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Digital Nudging in Information Systems: A Systematic Review of Mechanisms, Applications and Effects

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Digital Nudging in Information Systems: A Systematic Review of Mechanisms, Applications and Effects

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Digital Nudging in Information Systems: A Systematic Review of Mechanisms, Applications and Effects

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Abstract:

Digital nudging refers to the use of interface design elements to influence users' decisions and behaviors in digital environments without restricting their freedom of choice. Although digital nudging has attracted growing attention in information systems (IS) research, quantitative empirical evidence remains fragmented across theories, application domains, nudge mechanisms, and outcome measures. This study systematically reviews 66 quantitative empirical studies on digital nudging published in IS outlets between 2016 and 2025. The findings indicate that literature is dominated by online experiments, low- and moderate-stakes decision contexts, crowd-worker and student samples, and behavioral trace data, with sustainability and e-commerce emerging as the most common application domains. The review further reveals that decision information and decision structure nudges have received the greatest research attention, whereas decision assistance nudges remain underexamined, particularly as standalone interventions. Based on these findings, the review identifies six research avenues to support the continued development of digital nudging research.

Keywords: Digital Nudging, Nudge, Nudge Theory, Information Systems, Literature Review, Quantitative Research.

[Department statements, if appropriate, will be added by the editors. Teaching cases and panel reports will have a statement, which is also added by the editors.]

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This manuscript underwent [editorial/peer] review. It was received xx/xx/20xx and was with the authors for XX months for XX revisions. [firstname lastname] served as Associate Editor.] **or** The Associate Editor chose to remain anonymous.]

1 Introduction

Nudging, as originally defined by Thaler and Sunstein (2008, p. 6), refers to “any aspect of the choice architecture that alters people’s behavior in a predictable way without forbidding any options or significantly changing their economic incentives.” In digital environments, this concept is operationalized as digital nudging, the deliberate use of user interface (UI) design elements to guide individuals’ decision-making and behavior without restricting their freedom of choice (Weinmann et al., 2016). Digital nudges differ from mandates, bans, or financial incentives in that they operate through non-intrusive means while leveraging cognitive biases and heuristics (Münscher et al., 2016). Digital nudging in IS and related disciplines is generally regarded as a mechanism for influencing user behavior through subtle design features such as defaults, framing, simplification, and visual salience, known as nudges (Meske & Amojo, 2020; Weinmann et al., 2016). These nudges are commonly used to shape decisions and behaviors in domains such as education, health, privacy, and sustainability (Sadeghian & Otarkhani, 2024) and are often embedded in various digital applications and platforms.

Over the past decade, research on digital nudging has made significant advancements. To consolidate knowledge from literature, several systematic reviews have been conducted. These reviews have contributed to the field by offering taxonomies (Valta & Maier, 2025), exploring data-driven approaches to nudging (Sadeghian & Otarkhani, 2024), and examining domain-specific applications such as sustainability and pro-environmental behaviors (Zimmermann et al., 2021), customer journeys (Schaer & Stanoevska-Slabeva, 2019), recommender systems (Jesse & Jannach, 2021a), personal finance (Neuss & Zielke, 2022) and healthy and sustainable food choices in online grocery shopping (Alsaeed et al., 2025). Collectively, these reviews have provided valuable insights into the characteristics, mechanisms, and ethical considerations of digital nudging across diverse contexts.

However, recent studies have highlighted that the digital nudging research landscape is characterized by conceptual diffusion and methodological heterogeneity, mainly due to the proliferation of definitions and frameworks (Meske & Amojo, 2020; Valta & Maier, 2025). Theoretical approaches vary widely, ranging from those rooted in bounded rationality and choice architecture to others that emphasize user interface design. This variation has led to isolated streams of inquiry and limited cumulative knowledge (Mirsch et al., 2017; Valta & Maier, 2025). Furthermore, empirical studies have explored nudges across various domains, including privacy, sustainability, health, and e-commerce, using different measures and reporting outcomes that are difficult to compare or synthesize (Meske & Amojo, 2020; Zimmermann et al., 2021). Although previous reviews have attempted to synthesize the literature, they have typically focused on technical aspects, specific domains, or broader multidisciplinary perspectives. None has systematically synthesized research on nudging within IS to clarify its theoretical foundations and practical implications.

As digital nudges increasingly shape user behavior through digital tools, there is a pressing need to consolidate and critically examine the current state of knowledge. This review responds to calls for a deeper understanding of the contexts, forms, and effectiveness of digital nudges (Meske & Amojo, 2020; Valta & Maier, 2023). It addresses a gap in the literature by analyzing empirical quantitative studies to synthesize how nudge mechanisms have been applied and the behavioral and psychological effects they have produced across multiple application contexts. Specifically, the review addresses the following research question (RQ):

RQ: What digital nudges have been investigated across digital application contexts, and what behavioral and psychological effects have been observed?

By addressing the RQ, the study contributes a discipline-specific understanding of digital nudging within the IS field. First, it maps the empirical evidence base, revealing the dominance of online experiments and low-stakes tasks in application domains like sustainability and e-commerce. Second, it categorizes nudges investigated in the literature into four categories: decision information, decision structure, decision assistance, and decision social appeal. Third, it shows that nudge effectiveness is highly context-dependent, yielding significantly different results based on the specific application domain and user characteristics. Finally, the review offers six avenues for future research.

This paper is structured as follows: Section 2 presents related work; Section 3 outlines the methodological approach; Section 4 presents the findings; and Section 5 discusses the results, research opportunities, and limitations of the study. Section 6 presents the contributions and conclusion.

2 Related Work

Grounded in the theoretical frameworks of behavioral economics and choice architecture (Thaler & Sunstein, 2008), nudging involves subtle modifications to the presentation or structure of choices to steer individuals toward options they themselves deem in their best interest. Digital nudging refers to the deliberate use of user interface (UI) design elements in digital environments to influence individuals' decision-making and behavior, without restricting their freedom of choice (Weinmann et al., 2016). In contrast to more directive or coercive interventions, such as mandates, bans, or financial incentives, nudges operate through non-intrusive means, preserving autonomy while leveraging well-documented cognitive biases and heuristics (Münscher et al., 2016; Sunstein, 2019). Within the IS field, digital nudging has gained increasing scholarly attention as both a research phenomenon and a practical design strategy (Lembcke et al., 2019; Mirsch et al., 2018; Weinmann et al., 2016). IS researchers have explored the application of digital nudges across a range of domains, including e-commerce (Jesse & Jannach, 2021a; Mirsch et al., 2017), sustainability (Székely et al., 2016; Zimmermann et al., 2021), privacy and security (Acquisti et al., 2017), and enterprise technology adoption, among others.

In response to the rapidly expanding body of literature on digital nudging, several systematic and structured literature reviews have emerged to consolidate and critically assess the extant knowledge base. **Appendix A**, **Table A1** summarizes existing reviews spanning a diverse range of contexts, from pro-environmental behavior and customer journeys to recommender systems and data-driven personalization. These reviews collectively present taxonomies, conceptual frameworks, and research agendas that reflect the current state of scholarship and highlight important avenues for future inquiry. While these existing reviews have significantly advanced our understanding of digital nudging across various domains and applications, they remain largely fragmented in scope, often focusing on specific sectors (e.g., finance) and technological approaches (e.g., recommender systems, data-driven nudging). Moreover, many adopt a descriptive or taxonomic orientation but provide limited theoretical integration or cross-contextual synthesis. Our review focuses specifically on how digital nudging has been conceptualized and operationalized within the IS field, and examines the behavioral effects reported across diverse application domains. In doing so, our review responds to calls for greater conceptual clarity, stronger theorization of digital nudging effects (Meske & Amojo, 2020), and a better understanding of the different forms of digital nudging and their effectiveness in various contexts (Valta & Maier, 2025).

3 Methodology

Following the structured approach proposed by Webster and Watson (2002), we systematically reviewed empirical studies on digital nudging in the IS field. On September 16, 2023, we searched databases using the keywords "nudge" or "nudging" and focused on literature published between 2013 and 2023. We deliberately excluded the word "digital" from our search terms to avoid omitting studies that explore digital nudging but use alternative descriptions or terminology. Our search covered all journals listed in the Association for IS (AIS) Senior Scholars' List of Premier Journals: Decision Support Systems (DSS), European Journal of Information Systems (EJIS), Information & Management (IM), Information and Organization (IO), Information Systems Journal (ISJ), Information Systems Research (ISR), Journal of the Association for Information Systems (JAIS), Journal of Information Technology (JIT), Journal of Management Information Systems (JMIS), Journal of Strategic Information Systems (JSIS), and MIS Quarterly (MISQ). We also searched the proceedings of the four leading IS conferences: the International Conference on Information Systems (ICIS), the European Conference on Information Systems (ECIS), the Pacific Asia Conference on Information Systems (PACIS), and the Americas Conference on Information Systems (AMCIS). To expand our coverage, we also included two widely cited IS outlets outside the Senior Scholars' list, namely, Communications of the AIS (CAIS) and the International Journal of Information Management (IJIM). The selection of these outlets was guided by the objective of ensuring both rigor and representativeness of the IS knowledge base on digital nudging. We manually and independently examined each targeted outlet's collection or archives to reduce the risk of missing relevant papers due to indexing limitations or inconsistent metadata. **Figure 1** shows the search and selection process we followed to identify publications for review.

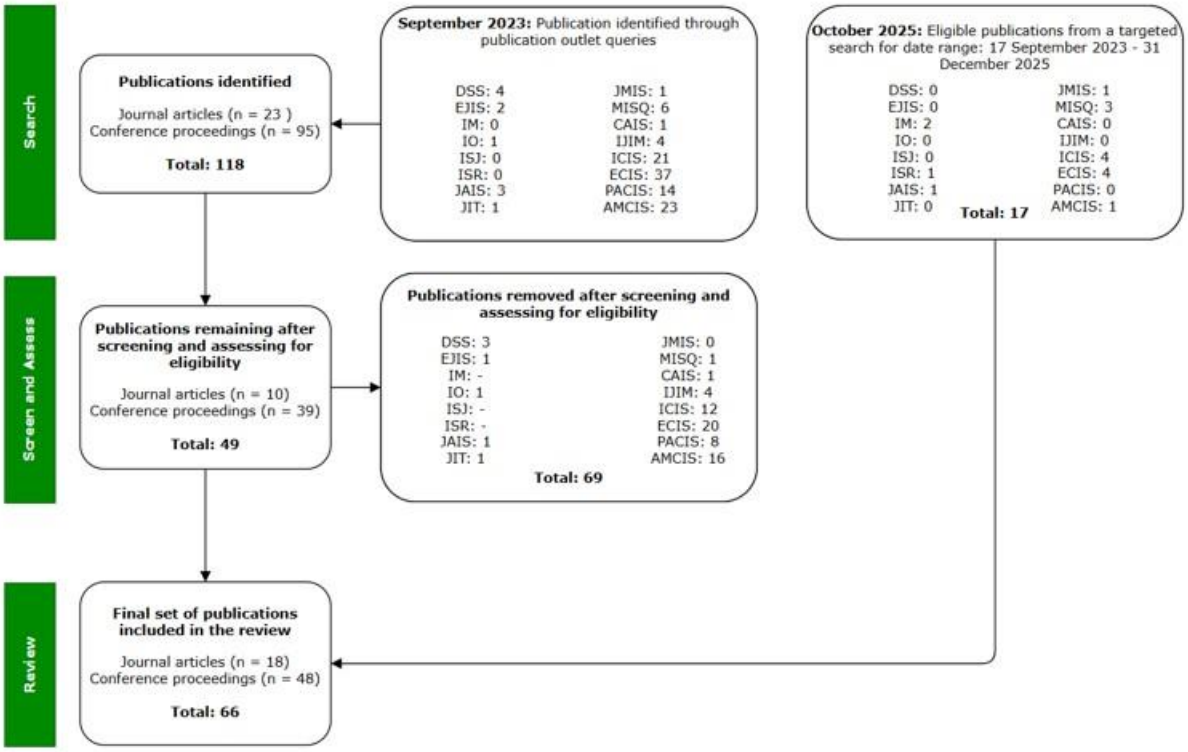


Figure 1. Search and Selection Process

Our initial search identified 118 articles. We then screened these articles using a predefined set of inclusion and exclusion criteria, which **Table 1** summarizes.

Table 1. Study Inclusion and Exclusion Criteria

Criterion	Inclusion	Exclusion
Type of study	Behavioral research with empirical focus	Conceptual papers, technology or modelling papers, TREO talks, abstracts, economic modelling, algorithm modelling
Methodological approach	Quantitative empirical studies (e.g., experiments, surveys, design science with results)	Case studies, qualitative research, descriptive work, reviews, design science without results, mixed methods (qualitative and quantitative research approaches)
Nudging constructs	Nudging present as a quantified variable	Nudging is not measured or only discussed theoretically

In applying the inclusion criterion for behavioral research with an empirical focus, we required that studies operationalize at least one behavioral or psychological outcome as a measurable variable, such as product choice, willingness to disclose, or click-through rate. We excluded studies that discussed nudging effects conceptually without empirical data. No restrictions were imposed on the level of analysis (individual or organizational) or on the participants' demographic profile, provided that the nudge was delivered via digital technology. We included studies regardless of whether authors used the term "digital nudging," as the operative criterion was that the intervention was technology-delivered.

From the 118 records we retrieved, we excluded 69 based on our selection criteria. Specifically, we excluded seven studies that referenced nudging conceptually but lacked an operationalized construct that could be empirically measured or compared, 18 that were theoretical or technical in nature, 27 that used qualitative or mixed methods, and 17 that lacked a results or findings section, for example, research-in-progress or work-in-progress papers presenting conceptual frameworks or preliminary designs without empirical outcomes. This exclusion does not filter out studies reporting null results. Studies with null or

non-significant findings are included in the review. We ultimately selected 49 eligible studies, all published between 2016 and 2023.

To ensure currency, we conducted another targeted search at each outlet in October 2025 to identify eligible articles published since the initial search. This search focused on studies published between 17 September 2023 and 31 December 2025 and applied the same inclusion and exclusion criteria, screening process as the original search. Eligibility decisions were reached by consensus between both coders. We identified 17 eligible studies during this search. In total, 66 studies are reviewed in this paper. **Appendix B**, **Table B1** summarizes the reviewed studies.

We applied a dual-coder approach that combined deductive and inductive strategies to guide data coding. We coded the studies using a standardized Excel-based template. Through deductive coding, we applied predefined theoretical categories, while inductive coding enabled us to identify unexpected themes. To avoid influencing each other's interpretations, we worked independently, but met regularly to compare coding results, resolve disagreements, and refine the coding scheme. We addressed discrepancies through evidence-based discussions informed by relevant literature and the content of the reviewed studies. When disagreements arose, we examined whether they resulted from ambiguous study descriptions, differences in interpretation, or limitations in the original coding categories. We iteratively refined the coding framework to resolve recurring ambiguities and accommodate emergent themes that the initial structure did not capture. In the next sections, we present our findings.

4 Findings

This section presents the findings from the analysis.

