) taxonomy. Additionally, while we used the first classification to develop guidelines for comprehensively defining digital nudging interventions, the second characterization has implications for the process of designing and selecting them. Hence, our taxonomy provides a link between whether a digital nudging intervention targets System 1 or System 2, transparency, and its design aspect. Further, based on our taxonomy, we recommend a standardized vernacular for the interventions and the underlying mechanisms that will play a pivotal role in analyzing the effectiveness of the approaches across contexts.

4.1 Archetypes for Digital Nudging Interventions

We found 234 overlapping digital nudging interventions in the 64 reviewed papers. In this context, we found that researchers have used similar but varying terminology to describe the interventions, given that a standard catalog for digital nudging interventions does not exist. We drew from the nudge categories that Thaler and Sunstein (2009) provided (incentives, understanding mappings, defaults, give feedback, expect error, and structure complex choices) and Acquisti et al.'s (2017) dimensions (information, defaults, incentives, reversibility, and timing) but adapted them to present a standard digital nudging intervention catalog. We believe that researchers will find the categorization useful in understanding digital nudging interventions while also assessing their effectiveness and suitability for different decision situations. We use the term archetype to denote the original pattern, setting, or model of a digital nudging intervention. We describe the 11 archetypes below.

4.1.1 Default

Among the most widely used tools in the choice architecture toolbox, defaults have delivered robust outcomes. We found that CAs used them when decision makers do not actively participate in altering the status quo, care less about the decision, or in situations with low transaction costs (Johnson et al., 2012). CAs can use default configurations (opt-out, opt-in, automatic choice, or forced choice) to diminish a decision maker's mental effort and can also indicate the recommended choice. The opt-in default setting assumes that decision makers have accepted the premise (Schneider et al., 2018), the opt-out default setting assumes that they have rejected the premise (Karlsen & Andersen, 2019; Lu et al., 2021), and the automatic choice default performs the action on decision makers" behalf (Jesse & Jannach, 2021). Forced choice default setting forces decision makers to choose from options explicitly, such as asking users to choose between going forward or not rather than the system making the choice for them (Jesse & Jannach, 2021).

4.1.2 Providing a Social Reference Point

Informing users about what others do can have normative effects, which can arouse the need for belongingness or acceptance in a group, and informational effects, which can encourage people to look for cues from others due to uncertainty. Associating choices with a social norm or a desirable behavior may elicit conformance as decision makers tend to follow the majority and not deviate from them. Piotrkowicz et al. (2020) found that displaying an opinion leader's endorsement (e.g., adding a professional organization logo) effectively increased engagement in an e-learning platform among healthcare professionals. Bawa et al. (2020) found the tendency to follow the crowd had a mediating effect on decision makers' choice accuracy and reduced informational load on convergence platforms. However, Li et al. (2021) found mixed results for peer information interventions with effects being higher for males than females in a competitive learning management system exercise.

4.1.3 Informational Provisions

Decision makers often base their decisions on the available information, and what one presents to decision makers can affect what they choose (Johnson et al., 2012). Providing sufficient information such as disclosures (Hummel & Maedche, 2019; Kitkowska et al., 2020), additional alternatives (Acquisti et al., 2017; Zimmermann & Renaud, 2021), and external information (Jesse & Jannach, 2021; Piotrkowicz et al., 2020) visible to users helps to reduce search overload and enhance their analytical capability. Providing different viewpoints can help users gain insights and develop a broader mindset about choices and the context (Díaz Ferreyra et al., 2020).

4.1.4 Translating Information and Understanding Mapping

Presenting decision makers with many choices can overwhelm them, impair the decision-making process, and inhibit their ability to choose the best alternative. In such a complex decision situation, CAs can frame information unambiguously and straightforwardly to reduce cognitive load (Dalecke & Karlsen, 2020; Karlsen & Andersen, 2019; Kroll & Stieglitz, 2021). Similarly, in situations with a significant temporal distance between the choice and the outcome or when decision makers cannot justifiably link choices to their outcomes, mapping actions to their outcomes can enhance their ability to engage more intensely in the decision-making process (Díaz Ferreyra et al., 2020; Karlsen & Andersen, 2019; Stryja & Satzger, 2019). Mapping alternatives' cost/benefits to the consequences can reduce cognitive load and mental accounting (Jesse & Jannach, 2021).

4.1.5 Salience, Ease, and Convenience

CAs can also use design elements to ease or decrease access to information, make relevant information more visible by altering the display's structure or highlighting certain parts, and reduce search time by enhancing navigability or displaying customized results (Adam et al., 2019; Esposito et al., 2017; Meske & Potthoff, 2017; Terres et al., 2019). For instance, Walser et al. (2019) found that reducing information load, such as by displaying a limited inventory of items on the screen, helped the participants in their experiment to make more accurate choices.

4.1.6 Giving Feedback, Warnings, and Reminders

By providing vivid warnings, notifications, reminders, and graphic messages, CAs can indicate to decision makers when they falter and provide recommendations and relevant notices. Feedback, warning, and reminders can show a system's existing state, relate the outcome to the choice, and bring unusual choices to decision makers' attention (Acquisti et al., 2017). Such interventions can instill trust in a system by confirming to people that they make the correct choices or can act as a deterrent when their judgment may have errors (Stryja & Satzger, 2019). In their experiment, Zimmermann and Renaud (2021) demonstrated support for feedback nudges when users who received nudges created significantly stronger passwords than those who did not.

