Essays on Nudges in Information Systems

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DEDICATION

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ABSTRACT

Individuals increasingly make important decisions utilizing information systems. Behavioral economics research shows that aspects of a choice-making environment can influence individuals' decision-making even though they have no impact on the rational elements of the decision. However, this perspective is under-studied in information systems research, which has primarily considered users to be rational actors. The purpose of this dissertation is to investigate how a particular design element of information systems impacts users' decision-making in non-rational ways. The design element of interest is nudges, which are aspects of choice architecture that predictably alter decision-makers' behavior without forbidding options or changing incentives. To date, the efficacy of nudges in IS has been understudied and the investigations that have been completed have been primarily empirical and lacking in theory. The three papers of this dissertation aim to 1) review and organize the existing fragmented IS nudge literature, 2) develop a deep theoretical understanding of a specific nudge type, and 3) empirically investigate this nudge type in a novel context with a theoretical foundation.

Specifically, the first paper of this dissertation is a literature review that summarizes the role nudges have played in extant IS literature, analyzes theoretical inconsistencies in the existing research, and provides methodological and theoretical guidance for future IS researchers investigating nudges. The second paper builds on the first by delving into the many competing theoretical explanations for a specific type of nudge: the default nudge, which is a choice that will be selected if the decision-maker does not actively choose. The final paper utilizes work from the first two projects to empirically investigate how default nudges affect decision-makers' charitable donations online. This empirical work helps to tease apart conflicting theoretical explanations and predictions to unpack what is currently a black box regarding how and why digital nudges impact behavior. It helps us understand charitable donation decision-making by

incorporating social value orientation, defaults, and proximity of social norms and using both animation and real-time personalization to capitalize on attributes of the IT artifact.

Overall, this dissertation enriches our understanding of nudges in general, but specifically in the context of information systems. The work contributes to future research on IS design and improves our understanding of decision-making online.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ESSAY 1: NUDGES IN INFORMATION SYSTEMS: A REVIEW AND PATH FORWARD

ABSTRACT: Nudges are aspects of choice problem design that influence decision-makers, and have garnered increasing attention in IS since their introduction in 2009. Although a number of empirical IS nudge studies have been published, the concept is not well-defined in IS literature, the research program lacks a theoretical basis, and results have been mixed and contradictory. To address these issues, this paper reviews 91 papers investigating nudges in technology at three levels: the IS research stream to which the project contributes, how the nudge concept is defined, and how IS nudges can be differentiated through use of a nudge typology that we elaborate here. Using these analyses, we explain mixed and confusing findings in the extant literature and suggest paths forward for the research program at all three levels of analysis – including multiple theoretical bases to support different nudge types. As the first review on nudges in IS, this paper serves as a repository of extant IS literature and a guide for conducting future IS nudge research.

Keywords: nudge; literature review; synthesis; behavioural economics; IS design

INTRODUCTION

As the use of digital tools and platforms increases both at work and at home, understanding the ways these tools can influence decisions has become increasingly important. While decision-making has been a popular topic in information systems research, scholars have only recently begun to investigate how the presentation of choice options in IS can influence decision-makers' choices. An important construct in this investigation is the concept of 'nudge.'

Nudges are elements of a choice problem presentation that predictably alter people's behavior without forbidding any options or significantly changing their economic incentives (Thaler & Sunstein, 2009). In practice, nudges have been used to impact a variety of choice behaviours (*The Behavioural Insights Team*, 2017). For example, manipulating which option is set as a default significantly impacts both rates of organ donation (Johnson & Goldstein, 2003) and pension enrolment (Service, 2015). In these and other contexts, when all important choice alternatives are presented, individuals are nudged toward choosing the default over other alternatives (The Behavioural Insights Team, 2017).

Nudging has been a popular mechanism studied in recent IS research across a variety of choice contexts. Although scholars have produced a vast amount of IS nudge research in the last decade, no comprehensive reviews or meta-analyses have been done. Insights regarding nudging in IS are therefore fragmented and piecemeal, a limitation that threatens the viability of an otherwise promising research program. To address this problem, we conducted a systematic literature review on nudges in IS-related research. Our literature review aims to consolidate and summarize existing IS-related nudge research, identify biases and knowledge gaps in the literature, and propose future research directions and theoretical and empirical guidelines for future IS nudge research (Rowe, 2014). To this end, we reviewed 91 papers investigating nudges in IS. We analysed this sample set at three different levels: the IS research stream to which the reviewed paper contributed, the nudge definitions used across the IS literature, and the differences in nudge types and operationalization in different projects. Through this review, we highlight both theoretical and empirical inconsistencies that have contributed to fragmentation in the research program and suggest solutions.

Thus, our review will serve both as a repository of IS nudge research and a practical tool for future researchers. We find that nudges have been investigated unevenly across IS research streams, despite their applicability to all decision-making and behavioural research areas, and suggest a diverse range of IS nudge research questions. We highlight definitional inconsistencies and propose an IS nudge definition to resolve current fragmentation. We demonstrate how these inconsistencies contribute to mixed results and provide theoretical and empirical recommendations to form a more coherent research program.

In the following sections, we discuss the theoretical background of nudges in general and their role in IS research. Then, we describe the methodology of our review and descriptive details of the research covered. Finally, we present our findings, including an analysis of where in IS research nudges are being implemented, a discussion of the definition of the nudge construct in IS research, an identification of the different forms nudges can take and the different theoretical bases that support them, and recommendations for future IS nudge research.

IS nudge research

Nudges have received considerable attention from IS researchers, but the treatment of nudges throughout IS research has been inconsistent. Therefore, we first elaborate on the definition of nudge used in other areas of research to ground our analysis of the IS literature and provide a definition for future IS nudge research.

WHAT IS A NUDGE

A nudge is "any aspect of the choice architecture that alters people's behaviour in a predictable way without forbidding any options or significantly changing their economic incentives" (Thaler & Sunstein, 2009). Unfortunately, there is much confusion regarding the nudge concept due in large part to the fact that Thaler and Sunstein's definition consists only of two negative conditions (Hausman and Welch 2010). However, they offer a number of rules, one of which appears to be key to a better theoretical understanding in that it relates nudges to the concepts of neoclassical economics and behavioural economics. The rule indicates that "a nudge is any factor that significantly alters the behaviour of Humans, even though it would be ignored by Econs" (Thaler & Sunstein, 2009, p. 8). Here, Econs refers to the neoclassical notion of individuals who "…reason brilliantly, catalogue huge amounts information that they can access instantly from their memories, and exercise extraordinary will power" (Thaler et al., 2013, p. 429). In contrast, Humans refers to the behavioural economics notion of individuals who "make plenty of mistakes (even when they are consciously thinking!) and suffer all types of breakdowns in planning, self-control, and forecasting" (Thaler et al., 2013, p. 429).