4.1 Publications Trends

We reviewed 66 articles. **Figure 2** shows yearly publication trends of the reviewed studies. The lower figure for 2025 may be because the second literature search was conducted in October, with many publications for the year still pending.

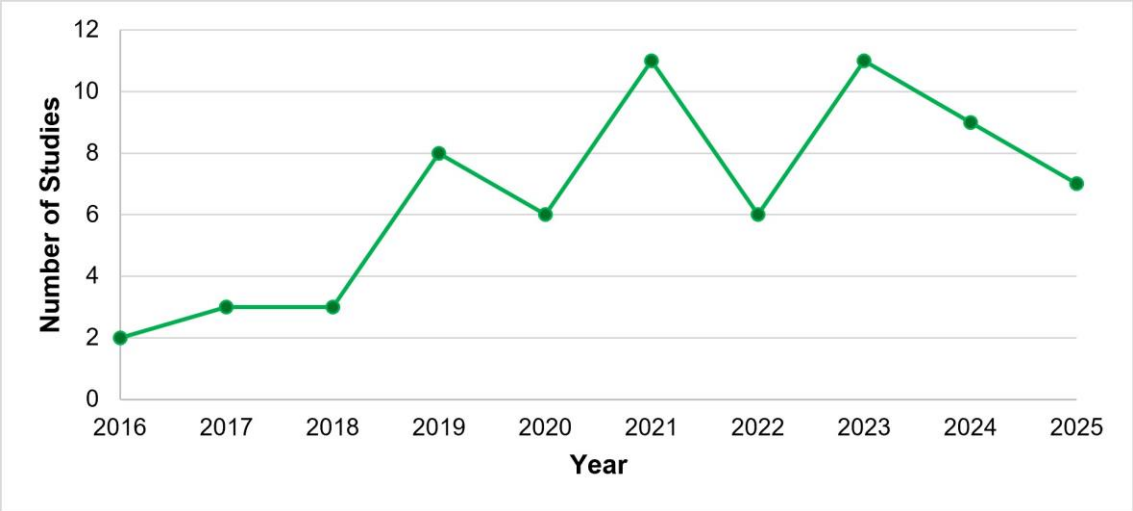


Figure 2. Yearly Publication Trends of Reviewed Studies

Figure 3 shows that 27 percent of the reviewed studies were journal articles, and 73 percent were conference proceedings.

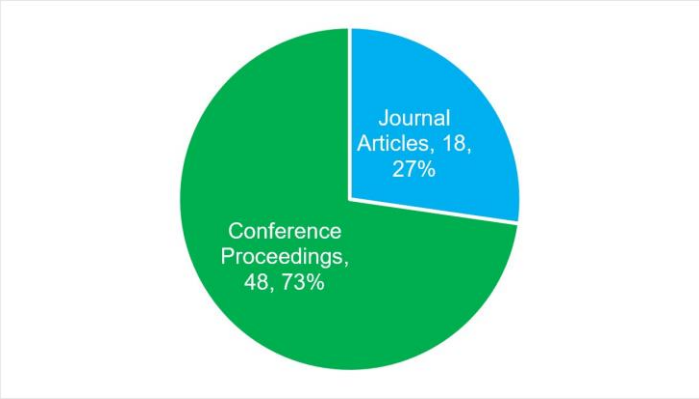
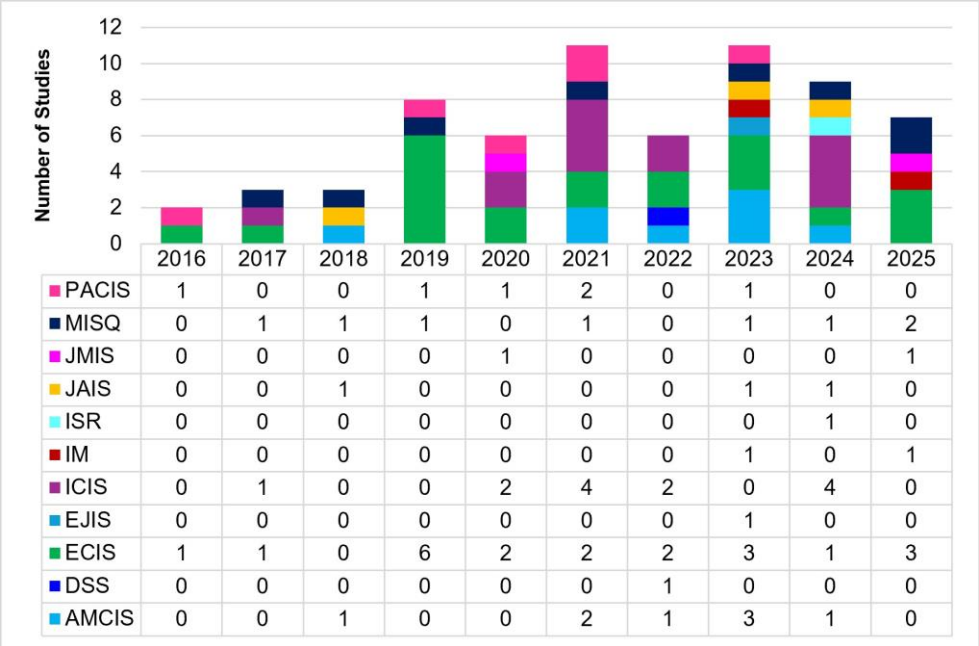


Figure 3. Distribution by Article Type

Figure 4 shows the distribution of publication trends across IS academic outlets from 2016 to 2025. Among the conferences, ECIS dominates with 21 studies, followed by ICIS with 13 publications. AMCIS and PACIS contributed eight and six studies, respectively. Among the journal articles, most contributions come from MISQ (8 studies), followed by JAIS (3 studies). JMIS and IM each contributed two publications, while the remaining journals (EJIS, ISR, and DSS) contributed one study each.



	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
PACIS	1	0	0	1	1	2	0	1	0	0
MISQ	0	1	1	1	0	1	0	1	1	2
JMIS	0	0	0	0	1	0	0	0	0	1
JAIS	0	0	1	0	0	0	0	1	1	0
ISR	0	0	0	0	0	0	0	0	1	0
IM	0	0	0	0	0	0	0	1	0	1
ICIS	0	1	0	0	2	4	2	0	4	0
EJIS	0	0	0	0	0	0	0	1	0	0
ECIS	1	1	0	6	2	2	2	3	1	3
DSS	0	0	0	0	0	0	1	0	0	0
AMCIS	0	0	1	0	0	2	1	3	1	0

Figure 4. Research Publication Trends

4.2 Study Design

The most prevalent design identified from the literature is online experiment (34 studies) (e.g., Berger et al., 2022; Bergram et al., 2024; Brylla & Walsh, 2023; Li & Guo, 2021; Schär et al., 2022; Schneider et al., 2017). This is followed by field experiments (17 studies) (e.g., Berger et al., 2020; Bernards et al., 2024; Degirmenci & Recker, 2018; Ho & Lim, 2018; Lee et al., 2023), lab experiments (10 studies) (e.g., Henkel et al., 2019; Kretzer & Maedche, 2018; Liu & Karahanna, 2017; Lu & Wang, 2023; Reeck et al., 2024), and multi-study designs (e.g., those combining lab and field experiments or field and online experiments) (3 studies) (e.g., Bergram et al., 2020; Shukla et al., 2025; Tsekouras et al., 2024). Additionally, one study used a natural experiment (Pethig et al., 2025) and another used an online survey design (Klesel et al., 2016).

In terms of population samples, the most common sample type was crowd working platform samples used in 21 studies (e.g., Cavegn et al., 2023; Habla et al., 2024; Jesse & Jannach, 2021b), followed by university students in 14 studies (e.g., Dennis et al., 2020; Henkel et al., 2019; Ho & Lim, 2018; Kretzer & Maedche, 2018; Li et al., 2021). Mixed samples (e.g., students and employees, students and crowd workers) (e.g., Auf Der Landwehr et al., 2021; Fang et al., 2023; Figl et al., 2021; Peters & Wieland, 2023; Tsekouras et al., 2024) and real users/field participants (e.g., patients, app users, EV users) (e.g., Huber et al., 2019; Lee et al., 2023; Mager & Kranz, 2021; Pethig et al., 2025) each accounted for 10 studies. General consumer samples were used in eight studies (e.g., Kroll et al., 2019; Schär et al., 2022; Sutanto et al., 2021; Terres et al., 2019; Zimmermann et al., 2023). Corporate employees were the least represented sample type, appearing in only three studies (Babar et al., 2023; Degirmenci & Recker, 2018; Klesel et al., 2016).

4.3 Application Domains and Tasks Explored

During our coding and analysis, we identified nine distinct application domains in which the identified nudge mechanisms have been applied. As **Table 2** shows, these application domains include sustainability, digital commerce, health and well-being, technology adoption and use, privacy and security, education and learning, social interaction, digital philanthropy, and innovation.

Table 2. Application Domains and Tasks Explored

Application domain (Number of studies)	Task(s) and reference(s)
Digital philanthropy (2)	Donating rewards or virtual currency to charity (Bergram et al., 2024; Lee et al., 2023).
E-commerce (13)	Purchasing or selecting products/services (Dennis et al., 2020; Figl et al., 2021; Ho & Lim, 2018; Moriguchi et al., 2022; Rafai et al., 2022), configuring or customizing products (Figl et al., 2021; Lu et al., 2019; Lu & Wang, 2023), reading or consuming information and selecting a provider (Schär, 2021; Schär et al., 2022), evaluating products or writing reviews (Liu & Karahanna, 2017; Poniatowski & Neumann, 2020), clicking ads and downloading apps (Tsekouras et al., 2024), and voicing complaints (Zhang et al., 2020).
Education (3)	Completing learning activities such as viewing videos, submitting assignments, and attending lectures (Bernards et al., 2024; Li et al., 2021; van Oldenbeek et al., 2019).
Health and wellbeing (7)	Choosing food or recipes (Jesse & Jannach, 2021b; Michels et al., 2021, 2023), performing or logging physical activity (Babar et al., 2023; Sengupta et al., 2020), indicating an intention to stop working (Klesel et al., 2016), and reading and comprehending health information (Li & Guo, 2021).
Innovation (1)	Eliminating weaker ideas from a set (Walser et al., 2019).
Privacy and security (7)	Selecting security settings (Bahreini et al., 2023), consenting to data use policies (Bergram et al., 2020; Mager & Kranz, 2021), verifying identity (Schneider et al., 2017), disclosing personal information (Reeck et al., 2024), responding to security-related requests (Pfaff et al., 2025), and disclosing or concealing identity (Shukla et al., 2025).
Social interaction (6)	Consuming or engaging with content (Fang et al., 2023; Kim & Dennis, 2019; Pethig et al., 2025), evaluating the believability of content (Olenberger et al., 2025), selecting partners and managing a profile (Shi et al., 2025), and completing collaborative tasks (Gupta et al., 2024).
Sustainability (23)	Selecting carbon-offset options (Cavegn et al., 2023; Franzoi & vom Brocke, 2022; Habla et al., 2024, 2025; Székely et al., 2016), choosing sustainable over conventional products (Berger et al., 2020; Gottschewski-Meyer et al., 2024; Helinski et al., 2024; Peters & Wieland, 2023; Sutanto et al., 2021; Wrabel, 2025), adjusting energy- or resource-saving settings (Berger et al., 2022; Degirmenci & Recker, 2018; Huber et al., 2019; Kroll et al., 2019), choosing delivery slots or transport modes (Auf Der Landwehr et al., 2021; Brylla & Walsh, 2023; Stryja et al., 2017; Zimmermann et al., 2023), donating to an environmental cause (Staudt et al., 2021), evaluating purchase or return motivation (Rauh et al., 2024), and searching for information (Henkel et al., 2019).
Technology adoption and use (4)	Installing a mobile app (Terres et al., 2019), engaging with a new feature (Li et al., 2022), searching for and analyzing information (Kretzer & Maedche, 2018), and reducing habitual app use (Purohit & Holzer, 2021).

We categorized studies into these application domains based on their primary objectives. For instance, we classified Staudt et al.'s (2021) and Franzoi and vom Brocke's (2022) studies under "sustainability" rather than "digital philanthropy" because even though both studies examined donations, their focus is on

environmental goals, such as carbon offsetting and sustainability-related initiatives, rather than general charitable giving.

4.4 Task Design Characteristics

In the following subsections, we briefly report how the tasks are designed as identified in the reviewed studies.

4.4.1 Temporality

Of the 66 studies reviewed, a slight majority employed a one-shot task design (36 studies), where participants made a single, bounded decision at one point in time, for example, a one-time cookie consent decision (Mager & Kranz, 2021) or a single carbon offset choice (Cavegn et al., 2023). The remaining 30 studies used a repeated-task design, involving multiple decisions across trials, such as eliminating ideas across 15 successive screens (Walser et al., 2019), selecting recipes across multiple food types (Jesse & Jannach, 2021b), tracking physical activity over several years (Babar et al., 2023), and multi-stage choice sequences (e.g., selecting a transport mode and then a fare class for a business trip) (Habla et al., 2024).

4.4.2 Complexity

Across the 66 studies reviewed, task complexity is fairly evenly split between complex (23 studies) and moderate (22 studies) designs, together accounting for over two-thirds of the literature. Complex tasks typically involve multiple attributes or large option sets (e.g., comparing 33 rental cars across 10 attributes (Stryja et al., 2017) or eliminating ideas from a pool of 30 (Walser et al., 2019)), effortful cognitive processing (e.g., writing product reviews (Poniatowski & Neumann, 2020) or evaluating fake news (Olenberger et al., 2025)), and repeated engagement combined with trade-offs (e.g., weighing flight costs against sustainability (Habla et al., 2024)). Moderate tasks involve selecting from a smaller number of options along one or a few dimensions (e.g., choosing between four t-shirts (Helinski et al., 2024)) or sustained but straightforward engagement (e.g., habit tracking (Babar et al., 2023) or recipe selection (Jesse & Jannach, 2021b)). Simple tasks (12 studies) involve performing tasks that require minimal cognitive effort, such as, choosing to accept/reject cookie consent (Mager & Kranz, 2021), complying/not complying with a donation request (Bergram et al., 2024). The simple-moderate (6 studies) and moderate-complex (3 studies) categories, which reflect intermediate levels of difficulty (e.g., a handful of options or a binary choice paired with a secondary evaluative element), are comparatively rare.