4.1.7 Deceptive Visualizations

Visualizations drive users' attention away from information by making other aspects of the decision frame more salient and attractive. Hiding the costs and information initially and displaying them later when users have spent time and effort in the decision frame can hinder their ability to analyze their decisions. Using a roach-motel approach (i.e., making it easier to enter the decision frame but difficult to exit) (Özdemir, 2020) can also have a similar effect. CAs can elevate or enhance the choice they want decision makers to make by placing inferior and improbable choices (placebos, decoys, and inferior choices) in the choice set as alternatives (Schneider et al., 2018). CAs can also exploit the scarcity bias (i.e., the tendency to attribute more value to an object based on the belief that it will be more challenging to acquire the object in the future). Placing a temporal limitation on a choice alternative's availability creates the urgency to act, which makes the limited alternative more attractive. Limiting the inventory of intended choices elevates their value by indicating that other users also have an interest in them (Kitkowska et al., 2020; Kozyreva et al., 2020).

4.1.8 Priming and Developing Empathy

CAs can develop an unconscious association with stimuli, design, or information to prime decision makers towards the intended choices. This unconscious association (i.e., priming) can act as a covert intervention (Shen et al., 2017; Caraban et al., 2019; Mota et al., 2020). Instigating the ability to sense other people's emotions can also nudge decision makers to reflect on their actions cognitively. When in co-operative communication, participants often reciprocate each other's communication style (Bawa et al., 2020); that is, while observing a messenger's emotional state, decision makers may alter their decision due to their affection towards the messenger. Adding anthropomorphic features to virtual assistants and robots can instigate positive emotions among users, which can enable them to adequately perceive the interventions that the assistants enable. Using familiar avatars may affect behavioral changes in users' actions. Using avatars of commonly known characters can also instill trust in an intervention. In their study on chatbots, Bawa et al. (2020) found that code-mixing (language mixing) resulted in higher ratings among the users.

4.1.9 Leveraging Commitment

Just as CAs can develop empathy towards messengers, they can also leverage decision makers' commitment to a context, decision, or outcome. CAs can leverage commitment to past actions as an intervention to influence decision makers to repeat decisions since switching to something new or making a decision again requires time and additional effort. For example, Terres et al. (2019) tested the effects of a commitment nudge on people's intention to use mobile apps and found support for their hypothesis. Interventions in this archetype include commitment to self (Piotrkowicz et al., 2020), pre-commitment intention elicitation (Meske & Potthoff, 2017), and recommitment intentions (Hummel & Maedche, 2019; Jesse & Jannach, 2021).

4.1.10 Incentives

Providing incentives, rewards, and punishments can influence decision makers towards intended choices. In our context, we view incentives in a broader light and consider elements such as time taken, effort involved, and social repercussions of decisions as factors that motivate or hinder behavior. We derived this conceptualization from Hansen and Jespersen (2013), who highlight these diverse aspects as crucial components shaping decision-making processes. While the core conceptual frame of nudging interventions suggests that nudges must not significantly alter the incentives of choices, we posit that positive reinforcement, praise, reward, and other non-monetary incentives can provide outcomes similar to economic incentives. Jesse and Jannach (2021) found that online recommender systems commonly use such interventions.

4.1.11 Just-in-time Prompts

The archetypes discussed thus far primarily capitalize on an intervention's content and visibility; however, interventions also possess a temporal dimension. Just-in-time interventions take effect at the precise time when decision makers engage in the decision-making process. Thus, due to their availability in the automatic memory (System 1), decision makers can recall them quickly (Caraban et al., 2019; Ho & Lim, 2018). CAs can use customized automated, interactive, and personalized just-in-time adaptive interventions when decision makers become the most vulnerable to engage in negative behavior (O'Raghallaigh & Adam, 2017).

Table 3. Digital Nudging Intervention Archetypes and Subtypes Used in the Papers Reviewed

Serial number	Archetype	Subtype	Definition
1	Default	Opt-in	An intervention that assumes the user to have accepted a premise by default.
		Opt-out	An intervention that assumes the user to have rejected a premise by default.
		Forced choice	An intervention that forces the user to choose between options explicitly to proceed.
		Automatic	An intervention in which the system automatically performs the action for the user
2	Providing a social reference point	Information about popular choices	An intervention that contains information about the general population's behavior.
		Information about group	An intervention that contains information about the behavior of a group that the user identifies with.
3	Informational provisions	External information	An intervention that displays information external to the current decision frame or that creates a means for the user to obtain external information.
		Own behavior	An intervention that displays the information about the user's behavior to influence the user's decision-making process.
		Providing viewpoints	An intervention that displays alternative viewpoints to the user to expand the user's horizons and encourage the user to better analyze alternatives.
		Suggesting alternatives	An intervention based on the user's existing position that suggests alternative choices to direct the user's attention towards uncommon choices.
		Tailored information	An intervention that provides the user with customized information tailored to the user's behavior to assist the user in evaluating alternatives.
4	Translating information and understanding mapping	Presenting information on consequences	An intervention that maps available choices to their outcomes to reduce the distance between the decision and outcome and aid the user.
		Providing risk scenarios	An intervention that adds scenarios that translate/simplify information and better explains the decision frame to help reduce cognitive load.
		Framing	An intervention that frames the decision statement in alternative ways to simplify the decision frame and aid the user in the decision-making process.
5	Salience: ease and convenience	Navigability	An intervention that can reduce the navigability hurdles in the decision frame by placing the right information where the user needs it or by adding navigational elements that aid the user in moving through the frame.
		Salience	An intervention that highlights and prominently displays relevant information to aid the user in reading and analyzing the decision frame. It can also reduce information overload for the user.
		Decision staging	An intervention that uses decision staging to divide complex decisions with significant consequences into several stages and, hence, aid the user.
6	Giving feedback, warning, and reminders		An intervention that aids the user when they need it by providing relevant feedbacks, warnings, and reminders.