The linkage between neoclassical economics and behavioural economics enables us to develop a coherent theory of nudges based on the distinctions between Econs and Humans, where only Humans are affected by nudges. Table 1 compares decision-making by Econs to that of Humans.

Table 1. Econs versus Humans.

Decision Making Components	Decision Making by Econs	Decision Making by Humans
Memory	Short and long term memory are unlimited (Thaler & Sunstein, 2009).	Limits to short and long term memory affect decision-making (Thaler & Sunstein, 2009).
Quantitative Calculations	• All calculations are done easily, without errors, and with perfect precision (Thaler & Sunstein, 2009). • Estimations and forecasts can be wrong but not systematically biased (Thaler & Sunstein, 2009)	• Calculations can be effortful, erroneous, and imprecise (Thaler & Sunstein, 2009). • Errors in estimations and forecasts can include systematic bias. (Thaler & Sunstein, 2009).
Utility Function	Utility functions are well ordered with the following properties: • Consistency: any collection A always have the same utility over a collection B; (Becker, 1976). • Transitivity: if A is preferred to B, and B to C, then A must be preferred to C. (Becker, 1976). • Considers revealed preferences only; does not consider emotions (Loewenstein, 2000). • Preferences are formed a priori and are stable throughout the decision process (Barr et al., 2012).	Utility functions are not well ordered, and have the following properties: • Consistency: Choices may not be consistent because choices are made by invoking external references (Sen, 1993). • Transitivity: If A is preferred to B, and B to C, then C may be preferred to A. This can happen, for example, when preferences are being formed as part of the decision process (Barr et al., 2012). • Considers revealed preferences as well as emotions (Loewenstein, 2000). • Preferences can be formed as part of the decision process and may change during the process (Barr et al., 2012).
Choice Process	• Chooses based on consistent calculations that maximize the individual's utility (Becker, 1976). • Only factors relevant to incentives are considered (Thaler & Sunstein, 2009). Thus, e.g., nudges are ignored.	• Chooses using rules of thumb, guesses, and heuristics (Gigerenzer & Brighton, 2009). • Factors irrelevant to incentives, such as commitment to past decisions, are considered (Thaler & Sunstein, 2009). Thus, e.g., nudges can alter choice behaviour.

To help understand the Human – Econ distinction, Hansen (2016) develops the following more explicit nudge definition. A nudge is "[1]… a function of the choice architecture that [2]… alters people's behaviour in a predictable way, [and] that is …[3] …[made possible] because of cognitive boundaries, biases, routines, and habits in individual and social decision-making…and which …[4] works by making use of those boundaries, biases, routines, and habits as integral parts of the choice architecture" (Hansen, 2016, p. 170). The implications of these four components are described next.

Nudges are a function of the choice architecture.

Choice architecture is everything about the way a choice is presented to a decision-maker. In an example of a user selecting among options online, a significant aspect of the choice architecture is the computer screen layout. A nudge would exist if one of the choices is the default, which is "chosen" without any action by a decision-maker. Another nudge would be the sequence of the choice alternatives. As will be explained in detail later these are nudges because, ceteris paribus, the default or the first alternative will have a greater likelihood of being chosen by a Human than the other alternatives but would not affect an Econ's choice. This computer screen layout, complete with its nudges, can be designed by a choice architect who might purposefully choose which alternative is the default and/or which is first on the list. However, all choice architectures contain nudges, regardless of whether they are purposefully designed (Thaler & Sunstein, 2009).

Nudges alter people's behaviour in a predictable way

Nudges are able to change, or cause to change, behaviours in ways that can be predicted. For example, default nudges increase the likelihood that individuals choose the default option (Dinner et al., 2011). Thus, a computer screen layout presentation, with a default nudge, provides a mechanism through which such a behavioural change can be effected. It is important to note that by definition, nudges alter *behaviour* and not necessarily intentions, feelings, thoughts, etc. Although some researchers have postulated that nudges' effects on behaviour are mediated by other constructs like intentions (Momsen & Stoerk, 2014) or emotions (Zhang & Xu, 2016), other scholars maintain that nudges can alter behaviour not only directly but even without conscious recognition by the decision-maker (Avineri, 2012).

Nudges are possible because of cognitive boundaries, biases, routines, and habits

In contrast to the assumptions behind the neoclassical rational choice model (Becker, 1976), behavioural economics proposes that "people are not always self-interested, benefits maximizing, and costs minimizing individuals with stable preferences" (Samson, 2014, p. 9). Specifically, we suffer from limited knowledge and processing abilities, and are influenced by our emotions and the information that is readily available in our memory and salient in the environment. We are susceptible to social norms, desire self-consistency, resist change, and are poor predictors of future behaviour (Samson, 2014). Nudges are possible because of these Human characteristics. For example, there are a number of ways that an IS can make specific information more salient, through the use of text, colour, pictures, and animation (Wang et al., 2014), which can affect which information is readily available in memory and, in turn, the decision that will ultimately be made.

Nudges work by making use of those cognitive boundaries, biases, routines, and habits

In order to better understand nudges in IS, we begin with Hansen's work on a nudge definition. Hansen suggests that a nudge can only be responsible for taking advantage of a Human’s cognitive limitations in order to promote that individual’s non-rational behaviour. However, this would preclude the use of nudges to overcome an individual’s less-than-rational choice behaviour. We believe that this is too restrictive and goes beyond that which was intended by Thaler and Sunstein (2009), who describe some nudges that present information in a more understandable form, and thereby enable the individual to make more rational decisions. We therefore keep Hansen’s definition, but alter the interpretation of “work by making use of” to include choice architecture components that affect Humans’ behaviour while not affecting Econs’ behaviour, independent of whether the Humans’ behaviour comes closer to or further away from the Econs’ behaviour.

Nudges cannot forbid or add rationally relevant choice alternatives

Because it would affect an Econ’s choice, a nudge cannot forbid or add any rationally relevant choice alternatives; though irrational and/or irrelevant choice alternatives may be nudges because they would not affect an Econ’s choices (Hansen, 2016). To forbid means “to hinder or prevent as if by an effectual command” (Merriam-Webster Inc., 2017a). Thus, any aspect of a choice architecture that effectively prevents the selection of a specific alternative forbids that option. For example, requiring a user to click a “See More” button to view all the results from a search engine does not forbid the user from seeing all the results. In contrast, requiring a user to call the IT department and wait a week for a software upgrade to see the rest of the results effectively negates the “see more” option for decision-makers who need to make a decision by the end of the day. Knowing when options are effectively forbidden requires an understanding of both the decision context and the individual decision-maker.