4.4.3 Stakes Level

Twenty-seven studies examine low-stakes task scenarios, where participants face hypothetical or simulated choices with no real consequences (e.g., Auf Der Landwehr et al., 2021; Berger et al., 2022; Cavegn et al., 2023; Degirmenci & Recker, 2018; Dennis et al., 2020; Fang et al., 2023; Figl et al., 2021; Gottschewski-Meyer et al., 2024; Habla et al., 2024; Helinski et al., 2024; Huber et al., 2019; Kim & Dennis, 2019; Li & Guo, 2021; Lu & Wang, 2023; Schneider et al., 2017). Another 13 studies investigate low-moderate-stakes task scenarios, which combine mostly simulated environments with minor real elements such as small incentives or mild time pressure (e.g., Brylla & Walsh, 2023; Franzoi & vom Brocke, 2022; Gupta et al., 2024; Habla et al., 2025; Henkel et al., 2019; Klesel et al., 2016; Kretzer & Maedche, 2018; Lee et al., 2023). Fifteen studies explore moderate-stakes task scenarios, placing participants in environments with real financial costs or incentives, privacy exposure, or moderate real-world behavioral consequences (e.g., Babar et al., 2023; Bahreini et al., 2023; Bergram et al., 2024; Ho & Lim, 2018; Reeck et al., 2024; Shi et al., 2025). High-stakes scenarios are much less frequent across literature. Six studies evaluate moderate-high-stakes task scenarios involving meaningful real consequences like privacy exposure or health-related risks (Berger et al., 2020; Bergram et al., 2020; Mager & Kranz, 2021; Pethig et al., 2025; Staudt et al., 2021; Tsekouras et al., 2024), while only five studies focus on high-stakes task scenarios that carry significant personal, financial, or health consequences (Bernards et al., 2024; Li et al., 2021; Rafai et al., 2022; Sengupta et al., 2020; Shukla et al., 2025).

4.5 Nudge Mechanisms Across Application Domains

In this paper, nudging mechanisms refer to design interventions used to influence decision-making and behavior. To identify these mechanisms, we conducted a detailed analysis of the literature using multiple frameworks. Specifically, we drew on the taxonomies proposed by Jesse and Jannach (2021a) and

Münscher et al. (2016). To identify and code the nudges, we read various sections of each study, including explicit statements in theoretical models and hypotheses, as well as experimental manipulations and intervention descriptions. After identifying and coding the nudges, we classified and grouped them into categories using Jesse and Jannach's (2021a) taxonomy, which comprises four high-level categories (decision information, decision structure, decision assistance, and social decision appeal) and 13 subcategories of nudge mechanisms. In some cases, we assigned certain nudges to more than one category depending on their descriptions. For instance, Li et al. (2022) examined a social nudge and a reminding social nudge, which combined elements of social influence and reminders. As a result, we assigned the study to two relevant subcategories: providing a social reference point and providing reminders, which fall under social decision appeal and decision assistance categories, respectively.

Our analysis found that research focuses heavily on decision information and decision structure nudges. Decision assistance and social decision appeal nudges are less studied. **Table 3** shows the number of studies from each application domain that have used a specific nudge mechanism in each nudge category. **Appendix B**, **Table B2** provides more details into the categories and the exact nudges investigated in the reviewed literature.

Table 3. Nudge Category, Mechanisms and Application Domains

Nudge category	Nudge mechanisms	SUS	COM	HW	TAU	PS	EDU	SI	INN	DP
Decision information	Translate information	4	2	0	0	0	0	0	0	0
	Increase salience of information	2	4	3	0	1	0	1	0	0
	Make information visible	6	3	5	2	3	2	2	0	0
	Phrase information	11	4	3	0	2	0	0	0	0
Decision structure	Change choice defaults	8	3	3	0	1	0	1	0	1
	Change option-related effort	0	0	1	0	2	0	0	0	1
	Change range or composition of options	0	1	1	0	0	0	1	1	0
	Change option consequences	2	0	0	0	1	0	0	0	1
Decision assistance	Provide Reminders	1	0	3	1	0	2	0	0	0
	Facilitate Commitment	1	0	1	1	0	0	0	0	0
Social decision appeal	Increase reputation of messenger	1	0	0	1	0	0	0	0	0
	Provide social reference point	8	3	2	2	0	1	3	0	2
	Instigate empathy	0	0	2	0	1	0	1	0	0

Notes:
- SUS: Sustainability; ECO: E-commerce; HW: Health and Wellbeing; TAU: Technology Adoption and Use; PS: Privacy and Security; EDU: Education; SI: Social Interaction; INN: Innovation; DP: Digital Philanthropy
- Cell values represent the number of studies using the nudge mechanisms and not the number of specific nudges falling under a nudge mechanism.

To better understand the contextual conditions under which different nudge categories have been studied, we cross-tabulated nudge categories with the task design characteristics discussed in Sections 4.4.1 - 4.4.3. **Table 4** provides the results of this cross-analysis. It is apparent from this table that deployment of

the nudges across task designs exhibits distinct and, in some cases, contrasting patterns. With respect to temporality, the analysis shows that social decision appeal nudges were commonly used in contexts involving single decisions, whereas decision assistance nudges were more often employed where behavior was repeated over time. By contrast, decision information and decision structure nudges were applied with similar frequency across both temporal contexts.

Moving on to task complexity, we see that the reviewed studies tended to examine decision information and decision structure nudges in more cognitively demanding tasks. In contrast, decision assistance and social decision appeal nudges were applied across a broader range of task complexities.

Turning to evidence on stakes levels, studies have predominantly examined decision information, decision structure, and social decision appeal nudges in lower-stakes decision contexts, whereas decision assistance nudges have been applied across contexts with a broader range of decision consequences.

Table 4. Cross-Analysis of Nudge Mechanisms Categories against Task Design Characteristics

	Task design characteristics											
	Temporality		Complexity					Stakes level				
Nudge category	One-shot	Repeated	Simple	Simple-moderate	Moderate	Moderate-complex	Complex	Low	Low-moderate	Moderate	Moderate-high	High
Decision information	24	24	10	2	19	2	15	24	8	8	4	4
Decision structure	12	10	2	4	5	1	10	10	6	3	3	0
Decision assistance	4	5	2	0	3	1	3	0	3	3	0	3
Social decision appeal	17	8	5	3	8	1	8	9	6	5	3	2

Note: Cell values represent the number of studies (out of 66 studies) in which each nudge category was identified as present, cross-tabulated against task characteristics

4.6 Theoretical Basis for Designing Digital Nudging

Table 5 summarizes the theories and theoretical frameworks used across the reviewed literature. We included only theories and theoretical frameworks explicitly stated in the studies and made no assumptions about unstated theoretical foundations. As such, we identified theories and frameworks from 46 studies. Given that all studies examined digital nudging, nudge theory was excluded to allow a clearer comparison of the additional theoretical perspectives informing this literature. We grouped the identified theories into six categories based on the psychological or organizational function they serve in explaining nudge effectiveness: 1) dual-process and cognitive processing; 2) decision-making, framing, and judgment; 3) self, motivation, and personality; 4) social and interpersonal; 5) behavior change and regulation; and 6) organizational, argumentation, and others.

The dual-process and cognitive processing theories focus on human information processing, cognition, and persuasion, specifically, how people attend to information, process it mentally, and arrive at judgments or decisions. Theories of decision-making, framing, and judgment seek to explain how individuals evaluate information, assess risks and benefits, make decisions, and form preferences when faced with limited information, cognitive constraints, or complex environments. The self, identity, motivation, and personality category is centered on the self, that is, how individuals understand themselves, regulate their behavior, explain their actions, pursue goals, and express their personal characteristics. The social and interpersonal theories explain how people's thoughts, attitudes, decisions, and behaviors are shaped by others' presence, actions, expectations, or opinions. The behavior change and regulation category addresses what causes people to act, change, resist, continue, or discontinue certain behaviors. The theories in the organizational, argumentation and others category seek to explain how individuals or groups react to change, uncertainty, or new opportunities.

Of the 46 studies, seven studies employed multiple theories (Babar et al., 2023; Li & Guo, 2021; Li et al., 2022; Peters & Wieland, 2023; Schneider et al., 2017; Sengupta et al., 2020; Shi et al., 2025). The use of multiple theoretical lenses indicates a growing recognition that digital nudging is a complex phenomenon that may require complementary perspectives to explain user behavior and decision-making.

Table 5. Theories and Theoretical Frameworks Used in Literature

Group and count *	Theory and references
Dual-process and cognitive processing (3)	Dual process theory (Berger et al., 2020, 2022; Dennis et al., 2020; Franzoi & vom Brocke, 2022; Habla et al., 2024, 2025; Mager & Kranz, 2021; Olenberger et al., 2025; Pfaff et al., 2025)
	Elaboration likelihood model (Li & Guo, 2021; Schär, 2021; Tsekouras et al., 2024)
	Cognitive load theory (Walser et al., 2019)
Decision-making, framing and judgment (9)	Prospect theory (Li & Guo, 2021)
	Salience theory (Cavegn et al., 2023; Michels et al., 2021, 2023)
	Framing theory (Brylla & Walsh, 2023)
	Goal framing theory (Huber et al., 2019)
	Perceived risk theory (Moriguchi et al., 2022)
	Privacy calculus theory (Reeck et al., 2024)
	Constructive preference theory (Liu & Karahanna, 2017)
	Theory of mood congruence (Ho & Lim, 2018)
	Theory of bounded rationality (Bahreini et al., 2023; Figl et al., 2021)
Self, motivation and personality (6)	Self-determination theory (Babar et al., 2023; Li et al., 2022; Rauh et al., 2024; Shi et al., 2025)
	Self-perception theory (Terres et al., 2019)
	Ego utility theory (Shi et al., 2025)
	Attribution Theory (Pethig et al., 2025)
	Regulatory focus theory (Schneider et al., 2017)
	Five factor model of personality traits (Poniatowski & Neumann, 2020)
Social and interpersonal (5)	Social comparison theory (Shi et al., 2025; Staudt et al., 2021)
	Social conformity (Li et al., 2021)
	Social impact theory (Schär et al., 2022)
	Social influence (Theory of isomorphism) (Kretzer & Maedche, 2018)
	Social presence theory (Li et al., 2022)
Behavior change and regulation (8)	Control theory (Sengupta et al., 2020)
	Cognitive dissonance theory (Sengupta et al., 2020)
	Theory of planned behavior (Peters & Wieland, 2023)
	Transtheoretical model (Babar et al., 2023)
	Technostress theory (Peters & Wieland, 2023)
	Boundary theory (Klesel et al., 2016)
	Fogg behavioral model (Bergram et al., 2020; Sutanto et al., 2021)
	Hook model (Purohit & Holzer, 2021)
Organizational, argumentation and others (5)	Innovation resistance theory (Stryja et al., 2017)
	Sensemaking theory (Degirmenci & Recker, 2018)
	Toulmin's model of argumentation (Schneider et al., 2017)
	Theory of team coaching (Gupta et al., 2024)
	Value co-creation theory (Lu & Wang, 2023)

Note: * counts the number of distinct theories within that group, not the number of studies.

4.7 Outcomes Measured

Table 6 shows the categories of outcomes (dependent variables) measured in the reviewed studies. The majority of studies (41 studies) assessed exclusively behavioral outcomes, while nine studies assessed a combination of behavioral and psychological (five studies) or behavioral and performance (four studies)

outcomes. Additionally, 12 studies assessed only psychological outcomes, three studies examined performance outcomes exclusively, and one study reported a combination of all three (behavioral, performance, and psychological outcomes). Behavioral outcomes refer to actual, observable actions and choices made by users. These are typically measured using objective trace data logged directly by the digital platforms, such as clicking a specific button or downloading an app (Tsekouras et al., 2024), purchasing a product (Gottschewski-Meyer et al., 2024), donating money (Lee et al., 2023; Staudt et al., 2021), or the exact amount of time a user spends engaging with an online platform (Bernards et al., 2024). Psychological outcomes capture users' internal cognitive and affective states. These are generally evaluated using self-reported survey scales that measure constructs such as users' attitudes and choice satisfaction (Figl et al., 2021), perceived autonomy and sense of manipulation (Bergram et al., 2024), or believability and cognitive models (Olenberger et al., 2025). Performance outcomes measure the objective success, execution, and quality of a completed task. Examples of performance metrics include achieving higher final exam scores in a digital learning environment (Bernards et al., 2024) or the objective quality and success of a user's contributions to an online community (Pethig et al., 2025).

Table 6. Outcome Types and Examples of Outcomes Measured

Outcome type (Number of studies)	References
Behavioral only (41)	(Auf der Landwehr et al., 2021; Babar et al., 2023; Bahreini et al., 2023; Berger et al., 2020, 2022; Cavegn et al., 2023; Degirmenci & Recker, 2018; Franzoi & vom Brocke, 2022; Gottschewski-Meyer et al., 2024; Habla et al., 2024, 2025; Huber et al., 2019; Jesse & Jannach, 2021b; Kretzer & Maedche, 2018; Kroll et al., 2019; Lee et al., 2023; Li et al., 2022; Lu et al., 2019; Mager & Kranz, 2021; Michels et al., 2021, 2023; Moriguchi et al., 2022; Peters & Wieland, 2023; Pfaff et al., 2025; Poniatowski & Neumann, 2020; Rafai et al., 2022; Schär, 2021; Schneider et al., 2017; Schürmann et al., 2023; Sengupta et al., 2020; Shi et al., 2025; Shukla et al., 2025; Staudt et al., 2021; Stryja et al., 2017; Sutanto et al., 2021; Székely et al., 2016; Tsekouras et al., 2024; van Oldenbeek et al., 2019; Wrabel, 2025; Zhang et al., 2020; Zimmermann et al., 2023).
Psychological only (12)	(Dennis et al., 2020; Fang et al., 2023; Helinski et al., 2024; Kim & Dennis, 2019; Klesel et al., 2016; Liu & Karahanna, 2017; Lu & Wang, 2023; Olenberger et al., 2025; Rauh et al., 2024; Reeck et al., 2024; Schär et al., 2022; Terres et al., 2019).
Performance only (3)	(Gupta et al., 2024; Henkel et al., 2019; Walser et al., 2019).
Behavioral and psychological (5)	(Bergram et al., 2024; Brylla & Walsh, 2023; Figl et al., 2021; Ho & Lim, 2018; Purohit et al., 2021).
Behavioral and performance (4)	(Bergram et al., 2020; Bernards et al., 2024; Li & Guo, 2021; Li et al., 2021).
Behavioral and psychological and performance (1)	Pethig et al. (2025).

Correspondingly, the analysis of the data sources used in the studies reveals a predominant reliance on trace/log data, such as clicks, purchases, and system logs (47 studies) (e.g., Auf der Landwehr et al., 2021; Bahreini et al., 2023; Cavegn et al., 2023; Gupta et al., 2024; Habla et al., 2025; Lee et al., 2023; Schürmann et al., 2023; Shukla et al., 2025; Zimmermann et al., 2023). In contrast, 13 studies used self-report data only (e.g., Babar et al., 2023; Brylla & Walsh, 2023; Fang et al., 2023; Helinski et al., 2024; Kim & Dennis, 2019; Klesel et al., 2016; Rauh et al., 2024). Additionally, six studies used both trace/log and self-report data (Bergram et al., 2020; Bergram et al., 2024; Bernards et al., 2024; Figl et al., 2021; Ho & Lim, 2018; Purohit et al., 2021).

4.8 Effects of Nudges on Measured Outcomes

This section synthesizes the effects of nudge mechanisms as reported in the reviewed studies. To facilitate comparison across studies, we organized the findings by the number of nudge categories used in each intervention. This structure enables us to examine whether nudge effects differ when mechanisms are applied in isolation versus in combination and to identify potential synergistic, substitution, or moderation effects across nudge categories.