Table 3. Digital Nudging Intervention Archetypes and Subtypes Used in the Papers Reviewed

7	Deceptive visualizations	Positioning	An intervention that positions choices such that some alternatives appear better than the others to deceive the user into perceiving the choices to differ in relevance.
		Sneaking into basket	An intervention that sneaks compatible but unwanted options in the product baskets to influence the user to perceive them as the recommended choices and, thus, buy them.
		Roach motel	An intervention that makes it easier for the user to enter the decision frame and spend effort in the process but that makes it difficult to exit when the user reneges in order to keep the user engaged.
		Limited resource inventory and time window	An intervention that makes a resource appear scarce and showcases it with a limited inventory or available for a limited time window to enhance the value of the decision alternative even though it may not be the case.
8	Priming and developing empathy	Anthropomorphism	An intervention that incorporates anthropomorphic features, such as in chatbots and messengers, that encourages the user to associate with the features and, hence, engage more in the decision frame.
		Image motivation	An intervention that motivates individuals with the desire to maintain or enhance a positive image of themselves (either in their own eyes or in the eyes of others).
9	Leveraging commitment		An intervention designed to take advantage of the user's commitment to the context, the decision, or the outcome to facilitate an engaged decision-making process.
10	Incentives	Rewards, punishments, and other non-monetary incentives	An intervention that includes rewards, punishments, and other non-monetary incentives to nudge the user.
11	Just-in-time prompts	Tailored timely prompts	An intervention that delivers nudges when the user needs assistance and is engaged in the decision-making process. Customized automated, interactive, and personalized "just-in-time" adaptive interventions tailored to the user's behavior can help the user in evaluating alternatives.

4.2 IS Elements used in Digital Nudging Interventions

In the previous section, we discuss eleven digital nudging intervention archetypes that are commonly found across the literature we reviewed. Across that literature, we also deduced three IS elements that help CAs develop and deliver digital nudges. These IS elements manifest in the digital artifacts that operationalize behavioral interventions. The first element, informational elements, combines Muncher's "decision information" and "decision assistance" (Münscher et al., 2016). Information elements can also relate to what information one presents to users, such as providing them with customized information (Johnson et al., 2012), translating the information to suit their mindset, presenting consequences (Caraban et al., 2019; Weinmann et al., 2016), presenting comparisons, providing disclosures, changing the composition of choices, and providing reminders (Weinmann et al., 2016). The second element, *structural elements,* relates to the decision structure (Münscher et al., 2016) and includes aspects such as the manner in which one presents choices, such as through increasing or decreasing information salience (Johnson et al., 2012), changing default choices (opt-out or opt-in) (Meske & Potthoff, 2017), and adding decoys and placebos (Caraban et al., 2019). The third element, *interaction elements*, shapes the user experience by capturing users' attention, keeping them engaged, and nudging them towards intended choices. One can use them to deliver nudging interventions (Meske & Potthoff, 2017). For example, adding anthropomorphic features to chatbots and robo-advisors (Adam et al., 2019) enhances users' engagement. One can derive interaction elements as hybrid informational and structural elements, such as an intuitive and aesthetic design and easy navigation, which garner trust, make it easier to find the desired information and, thus, lead to faster decision-making (Mejtoft et al., 2019).

4.3 Underlying Psychological Effects, Biases, and Heuristics

Early literature on decision-making identified dominant biases such as anchoring heuristic, availability heuristic, and representativeness heuristic (Tversky & Kahneman, 1974). Subsequently, further research has defined specific psychological effects, biases, and heuristics in a more fine-grained manner. In this review, drawing from Mirsch et al. (2017), we adopted definitions for 19 underlying heuristics and biases based on nudging practice and research. To the best of our knowledge, Mirsch et al. (2017, 2018) have conducted the most exhaustive efforts in the IS domain to delineate psychological effects, heuristics, and biases in the digital nudging context. Table 4 summarizes the 19 biases and heuristics that we used in our structured literature review along with how frequently they occurred, while we describe each one in more detail in Appendix A. While anchoring and adjustment, framing, and loss-aversion biases have received more attention, a significant number of studies have tried to replicate the success of "defaults" as an intervention in influencing decision-making and behavioral outcomes via the status quo bias.

Table 4. Frequency of Psychological Effects, Biases, and Heuristics Discussed in the Papers Reviewed

Psychological effects, biases, and heuristics	Number of publications
Status quo bias	16
Anchoring and adjustment	15
Framing	14
Social desirability bias	14
Priming	11
Loss aversion	10
Hyperbolic discounting	8
Optimism and over-confidence	6
Attentional collapse	4
Endowment effect	4
Representativeness and stereotypes	4
Availability heuristic	3
Decoupling	3
Image motivation	3
Intertemporal choice	3
Mental accounting	3
Messenger effect	3
Spotlight effect	3
Commitment	2

As Mirsch et al. (2017) have observed, digital nudges often rely on more than one psychological effect or bias, and CAs often leverage the interplay between them. Our systematic literature review also revealed such interplay between a particular digital nudging approach and the underlying psychological effects. For instance, while the "default" setting intervention uses the status quo bias (i.e., a user's aversion to shifting away from the default choice), it does so via enabling loss aversion. Instilling the fear that users will lose out on something if they move away from the default enables the loss aversion bias. Hence, CAs have the responsibility to identify which types of biases they want to exploit/diminish in a nudge to meet their objective. Johnson et al. (2012) suggested that CAs can keep in mind psychological biases that consciously structure the choice task and describe the alternatives: in the former, CAs need to balance the number of options presented in a way that increases the preference match but reduces the cognitive burden on users; while, in the latter, CAs can redesign attributes and option partitions. The aggregated information presented in Table 4 resonate with Mirsch et al.'s (2017) findings about status quo bias, framing, social desirability bias, and loss aversion being the most used/exploited biases.