Nudges cannot significantly change incentives

A nudge cannot significantly change economic incentives (in terms of time, trouble, social sanctions, costs, etc.), because such changes could affect an Econ's choices (Hansen, 2016; Thaler & Sunstein, 2009). An incentive is anything "that incites or has a tendency to incite determination or action" (Merriam-Webster, Inc., 2017). For a nudge to exist, the value an Econ receives or the cost an Econ incurs must remain roughly the same with or without the presence of the nudge, so that the nudge would not change the Econ's choice behaviour – but it could have an impact on Humans' behaviour. For example, a price reduction from $100 to $99.99 would have a very small, likely insignificant, impact on an Econ's choice behaviour when compared to the other attributes of the item. Humans facing such a reduction, however, exhibit significantly greater changes in their choice behaviours than could be reasonably explained by an increase in utility commensurate with a one cent price reduction (Melina, 2011). Of course, a discount price of $80 from an original price of $100, ceteris paribus, would be expected to significantly influence Econs as well as Humans and thus would not be considered a nudge.

Note that economic "incentives can come in many forms" (Thaler & Sunstein, 2009, p. 8). For example, moving an item behind the counter in a store such that a shopper must ask for it could be argued to increase the cost of choosing that item and thereby alter the economic incentives of the choice problem.

Nudges' effectiveness depend on preference strength

Nudges tend to be more effective when an individual has no strongly preferred alternative as a result of any of the following conditions. First, a Human may be uncertain about his or her preferences because of ambivalence or lack of familiarity with the available choices (Acquisti et al., 2017). Second, research suggests that a

Human's preferences can be formed or altered during the decision-making process (Barr et al., 2012; Dinner et al., 2011), meaning that preferences themselves can be influenced by nudges. Third, Humans with preferences known a priori may not reflect on those preferences in certain choice situations, for example, when they are distracted (Meske & Potthoff, 2017). Finally, Humans with strong preferences may be nudged when a satisfactory alternative exists if the choice problem is complex and thereby obscures the alternative (Thaler & Sunstein, 2009). None of these conditions would hold for Econs because their preferences are established prior to, and are consistent within, the decision-making process (Barr et al., 2012), and their superior and consistent decision-making capabilities preclude problems associated with distraction and complexity.

Theoretical advancements in nudge research

The nudge research has generally had a more empirical than theoretical focus. The few researchers who have focused on theoretically developing the nudge construct have mostly aimed to do so through categorizations, taxonomies and typologies. Münscher et al. suggest that these efforts have generally followed one of two approaches: 1) focusing on the "underlying (cognitive) processes, that is, the mental constraints and cognitive biases targeted by an intervention" or 2) focusing on the kinds of techniques "used to modify the decision situation" (2016, p. 512).

One reason that researchers have opted for one of these two approaches to categorizing nudges is because there is no one-to-one relationship between a nudge and the cognitive process or theoretical reason the nudge impacts behaviour (Münscher et al., 2016). For example, loss aversion may explain why a decision-maker chooses a default option, but may also explain why he or she selects an option with a description framed to highlight losses over gains. The inherent many-to-many relationship between nudges and the theory that supports them led Münscher et al. to suggest that "attempts to systematize the field need to opt for either techniques or processes as the basic categorization logic" (2016, p. 512). Unfortunately, research efforts that do not relate techniques to processes have notable disadvantages. Next, we briefly review the theoretical efforts toward both cognitive-process-focused taxonomies and technique-focused taxonomies and their benefits and drawbacks and describe the categorization we selected for the nudge-level analysis of this review.

Categorizations focusing on cognitive processes

While researchers who focus exclusively on cognitive processes can offer convincing explanations for why nudges impact behaviour, they are often unable to suggest nudge designs to trigger these cognitive processes, relying instead on illustrative examples speculated to activate the cognitive processes (Mirsch et al., 2017). Thus, these taxonomies are limited regarding guidance to researchers interested in implementing nudges.

Researchers focusing on cognitive processes as the structuring principle of their taxonomies also face challenges related to the definition and demarcation of such processes. These challenges are reflected in the different terms researchers have used, such as: "cognitive processes" (Münscher et al., 2016), "basic mental resources" (Datta & Mullainathan, 2014), "targeted hurdles" (Acquisti et al., 2017), and "psychological effects" (Mirsch et al., 2017). Some taxonomies of this type lack descriptions or definitions of some or all of the cognitive processes included (Mirsch et al., 2017) and others present only a subset of the cognitive processes that may be relevant (Acquisti et al., 2017; Datta & Mullainathan, 2014). The cognitive processes included are often oversimplified. For example, some of these taxonomies include reference to the "status quo bias" which merely states that individuals tend to stick with the status quo (Acquisti et al., 2017; Mirsch et al., 2017). For a taxonomy to meaningfully guide future research, it would need to provide more details and boundary conditions about this tendency.

In addition to these definition and demarcation issues, these taxonomies do not have orthogonal categories (Acquisti et al., 2017; Datta & Mullainathan, 2014; Dolan et al., 2012; Mirsch et al., 2017) and tend to lack rigor in their methods (Acquisti et al., 2017; Datta & Mullainathan, 2014; Dolan et al., 2012; Mirsch et al., 2017).

Categorizations focusing on techniques

Taxonomies focusing on nudging techniques suffer from a lack of both explanatory and predictive power. For example, Johnson et al. (2012, p. 488) state that their taxonomy of tools neither provides a theoretical explanation of why the tools impact choice nor offers suggestions on how to design choice architecture or when to use which tool. When utilized in research, these technique-based taxonomies offer a meaningful way to group nudges that share some characteristics to describe or present them, but not to explain or predict behaviour (Dimitrova et al., 2017).

Many researchers who focus on techniques also draw connections to underlying cognitive processes or theories. At times this is nearly inevitable, because some terms are used interchangeably to describe underlying theory and the nudge technique (see for example framing in Mirsch et al. 2017). Other times, authors provide a list of cognitive processes as “problems” that are resolved by the nudge techniques but do not define or describe these cognitive processes (Johnson et al., 2012).