4.8.1 Effects of Interventions Using a Single Nudge Category

Thirty-three studies examined interventions comprising nudges from a single category, either **decision information**, **decision structure**, or **social decision appeal**. In contrast, decision assistance nudges were never examined in isolation and appeared only in conjunction with nudges from other categories.

Twenty-two studies exclusively used **decision information** nudges, across seven application domains, including e-commerce (Dennis et al., 2020; Ho & Lim, 2018; Liu & Karahanna, 2017; Moriguchi et al., 2022; Poniatowski & Neumann, 2020; Rafai et al., 2022; Tsekouras et al., 2024), sustainability (Brylla & Walsh, 2023; Degirmenci & Recker, 2018; Habla et al., 2024; Helinski et al., 2024; Huber et al., 2019; Peters & Wieland, 2023; Rauh et al., 2024), privacy and security (Pfaff et al., 2025; Reeck et al., 2024; Schneider et al., 2017), health and well-being (Michels et al., 2021), education (van Oldenbeek et al., 2019), technology adoption and use (Purohit et al., 2021), and social interaction contexts (Fang et al., 2023; Olenberger et al., 2025). The studies used mechanisms that *make information visible*, *increase the salience of information*, *phrase information*, and *translate information*. Findings from these studies suggest that mechanisms that make information visible and increase its salience produce more consistent positive effects across contexts than mechanisms that phrase or translate information, whose effectiveness appears more sensitive to contextual differences and individual preferences.

Mechanisms that *make information visible* were associated with predominantly positive effects across sustainability, privacy and security, education, technology use, social interaction, and e-commerce contexts. However, several studies identified important boundary conditions and unintended consequences. Disclosure nudges increased sustainable choices and behaviors (Degirmenci & Recker, 2018; Helinski et al., 2024; Peters & Wieland, 2023), although the effectiveness of digital information nudging weakened as technostress increased (Peters & Wieland, 2023). Informing users about the environmental consequences of product returns reduced return intentions and purchase motivation, highlighting potential unintended consequences (Rauh et al., 2024). In privacy and security contexts, disclosure risk education reduced willingness to disclose personal information (Reeck et al., 2024), explanatory nudges increased compliance (Pfaff et al., 2025), and providing targeting descriptions increased click intentions despite negative reactions to explicit targeting disclosures (Tsekouras et al., 2024). Feedback nudges increased learning engagement and reduced digital consumption (Purohit et al., 2021; van Oldenbeek et al., 2019), while warning nudges reduced the believability of misinformation and increased acceptance of more diverse content (Fang et al., 2023; Olenberger et al., 2025). Furthermore, comparative information and personalized matching information increased the weight consumers assigned to available information and influenced purchasing intentions (Ho & Lim, 2018; Liu & Karahanna, 2017).

The limited evidence on mechanisms that *increase the salience of information* suggests mostly positive effects, although effectiveness varied across application domains. Eco-label nudges increased sustainable transport and fare selections (Habla et al., 2024), visual salience nudges improved healthy choices (Michels et al., 2021), visual security nudges increased compliance (Pfaff et al., 2025), and increasing the amount of information available increased the weight consumers assigned to information during decision-making (Liu & Karahanna, 2017). However, information retargeting in e-commerce settings generally failed to increase purchase responses except when emphasizing return information (Moriguchi et al., 2022). Notably, combining visual and informational security nudges produced stronger compliance effects than either nudge alone (Pfaff et al., 2025).

Evidence for mechanisms that *phrase information* was mixed. Framing nudges increased sustainable choices when emphasizing cost, job conditions, or personal convenience (Brylla & Walsh, 2023; Huber et al., 2019), while promotional and prevention claims became more effective when accompanied by supporting data (Schneider et al., 2017). Greater information coherence also increased the weight consumers assigned to review information (Liu & Karahanna, 2017). However, environmental framing produced no significant effects, social framing reduced sustainable behavior (Huber et al., 2019), prevention-focused claims reduced conversion rates when presented alone (Schneider et al., 2017), decoy nudges produced no significant effects (Rafai et al., 2022), and priming effects were generally small and dependent on the purchasing context (Dennis et al., 2020). Similarly, the effectiveness of utilitarian and hedonic framing varied depending on whether consumers were explicitly informed about targeting practices (Tsekouras et al., 2024).

Although limited, the evidence available on mechanisms that *translate information* suggests positive effects. Explicitly mapping information increased review quality and review length (Poniatowski &

Neumann, 2020), while reducing ambiguity and providing personalized matching information influenced consumers' purchase evaluations and urge to buy, with the effects varying according to users' mood states (Ho & Lim, 2018).

Next, we turn to studies that used **decision structure** nudge mechanisms only (five studies). These studies investigated nudges in privacy and security (Bahreini et al., 2023; Mager & Kranz, 2021), e-commerce (Figl et al., 2021), sustainability (Franzoi & vom Brocke, 2022), and innovation (Walser et al., 2019) contexts. The studies drew on mechanisms that *change choice defaults*, *change the range or composition of options*, *change option-related effort*, and *change option consequences*. Although the small number of studies limits broader conclusions about the relative effectiveness of different decision structure mechanisms, evidence suggests that mechanisms that *change choice defaults* are generally effective. High-security default settings increased users' security levels in privacy and security contexts (Bahreini et al., 2023), while status quo defaults increased sustainability-related contributions (Franzoi & vom Brocke, 2022). In e-commerce settings, defaults were associated with greater acceptance; however, high-priced defaults also increased consumer skepticism (Figl et al., 2021). Mechanisms that *change the range or composition of options* likewise produced positive outcomes. Presenting options in decreasing order increased acceptance, reduced perceived difficulty, and improved satisfaction (Figl et al., 2021), while partitioning information into categories improved decision accuracy by encouraging more deliberate processing (Walser et al., 2019). Evidence for mechanisms that *change option-related effort* and *change option consequences* was limited to a single study in a privacy and security context. This study found that creating friction by omitting a reject option produced only a small, non-significant increase in acceptance, whereas monetary incentives significantly increased acceptance rates (Mager & Kranz, 2021). Moreover, the combination of friction and monetary incentives produced stronger effects than either mechanism alone (Mager & Kranz, 2021).

Lastly, six studies examined **social decision appeal** nudge mechanisms exclusively. These studies investigated nudges in social interaction (Pethig et al., 2025; Shi et al., 2025), e-commerce (Schär, 2021; Schär et al., 2022; Zhang et al., 2020), and technology adoption and use contexts (Kretzer et al., 2018). The studies examined mechanisms that provide a *social reference point*, *instigate empathy*, and *increase the reputation of the messenger*.

Mechanisms that provide *social reference points* were examined most often. Evidence from e-commerce contexts was mixed. While descriptive social norms increased consumer voice (Zhang et al., 2020) and positively influenced pre-purchase decisions (Schär, 2021), they had no significant effect on consumption behavior in a follow-up study (Schär et al., 2022). Similarly, comparative popularity feedback in social interaction settings produced heterogeneous effects, increasing self-marketing efforts and reducing selectivity among low-popularity users, while having the opposite effects among high-popularity users. In contrast, absolute popularity feedback did not significantly affect users' adaptation strategies or engagement (Shi et al., 2025). In technology adoption and use settings, social cohesion and institutional isomorphism increased the likelihood of acceptance of recommendations (Kretzer & Maedche, 2018).

Evidence for mechanisms that *instigate empathy* and *increase the reputation of the messenger* was limited but positive within the contexts examined. Invoking reciprocity through a newcomer nudge increased comment volume, positive sentiment, and user retention in an online community, although it did not significantly affect contribution quality or effort (Pethig et al., 2025). Likewise, hierarchical power cues increased recommendation acceptance in technology adoption and use settings (Kretzer & Maedche, 2018).

4.8.2 Effects of Interventions Using Two Nudge Categories

We identified 29 studies that examined interventions combining nudges from two categories. Five two-category combinations were observed: **decision information** and **decision structure**; **decision information** and **social decision appeal**; **decision information** and **decision assistance**; **decision assistance** and **social decision appeal**; and **decision structure** and **social decision appeal**. No study used the decision structure - decision assistance combination without at least one additional nudge category.

The ten studies that used a combination of **decision information** and **decision structure** nudges were conducted in sustainability (Berger et al., 2022; Gottschewski-Meyer et al., 2024; Henkel et al., 2019; Stryja et al., 2017; Székely et al., 2016; Zimmermann et al., 2023), e-commerce (Lu et al., 2019; Lu & Wang, 2023), privacy and security (Bergram et al., 2020), and health and well-being contexts (Michels et

al., 2023). Most studies combined decision structure mechanisms that *change choice defaults* with decision information mechanisms that either *phrase information* (Berger et al., 2022; Gottschewski-Meyer et al., 2024; Henkel et al., 2019; Stryja et al., 2017; Székely et al., 2016; Zimmermann et al., 2023) or *increase the salience of information* (Lu et al., 2019; Lu & Wang, 2023; Michels et al., 2023). Less frequently, mechanisms that *make information visible* were paired with mechanisms that change choice defaults (Michels et al., 2023) or *change option-related effort* (Bergram et al., 2020). Only one study combined decision information (*phrase information*) with mechanisms that *change option consequences* (Gottschewski-Meyer et al., 2024). The findings from these studies suggest that decision structure nudges, particularly defaults, generally produce more reliable effects than decision information nudges. However, combining the two approaches can strengthen outcomes when the informational component complements the structural intervention, although such effects are not consistently observed across contexts. In sustainability contexts, default nudges repeatedly increased pro-environmental behavior (Berger et al., 2022; Gottschewski-Meyer et al., 2024; Henkel et al., 2019; Székely et al., 2016), and in some cases outperformed competing decision information nudges, including anchoring, hyperbolic discounting, and priming (Gottschewski-Meyer et al., 2024; Henkel et al., 2019). However, combining defaults with decision information mechanisms yielded mixed results. For example, while framing strengthened the effectiveness of default rules (Berger et al., 2022), and decoy nudges became effective only when paired with defaults (Zimmermann et al., 2023), priming provided no additional benefit beyond defaults alone (Henkel et al., 2019; Stryja et al., 2017). Evidence from e-commerce contexts similarly showed that both recommendation labels and default options improved outcomes independently, although combining them generated only limited gains beyond the strongest individual intervention (Lu et al., 2019; Lu & Wang, 2023). Furthermore, their effectiveness depended on user expertise, benefiting novices but reducing satisfaction among experts (Lu & Wang, 2023). In health and well-being contexts, digital salience nudges substantially improved healthy choices, while transparency enhanced the effectiveness of self-nudging interventions that were otherwise less effective than preset defaults (Michels et al., 2023). Finally, in privacy and security contexts, explicit choice mechanisms increased engagement with privacy information, and providing simplified alternatives further increased information-viewing behavior, although neither intervention improved information recall (Bergram et al., 2020).

Eight studies combining **decision information** and **social decision appeal** nudges were conducted in sustainability (Auf der Landwehr et al., 2021; Cavegn et al., 2023; Habla et al., 2025; Schürmann et al., 2023; Staudt et al., 2021), health and well-being (Li & Guo, 2021), privacy and security (Shukla et al., 2025), and social interaction contexts (Kim & Dennis, 2019). Studies combined social decision appeal mechanisms that provide a *social reference point* with decision information mechanisms that either *translate information* (Habla et al., 2025; Schürmann et al., 2023), *phrase information* (Auf der Landwehr et al., 2021; Kim & Dennis, 2019), or *make information visible* (Cavegn et al., 2023; Staudt et al., 2021). Less frequently, mechanisms that *instigate empathy* were paired with mechanisms that *phrase information* (Shukla et al., 2025) or *make information visible* (Li & Guo, 2021). One study combined social decision appeal mechanisms that *increase messenger reputation* with decision information mechanisms that *make information visible* (Staudt et al., 2021). Findings indicate that decision information nudges tend to have more predictable effects, whereas social decision appeal nudges are more sensitive to contextual factors such as culture, transparency, and personal relevance. In sustainability contexts, simplification, anchoring, and hyperbolic discounting were repeatedly found to increase sustainable behavior (Auf der Landwehr et al., 2021; Habla et al., 2025; Schürmann et al., 2023), whereas the effectiveness of social norms was highly context dependent. Social norm interventions were effective when aligned with contextual factors such as collectivist cultural values (Habla et al., 2025) or when accompanied by transparent explanations of their purpose (Cavegn et al., 2023) but were otherwise ineffective or even counterproductive (Auf der Landwehr et al., 2021; Schürmann et al., 2023). Similarly, social comparison rankings increased engagement, whereas social distance and messenger-status interventions produced no significant effects (Staudt et al., 2021). In health and well-being contexts, framing had no significant effect, although emotional appeals improved message comprehension relative to rational appeals (Li & Guo, 2021). In privacy and security contexts, self-benefit and physician-benefit framing, as well as open moral appeals, positively influenced review submission and identity disclosure, whereas appeals emphasizing benefits to others were ineffective (Shukla et al., 2025). Likewise, in social interaction settings, source ratings influenced judgments of article credibility more strongly than informational formatting cues (Kim & Dennis, 2019).

Four studies combined **decision information** and **decision assistance**, pairing nudges that *make information visible* or *phrase information* with those that *provide reminders* (Bernards et al., 2024;

Sengupta et al., 2020; Sutanto et al., 2021) or *facilitate commitment* (Terres et al., 2019). Studies were conducted in the contexts of technology adoption and use (Terres et al., 2019), education (Bernards et al., 2024), health and well-being (Sengupta et al., 2020), and sustainability (Sutanto et al., 2021). The studies show that while both decision information and decision assistance nudges can positively influence behavior, decision assistance nudges are most effective when they reinforce or complement informational interventions. At the same time, individual differences play an important role in determining their effectiveness. In technology adoption contexts, both personalization and commitment nudges independently increased intentions to use technology, while their combination produced a substantially stronger effect than either intervention alone, indicating a complementary relationship between commitment and personalized information (Terres et al., 2019). In educational contexts, individualized digital nudges improved engagement with course content but did not significantly affect exam performance, learning time, or attendance. Their effect was also stronger among students with lower self-regulated learning skills (Bernards et al., 2024). In health and well-being contexts, both ecological momentary assessment prompts and reminder messages increased daily physical activity, with evidence suggesting that their combined use further reinforced behavioral change (Sengupta et al., 2020). Finally, in sustainability contexts, the effectiveness of nudges depended on consumer characteristics, with framing messages proving more effective for cynical consumers and reminder-based interventions proving more effective for caring consumers (Sutanto et al., 2021).