5 Discussion

We extracted 234 digital nudging mechanisms from the structured literature review, which we then categorized into 11 archetypes related to the 19 underlying psychological biases and heuristics that leveraged three dominant IS elements. In Figure 3, we map the reviewed studies into Hansen and Jespersen's (2013) framework.

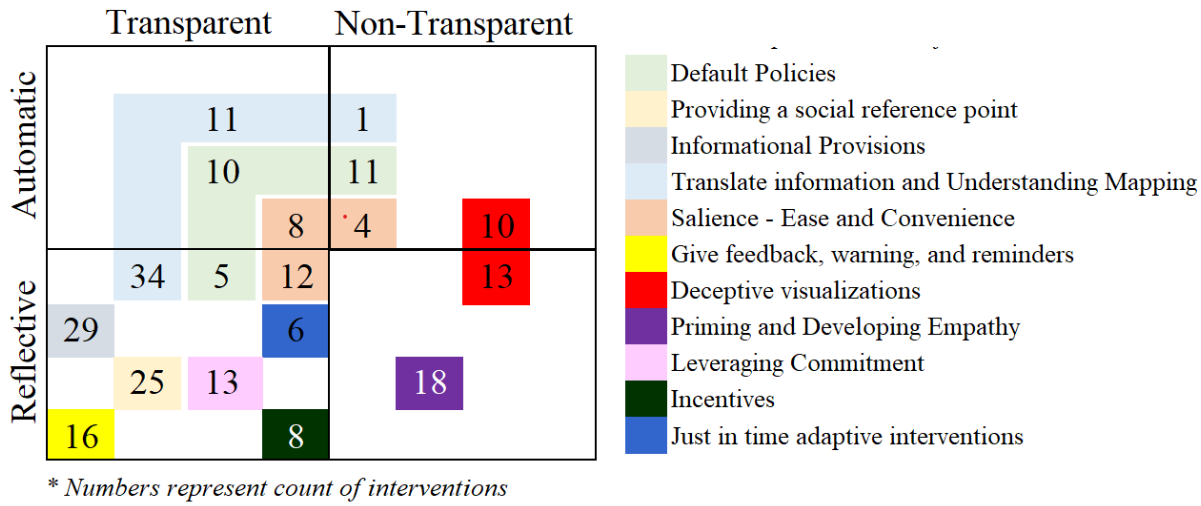


Figure 3. Mapping of Vernacular Archetypes to Hansen and Jespersen's (2013) Framework

While we could map most vernacular archetypes into specific quadrants, we mapped the archetypes "incentives", "salience-ease and convenience", "translate information", and "change default rules" across multiple quadrants. Such an overlap indicates that the dimensions lie on a continuum rather than discrete alternatives. One can also view the two-system or dual-process theory, which the vertical axis indicates – (i.e., automatic–reflective) (Evans & Stanovich, 2013) as a continuum rather than opposing systems, a criticism that the dual-process theory often faces. Similarly, one can view transparency as a continuum given that transparent nudges are both visible and easy to monitor, while, with non-transparent nudges, users "cannot reconstruct either the intention or the means by which behavioral change is pursued" (Hansen & Jespersen, 2013, p. 18). Moreover, some research has purported transparency to differ along a continuum that reflects general information (type interference transparency) on the one end to disclosing situation-specific information (token interference transparency) on the other (Bovens, 2008). Furthermore, transparency depends on a nudge's design and can differ based on users' characteristics and capabilities (Ivanković & Engelen, 2019). Additionally, quite similar to Hansen and Jespersen's (2013) argument for offline nudges, digital nudges also adopt multi-layered structures in their design and, due to the variations in how different studies have defined and designed these nudges, we can map them across multiple categories.

Based on the structured literature review, we categorized 77 percent of interventions as focusing on the reflective system and only 23 percent as non-transparent. In turn, these results imply that CAs have predominantly designed and developed digital nudging interventions with transparency in mind. However, one could label nearly a quarter of the interventions as manipulative. Figure 3 shows how many studies used each archetype.

Our analysis also revealed that, even though normative expectations from digital nudging interventions (see Table 1) emphasize transparency, some covert interventions deliberately focused on manipulating choice. Appendix B presents a representative taxonomy extract.

6 Re-defining Digital Nudging Interventions

Both the academic and practice literatures have raised concerns relating to the philosophical underpinnings, ethical considerations, and design aspects of behaviorally informed nudging interventions. The first ethical premise posits that one can design nudging interventions to limit individuals' control over how they evaluate choices (Alemanno & Spina, 2014). For example, creating scarcity among the available choices makes the scarce options more attractive (Schneider et al., 2018). Though researchers and practitioners have raised several arguments against this concern, the traditional definition is inadequate in clarifying this aspect. The second concern labels interventions as manipulative (Hausman & Welch, 2010). Using interventions in a situation where the intended goal does not align with a user's value system would disrespect the user's decision-making process. In such a case, value substitution via interventions would lead to manipulation. However, digital nudging interventions represent unavoidable aspects of digital design (i.e., no design is neutral). Merely presenting options on the screen can shift a decision's outcome. CAs can use knowledge about heuristics and biases (see Table 4) from the decision-making process to nudge decision makers towards intended choices (Johnson et al., 2012). Thus, nudging interventions remain open to abuse from CAs. Table 5 lists quotes on philosophical and ethical concerns in nudging interventions from different authors.