Finally, the taxonomies focusing on techniques all utilized inductive (a-theoretical) category development (Meske & Potthoff, 2017; Michie et al., 2011; Münscher et al., 2016; Promann & Brunswicker, 2017) or were developed through an undefined process (Johnson et al., 2012; Lehner et al., 2016; Oinas-Kukkonen & Harjumaa, 2008). While a review of current nudges in research is valuable, the evidence does not agree with Münscher et al.'s statement that such a review would facilitate "the development of new, testable choice architecture interventions" (2016, p. 512), since the effects of existing taxonomies on research thus far has been limited.

Categorization for this review

One of the goals of this review is to synthesize the literature; that is, to summarize research based on analytical categories to provide an overview of the literature for future scholars (Rowe, 2014). As we describe in detail later, IS scholars define nudges differently, which results in mixed empirical findings. We therefore posit that what has been treated as one phenomenon in the literature (*nudge*) is actually composed of multiple phenomena. This heterogeneity can be identified and reconciled by applying a typology, which can add structure to otherwise disorderly concepts (Nickerson et al., 2013). A useful typology should be: (1) orthogonal so that each type of nudge will fit within only one category; (2) explanatory, providing useful types of the nudges under study; and (3) comprehensive, with the ability to classify all known nudges within the domain of interest (Nickerson et al., 2013).

We start with the high-level categorization suggested in the original *Nudge* book by Thaler and Sunstein (2009), who organize their examples into six categories: iNcreasing Salience, Understanding Mapping, Default, Giving Feedback, Expecting Error, and Structuring Complex Choices (forming an acronym: NUDGES), which have been used by IS researchers in the past (Acquisti et al., 2017). We next considered the properties of this nudge categorization that could undermine the orthogonality requirement for a typology (Nickerson et al., 2013). Orthogonality is important because it enables us to focus on and identify distinct types of nudges. We found that two of the suggested categories violate the orthogonality requirement.

The giving feedback category describes a (typically real-time) process by which one of the other types of nudges is conveyed to an individual, with the result that many nudges are categorized in at least two categories. Therefore, to maintain orthogonality, we have excluded the giving feedback category from our initial typology. However, the many ways in which nudges are conveyed to individuals can be key to their effectiveness. IS enables the personalization of nudges, a specific type of feedback. Thus, the concept of feedback is important for the study of IS nudges, though not helpful in an initial categorization of them. We discuss giving feedback and its role in IS nudge research later.

The expecting error category also results in orthogonality issues. As described above, by definition a nudge works by making use of Humans' boundaries, biases, routines, and habits. Therefore, when compared to Econs, all nudge-related choice behaviours can be error-prone in that they can be non-rational. Thus, all nudges that attempt to overcome the foibles of Humans' choice behaviours could be categorized as expecting error, and also can be placed into one of the other typology categories. In accord with typological principle of orthogonality, the expecting error category is thus excluded from our typology.

Although Thaler and Sunstein suggested the NUDGES taxonomy, they did not provide (1) definitions for their categories, (2) criteria to distinguish among categories, or (3) theoretical explanations for why nudges in each category can change behaviour. One contribution of our work is to provide insight into Thaler & Sunstein's categories by defining and differentiating among them theoretically so that the typology can be meaningfully applied here and in future research. Next, we provide definitions for the remaining four categories of the Thaler and Sunstein (2009) taxonomy. To gain a comprehensive understanding of these categories, we considered research following and related to that of Thaler and Sunstein. Based on that subsequent work, we included theoretical explanations that help define the categories and explain how nudges that fit into those categories affect Humans' choice behaviours.

Increasing salience of incentives. A nudge to increase the salience of incentives is information communicated by the choice architecture that causes an incentive to become more noticeable, conspicuous, or prominent in a choice problem. For example, when the choice architecture exists on a computer screen, communication can include the existence of an element such as text or a picture, the contrasting colour of the element, the brightness of the element, and/or the placement of the element on a screen (Higgins, 1996). When the increasing salience of incentives nudge is present, a Human places more weight (or importance) on the salient incentive than he or she would have without the nudge (Taylor & Thompson, 1982). The Human then considers the relative weights of that and other incentives in choosing among alternatives. However, due to bounded rationality, Humans may not be able to systematically compare all weighted incentives for all alternatives. As a result, increasing the salience of an incentive will increase the likelihood that a Human will choose an alternative that scores high in terms of the more salient incentive. Nudges that increase incentive salience will have no effect on Econs' weighting of incentives.

Understanding mapping. Thaler and Sunstein defined mapping as the relationship between one's choice alternatives and the ultimate welfare one perceives to be associated with those values (2009). Understanding this mapping is important for the choice process. While the increasing salience of incentives nudge makes incentives relatively important, the mapping nudge helps Humans understand the relationships among alternatives' attributes and those incentives. To this end, nudges in this category typically use analogies to make the attributes of each alternative more understandable, comparable, and relatable to incentives. An important assumption that underlies this type of nudge is that Humans can effectively apply the cognitive device of analogy that enables them to relate unfamiliar information to schemes with which they are familiar. Understanding mapping nudges will have no effect on Econs, since they don't need analogies to help them understand the relationships among alternatives' attributes and incentives.

The use of analogy is predicated on the assumption that individuals have representational systems that are sufficiently explicit about relational structure that they can use to match elements of a nudge across domains (Gentner & Markman, 1997). Indeed, this was suggested by Weinmann et al. (2016) who described this type of nudge as relating information that is difficult to understand to schemes more familiar to decision-makers.

Default. Thaler and Sunstein described a default option as what would be selected if a chooser did nothing (2009). Humans' non-rational acceptances of a default nudge can occur as the result of 1) flawed utility functions, e.g. those informed by loss aversion (Samuelson & Zeckhauser, 1988; Tversky & Kahneman, 1991) or those incorporating emotions such as regret avoidance (Samuelson & Zeckhauser, 1988), 2) consideration of factors irrelevant to incentives, such as endorsement of the default by others (Gigerenzer & Brighton, 2009; McKenzie et al., 2006; Meske & Potthoff, 2017), commitment to past decisions due to a drive for consistency (Festinger, 1962; Samuelson & Zeckhauser, 1988), or the assumption that one's past decisions are indicative of one's current preferences (Bem, 1972; Samuelson & Zeckhauser, 1988), or 3) a lack of engagement in the choice process, for example, due to inattention (Meske & Potthoff, 2017; Thaler & Sunstein, 2009). Bounded rationality plays a significant role in these mechanisms. For example, Humans are sometimes inattentive because they have limited attentional resources and they incorporate (often irrelevant) information like consistency and self-perception into decisions as heuristics to avoid decision-making methods that require more of their limited cognitive resources. Since Econs are not affected by such issues, they will only accept defaults when it is rational to do so.