In addition, four studies combining **decision assistance** and **social decision appeal** nudges were conducted in sustainability (Kroll et al., 2019), health and well-being (Babar et al., 2023), education (Li et al., 2021), and technology adoption and use contexts (Li et al., 2022). These studies paired decision assistance mechanisms that *provide reminders* with social decision appeal mechanisms that *provide social reference points* (Li et al., 2021; Li et al., 2022) or *instigate empathy* (Babar et al., 2023). Kroll et al. (2019) combined mechanisms that *facilitate commitment* (decision assistance) with mechanisms that *provide a social reference point* (social decision appeal). Results from these studies show that social decision appeal mechanisms are generally more effective when reinforced by decision assistance interventions, although individual characteristics, context, and intervention duration often moderate their impact. In sustainability contexts, neither social norms nor self-commitment interventions produced significant effects when implemented independently; however, their combination resulted in the highest level of energy-saving behavior, indicating a complementary effect between the two approaches (Kroll et al., 2019). In health and well-being contexts, motivational reminder messages increased engagement among inactive users, while social support cues initially produced positive effects that diminished over time and became negative after extended exposure (Babar et al., 2023). The effectiveness of reminder messages also varied according to users' tenure, becoming more positive among long-term users (Babar et al., 2023). In educational contexts, reminder messages alone did not reduce procrastination, whereas peer information produced mixed effects that were strongly moderated by individual and contextual characteristics. Peer information was particularly effective for male students, students with poorer prior performance, and those operating in competitive or male-majority environments (Li et al., 2021). Similarly, in technology adoption contexts, social nudges increased engagement during implementation, whereas reminder-enhanced social nudges produced weaker immediate effects but greater persistence after the intervention was removed (Li et al., 2022).

Finally, three studies used **decision structure** and **social decision appeal** mechanisms. All three studies paired social decision appeal mechanisms that *provide social reference points* with decision structure mechanisms that either *change choice defaults* (Bergram et al., 2024; Gupta et al., 2024), *change option consequences* (Lee et al., 2023), *change the range or composition of options* (Gupta et al., 2024) or *change option-related effort* (Bergram et al., 2024). The studies' findings show that decision structure nudges, particularly those that alter effort or incentives, tend to produce more reliable effects than social decision appeal nudges, and that combining them may enhance behavioral outcomes when the interventions reinforce one another. In digital philanthropy contexts, friction-based interventions significantly increased donations and compliance, whereas default settings and social norms alone had little or no effect. However, combining all three interventions substantially improved outcomes, resulting in almost fourfold higher odds of compliance than in the control condition (Bergram et al., 2024). Similarly, Lee et al. (2023) found that both micro-incentives and audience visibility cues increased donation rates, although their effectiveness depended on factors such as subsidy rates and timing. In social interaction contexts, Gupta et al. (2024) found that a skill-facilitator bot improved skill use, whereas a strategy-facilitator bot had no significant effect. Prompted choice interventions (to-do lists) produced mixed results, while feedback displays reduced user effort (Gupta et al., 2024).

4.8.3 Effects of Interventions Combining Three or More Nudge Categories

We identified only four studies that combined nudges from more than two nudge categories. Three studies combined **decision information**, **decision structure**, and **social decision appeal** nudges (Berger et al., 2020; Jesse & Jannach, 2021b; Wrabel, 2025), while one study combined all four nudge categories, including **decision assistance** (Klesel et al., 2016). Decision information mechanisms included those that *translate information* (Berger et al., 2020; Wrabel, 2025), *increase the salience of information* (Jesse & Jannach, 2021b), *make information visible* (Jesse & Jannach, 2021b; Klesel et al., 2016), and *phrase information* (Klesel et al., 2016; Wrabel, 2025). These were combined with decision structure mechanisms that *change choice defaults* (Berger et al., 2020; Jesse & Jannach, 2021b; Klesel et al., 2016), *change option consequences* (Wrabel, 2025), *change option-related effort* (Klesel et al., 2016), and *change the range or composition of options* (Klesel et al., 2016). All four studies employed social decision appeal mechanisms that *provide social reference points*. In addition, Klesel et al. (2016) incorporated decision assistance mechanisms that *facilitate commitment* and *provide reminders*.

Findings provide limited evidence that combining multiple nudge categories consistently improves outcomes. Berger et al. (2020) found that default rules positively influenced sustainable food choices when environmental motives were controlled for, whereas social norms had no significant effect, and simplification was effective only among environmentally conscious individuals. Similarly, Jesse and Jannach (2021b) found that defaults, highlighting, and social nudges were ineffective when implemented individually, although combining social and default nudges increased healthy food choices, and a warning nudge was effective when implemented alone. Wrabel (2025) found that a simplification nudge increased sustainable product choices when evaluated in isolation, but its effectiveness declined when users were simultaneously exposed to competing popularity, recommendation, scarcity, and price-discount nudges. In the only study combining all four nudge categories (Klesel., 2016), disclosure, ease, and eliciting intention nudges produced higher work discontinuance intentions than an enforcement baseline, whereas reminder nudges had a negative effect, and the remaining nudges, including defaults, decision aids, rescaling, social norms, precommitment, past-experience prompts, time-window framing, labels, and warnings, did not significantly differ from the baseline.

5 Discussion

This study reviewed 66 quantitative empirical studies on digital nudging in information systems. Based on the substantive synthesis of the reviewed literature, we identified six key research avenues. These avenues reflect recurring patterns and gaps across study designs, samples, application domains, nudge types, theoretical foundations, and outcomes measured. Collectively, the research avenues highlight areas where the current evidence base remains limited and where further research is needed. In the following sections, we discuss identified research avenues, and the limitations of our review.

5.1 Summary of Findings and Research Avenues

In the following sections, we summarize the findings, outline research avenues, and provide specific recommendations for future work.

5.1.1 Research Avenue 1: Ecological Validity and Population Generalizability

We found that a substantial proportion of the reviewed literature examined low- or moderate stakes decisions, frequently through online or laboratory experiments. Only a handful of studies involved high-stakes scenarios with significant personal, financial, educational, or health consequences (namely, Bernards et al., 2024; Li et al., 2021; Rafai et al., 2022; Sengupta et al., 2020; Shukla et al., 2025). The cross analysis of nudge categories and task design characteristics further shows that decision information, decision structure, and social decision appeal nudges have been examined primarily in low-stakes contexts (see **Table 4**). As a result, the current knowledge about the effectiveness of most digital nudges is largely derived from decisions with low-level consequences, creating uncertainty about whether these findings generalize to high-stakes environments where users face consequential, potentially irreversible outcomes. Participants who face no real financial cost or consequence may behave differently from those making real purchases or other consequential decisions. Their intended behavior in hypothetical experiments may therefore differ from their actual behavior in real-world settings (Auf der Landwehr et al., 2021; Dennis, 2020; Franzoi & vom Brocke, 2022; Habla et al., 2024; Michels et al., 2023; Schneider et al., 2017). Thus, the resulting ecological validity gap concerns not only whether a nudge works outside an

experimental setting, but also whether the magnitude, direction, persistence, and unintended consequences of its effects change as the stakes increase. Future research should therefore compare the same nudge mechanism across controlled low-stakes conditions and consequential field settings. Multi-study designs that maintain comparable interventions and outcome measures across settings would help isolate whether observed differences arise from stakes levels, experimental contexts, participant composition, or the nudge itself. Researchers should also prioritize preregistered field experiments embedded in operational digital environments, such as live checkouts, workplace systems, educational platforms, healthcare applications, and genuine online marketplaces, while implementing the ethical and practical safeguards required in high-stakes settings.

Additionally, a substantial proportion of the reviewed research relied on samples from crowdsourced work platforms (e.g., Bergram et al., 2024; Michels et al., 2023) and university student cohorts (e.g., Henkel et al., 2019; van Oldenbeek et al., 2019). By comparison, only 10 studies evaluated real-world platform users or clinical participants, such as medical patients (Sengupta et al., 2020; Shukla et al., 2025), active mobile application users (Terres et al., 2019), or electric vehicle owners (Huber et al., 2019). Furthermore, only three studies featured actual corporate employees operating in their professional environments (Babar et al., 2023; Klesel et al., 2016; Pfaff et al., 2025). This distribution highlights a significant generalizability gap regarding whether findings from convenience samples generalize to the broader consumer, employee, and patient populations that digital choice architectures are ultimately built to influence. Because digital nudges increasingly shape daily work routines, healthcare interactions, and high consequence consumption decisions (Jesse & Jannach, 2021a; Ruehle, 2023; Sadeghian & Otarkhani, 2024; Steinhauser & Raptis, 2023), evaluating the behavioral responses of actual target populations in situ remains a critical priority. The concentration of evidence among crowd workers and university students restricts the external validity of the current literature, as these cohorts may systematically differ from intended end-users in cognitive traits, motivation, and situational constraints. However, because these differences were rarely measured or modeled directly, it remains unclear whether variations in nudge effectiveness are attributable to interface design, participant characteristics, or the decision context. Future research should therefore replicate established digital nudge effects among target populations in their natural environments. Studies must systematically capture and control key individual characteristics, such as age, occupation, digital literacy, prior platform experience, and decision familiarity, rather than assuming sample categories are homogeneous, thereby identifying the boundary conditions of digital interventions.

5.1.2 Research Avenue 2: Long-Term Behavioral Persistence, Habituation, and Post-Intervention Dynamics

Another key limitation of the current digital nudging literature is its overwhelming focus on one-shot decisions or brief experimental windows. This leaves a significant gap in our understanding of whether nudge-induced behavioral changes endure over time or vanish once the intervention is withdrawn. As shown in **Table 4**, this limitation is particularly pronounced for social decision appeal nudges, which were examined more often in one-shot decision contexts than in repeated-task settings. As a result, relatively little is known about whether social influence mechanisms such as social norms, comparison cues, and reputation signals remain effective under repeated exposure or whether their influence diminishes through habituation over time. Repeated exposure to basic nudges can lead to habituation or mental fatigue, making them less effective over time. For example, in a longitudinal field study of a corporate wellness program, Babar et al. (2023) demonstrated that while light social support (such as digital “kudos”) motivates initial physical activity, repeated exposure over several months accelerates the onset of tedium and renders the intervention less effective as its novelty wears off. Similarly, routine reminders often lose their potency over time. Klesel et al. (2016) noted that simple temporal notifications failed to curb work habits because employees quickly habituated to repetitive stimuli in an already notification-saturated environment. Conversely, certain interactive and context-aware interventions can sustain engagement without triggering habituation, as shown by Sengupta et al. (2020), who demonstrated that repeatedly prompting cardiac patients with daily ecological momentary assessment (EMA) surveys successfully nudged and sustained walking behaviors over a continuous 91-day period.

Furthermore, the relationship between active nudge deployment and post-intervention behavior is highly complex, frequently involving a trade-off between short-term friction and long-term autonomy. In a large-scale randomized field experiment, Li et al. (2022) revealed that during active deployment, appending a red-dot reminder to a social nudge (a “reminding social nudge”) actually decreased immediate user engagement compared to a social nudge alone, as the aggressive reminder incurred interruption costs

and threatened users' self-determination. Remarkably, however, once the interventions were removed, the reminding social nudge group exhibited significantly higher and more persistent engagement than the social nudge group. This delayed post-intervention effect occurred because the high-salience red-dot notifications had successfully driven conscious cognitive processing and habit formation during the treatment period; once the annoying reminder was removed, users regained their perceived autonomy, internalizing the newly formed habit as intrinsically motivated.

To resolve these temporal complexities, future research should prioritize longitudinal field studies that incorporate explicit post-treatment observation phases to evaluate behavior after nudges are systematically withdrawn. In particular, studies could examine the temporal persistence of social decision appeal nudges in repeated decision environments and compare their long-term effectiveness with decision information and decision structure nudges, which have been studied across a broader range of temporal settings. Researchers should investigate how the long-term trajectory of digital nudges varies by mechanism type, contrasting passive, structure-based nudges (such as defaults) with active, informational nudges (such as feedback and reminders). Future work should also explore adaptive and dynamic choice architectures that automatically taper, randomize, or fade the frequency of interventions over time, minimizing cognitive fatigue and reactance while fostering genuine, long-term habit internalization.

5.1.3 Research Avenue 3: Application Domain Coverage and Cross-Domain Generalizability

While this systematic review mapped nine distinct application domains, empirical coverage across literature is highly uneven. Most current knowledge comes from sustainability (e.g., green defaults and carbon offsetting) and e-commerce (e.g., shopping carts, recommendation agents, and product returns). In stark contrast, critical digital environments remain significantly underexplored: innovation was investigated in only one study (namely, Gupta et al., 2024, evaluating collective intelligence in collaborative teams), digital philanthropy in just two (e.g., Dennis, 2020, on charitable bidding), and education in only three (Bernards et al., 2024; Li et al., 2021; van Oldenbeek et al., 2019). Consequently, our understanding of digital choice architecture is heavily biased toward consumer-oriented domains, and it remains unclear whether these nudge mechanisms generalize to domains characterized by different goals, motivations, and decision-making processes. The concentration of studies in certain domains represents a major boundary condition because task structures, user motivations, and cognitive processing modes differ fundamentally across domains. In e-commerce and sustainability, choices are often driven by quick, low-involvement heuristic processing (System 1), where passive defaults or simple visual salience cues are highly effective. However, in domains such as education, healthcare, and corporate innovation, decisions are often driven by high-involvement, deliberate reasoning (System 2), professional norms, and deeply ingrained intrinsic motivations. For example, a student's engagement on a learning platform or a team's collaborative problem-solving process cannot be easily guided by simple aesthetic nudges without considering their cognitive capacity and personal goals (Fiore & Wiltshire, 2016; Järvelä et al., 2018). Future research should therefore systematically test established choice architecture mechanisms in understudied domains such as digital philanthropy, workplace collaboration, and patient-centered healthcare. Replicating and comparing identical nudge mechanisms across contrasting domains would allow researchers to isolate how domain-specific cognitive demands and motivational profiles shape user receptivity to digital interventions.

5.1.4 Research Avenue 4: Isolating Decision Assistance Nudges

Of the 33 studies that tested only one nudge category, decision information nudges were used far more often (22 studies) than decision structure nudges (five studies) or social decision appeal nudges (six studies). None of the included studies examined decision assistance nudges alone; all nudges in this category were combined with one or more from other categories, making it difficult to isolate their behavioral and psychological effects. This gap is important because decision assistance nudges have produced mixed, and sometimes counterproductive, outcomes. Klesel et al. (2016), in their empirical study of work-life boundaries, found that while nudges such as disclosure and ease significantly increased work-discontinuance intentions, the reminder nudge was the only design option that exhibited a significant negative relationship with user intentions. The authors found that merely alerting participants that their shifts were over actually discouraged, instead of encouraging them to disconnect. They theorized that, because modern workers are already bombarded with notifications, users may quickly habituate routine reminders that lack cognitive substance or a compelling contextual rationale explaining why they should stop working, thereby rendering such reminders ineffective or even irritating. Similarly, Li et al. (2022)

found that adding a red-dot reminder to a social nudge reduced immediate engagement, even though the social nudge was effective on its own. Without control groups that test each mechanism separately, it is difficult to identify whether outcomes are driven by the choice structure, the assistance provided, or the interaction between the two. Future research should systematically test decision assistance nudges on their own before combining them with other nudge types, so that their effects can be properly identified. Researchers should also explore how the delivery modality of decision assistance influences user receptivity. Future research should contrast low-friction, ambient assistance, such as passive progress bars or in-app visual cues, with high-friction, interruptive assistance, such as pop-ups or haptic device alerts. Such comparisons would help identify the threshold at which helpful digital guidance becomes cognitive overload, interruptions, and user fatigue. Finally, future studies should investigate adaptive and user-controlled forms of decision assistance to help users remain engaged and receptive to the support provided. Such interventions could dynamically adjust notification frequency or allow users to co-create and customize their reminder parameters, as illustrated by the customizable feedback shortcuts evaluated by Purohit et al. (2021). Providing users with greater control over the timing, frequency, and delivery of assistance may preserve their sense of autonomy while promoting the long-term internalization of newly formed habits.