Table 5. Philosophical and Ethical Concerns in Nudging Interventions

Concern	Quote
Autonomy and freedom of choice	"By intervening in the human decision-making process, behaviorally informed regulation could interfere substantially and can be perceived as incompatible, with fundamental rights of citizens to freedom of expression, privacy, and self-determination" (Alemanno & Spina, 2014, p. 431).
	"[Nudge] appears as a mere proxy for behaviorally informed rule-making, and as such it fails rigorously to identify those regulatory approaches capable of operationalizing these…" (Alemanno & Spina, 2014, p. 438).
Manipulation	"We intend 'shaping' to exclude rational persuasion. 'Manipulation' would be a more natural label, but since we are concerned with whether shaping people's choices is justified, we have avoided using a word with such pejorative connotations" (Hausman & Welch, 2010, pp. 128-129).
Open to abuse	"Choice architects can project the values and preferences of their conceptions of ideal decision makers onto those who are nudged. There is no guarantee that these projections are in line with what users actually prefer to choose" (Selinger & Whyte, 2011, p. 929).
	"However, the same techniques can also be used for more nefarious ends. Sometimes, referred to as dark patterns, they have become essentially tricks that websites and apps use to make users do things they didn't intend doing, such as buying or signing up for something" (Paay & Rogers, 2019, p. 2).
Reactance to conformance	"'Social nudges' are not only more likely to be 'found out', but that they have considerable potential to trigger reactance—especially among those who are politically opposed to the intended outcomes" (Mols et al., 2015, p. 6).

Based on this discussion, we need to broaden how we define nudging and digital nudging to reconcile the inconsistencies and present a coherent frame for academic researchers and practitioners. In order to extend the definition, we next present a taxonomical approach to identify characteristics of digital nudging practices. Given the paucity of a systematic classification of digital nudging interventions and the corresponding balanced measures of success in the literature, especially from the behavioral perspective, a taxonomy will help provide a comprehensive yet structured conceptual framework for digital nudging interventions.

In this paper, we provide a conceptualization of digital nudging interventions and posit their importance in the IS field; it also earmarks the lack of a syntactically, semantically, and pragmatically comprehensive definition. We found that past research has largely conceptualized digital nudging interventions merely via transferring concepts from the analog counterpart without any limitation or constraint to the approaches. In turn, they have placed myriad mechanisms under the umbrella of digital nudging interventions, which creates conflicts for CAs (Hansen & Jespersen, 2013). In addition, authors have raised several ethical concerns to which the current conceptualization does not cater. Another issue in this context concerns the inability to distinguish digital nudging interventions from their underlying heuristics and biases. Many publications, we found, used the biases to represent nudges. Doing so confounds design, analysis, and comparison efforts across studies. We developed our vernacular archetypes and, therefore, our taxonomy to resolve this issue, which we draw on to define digital nudging (see Table 6).

We label digital nudging interventions as intentional because, ignoring their intentional aspect makes the notion of responsibility redundant (Hansen & Jespersen, 2013). By doing so, we contest authors who label all behavior modulations as digital nudging interventions. To this definition, we append Hausman and Welch's (2010) qualification: "they [digital nudging interventions] are called for because of flaws in individual decision-making, and they work by making use of those flaws". This addition clarifies the need for digital nudging interventions while clarifying the underlying proposition that these interventions use the flaws (the heuristics and psychological biases).

Table 6. An Integrated Definition for Digital Nudging Interventions

Term	Digital nudging intervention refers to using
Artifact	Any digital artifact that includes information, design, or interactive elements
Realm	In the digital sphere
Potential Outcomes	Intentionally designed to form, alter, reinforce
Target	People's behavior
Predictability	In a predictable way
Guidelines	While: • Being transparent, • Preserving choice (Libertarian-Paternalist) without altering the incentives to make other choices, and • Adhering to pro-social (increasing social welfare) and pro-self (increasing the welfare of the decision maker) objectives and not to the selfish goals of choice architects.

Next, we envisage digital nudging interventions to have three potential outcomes: "forming", "altering", and "reinforcing". "Forming" refers to developing a conformance attitude, behavior, or act where none existed before. In the "forming" outcome, we propose to include stopping as a conformance attitude, behavior, or act since, in practice, starting an alternative/new attitude or behavior may lead to stopping a prior behavior. "Altering" in potential outcomes implies a digital nudging intervention intended to bring about a change in an existing conformance attitude, behavior, or act without forming a new attitude, behavior, or act. A digital nudging intervention intended to generate an "altering" outcome may lead to a change in the frequency, intensity, or duration of the behavior. The "reinforcing" outcome means providing ground to an already existing conformance attitude, behavior, or act, such as providing users with an attractive outcome (reward) when they achieve a desired behavior.

We further add three guidelines to the definition to make digital nudging interventions coherent with the libertarian-paternalistic principle that traditional nudges adopt and to cater for some ethical concerns that we highlight in this paper. These will aid the evaluation of the ethical dimensions of the nudge. The guideline of transparency here includes the interventions, the goal of the interventions, and the means of behavioral change which are reasonably transparent to the agent being nudged (Dalecke & Karlsen, 2020). A non-transparent nudge, on the contrary, would be one where the agent would fail to reconstruct either of these characteristics (Hansen & Jespersen, 2013). The second guideline caters to the liberty-preserving nature of digital nudging interventions, and prevents manipulations of choices and the associated incentives. Responding to Hansen and Jespersen (2013)'s call, we propose a broader definition of incentives such as time, trouble, social sanctions, or otherwise. Finally, the third guideline is directed towards the ethical concern of missing responsibility and provides a resolution to the manipulative means and the outcome goals of the digital nudging interventions. It guarantees that the nudge design would be consistent with the decision maker's judgment or at least to the decision maker's pro-social goal. This, in turn, counters the concerns arising from elitism among CAs (i.e., the notion that designers know what would best benefit decision makers).