Structuring complex choices. Thaler and Sunstein (2009) described the structuring complex choices category as nudges that provide structure for decisions with large choice sets, choices that vary in many dimensions, or decisions that are otherwise precluded from a "rational" decision-making process of examining all the attributes of all the alternatives and making trade-offs as necessary. It is difficult to determine which choices are complex because this varies, for example, based on a decision-maker's experience with the specific choice at hand. Thus, to place nudges in this category, we focused on nudges that provide structure (a coherent form or organization) to the problem without considering whether a specific decision-maker required the structure. Econs would not be aided by such structure.

A nudge concerned with the structuring of complex choices is informed in large part by bounded rationality. Humans' limited mental abilities prevent them from directly comparing a large number of alternatives (or alternatives with a large number of attributes), so they rely instead on the heuristic of grouping alternatives and distributing resources among the groups, or selecting a satisficing combination of attributes from mental or physical groupings (Fox et al., 2005). Humans are further limited in the way they distribute resources among the groupings such that they are influenced by the way the groups or alternatives are presented; that is, their order and hierarchy. For example, Humans tend to use the heuristic of evenly dividing resources among available choices or selecting alternatives equally from choice categories (Martin & Norton, 2009; Münscher et al., 2016).

Adding structure to the available alternatives can change the way Humans distribute resources by enabling them to envision different grouping mechanisms and/or breaking the choice problems into segments to facilitate the comparison of smaller sets of alternatives (Weinmann et al., 2016).

Summary of the categorization utilized for this review. The altered NUDGES taxonomy is summarized in Table 2. Our findings from the application of this taxonomy to the sample set of this review are presented later. First, we provide a description of the literature review methodology and descriptive details of the articles reviewed.

Table 2. Summary of altered NUDGES taxonomy.

Nudge Type	Defining Characteristics	Theoretical Mechanism Affecting Choice
Increasing salience of incentives	Makes certain incentive values associated with some attributes of choice alternatives more prominent or noticeable.	A Human places more weight (or importance) on the salient incentive than he or she would have done without the nudge. This increases the likelihood that an individual will choose an alternative that scores high in terms of the more salient incentive.
Understanding mapping	Makes information about one or more choice alternatives more understandable relative to incentives.	Analogies are used to relate information that is difficult to understand to schemes that are more familiar to Humans.
Default	A choice alternative that will be selected if the chooser does nothing.	The acceptance of a default nudge can occur due to a Human's flawed utility function (e.g. loss aversion), lack of engagement with the choice process (e.g., inattention) or considering irrelevant factors (e.g., drive for consistency).
Structuring complex choices	Choice alternatives are presented in an organized way.	Adding structure to the available alternatives can enable Humans to envision different grouping mechanisms and/or breaking the choice problems into segments to facilitate the comparison of smaller sets of alternatives.

RESEARCH METHODOLOGY

To conduct our literature review, we used the approach outlined by Leidner and Kayworth (2006), which recommends developing (1) a data collection strategy to search prior literature, (2) a set of criteria to determine the inclusion of studies, and (3) a strategy that includes a scheme for documenting, coding, and analysing included studies.

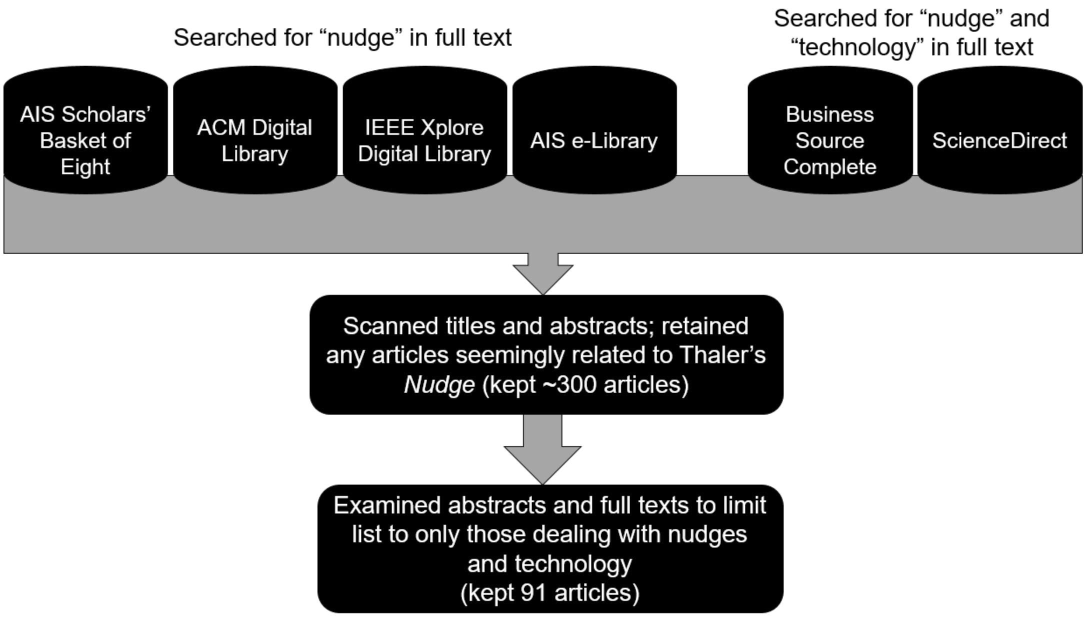
We initially conducted full text searches via online databases for the word "nudge" in various IS sources, including the Association for Information Systems Senior Scholars' Basket of Eight Journals (Members of the College of Senior Scholars, 2011), the ACM Digital Library, the AIS e-Library, and the IEEE Xplore Digital Library. We additionally searched more general databases (including Business Source Complete and ScienceDirect) for the words "nudge" and "technology." After each search, we did manual scans of the title, abstract, keywords, and full text of the articles to ascertain their relevance to our purpose. We retained those articles that included a mechanism aiming to alter behaviour in line with the nudge definition in the context of IS technology, e.g. computer hardware, software, and data (Goodhue & Thompson, 1995). We thus included papers referencing any IS, Internet-based tools or websites, mobile applications, social media, etc. Papers using a broader definition of technology (e.g., non-IS related research and development efforts) were excluded to maintain a focus on IS. In other words, we included papers that discussed, proposed, and/or investigated a change to choice presentations facilitated by technology and expected to alter behaviour. We did not limit the sample set on any other criteria. This data collection process is summarized in

Figure 1. We identified 91 peer-reviewed articles published between 2009 and 2017, most of which (69%) were published in conference proceedings; the rest were journal publications. A full list of the articles reviewed can be obtained from the authors.