5.1.5 Research Avenue 5: Overcoming Theoretical Fragmentation

Only 46 of the 66 studies clearly stated a theoretical basis beyond nudge theory itself, and together these studies drew on 36 different theories. Most of these theories, such as ego utility theory (Shi et al., 2025), sensemaking theory (Degirmenci & Recker, 2018), and theory of team coaching (Gupta et al., 2024), were used in only one study each, and only seven studies drew on more than one theory at all (Babar et al., 2023; Li & Guo, 2021; Li et al., 2022; Peters & Wieland, 2023; Schneider et al., 2017; Sengupta et al., 2020; Shi et al., 2025). This scattered use of theory makes it difficult to compare and build on findings across studies, as similar nudge mechanisms are often explained through different theoretical perspectives or not explicitly grounded in theory. Future research should therefore use theory not merely to justify interventions but to test why they work. Researchers could compare competing explanations within the same study, for example, whether defaults influence behavior by reducing cognitive effort or because users interpret them as recommendations. They should also directly measure proposed mechanisms, such as cognitive load, perceived autonomy, or social comparison, rather than assuming that these mechanisms explain the observed effects. This approach could support the development of integrative frameworks explaining how digital interface features interact with user characteristics to influence behavior.

5.1.6 Research Avenue 6: Integrating Behavioral, Psychological, and Performance Outcomes

Another key gap in the reviewed literature is the limited integration of behavioral, psychological, and performance outcomes within the same study. Most studies assessed behavioral outcomes only, often through trace or log data such as clicks, purchases, downloads, donations, or time spent on a platform. Although such measures are useful because they capture actual behavior rather than stated intentions, they provide only a partial account of how digital nudges work. Behavioral data can show whether users responded to a nudge, but they cannot explain, for example, why they responded, how they interpreted the intervention, or whether the behavior reflected acceptance, confusion, habit, or perceived pressure. This limitation is important because digital nudging operates through changes to the choice architecture of digital interfaces, where design features can influence decisions without users necessarily noticing or consciously evaluating them (Mirsch et al., 2017; Weinmann et al., 2016).

This gap is particularly relevant for questions of autonomy, transparency, manipulation, trust, and user agency. Prior work has argued that the ethical acceptability of nudging cannot be judged solely by its behavioral effectiveness but must also consider whether individuals retain meaningful freedom of choice and whether interventions respect autonomy, remain transparent, and avoid manipulation (Schmidt & Engelen, 2020). In digital environments, these concerns may be more pronounced because interface features can be personalized, continuously tested, and embedded into routine interactions at scale (Sadeghian & Otarkhani, 2024). For example, a user may click a recommended option, purchase a product, or donate money, but these behaviors do not show whether the user understood the nudge, endorsed its goal, trusted the interface, or felt free to choose otherwise. Studies that rely only on observable behavior may therefore overstate the effectiveness or legitimacy of nudges by overlooking users' subjective experiences.

Future research should make greater use of mixed outcome designs that combine trace or log data with validated self-report measures. Such designs would allow researchers to examine both the behavioral effects of digital nudges and the psychological outcomes, or user experiences associated with those effects. Some of the reviewed studies show the value of this approach. Bergram et al. (2024), for instance, measured actual donation behavior alongside perceived threat to autonomy, perceived manipulation, and user experience, while Helinski et al. (2024) combined a behavioral choice task with post-decision measures of perceived autonomy and decision comfort. Rauh et al. (2024) also illustrate the usefulness of theoretically grounded psychological measures by drawing on self-determination theory to assess perceived autonomy in the context of green nudges. Building on such work, future studies could assess actual choices, clicks, purchases, donations, or task completion together with perceived autonomy, perceived manipulation, trust, comprehension, perceived transparency, satisfaction, and decision comfort.

More studies are also needed that include performance outcomes, particularly in contexts where the quality of the user's action matters as much as the action itself. In digital learning, online collaboration, health, or community platforms, the desired outcome is often not merely that users engage, click, or participate, but that they perform a task well, make informed decisions, or contribute meaningfully. Thus, research in this area would help move the field beyond measuring surface-level behavioral responses toward assessing whether nudges support meaningful and beneficial outcomes.

5.2 Limitations of the Study

This review has several limitations. First, the search period covered studies published between 2013 and 2025. Consequently, the review did not include potentially relevant papers published after October 2025. Nevertheless, the studies included in the final review span 2016 to 2025, representing a decade of research and capturing a substantial body of literature that provides valuable insights into the field. Future reviews should consider incorporating studies published after October 2025 to further update and extend these findings. Second, by design and in alignment with the research questions, the review excludes all conceptual, qualitative, and mixed-methods papers with qualitative components. While this decision ensures a focus on quantifiable behavioral and psychological effects of nudging, it excludes valuable insights from qualitative, mixed-methods, and conceptual research, especially regarding how users perceive, interpret, resist, and experience digital nudges, as well as broader ethical and societal implications. Furthermore, the review provides limited insight into broader organizational, institutional, and socio-political dimensions of digital nudging, including issues of legitimacy, autonomy, and power relations. Future research could further explore these perspectives through qualitative and conceptual perspectives. Third, while the selection of AIS Senior Scholars' journals and the top four IS conferences enhances the quality of the review insights, this criterion may have introduced disciplinary and topical blind spots. For example, nudging studies published in human-computer interaction or other interdisciplinary journals are excluded from consideration. Lastly, although the dual-coder approach helps mitigate individual bias, it may still introduce interpretive subjectivity, particularly in complex or multi-component interventions where various nudges are combined (for example, social norms with transparency). While we consistently and thoroughly discussed and resolved coding inconsistencies, some nudges may still have been overlooked, misclassified, or coded inconsistently.

6 Conclusion

This review synthesized 66 quantitative empirical studies on digital nudging in information systems published between 2016 and 2025. By focusing on studies that operationalize nudges as measurable constructs and report empirical findings, the review provides a consolidated account of how digital nudges have been designed, tested, and evaluated across IS research. The study makes three main contributions. First, it maps the current quantitative empirical evidence base by examining publication trends, study designs, samples, application domains, task characteristics, theories, nudge mechanisms, and outcome measures. The findings show that the literature is dominated by online experiments, low- and moderate-stakes tasks, crowd-worker and student samples, and studies focused on sustainability and e-commerce. In contrast, high-stakes field settings, organizational samples, psychological outcomes, and performance measures remain significantly less developed. Second, the review synthesizes the nudge mechanisms studied in IS across four categories: decision information, decision structure, decision assistance, and social decision appeal. It shows that decision information and decision structure nudges receive the most attention, while decision assistance nudges are rarely examined in isolation. This categorization highlights where the current empirical evidence is concentrated and identifies areas where

further empirical testing is needed. Third, the review shows that nudge effectiveness is highly context dependent. Mechanisms such as defaults, framing, salience, simplification, social norms, reminders, and commitment devices can successfully influence behavioral, psychological, and performance outcomes. However, their effects vary widely by application domain, task design, and user characteristics. When implemented together, nudges can strengthen one another's effects. However, combining multiple nudges can also be a double-edged sword. If too many nudges are layered together or applied too forcefully, they may become redundant, annoy users, or produce unintended outcomes. For researchers, these findings mean moving beyond isolated demonstrations of nudge effects toward more cumulative, theory-informed, and context-aware explanations of when, why, and for whom digital nudges work. For practitioners and system designers, the findings suggest that digital nudges should be carefully designed and evaluated, with attention not only to behavioral effectiveness but also to user autonomy, trust, transparency, and ethical acceptability.

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During the preparation of this work, the authors used Grammarly and Microsoft Copilot in order to clarify sentences, verify spelling and grammar, as well as refine the logical structure of some arguments.

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Appendix A: Existing Reviews

Table A1. Existing Literature Reviews on Nudging

Authors	Review question / objective	Type of review and number of papers	Focus/context	Core contribution
Valta and Maier (2025)	What are the conceptually grounded and empirically validated characteristics that describe digital nudges?	Systematic literature review (SLR) (88 quantitative and qualitative peer-review studies)	Broad/multi-domains	Developed a four-dimensional taxonomy (context, form, intrusiveness, user impact); clarification and consistent definition of digital nudge.
Sadeghian and Otarkhani (2024)	RQ1: What is the definition of Data-Driven DN, and what are its characteristics? RQ2: What types of data are employed in data-driven DN approaches? RQ3: What are the main approaches in designing and implementing data-driven digital nudges, and what roles do AI and data analytics play? RQ4: What are the main issues and challenges associated with data-driven DN interventions?	SLR (57 theoretical and conceptual studies, as well as applied and empirical studies)	Broad/multi-domains	Definitions of data-driven digital nudging; identification of key data sources of digital nudging (user profile, social media, contextual), digital nudging design approaches; ethical, privacy, and transparency issues
Zimmermann et al. (2021)	Organize, structure, integrate, and analyze the extant work on	SLR (43 empirical studies analyzing actual effect at individual level)	Sustainability (Pro environmental behavior)	A theoretical model categorizing nudges and discussion their effectiveness based on application timeline (before, during or after an action).
Schaer and Stanoevska-Slabeva (2019)	Digital nudges for pro-environmental behavior	SLR (Empirical (e.g., quantitative and qualitative) and literature reviews)	multi-channel, multi-owner customer journeys	Synthesized digital nudging along customer journeys (categorizing nudges by type and stage (pre-purchase, purchase, post-purchase)).
Jesse and Jannach (2021a)	What is the current state of research regarding the application of nudging along customer journeys?	SLR (63 empirical, conceptual/model papers and other reviews)	Recommender systems	Taxonomy of nudge mechanisms; mapping nudge mechanisms to underlying psychological phenomena; summarizing the effects of nudging mechanisms on user behavior in the context of recommender systems.
Fabricius et al. (2023)	Examine the relationship between digital nudging and recommender system	SRL (14 peer-review studies)	Digital dark nudging across multi-domains	Identify seven digital dark nudging instances (e.g., priming, scarcity, decoy, near miss, change effort, false expectations) across five domains.
Neuss and Zielke (2022)	What are instances of digital dark nudging across various research disciplines?	SRL (24 qualitative, quantitative, conceptual studies)	Personal finance	Identified useful nudge categories for finance applications.
Alsaeed et al. (2025)	What is the current state of research on using digital nudges to promote healthy and sustainable food choices in online grocery shopping?	Scoping review (74 peer-reviewed empirical studies)	Online grocery shopping / online supermarkets	Developed a conceptual framework based on the stimulus-organism-response (S-O-R) model summarizing digital nudging types (nudge function, design properties, decision points, and focus), their influence on human processing and perception, and their effectiveness for driving food choices.

Appendix B: Studies Reviewed in this Paper

Table B1. Summary of Reviewed Studies

Author (Year) / Outlet	Domain	Theoretical lens	Research design / Sample	Task design: repetition /complexity / stakes level	Nudges tested	Outcome measured	Data source	Summary of findings
Auf der Landwehr et al. (2021) / ECIS	SUS	Unclear	Online experiment /Mixed (students & employees)	One-shot / complex / low	Social Norms; Loss Aversion; Hyperbolic Discounting; Anchoring	Behavior (Nudge conversation rate)	Trace data	Hyperbolic discounting and anchoring positive; social norms and loss aversion ineffective.
Babar et al. (2023) / JAIS	HW	Self-determination theory; Transtheoretical model	Field experiment / Corporate employees	Repeated / moderate / moderate	Motivational messages; Light social support (kudos)	Behavior (Physical activity)	Self-report	Motivational messages help inactive and long-tenure users; kudos help initially but become negative over time.
Bahreini et al. (2023) / IM	PS	Theory of bounded rationality	Field experiment / Crowd working platform sample	One-shot / moderate-complex / moderate	Default security settings level	Behavior (user's decision security level)	Trace data	High-level security defaults significantly increased the security level
Berger et al. (2020) / ICIS	SUS	Dual process theory	Field experiment / General consumer sample	One-shot / moderate / moderate-high	Default rules; Simplification; Social norms	Behavior (Sustainable food choices)	Trace data	Defaults effective; simplification only works for environmentally conscious users; social norms ineffective.
Berger et al. (2022) / ECIS	SUS	Dual-process theory	Online experiment / Mixed (students & employees)	One-shot / moderate / low	Default Rules; Framing; Combined	Behavior (Energy conversation score)	Trace data	Defaults and framing both effective, with combined interventions producing the strongest results.
Bergram et al. (2020) / ECIS	PS	Fogg's Behavioral Model (FBM)	Multi-study (lab & field) / Crowd working sample & real app users	One-shot / simple-moderate / moderate-high	Explicit choice (throttling mindless activity); Suggesting user alternatives	Behavior (Viewed ToS /Privacy Policy; Reading time); Performance (Recall)	Trace data; Self-report	Explicit Choice effective for viewing behavior and reading time but not recall. Explicit Choice with Suggesting Alternatives effective for viewing behavior but not for reading time and recall.

Bergram et al. (2024) / ICIS	DP	Unclear	Online experiment / Crowd working platform sample	One-shot / simple-moderate / moderate	Default; Friction; Social Norm; Combined nudges	Behavior (Donation amount and compliance); Psychological (Perceived threat to autonomy; Perceived sense of manipulation; User experience)	Trace data; Self-report	Friction is the main driver of compliance; defaults and social nudges alone ineffective; combined nudges effective.
Bernards et al. (2024) / ICIS	EDU	Unclear	Field experiment /University students	Repeated / complex / high	Individualized Digital Nudges	Behavior (Time spent on online platform; Lecture attendance; Engagement with course material); Performance (Exame scores)	Trace data; Self-report	Increase engagement but not learning outcomes; strongest for low self-regulated learners.
Brylla and Walsh (2023) / ECIS	SUS	Framing theory	Online experiment / Crowd working platform sample	One-shot / simple / low-moderate	Job conditions frame; Environmental frame; Personal convenience frame	Behavior (Sustainable delivery choice); Psychological (Warm glow; Order completion; Loyalty; Word-of-mouth (WOM))	Self-report	All frames increase sustainable choices; environmental framing weakened by fees.
Cavegn et al. (2023) / AMCIS	SUS	Salience Theory	Online experiment / Crowd working platform sample	One-shot / moderate / low	Social norm (non-transparent); Social norm (transparent function); Social norm (transparent function/purpose)	Behavior (CO2 offset contribution)	Trace data	Social norms effective only when both function and purpose are transparently explained.
Degirmenci and Recker (2018) / AMCIS	SUS	Sensemaking Theory	Field experiment / Corporate employees	Repeated / moderate / low	Reflective disclosure; Information democratization	Behavior (Paper consumption)	Trace data	Both reflective disclosure and information democratization influence outcomes; combining them adds no further benefit.
Dennis et al. (2020) / JMIS	ECO	Dual Process Theory (System 1 and System 2)	Lab experiment / University students	Repeated / moderate / low	Numeric Priming; Semantic Priming	Psychological Outcomes (Willingness to pay)	Trace data	Both numeric and semantic priming have small positive effects in auctions; little effect in fixed-price settings.
Fang et al. (2023) / PACIS	SI	Unclear	Lab experiment / Mixed age general sample	Repeated / moderate / low	Warning label	Psychological Outcomes (Information narrowing: Acceptance of personalized content; Acceptance of diversified content)	Self-report	Warning label reduces acceptance of personalized content and increases acceptance of diversified content.