7 Conclusion

We conducted a structured literature review and found that research related to applying digital nudging initiatives continues to represent a nascent theme in the IS domain. In overviewing and classifying published studies on digital nudging interventions, we found that existing research has concentrated mainly on mapping the many ways in which traditional nudges can succeed in the digital domain. We found that transferring nudges from the offline to the online context has resulted in more potent interventions and accompanying ethical concerns. Simplistic definitions and insufficient/non-existent guidelines for designing and developing digital nudging interventions have led to multiplicity in digital nudging intervention types, which makes comparing and contrasting findings across studies significantly difficult. Our taxonomy, therefore, has several implications for theory and practice. First, the standard vernacular that we have proposed—11 digital nudging archetypes that we mapped to the four categories in Hansen and Jespersen's

(2013) framework along with the three information systems elements—distinctly identifies digital nudging interventions. Our taxonomy will enable further efforts to design digital nudging interventions, allow for explicit comparisons, and human-computer interaction researchers to integrate digital nudging interventions as a concept more actively in the IS domain. The standard vernacular can aid scholars in designing processes and guidelines for designing and developing interventions while integrating them with the underlying psychological biases.

Second, one can consider our taxonomy and the accompanying definition for digital nudging interventions as a theoretical framework for further work (Webster & Watson, 2002). Researchers can further explore our taxonomy and the associated concepts we identified by applying them in broader contexts and applications. In conducting our structured literature review, we focused on existing research on digital nudging in the IS domain. While prior work has focused predominantly on simply classifying interventions, we linked their three aspects (i.e., the IS elements, the interventions, and the psychological effects). Future work can leverage our findings to identify how effectively the three aspects work in various contexts and decision frames.

Third, we define digital nudging interventions in a way that caters to several ethical and philosophical concerns while clarifying their goals and boundaries. Our definition resolves several limitations of the original definition and adds to the nudging theory. Through its various components, the definition also clarifies the responsibilities that CAs have and lays the groundwork for labeling unintentional interventions as digital nudging interventions. This definition will allow researchers to appreciate digital nudging interventions' nuances and build on them as the foundation for further research.

As with any study, ours has several limitations. First, we used a simple search string to locate research that used nudging in the online and technology-enabled contexts. A more detailed search could include other studies that used digital nudges without naming them so. For instance, a recent paper on anthropomorphic conversational agents found that response failures have a negative impact on how decision makers perceive conversational agents (Diederich et al., 2021). Although anthropomorphism is a nudge mechanism to prime users and show empathy, we did not include it in our review since our search string did not include terms to capture it. We also could have conducted a more exhaustive search by specifically choosing journals and conference proceedings to further substantiate our taxonomy.

A fallacy of taxonomies, in general, is that one can often better describe the relationships between their categories when one creates more categories and lays out each one's nuances well. However, in doing so, one may impose "a discrete system on a continuous process (evolution) that leads to fuzzy boundaries" (Zachos, 2018). Developing a taxonomy is often a balancing act—one that tries to maximize comprehensiveness while minimizing complexity. In doing so, we restricted our focus to certain digital nudge aspects. For instance, while we mapped individual-level biases, we have limited our examination to interactional or social-level biases. We included social desirability bias and image motivation. However, we excluded some others such as herding, deindividuation, correspondence bias, or illusory superiority, since CAs rarely use them in digital nudging interventions. Similarly, in creating higher-order digital nudging intervention archetypes, we thematically classified digital nudging interventions that researchers and practitioners have commonly used while also finding parallels to nudges in the offline context while keeping in mind the distinction between online and offline nudging. Accordingly, we may have created a non-exhaustive set of categories. In the same breath, we must also mention the possibility that the occasional complex digital nudging interventions that combined multiple psychological biases and heuristics that we found made it near impossible to categorize them in a distinct and unambiguous way. Thus, we consider the categories that we mention in this study to be neither mutually exclusive nor exhaustive. Similarly, cascading nudges, which deploy multiple nudges sequentially to create a desired effect, appear more commonly these days given the sophisticated digital tools now available to execute them. Our current taxonomy does not account for cascading nudges.

However, despite these limitations, the taxonomy that we developed categorizes digital nudging interventions and explicitly describes the relationship between them, IS elements, and psychological biases. Furthermore, we drew on the taxonomy to define digital nudging interventions in an integrated manner and in a way that remains stable across their many uses. Future work can not only extend the taxonomy further but also discern the debates surrounding digital nudging and develop ethical guidelines for CAs to design choice-preserving, transparent digital nudges in a more detailed manner.

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Appendix A

Table A1. Pivotal List of Psychological Effects, Heuristics, and Biases for Behavioral Change (Adapted from Mirsch et al., 2017)