Because our goal was to broadly review the relevant literature, we did not limit our sample set to articles citing Thaler and Sunstein's seminal *Nudge* work (2009).

However, most of the articles (87%) referenced either the seminal work, another article that itself referenced the seminal work, or another related work by Thaler. The remaining 12 articles (13%) were included because they discussed, proposed, and/or investigated a mechanism that met the nudge definition, even if the term “nudge” was not used.

Figure 1. Data collection process.



After searching the literature and determining which works met the inclusion criteria, we moved into several stages of coding the papers to address the goals of our review. We coded the papers for (1) descriptive information, (2) definitions of the nudge concept, when provided, and (3) research topics within IS to which the paper contributed. Additionally, we coded at the nudge level by applying the NUDGES typology with the alterations described earlier. Each of these efforts and their findings are described later.

DESCRIPTIVE ANALYSIS

The earliest publication included was published in 2009 and publications steadily increased over time, with 31 publications from 2017 (the year in which this search was conducted). Of the 91 articles total, 63 were published in conference proceedings and 28 published in journals. Using the Scimago journal rankings (SCImago, n.d.), we found that the average h-index of the journals was 86. In comparison, the average h-index of the eight journals included in the Senior Scholar's Basket is 106 (Members of the College of Senior Scholars, 2011).

We used the framework provided in Palvia et al. (2003) to analyse the methodologies used by the research included in our sample set. Most researchers utilized either a field study/experiment (19 articles) or a lab experiment (22 articles) for their research of nudges. The sample set also included 12 research proposals, indicating the youth of the research area. The methodologies are summarized by year in Table 3.

KEY FINDINGS

At the research project level – IS research streams

The highly flexible nature of the nudge construct enables researchers to apply it to a variety of topic areas within IS. To identify the network space (Roberts et al., 2012) of the nudge construct and understand how it has contributed to IS research, we examined how and with what frequency nudge has been applied across different IS research streams. To this end, we conducted a card-sorting study. Six individuals, all research faculty or doctoral students from the MIS Department of a Tier 1 research university in the United States, participated in the exercise.

Table 3. Methodologies used by year.

Year	Research Method								
	Commentary	Field study or experiment	Frameworks and conceptual models	Lab experiment	Library research	Research proposal	Secondary data	Survey	Total
2009	1								**1**
2010	1	1	1						**3**
2011		2							**2**
2012					1	2			**3**
2013		6	1	1	1	1		1	**11**
2014	1	1		1	2	4		3	**12**
2015		2	1	6	1	1		2	**13**
2016		2	1	4	4	1		3	**15**
2017		5	4	10	4	3	1	4	**31**
Total	**3**	**19**	**8**	**22**	**13**	**12**	**1**	**13**	**91**

We created one card for each of the 91 articles we found during our literature review, with each card containing the following information: article title, journal or conference name, author(s), abstract, and keywords. In accord with Walsh (1988), participants were instructed to sort the cards into research streams of their own creation (an open card sort), although we provided a single category (Privacy) as an example. We randomly separated the articles into three nearly equivalent sets and assigned each set to be categorized by two researchers independently. In addition, one of the authors independently assigned a research stream to each article. Thus, each paper was categorized by three individuals (one of the authors and two card-sorting participants), with each of the six card-sorting participants categorizing 30-31 papers and providing their own names and definitions to the research streams. When two or more researchers agreed on a stream (i.e., with similar names and definitions), the article was assigned to that research stream. When there was no agreement (as happened with seven articles), the article was assigned to an "Other" stream. Although researchers were allowed to assign articles to more than one stream (e.g., Privacy and Social Media), there was never agreement on multiple streams for any one article, so all articles were assigned to only one research stream. The results of this card-sorting study are presented in Table 4.

Since Privacy was the most frequently listed research stream and was also the stream used as an example, it is possible that the example served as a prime that skewed the results. To mitigate this concern, we replicated the card sorting study without using any example. Five faculty members and four Ph.D. students in the MIS program of a tier one research university in the United States participated in the replication, none of whom participated in the original study. Each of the nine participants received a random subset of 30-31 cards with identical information to the first study and was encouraged to assign the cards to self-generated research streams. Thus, each card was sorted by three individuals. Like in the first study, a card was assigned to a stream when two or more participants agreed on its research stream.

In both studies, the most frequent applications of IS nudge research were Privacy, followed by Green IS and then Health. In both card sorting studies, the participants were blind to any purpose of the study outside of the task they were asked to complete. Next, we describe the role of nudging in these three IS research streams.

Table 4. Research streams and nudge article counts.

Research Stream	**Number of Articles**
Privacy	24
Environmental Conservation & Green IS	16
Health	9
Other	7
Design	7
Security	7
Education	5
Crowdsourcing	5
Commerce & E-Commerce	3
Social Media	3
Persuasive Technology	2
Behavioural Change	1
Mobile	1
Recommender Systems	1
Total	**91**

Privacy

Participants most frequently assigned articles to the Privacy research stream, which they generally described as studies evaluating decision-making about the disclosure and protection of users' personal information. The articles in this stream were mainly empirical investigations of how nudges can influence people to reduce the amount of information they disclose on digital platforms. Most articles focused specifically on information disclosure via social media platforms, but a handful of papers focused more generally on activities like strong password creation as a way to protect information privacy (Khern-am-nuai et al., 2017; Renaud & Zimmerman, 2017), the right to be forgotten policy for data published online (Hermstrüwer & Dickert, 2017), and auto-completion Web tools as a threat to over disclosure of personal information (Knijnenburg et al., 2013).

In many of these articles, scholars hypothesized that their nudges would reduce information disclosure by encouraging individuals to reflect more on their social media posts (Wang et al., 2013, 2014), inducing psychological ownership of personal information (Kehr et al., 2014), and changing default privacy settings (Dogruel et al., 2017; Hermstrüwer & Dickert, 2017; Knijnenburg et al., 2013). A few scholars also investigated nudges that attempted to *increase* information disclosure (Chang et al., 2016).

Findings in these IS privacy-related nudge studies were mixed, with one author remarking that “nudges evaluated thus far have yielded disappointing results” (Knijnenburg, 2017, p. 63). Researchers consistently discussed the need for nudges to be defined and evaluated with specific contexts, situations, and/or user personalities in mind (Egelman & Peer, 2015; Kehr et al., 2014, 2013; Knijnenburg, 2017; Micallef et al., 2017; Wisniewski et al., 2017).