Figl et al. (2021) / ICIS	ECO	Theory of bounded rationality	Online experiment / Mixed convenience sample (mostly students)	Repeated / complex / low	Defaults; Decision Staging / Order	Behavior (Choice of default option); Psychological Outcomes (Choice satisfaction; Choice difficulty; Purchase intention; Skepticism toward defaults)	Trace data; Self-report	High-to-low ordering improves acceptance and satisfaction; high-priced defaults increase skepticism.
Franzoi and vom Brocke (2022) / ECIS	SUS	Dual-process theory	Online experiment / Crowd working platform sample	One-shot / moderate / low-moderate	Status quo bias / Default nudge	Behavior (Carbon offset donation)	Trace data	Positive effect: increased contributions by 33% compared to low default
Gottschewski-Meyer et al. (2024) / ECIS	SUS	Unclear	Online experiment / Mixed (students & crowd workers)	One-shot / complex / low	Price Discounts; Anchoring; Defaults; Hyperbolic Discounting	Behavior (Product purchase frequency)	Trace data	Default, anchoring, and hyperbolic discounting nudges all increased purchases; hyperbolic discounting was most effective and outperformed price discounts, while anchoring offered no advantage over discounts.
Gupta et al. (2024) / MISQ	SI	Theory of team coaching	Online experiment / Crowd working platform sample	Repeated / complex / low-moderate	Skill Facilitator Bot; Strategy Facilitator Bot; ToDo List; Feedback Display	Performance (Collective intelligence)	Trace data	Skill facilitator bot improved skill use; strategy facilitator bot showed no effect; to-do lists had mixed results and could reduce strategy use; feedback displays reduced effort.
Habla et al. (2024) / ICIS	SUS	Dual-process theory	Online experiment / Crowd working platform sample	Repeated / simple-moderate / low	Eco-label nudge (mode vs fare)	Behavior (Pro-environmental employee behavior: Sustainable decision)	Trace data	Eco-labels increased selection of sustainable travel modes and fare options.
Habla et al. (2025) / ECIS	SUS	Dual-process theory	Online experiment / Crowd working platform sample	One-shot / simple / low-moderate	Simplification; Social Norm	Behavior (Sustainable decision)	Trace data	Simplification less effective in uncertainty-avoidant cultures; social norms stronger in collectivist cultures.

Helinski et al. (2024) / ICIS	SUS	Unclear	Online experiment / General consumer sample	One-shot / moderate / low	Undisclosed eco-label; Disclosed eco-label	Psychological (Satisfaction with vendor)	Self-report	Eco-label nudges increased sustainable choices whether disclosed or not; transparency improved autonomy and satisfaction without reducing effectiveness.
Henkel et al. (2019) / ECIS	SUS	Unclear	Lab experiment / University students	Repeated / complex / low-moderate	Priming nudge; Status quo bias nudge	Performance (Pro-environmental behavior (PEB) performance)	Trace data	Status quo bias significantly improves pro-environmental behavior; priming ineffective.
Ho and Lim (2018) / MISQ	ECO	Theory of Mood Congruence	Field experiment / University students	One-shot / simple / moderate	Trade-off descriptor nudges (partial vs complete); Personalized matching trade-offs (need, taste, location)	Psychological (Urge to buy); Behavior (Unplanned purchase action)	Trace data; Self-report	Personalized nudges increased purchase intentions, with need- and location-matching particularly effective for users in negative moods; partial descriptors outperformed complete descriptions among users in positive moods.
Huber et al. (2019) / ECIS	SUS	Goal Framing Theory	Online experiment / Real users (EV owners)	One-shot / moderate / low	Framing - Cost; Framing - Environmental; Framing - Social	Behavior (Charging Flexibility)	Trace data	Cost framing positive; environmental framing ineffective; social framing negative.
Jesse and Jannach (2021b) / PACIS	HW	Unclear	Online experiment / Crowd working platform sample	Repeated / moderate / low	Defaults; Highlighting; Social; Combine (hybrid); Warning	Behavior (Online Food choices)	Trace data	Defaults, highlighting, and social nudges alone were ineffective; hybrid social-default and warning nudges successfully influenced behavior.
Kim and Dennis (2019) / MISQ	SI	Unclear	Online experiment / General consumer sample	One-shot / moderate / low	Source primacy presentation format; social rating cue	Psychological (Believability of article User actions: Likelihood to read Likelihood to like Likelihood to comment (supporting or opposing) Likelihood to share)	Self-report	Source-primacy formatting and low source ratings reduced article believability, with source ratings having the strongest effect; combining both produced diminishing returns, as ratings dominated the effect.

Klesel et al. (2016) / PACIS	HW	Boundary Theory	Online survey / Corporate employees	One-shot / simple / low-moderate	Default; Ease; Decision Aid; Rescale; Social; Precommitment; Reminder; Past experience; Elicit intention; Time window; Label; Warning; Disclosure	Psychological (Work discontinuance intention)	Self-report	Disclosure, ease, and intention-elicitation nudges increased intentions more than enforcement; reminders reduced intentions, while most other nudges performed no better than enforcement.
Kretzer et al. (2018) / JAIS	TAU	Social influence (theory of isomorphism)	Lab experiment / University students	Repeated / complex / low-moderate	Social Cohesion (Proximity); Institutional Isomorphism (Business Function); Institutional Isomorphism (Location); Hierarchical Power	Behavior (Recommendation choice)	Trace data	Social cohesion, hierarchy, and institutional similarity all increase compliance.
Kroll et al. (2019) / ECIS	SUS	Unclear	Online experiment / General consumer sample	One-shot / moderate / low-moderate	Social norm; Self-commitment	Behavior (Energy saving behavior)	Trace data	Social norms and self-commitment alone ineffective but effective when combined.
Lee et al. (2023) / MISQ	DP	Unclear	Field experiment / Real users (app users)	One-shot / simple-moderate / low-moderate	Matching rebate; Rebate incentives; Audience visibility nudge	Behavior (Decision to donate; donation amount)	Trace data	All nudges significantly increased donation rates; effectiveness influenced by subsidy rates and timing
Li and Guo (2021) / PACIS	HW	Prospect theory; Elaboration Likelihood Model	Online experiment / Crowd working platform sample	One-shot / complex / low	Message Framing (risk, vs benefit); Rational Appeal; Emotional Appeal	Behavior (Attention to health information); Performance (Comprehension of health knowledge)	Trace data	Emotional appeals improve comprehension but not attention; framing differences insignificant.
Li et al. (2021) / MISQ	EDU	Social Conformity	Field experiment / University students	One-shot / complex / high	Peer information; reminder	Behavior (Procrastination); Performance (Grade)	Trace data	Reminders alone were ineffective; adding peer progress information reduced procrastination and improved grades, especially for males and lower-performing students.
Li et al. (2022) / ICIS	TAU	Self-determination Theory; Social Presence Theory	Field experiment / Real users (Real social-media users)	Repeated / complex / moderate	Social Nudge (Avatars); Reminding Social Nudge (Red-dot + Avatars)	Behavior (User Engagement (with existing function during, new function after treatment))	Trace data	Social nudges increase engagement; reminders reduce short-term but improve long-term engagement.

Liu and Karahanna (2017) / MISQ	ECO	Constructive preference theory	Lab experiment / University students	Repeated / complex / low-moderate	attribute-information amount; degree of information conflict; Coherence (overall numeric rating coherence)	Psychological (Attribute preference construction)	Self-report	More information, greater information conflict, and stronger coherence increased the influence of information on decision-making, particularly among motivated individuals.
Lu and Wang (2023) / AMCIS	ECO	Value Co-creation Theory	Lab experiment / Mixed (online panel/students/consumers)	One-shot / complex / low	Default option (overt digital nudges; Recommendation labels (covert digital nudge)	Psychological (User satisfaction with customization process)	Self-report	Defaults and recommendations improved satisfaction and reduced effort for novices, but decreased satisfaction and sense of accomplishment for experts.
Lu et al. (2019) / PACIS	ECO	Unclear	Online experiment / University students	Repeated / complex / low	Default option (overt digital nudge); Recommendation labels (covert digital nudge)	Behavior (Number of intermediate options selected)	Trace data	Both ODN and CDN encourage moderate choices; ODN more effective than CDN.
Mager and Kranz (2021) / ICIS	PS	Dual process theory	Field experiment / Real users (real website visitors)	One-shot / simple-moderate / moderate-high	Covert (Omitted reject button); Overt (Monetary coupon levels); Combined interventions	Behavior (The cookie consent decision (rate))	Trace data	Overt incentives effective; combining covert and overt nudges works best.
Michels et al. (2021) / ECIS	HW	Salience theory	Online experiment / Crowd working platform sample	Repeated / moderate / low	Digital Salience Nudge (Visual reduction); Transparent Disclosure	Behavior (Healthy food choices)	Trace data	Digital salience nudge improves healthy choices; transparency does not reduce effectiveness of the salience nudge.
Michels et al. (2023) / EJIS	HW	Salience theory	Online experiment / Crowd working platform sample	Repeated / complex / low	Digital Salience Nudge (Visual salience reduction); Transparency (Disclosing purpose and mechanism); Self-nudging (Empowering users to choose)	Behavior (Food product choice Healthy Unhealthy)	Trace data	Digital salience nudges strongly promoted healthier choices; self-nudging was less effective than preset nudges, but transparency enhanced its effectiveness without reducing overall impact.
Moriguchi et al. (2022) / ICIS	ECO	Perceived Risk Theory	Field experiment / Real users (Real customers)	One-shot / simple / moderate	Information retargeting (Product/Ship/Return)	Behavior (Sales conversion)	Trace data	Return information increases purchases; other information types ineffective.

Olenberger et al. (2025) / IM	SI	Dual Process Theory	Online experiment / Crowd working platform sample	Repeated / complex / low	Ex ante intervention (Warning before fake news); Ex post intervention (Warning after fake news)	Psychological (Believability Mental model Recognition of the articles)	Self-report	Ex post interventions were more effective than ex ante interventions at reducing belief in misinformation and limiting its integration into mental models over time, although benefits for integrating verified information weakened over time.
Peters and Wieland (2023) / AMCIS	SUS	Theory of Planned Behavior; Technostress Theory	Online experiment / Mixed (students & snowball sample)	One-shot / moderate / moderate	Digital Information Nudging	Behavior (Sustainable product decision)	Self-report	Positive effect overall, but weakened or reverse as technostress increases
Pethig et al. (2025) / MISQ	SI	Attribution Theory	Natural experiment /Real users (Real users /consumers)	One-shot / complex / moderate-high	Newcomer Nudge	Behavior (Number of comments; Retention); Performance (Contribution Quality); Psychological (Comment sentiment (Positive, Neutral, Negative)	Trace data	Significant increase in comments, positive sentiment, and retention but no significant effect on neutral / negative sentiment, quality, or effort.
Pfaff et al. (2025) / ECIS	PS	Dual-Process Theory	Online experiment / Crowd working platform sample	Repeated / simple / low	System 1 (Visual); System 2 (Informative); Combined	Behavior (Information security policies (ISPs) behavior)	Trace data	Both System 1 and 2 improve compliance; combined nudges have synergistic effects.
Poniatowski and Neumann (2020) / ECIS	ECO	Five Factor Model of Personality Traits	Online experiment / Crowd working platform sample	One-shot / complex / low-moderate	Feature-based review template	Behavior (Review length)	Trace data	Nudges increased review length compared to plain text, with stronger effects for highly conscientious users and limited evidence of stronger effects for agreeable users.
Purohit et al. (2021) / AMCIS	TAU	Hook Model	Field experiment / University students	Repeated / moderate / moderate	MISFEED Nudge (Mindful scrolling feedback)	Behavior (Total amount of time spent on Instagram per week; Number of times participants opened Instagram); Psychological (Participants' self-reported mindfulness and awareness of their digital behavior on Instagram)	Trace data; Self-report	Reduce digital consumption and increase mindfulness but not app-opening frequency.

Rafai et al. (2022) / DSS	ECO	Unclear	Field experiment / Real users	One-shot / complex / high	Decoy	Behavior (Conversion rate)	Trace data	Decoy has no significant effect.
Rauh et al. (2024) / AMCIS	SUS	Self-determination theory (SDT)	Online experiment / Crowd working platform sample	One-shot / moderate / moderate	Green Nudge (Impact info)	Psychological (Return Motivation; Purchase Motivation)	Self-report	Nudges reduced return intentions, but some effects occurred indirectly through lower purchase motivation, creating an unintended reduction in purchasing behavior.
Reeck et al. (2024) / ISR	PS	Privacy calculus theory	Lab experiment / University students	Repeated / complex / moderate	Disclosure risk education	Psychological (Willingness to disclose private information)	Self-report	Increased weighting of intrusiveness / risks and discouraged disclosure willingness.
Schär (2021) / AMCIS	ECO	Elaboration Likelihood Model	Online experiment / Crowd working platform sample	One-shot / simple / low	Social Norm Nudge	Psychological (Information Consumption intention)	Trace data	Positive overall effect, but weaker among high-need-for-cognition individuals.
Schär et al. (2022) / AMCIS	ECO	Social impact theory	Online experiment / General consumer sample	One-shot / simple-moderate / low	Social norm nudge	Behavior (pre-purchase decision)	Self-report	No significant effect observed.
Schneider et al. (2017) / ICIS	PS	Toulmin's model of argumentation; Regulatory Focus Theory	Online experiment / Crowd working platform sample	One-shot / simple / low	Promotion claim focus; prevent claim focus	Behavior (Online verification conversion rate)	Trace data	Claims alone were ineffective or harmful, with prevention claims reducing conversions; adding supporting data improved conversion rates, and prevention claims with data produced the strongest results.
Schürmann et al. (2023) / ECIS	SUS	Unclear	Online experiment / Mixed (mostly students)	Repeated / moderate / low	Simplification; Social Norm	Behavior (Sustainable consumer behavior in online fashion retail)	Trace data	Simplification is effective but causes negative spillovers; social norms ineffective or harmful.
Sengupta et al. (2020) / ICIS	HW	Control Theory; Cognitive Dissonance Theory	Field experiment / Real users (Real Patients)	Repeated / moderate / high	Priming (EMA Surveys prompts); Intervention messages	Behavior (Physical activity)	Trace data	EMA Surveys intervention messages increase physical activity; combined approach strongest.