Psychological effects, biases, and heuristics	Description
Anchoring and adjustment	When decision makers lack sufficient information, they anchor their assessment on the individual cues and starting points. This anchor could be high, low, or even arbitrary and, hence, lead to an inappropriate judgment.
Attentional collapse	The failure to notice objects and information when the attention and cognitive resources are intentionally directed somewhere else. For example, CAs can develop a stimulus to nudge decision makers' attention away from harmful choices.
Availability heuristic	Decision makers make judgments about the context based on the ease of their recall. For instance, they perceive more frequent, relatable, and fresh events as more likely without any contextual analysis than how frequently they occur. By relating an infrequent event to more frequent specific events, CAs can increase an individual's sensitivity towards it.
Commitment	People often commit to a course of action but fall short in their behavior towards achieving it. However, research has found pre-commitment to engage in a specific course of action to be a source of motivation towards it. CAs can leverage pre-commitment to reduce procrastination and to nudge decision makers towards targeted decisions.
Decoupling	When the decision and the outcome are decoupled from each other, it may be difficult for decision makers to analyze the consequence(s). For instance, decision makers tend to overspend when using credit payments compared to cash.
Endowment effect	People tend to evaluate objects that they own more favorably than their fair market value since they have established ownership over the former. Due to this effect, people tend not to cancel their subscription to a process once they have invested some time or effort in it.
Framing	Framing refers to consciously phrasing information in a decision frame such that the presentation guides decision makers toward the targeted behavior. CAs can, by placing decoy options, enhance the choice of the targeted alternative or people's tendency to choose the middle option by placing the targeted alternative in the middle.
Hyperbolic discounting	Hyperbolic discounting means that individuals behave inconsistently when considering time-based information. They value the present and the near-present stronger than the future, which implies that nudges presenting immediate or short-term benefits are more effective than nudges focusing on long-term benefits.
Image motivation	Decision makers tend to behave in a pro-social manner so that other societal members perceive them positively, which increases the likelihood that decision makers will accept motivational factors or incentives related to their own self-image or the image they project to others.
Inter-temporal choice	Inter-temporal choice refers to the psychological evaluative processes involved in decision-making when a decision's consequences appear across time or one can only observe their effect in multiple periods
Loss aversion	Decision makers often avoid taking risks to avoid a loss than to make a gain. They weigh the perceived dis-utility of a loss or giving up the status quo as larger than the utility of a gain or acquiring some new object even with smaller impacts.
Mental Accounting	People think of value in relative terms (i.e., they derive the value not just from actual worth but also by the relative transactional utility). For example, people give money that has an objective value a subjective estimate depending on its source. The CA can develop interventions that reduce such evaluations and nudge decision makers to value decisions more objectively.

Table A1. Pivotal List of Psychological Effects, Heuristics, and Biases for Behavioral Change (Adapted from Mirsch et al., 2017)

Messenger effect	The perceived authority and importance of the messenger weighs upon the evaluation of the message itself. It is based on the human tendency to bias opinions to match those that people perceive as the authority on the given subject. Hence, the evaluation of the value of messenger is called the messenger effect.
Optimism & overconfidence	Decision makers tend to overestimate their capabilities and possess an overly optimistic estimate about themselves. This belief, in turn, leads them to feel overly confident in their probabilistic estimates of their decisions' outcomes.
Priming	Before people make a decision, CAs can introduce specific topics, moods, questions, or information that can impact the decision. Priming activates knowledge hidden in the subconscious before people make a decision.
Representativeness & Stereotypes	In the decision frame, when the choices or the consequences are complex and challenging to evaluate, decision makers may apply probabilistic judgments by comparing the current complex scenarios to other simple resembling situations.
Social desirability bias	Social norms refer to non-explicit rules and standards often perceived as ideal behavior derived through an individual's belief about widespread audience's beliefs and acceptance. Non-conformance to these norms is likely to cause fear of isolation and ridicule.
Spotlight effect	The tendency for individuals to believe that the world around them constantly evaluates them.
Status quo	People follow an inertial lifestyle and possess an emotional bias, a preference to remain in the present state or towards a state of no action. Thus, they analyze any change in comparison to the current state and perceive it as a loss. Although this bias may seem irrational, it also relates to mental accounting in situations with cognitive overload and high uncertainty.

Appendix B

Table B1. Representative Extract from the Data Analysis

Source	Intervention[3]	Author's definition/quote
Bawa et al. (2020)	Code-mixing chatbots	*Multilingual users mix languages while interacting with others, as well as in their interactions with computer systems (such as query formulation in text-/voice-based search interfaces and digital assistants). Linguists refer to this phenomenon as code-mixing or code-switching.* (p. 1)
Díaz Ferreyra et al. (2020)	Providing risk scenarios	*These are descriptions of privacy harms that may occur when certain pieces of personal data are revealed to untrusted audiences in SNSs. For instance, a scenario describing "Revealing bank account details can increase the chances of financial fraud" can be leveraged for motivating a user to keep her financial information away from public disclosure.* (p. 2)
DiCosola & Neff (2020)	Social Comparisons	*While it has become relatively commonplace for social comparisons in online contexts to rely solely on in-group comparisons (i.e., "people like you" comparisons), this pilot study introduces out group comparisons. In the experimental conditions, participants were shown a prompt at checkout that informed them that they were projected to consume a weekly caloric surplus that would result in weight gain (i.e., 3,500 extra calories). Participants' weekly caloric was compared to other 'healthy adults like you' in the in-group condition and to 'overweight adults' in the out-group condition.* (p. 2)
Esposito et al. (2017)	Information placement	*A change in the stage in the purchasing process at which this information was provided (For example: placing product compatibility information on the checkout page instead of the page where detailed information about the product is usually provided (the "product description page").* (p. 3)
Gena et al. (2019)	Group-Ad Populum	*We took inspiration from recommendation strategies based on item–item associations by making no appeal to a generic majority, but to the majority of a particular group, i.e., the users who also read the current news item. For example: Similar-to-You Users who read this news also read….* (p. 10)
Gena et al. (2019)	Argumentum Ad Populum	*…All members of the society. For example: Similar-to-You Users who read this news also read….* (p. 10)
Huang et al. (2018)	Monetary incentive framed message	*Share this webpage with your friends! You will receive a free subscription service from Company I!* (p. 4)
Huang et al. (2018)	Relational capital framed message	*Share this webpage with your friends! They may find the information helpful! (p. 4)*
Koning et al. (2020)	Signature nudge	*It obtains self-commitment to act morally prior to behavior. For example: checkbox to show acceptance of a policy.* (p. 260)
Kozyreva et al. (2020)	Scarcity	*Signaling that a product is likely to become unavailable, thereby increasing its desirability to users. For example: Low-Stock Message Indicating to users that limited quantities of a product are available, increasing its desirability. High-Demand Message Indicating to users that a product is in high demand and likely to sell out soon, thereby increasing its desirability.* (p. 114)
Lu et al. (2021)	Overt digital nudge	*…the recommended option design, the vendor provides recommended information or description for a target option (nudged option).* (p. 11)
Mejtoft et al. (2019)	Framing combined with loss aversion	*You will lose $350 per year if you do not use the energy saving Plug.* (p. 433)
Mota et al. (2020)	Covert Digital Nudge	*…implicitly change the default ranking of shown projects to a poverty-based one.* (p. 10)
Mota et al. (2020)	Overt Digital Nudge	*..explicitly show the poverty level of the school associated with each project proposal.* (p 10)