Environmental conservation & green IS

Although participants in the card-sorting study provided a few different titles for this research stream (Sustainability, Green IT/IS, Environment, Environment/Conservation), all definitions referenced individual decision-making regarding environmental conservation and sustainability behaviours. Compared with the privacy research stream, the contexts and behaviours studied in this grouping were much more varied. Many of the studies investigated the implementation of nudges in digital tools to reduce individuals' personal energy consumption in their homes (Di Cosmo & O'Hora, 2017; Graml et al., 2011; Loock et al., 2013; Lossin et al., 2016) while others focused on encouraging users to select sustainable options, including electric rental cars (Stryja, Dorner, et al., 2017; Stryja, Satzger, et al., 2017). Scholars investigated manipulating users' route planning methods to reduce overall CO_2 emissions from vehicular traffic (Bothos et al., 2016; Cheng & Langbort, 2016) and encouraging users to pay CO_2 offsets when booking flights (Székely et al., 2016). Despite variations in the contexts and specific behaviours investigated in this stream, the research hypotheses in it reflected similar goals across studies: nudges implemented in IS should increase sustainability behaviours.

However, findings in this stream were mixed. Authors who tested multiple nudges found some effective and others ineffective (Momsen & Stoerk, 2014; Stryja, Satzger, et al., 2017). Bothos et al. concluded that their results, "show that we cannot draw significant conclusions on the impact of the [nudges]" (2016, p. 6). Authors called for more focus on individual users and contexts, including personality traits like resistance to innovation (Stryja, Satzger, et al., 2017) and tendency to resist change (Stryja, Dorner, et al., 2017) as well as "types" of users and contexts in transportation (Bothos et al., 2016).

Health

The third most identified research stream focused on the use of IS nudges to increase the mental or physical health of users. Most of the papers categorized were nearly evenly split between nudges aiming to increase physical activity (Mohamed et al., 2017; O'Raghallaigh & Adam, 2017; van Dantzig et al., 2013) and nudges aiming to improve eating habits (Cordeiro et al., 2015; Hou, 2014). A minority of papers focused on other health behaviours, including opting in to vaccines (Langley et al., 2015) and changes to behaviours of medical staff and patients to reduce hospital readmissions (Gregor & Lee-Archer, 2016).

All the health papers predicted that IS nudges could increase behaviours that improve personal health (with one notable exception that examined how "negative nudges" could lead to a reduction in health-focused digital food journaling, Cordeiro et al., 2015). Findings throughout the research stream were mixed to the degree that two of the nine health-related articles reported null findings (Langley et al., 2015; van Dantzig et al., 2013). Scholars in this area called for a focus on individuals and contexts (Carter, 2015).

Summary of findings from the research stream analysis

Although the research on IS nudges is progressing in several different streams, similarities appear across the popular streams. Nudges are typically conceptualized as ways to "improve" behaviours. Most of the work has focused on changing behaviour for the benefit of the individual, with fewer studies investigating behavioural change for the good of society. None investigated neutral or organization-benefitting behaviours. In all research streams, empirical findings of the effects of nudges were mixed, and authors called for an increased focus on individuals and specific contexts in future studies of nudges in IS.

At the nudge concept level – definitional analysis

Most of the papers we reviewed referenced Thaler and Sunstein's (2009) original definition of a nudge, but we found over 20 definitions of nudge in the IS literature that contained fewer, more, and/or different elements than the original definition. When comparing research across articles, these inconsistencies in the definition of the nudge construct can result in mixed, contrary, and incommensurable empirical outcomes. Appendix A in the supplementary material provides details regarding these definitional inconsistencies. We frequently found the following three additions to Thaler and Sunstein's nudge definition.

First, many researchers define nudges as being simple, subtle, inexpensive, small, minor, indirect, or use a number of other synonyms (Avineri, 2012; Dogruel et al., 2017; Klein & Ben-Elia, 2016; Mirsch et al., 2017; Momsen & Stoerk, 2014; Wisniewski et al., 2017; Zhang & Xu, 2016). We speculate that the addition of these adjectives stems from the everyday definition of *nudge* ("to touch or push *gently*; to prod *lightly*," Merriam-Webster Inc., 2017c, emphasis added). This conceptualization of nudge may also serve to emphasize the role of nudges in *not* changing incentives; however, even a subtle, simple, or inexpensive intervention can have a profound effect on the incentives of a choice. For example, mailing and handling fees added to an online purchase may be communicated subtly in the interface (e.g., only displayed after a choice has been made and/or displayed only in fine print) but may significantly change the incentives of the purchase and therefore are not nudges. Alternatively, nudges that do not change incentives may lack subtlety: in fact, an entire category of nudges (increasing salience) in the typology used here operate by making certain incentives *less* subtle. For example, Kalnikaitė et al. (2013) developed an interface to make the environmental friendliness and organic status of supermarket items more obvious to shoppers.

Second, nearly all research projects conceptualize nudges as beneficial mechanisms that can be used to improve peoples' lives, decisions, outcomes, or behaviours (Dimitrova et al., 2017; Dogruel et al., 2017; Hou, 2014; Hummel et al., 2017; Klein & Ben-Elia, 2016; Weinmann et al., 2016). This trend speaks to the main focus of Thaler and Sunstein's presentation of nudges (2009), which is to alter behaviour for the better. However, conceptualizing nudges solely as ways to improve people's lives limits our understanding of their potential effects. For example, nudges can encourage behaviours that are neutral to the individual but beneficial to an organization (e.g. technology use and security policy compliance), rendering them highly useful to IS and management research. Moreover, because no choice architectures are neutral (i.e., they all contain nudges: Thaler & Sunstein, 2009), focusing only on beneficial nudges may preclude our identification and understanding of unintended nudges. In addition, defining behaviours that are *better* than others brings its own challenges, such as which stakeholders should be used to derive values that are associated with choice results.

Finally, several researchers defined nudges based on their role in the decision-making process. Many defined them as associated with bounded rationality (Almuhimedi et al., 2015) or overcoming cognitive biases (Avineri, 2012; Hummel et al., 2017), perhaps by triggering conscious decision-making processes (Dogruel et al., 2017). In contrast, others define nudges as exploiting cognitive biases (Elsweiler et al., 2017) or encouraging the use of heuristics to make decisions (Székely et al., 2016). These definitions relate to nudging's underlying assumptions and associated theories; we will use them to help categorize nudge results into cohesive theoretical subsets within which generalizations can be made.