Shi et al. (2025) / MISQ	SI	Ego utility theory; self-determination theory; social comparison theory	Field experiment / Real users (app users)	One-shot / complex / moderate	Comparative popularity feedback; Absolute popularity feedback	Behavior (Selectivity calibration; Self-marketing; Level of engagement)	Trace data	Comparative feedback prompted different responses by user status: lower-performing users became less selective but increased self-promotion, while higher-performing users became more selective but reduced self-promotion. Absolute feedback had no significant effect.
Shukla et al. (2025) / JMIS	PS	Unclear	Multi-study (field & lab) / Real users (Real patients)	Repeated / moderate-complex / high	Benefits others; Benefits self; Benefits many; Benefits physician; Open appeal	Behavior (Word of mouth (WOM) quantity (email opened, rated and reviewed); Identity disclosure; Sensitive data disclosure; Review length)	Trace data	Open appeals were most effective for encouraging reviews; self-benefit and physician-benefit appeals also increased review contributions, while privacy controls promoted identity disclosure without reducing willingness to share sensitive information.
Staudt et al. (2021) / ICIS	SUS	Social Comparison Theory	Lab experiment / University students	Repeated / moderate / moderate-high	Social comparison (ranking); social distance (names); social status	Behavior (Willingness to donate; Donation amount)	Trace data	Social comparison through rankings increased engagement, while social distance and status cues had no effect; the perceived importance of the cause was the strongest driver of contribution levels.
Stryja et al. (2017) / ECIS	SUS	Innovation resistance theory	Lab experiment / University students	Repeated / complex / low	Default; Priming; Combined	Behavior (Innovation trial decision)	Trace data	Default options increased trial uptake, while priming had no effect and provided no additional benefit when combined with defaults.
Sutanto et al. (2021) / ICIS	SUS	Fogg Behavioral Model	Lab experiment / General consumer sample	Repeated / moderate-complex / low-moderate	Spark agent (Fear/Hope); Signal agent (Reminder)	Behavior (Sustainable product selection)	Trace data	Spark appeals effective for cynical consumers; signal appeals effective for caring consumers.

Székely et al. (2016) / ECIS	SUS	Unclear	Online experiment / Crowd working platform sample	Repeated / moderate / low-moderate	anchoring; defaults	Behavior (Carbon-offset: Absolute donation; Relative donation)	Trace data	Higher default values significantly increased carbon-offset donations.
Terres et al. (2019) / ECIS	TAU	Self-perception theory	Online experiment / General consumer sample	One-shot / simple / moderate	Commitment nudge; Personalization nudge	Psychological (intention to use the mobile app)	Trace data	Both commitment and personalization nudges increased intention to use, with the combination producing a substantially stronger effect than either intervention alone.
Tsekouras et al. (2024) / JAIS	ECO	Elaboration Likelihood Model	Multi-study (field & lab) / Mixed (Real social-media users & Crowd working platform sample	One-shot / simple / moderate-high	Explicit targeting; framing (Utilitarian; Hedonic information framing); Targeting description	Behavior (Click; Action; Download)	Trace data	Explicit targeting reduced click intentions compared to non-explicit targeting; utilitarian framing was effective only when targeting was not explicit, while hedonic framing partially mitigated negative reactions to explicit targeting. Clear targeting descriptions increased click intention.
van Oldenbeek et al. (2019) / ECIS	EDU	Unclear	Field experiment / University students	Repeated / moderate / moderate	Individualized Progress Feedback	Behavior (Online learning behavior Behavioral extent of online activity Behavioral intensity of online study activity)	Trace data	Nudges increased video viewing and watch time, were more effective for male learners, and weakened over time.
Walser et al. (2019) / ECIS	INN	Cognitive Load Theory	Online experiment / University students	Repeated / complex / moderate	Decomposition of information load (DIL)	Performance (Choice accuracy)	Trace data	High DIL improved accuracy by encouraging deliberate thinking.
Wrabel (2025) / ECIS	SUS	Unclear	Online experiment / Crowd working platform sample	One-shot / simple / low	Simplification (sustainability nudge); Popularity cue; Recommendation; Scarcity cue; Price Discount	Behavior (Sustainable product choice)	Trace data	Sustainability nudges increased sustainable choices when used alone, but their effectiveness decreased when competing nudges present.
Zhang et al. (2020) / PACIS	ECO	Unclear	Field experiment / Mixed consumer sample	One-shot / simple / moderate	Descriptive social norm	Behavior (Consumer voice behavior)	Trace data	Increased percentage of consumer voice

Zimmermann et al. (2023) / ECIS	SUS	Unclear	Online experiment / General consumer sample	Repeated / complex / low	Decoy; Default; Combined	Behavior (Public transport choice (private vs public)	Trace data	Decoy and default nudges were ineffective alone, but effective when combined.
Notes: SUS: Sustainability; ECO: E-commerce; EDU: Education; PS: Privacy and Security; HW: Health and Wellbeing; INN: Innovation; DP: Digital Philanthropy; SI: Social Interaction; TAU: Technology Adoption and Use								

Table B2. Classification of Nudges Identified in the Reviewed Studies based on Jesse and Jannach, 2021a*

Author(s)	Decision information	Decision structure	Decision assistance	Social decision appeal
Auf der Landwehr et al. (2021)	Phrasing information: Loss aversion (Loss Aversion); Phrasing information: Hyperbolic discounting (Hyperbolic Discounting); Phrasing information: Anchoring and adjusting (Anchoring)			Provide social reference point: Following the herd/Norms (Social Norms)
Babar et al. (2023)			Provide reminders: Remind of goal (Motivational messages)	Instigate empathy: Positive reinforcement (Light social support/kudos)
Bahreini et al. (2023)		Change choice defaults: Setting defaults (default security settings level)		
Berger et al. (2020)	Translate information: Simplification (Simplification)	Change choice defaults: Setting defaults (Default rules)		Provide social reference point: Following the herd (Social norms)
Berger et al. (2022)	Phrasing information: Framing (Framing)	Change choice defaults: Setting defaults (Default Rules)		
Bergram et al. (2020)	Make information visible: Suggesting alternatives (Suggesting user alternatives)	Change option-related effort: Throttle mindless activity (Explicit choice)		
Bergram et al. (2024)		Change choice defaults: Setting defaults (Default); Change option-related effort: Create friction (Friction)		Provide social reference point: Following the herd (Social Norm)
Bernards et al. (2024)	Make information visible: Customized information (Individualized Digital Nudges)		Provide reminders: Remind of goal (Individualized Digital Nudges - reminder component)	
Brylla and Walsh (2023)	Phrasing information: Framing (Job conditions frame; Environmental frame; Personal convenience frame)			
Cavegn et al. (2023)	Make information visible: transparent function /purpose of social norms			Provide social reference point: Following the herd/Norms (Social norm - non-transparent/transparent function/transparent function + purpose)
Degirmenci and Recker (2018)	Make information visible: Disclosure (Reflective disclosure); Give comparative information (Information democratization)			
Dennis et al. (2020)	Phrasing information: Priming (Numeric Priming; Semantic Priming)			
Fang et al. (2023)	Make information visible: Warning (Warning label)			

Figl et al. (2021)		Change choice defaults: Setting defaults (Defaults); Change range or composition: Decision staging/Order effects (Decision Staging/Order)		
Franzoi and vom Brocke (2022)		Change choice defaults: Setting defaults (Status quo bias/Default nudge)		
Gottschewski-Meyer et al. (2024)	Phrasing information: Anchoring and adjusting (Anchoring); Phrasing information: Hyperbolic discounting (Hyperbolic Discounting)	Change choice defaults: Setting defaults (Defaults); Change option consequences: Micro-incentives (Price Discounts)		
Gupta et al. (2024)		Change choice defaults: Prompted choice (ToDo List); Change range or composition: Structure complex choice (Strategy Facilitator Bot; Skill Facilitator Bot);		Provide social reference point: Social influence/Comparison (Feedback Display)
Habla et al. (2024)	Increase salience of information: Increase salience of attribute (Eco-label nudge)			
Habla et al. (2025)	Translate information: Simplification (Simplification)			Provide social reference point: Following the herd (Social Norm)
Helinski et al. (2024)	Increase salience of information: Using visuals to increase salience (Undisclosed eco-label); Make information visible: Disclosure (Disclosed eco-label)			
Henkel et al. (2019)	Phrasing information: Priming (Priming nudge)	Change choice defaults: Setting defaults (Status quo bias nudge)		
Ho and Lim (2018)	Translate information: Decrease vagueness and ambiguity (Trade-off descriptor nudges); Make information visible: Customized information (Personalized matching trade-offs)			
Huber et al. (2019)	Phrasing information: Framing (Cost, Social, Environmental)			
Jesse and Jannach (2021b)	Increase salience of information: Increase salience of attribute (Highlighting); Make information visible: Warning (Warning)	Change choice defaults: Setting defaults (Defaults)		Provide social reference point: Following the herd (Social)
Kim and Dennis (2019)	Increase salience of information: Attracting/Reducing attention (Source primacy presentation format)			Provide social reference point: Social influence/Comparison (social rating cue)
Klesel et al. (2016)	Make information visible: Providing an explanation (Decision Aid); Warning (Warning); Disclosure (Disclosure); Give comparative information (Label); Phrasing information: Limited time window (Time window)	Change choice defaults: Setting defaults (Default); Change option-related effort: Change ease and convenience (Ease); Change range or composition: Change scale (Rescale)	Facilitate commitment: Precommitment strategy (Precommitment); Nature and consequences of own past choices (Past experience); Eliciting implementation intentions (Elicit intention); Provide reminders: Remind of goal (Reminder)	Provide social reference point: Following the herd (Social)

Kretzer et al. (2018)				Provide social reference point: Social influence/Comparison (Social Cohesion-Proximity); Following the herd (Institutional Isomorphism-Business Function; Institutional Isomorphism-Location); Increase reputation of messenger: Messenger effect (Hierarchical Power)
Kroll et al. (2019)			Facilitate commitment: Support public commitment (Self-commitment)	Provide social reference point: Following the herd (Social norm)
Lee et al. (2023)		Change option consequences: Micro-incentives (Matching rebate; Rebate incentives)		Provide social reference point: Social influence/Comparison (Audience visibility nudge)
Li and Guo (2021)	Phrasing information: Framing (Message Framing risk vs benefit); Make information visible: Providing an explanation (Rational Appeal)			Instigate empathy: Instigate empathy with characters (Emotional Appeal)
Li et al. (2021)			Provide reminders: Remind of goal (reminder)	Provide social reference point: Social influence/Comparison (Peer information)
Li et al. (2022)			Provide reminders: Remind of goal (Reminding Social Nudge - red-dot component)	Provide social reference point: Following the herd (Social Nudge - Avatars)
Liu and Karahanna (2017)	Increase salience of information: Increase salience of attribute (attribute-information amount); Make information visible: Give comparative information (degree of information conflict); Phrasing information: Representativeness (Coherence)			
Lu and Wang (2023)	Increase salience of information: Increase salience of attribute (Recommendation labels)	Change choice defaults: Setting defaults (Default option)		
Lu et al. (2019)	Increase salience of information: Increase salience of attribute (Recommendation labels)	Change choice defaults: Setting defaults (Default option)		
Mager and Kranz (2021)		Change option-related effort: Create friction (Covert-Omitted reject button); Change option consequences: Micro-incentives (Overt-Monetary coupon levels)		
Michels et al. (2021)	Increase salience of information: Hiding information (Digital Salience Nudge-Visual reduction); Make information visible: Disclosure (Transparent Disclosure)			

Michels et al. (2023)	Increase salience of information: Hiding information (Digital Salience Nudge); Make information visible: Disclosure (Transparency)	Change choice defaults: Enhancing or influencing active choosing (Self-nudging)		
Moriguchi et al. (2022)	Increase salience of information: Attracting/Reducing attention (Information retargeting)			
Olenberger et al. (2025)	Make information visible: Warning (Ex ante intervention; Ex post intervention)			
Peters and Wieland (2023)	Make information visible: Informing (Digital Information Nudging)			
Pethig et al. (2025)				Instigate empathy: Invoking feelings of reciprocity (Newcomer Nudge)
Pfaff et al. (2025)	Increase salience of information: Using visuals to increase salience (System 1-Visual); Make information visible: Providing an explanation (System 2-Informative)			
Poniatowski and Neumann (2020)	Translate information: Explicitly mapping (Feature-based review template)			
Purohit et al. (2021)	Make information visible: Providing feedback (MISFEED Nudge)			
Rafai et al. (2022)	Phrasing information: Decoy effect (Decoy)			
Rauh et al. (2024)	Make information visible: Informing (Green Nudge-Impact info)			
Reeck et al. (2024)	Make information visible: Disclosure (Disclosure risk education)			
Schär (2021)				Provide social reference point: Following the herd (Social Norm Nudge)
Schär et al. (2022)				Provide social reference point: Following the herd (Social Norm Nudge)
Schneider et al. (2017)	Phrasing information: Framing (Promotion claim focus; prevent claim focus)			
Schürmann et al. (2023)	Translate information: Simplification (Simplification)			Provide social reference point: Following the herd (Social Norm)
Sengupta et al. (2020)	Phrasing information: Priming (EMA Surveys prompts)		Provide reminders: Remind of goal (Intervention messages)	
Shi et al. (2025)				Provide social reference point: Social influence/Comparison (Comparative popularity feedback; Absolute popularity feedback)

Shukla et al. (2025)	Phrasing information: Framing (Benefits others; Benefits self; Benefits many; Benefits physician)			Instigate empathy: Moral suasion (Open appeal)
Staudt et al. (2021)	Make information visible: Reduce the distance (social distance-names)			Provide social reference point: Social influence/Comparison (Social comparison-ranking); Increase reputation of messenger: Messenger effect (social status)
Stryja et al. (2017)	Phrasing information: Priming (Priming)	Change choice defaults: Setting defaults (Default)		
Sutanto et al. (2021)	Phrasing information: Framing (Spark agent-Fear/Hope)		Provide reminders: Remind of goal (Signal agent-Reminder)	
Székely et al. (2016)	Phrasing information: Anchoring and adjusting (anchoring)	Change choice defaults: Setting defaults (defaults)		
Terres et al. (2019)	Make information visible: Customized information (Personalization nudge)		Facilitate commitment: Precommitment strategy (Commitment nudge)	
Tsekouras et al. (2024)	Make information visible: Disclosure (Explicit targeting); Providing an explanation (Targeting description); Phrasing information: Framing (Utilitarian; Hedonic information framing)			
van Oldenbeek et al. (2019)	Make information visible: Providing feedback (Individualized Progress Feedback)			
Walser et al. (2019)		Change range or composition: Partition of options/categories (Decomposition of information load)		
Wrabel (2025)	Translate information: Simplification (Simplification); Phrasing information: Make resources scarce (Scarcity cue)	Change option consequences: Micro-incentives (Price Discount)		Provide social reference point: Argentum-Ad Populum (Popularity cue); Referring to opinion leader (Recommendation)
Zhang et al. (2020)				Provide social reference point: Following the herd (Descriptive social norm)
Zimmermann et al. (2023)	Phrasing information: Decoy effect (Decoy)	Change choice defaults: Setting defaults (Default)		

Note: * Nudge categories and mechanisms are classified according to Jesse and Jannach (2021a). The labels shown in parentheses represent the exact nudge names or intervention terms used in the reviewed studies, if specifically mentioned).

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