[3] Intervention as mentioned by the authors of the paper

Table B1. Representative Extract from the Data Analysis

Piotrkowicz et al, (2020)	External information	*Make external information visible. For example: "In your profession you are likely to meet people with sleep difficulties, which affect 62% of the UK population."* (p. 288)
Piotrkowicz et al. (2020)	Self-commitment	*Facilitate commitment. For example: "Save this module for later." (p. 288)*
Shen & Hsee (2017)	Numerical nudging	*…using inherently meaningless numbers to strategically alter behaviours. For example: Accelerating progress bars.* (p. 1077)
Terres et al. (2019)	Commitment Cues	*…users strive to be consistent with previous or reported behavior to avoid cognitive dissonance).* (p. 1)
Walser et al. (2019)	Decomposition of information load	*Presentation of ideas in presentation modes with either a high (15 subsets of two ideas at a time) or low (30 ideas displayed at once) decomposition of information load.* (p. 182)
Zimmermann & Renaud (2021)	Simple nudge	*The simple nudge was based on the positioning heuristic, that is, people's tendency to pick the first option of a list. Thus, to increase the number of secure choices, the list of WiFis was sorted from most to least secure, ensuring that the secure option always appeared at the top of the list.* (p. 14)
Zimmermann & Renaud (2021)	Simple nudge	*This nudge utilized a default setting, that has delivered robust outcomes in related work. The "Yes" checkbox was pre-selected, but participants could change the selection. (p. 16)*
Zimmermann & Renaud (2021)	Simple nudge	*An additional strength bar was displayed, appealing to learned associations by using color-coding (green = good/secure; red = bad/insecure) and providing users with feedback related to strength but not supporting an understanding of what a good password looks like (p. 17)*

Table B2. Representative Extract from the Data Analysis

Source	**Subtype**	**Standard archetype**	**Type of intervention (H&J)[4]**	**Artefact Used**
Bawa et al. (2020)	Anthropomorphism in robots and virtual assistants	Priming and developing empathy	Manipulation of choice	Interaction
Díaz Ferreyra et al. (2020)	Providing Risk Scenarios	Translating information and understanding mapping	Facilitation of consistent choice	Informational
DiCosola & Neff (2020)	Information about group-members and non-members	Providing a social reference point	Facilitation of consistent choice	Informational
Esposito et al. (2017)	Convenience	Salience: ease and Convenience	Influence behavior	Structural
Gena et al. (2019)	Information about group	Providing a social reference point	Facilitation of consistent choice	Informational
Gena et al. (2019)	Information about society	Providing a social reference point	Facilitation of consistent choice	Informational
Huang et al. (2018)	Incentives (monetary)	Incentives	Facilitation of consistent choice	Informational
Huang et al. (2018)	Framing	Translating information and understanding mapping	Facilitation of consistent choice	Informational

[4] Type of intervention classification adapted from Hensen & Jespersen (2013)

Table B2. Representative Extract from the Data Analysis

Koning et al. (2020)	Commitment to self	Leveraging commitment	Facilitation of consistent choice	Structural
Kozyreva et al, (2020)	Scarcity Effect	Deceptive visualizations	Manipulation of choice	Informational
Lu et al. (2021)	Providing viewpoints	Informational provisions	Facilitation of consistent choice	Informational
Mejtoft et al. (2019)	Framing	Translating information and understanding mapping	Facilitation of consistent choice	Informational
Mota et al. (2020)	Priming	Priming and developing empathy	Manipulation of choice	Structural
Mota et al. (2020)	Framing	Translating information and Understanding Mapping	Facilitation of consistent choice	Informational
Piotrkowicz et al. (2020)	External Information	Informational provisions	Facilitation of consistent choice	Informational
Piotrkowicz et al. (2020)	Commitment to self	Leveraging commitment	Facilitation of consistent choice	Informational
Shen (2017)	Priming	Priming and developing empathy	Manipulation of choice	Informational
Terres et al. (2019)	Commitment to self	Leveraging commitment	Facilitation of consistent choice	Informational
Walser et al. (2019)	Simplification	Translating information and understanding mapping	Influence behavior	Structural
Zimmermann & Renaud (2021)	Positioning	Deceptive visualizations	Manipulation of behavior	Structural
Zimmermann & Renaud (2021)	Opt-out default	Default	Influence behavior	Structural
Zimmermann & Renaud (2021)	Feedback	Giving feedback, warnings, and reminders	Facilitation of consistent choice	Structural

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