We can utilize this discussion of the nudge definition to clarify mixed and unexpected findings in the extant IS nudge literature. See Appendix B in the supplementary material for an example of this application.

Differentiating concepts similar to nudges

In our review of this literature, we were introduced to multiple concepts that are similar to nudges but with some differences, extensions, or exclusions. These concepts help provide a more complete view of the work being done in decision-making technology research and offer more specific definitions of particular types of nudges or behavioural interventions. Below is a brief description of each.

Persuasive technology. Persuasive technology is defined as "interactive information technology designed for changing users' attitudes or behavior" (Oinas-Kukkonen & Harjumaa, 2008). Nudges are more general than this concept in that they are not limited only to technology. Persuasive technology includes more than just nudges, given that the definition does not exclude forbidding options or changing economic incentives the way nudges are limited. Thus, one might conceptualize nudges as *one element of* a persuasive system (if the element meets the criteria of the nudge definition) and as part of what makes the system persuasive. See Meske and Potthoff (2017) for a more in-depth discussion.

Mindless computing. The concept of mindless computing builds on that of persuasive technology and integrates the idea of dual-process psychology. Mindless computing is defined as "a mobile or ubiquitous persuasive technology designed to subtly influence the behavior of the user without requiring their conscious awareness" (Adams et al., 2015). Mindless computing thus further limits the scope of persuasive technology to only those technologies that are mobile and ubiquitous *and* achieve their behavior change without conscious awareness of the user. This concept is more limited than that of nudging, as nudges are not required to be subtle or influence an individual's behavior without their conscious awareness, but more broad in the sense that mindless computing does not exclude forbidding options or changing incentives.

Digital nudging. Digital nudging has emerged in technology-related literature based on the nudging concept from behavioral economics. Digital nudging is "the use of user-interface design elements to guide people's behavior in digital choice environments" (Weinmann et al., 2016). The creators of this construct have thus limited the realm of nudges to only those occurring as user-interface design elements specifically in digital choice environments. It is worth noting that this definition of digital nudges does not exclude forbidding options or changing economic incentives as does Thaler's definition of a nudge.

Digitally Based Change Interventions. Digitally Based Change Interventions (DBCI) are "interventions that utilize digital technologies to promote and maintain health and wellbeing through monitoring, managing and preventing personal health problems" (O'Raghallaigh & Adam, 2017). From this definition, we can glean that DBCIs are specific elements of choice architecture that are digital and health-focused. Again, there is no exclusion in the definition for forbidding options or changing incentives, so a DBCI may or may not be a nudge depending on these features. DBCIs are not defined by behavior change, so these elements may "promote" health and well-being but are not defined by their success in causing specific behavioral changes.

Gamification. Gamification is defined as "the use of game design elements in non-game contexts" (O'Raghallaigh & Adam, 2017). Typically, gamification is utilized with the goal of behavior change – game design elements are constructed and deployed in non-game contexts to increase a user's motivation to complete some task. This bears some similarity to nudges, and certain gamification elements are nudges (if they cause a predictable behavior without forbidding any options or significantly changing incentives).

Purchase Pressure Cues. Purchase Pressure Cues (PPC) have a more specific context than the other concepts discussed here. PPCs are defined as "graphical depictions on websites that attempt to subliminally put customers under pressure to make a transaction and ultimately boost sales" (Amirpur & Benlian, 2015). PPCs and nudges both cause predictable behavior change. PPCs bear the additional requirements of 1) being graphical depictions on websites, 2) achieving their behavior change "subliminally" and by putting customers "under pressure", and 3) boosting sales. PPCs are not required to avoid forbidding options or changing economic incentives.

Summary of concepts similar to nudges. Although this discussion is not intended to be a comprehensive review of all IS constructs bearing any resemblance to nudges, noting the differences from this set of constructs can help future scholars determine the appropriateness of each behavioral mechanism in a given context or theoretical basis. We found that this set of concepts could be meaningfully distinguished based on whether they are defined specifically for the technology context or applicable across contexts and whether they utilize conscious processing or are expected to affect behavior without the decision-maker's conscious awareness. These concepts are summarized in Table 5.

Table 5. Concepts similar to nudging.

	Conscious Awareness	**No Conscious Awareness**
Specific to technology context	DBCI (*health context)* Digital nudging Persuasive technology	Purchase pressure cues (*e-commerce context*) Mindless computing
Across technology and non-technology contexts	Nudging Gamification	

At the individual nudge level – typological analysis

We applied the modified typology based on Thaler and Sunstein's NUDGES taxonomy by considering the empirical evidence for nudges that exist in the literature. The resulting four-category typology should have orthogonal categories and should be comprehensive, thereby allowing all IS nudges to be placed in one and only one category (Nickerson et al., 2013). To evaluate the orthogonality of the nudge categories described in Table 2, using the literature review described above, we coded a total of 205 unique mechanisms that scholars operationalized as nudges in the 91 papers.

A member of the research team coded all 205 mechanisms. However, to ensure rigorous and repeatable categorization, a research assistant was trained in the typology and subsequently coded the mechanisms in a random subset of 30 papers (~33% of the sample set). The two coders had an initial agreement rate of 88% on the coding of the mechanisms. All disagreements were resolved by discussions between the coders. Of the 205 unique potential nudge mechanisms, 15 were excluded from categorization because they did not meet the definitional requirements of the nudge construct (details are provided in Appendix C in the supplementary material). We classified the remaining 190 nudges within the typology and found the four categories to be both orthogonal and comprehensive, with 111 increasing salience of incentives, 45 understanding mapping, 22 defaults, and 12 structuring complex choices. Table 6 presents some examples from the sample set of each nudge type. Full details of this classification are available from the authors upon request.

One purpose of this typological analysis is to explain mixed and unexpected findings in the extant IS literature. See Appendix D in the supplementary material for an example of how we can apply the typology to better understand mixed results in the literature.

Table 6. Examples of the nudge types in the sample set.

Nudge Type	Count	Examples	
Increasing salience of incentives	111	While Facebook users are typing a new post, presenting them with the profile pictures of five random people who will be able to view the post reminds them of who will be able to see the post (Wang et al., 2014). This reminder can increase the salience of social norms pertaining to the kinds of information that is appropriate to post.	When individuals are choosing a rental car, reminding them of the innovativeness and eco-friendliness of alternative electric cars (Stryja, Satzger, et al., 2017) can increase the salience of incentives associated with being innovative and with being eco-friendly.
Understanding mapping	45	When users are typing in a password, provide them with a warning that evaluates the strength of their password in terms of the time a hypothetical hacker would require to crack it or the estimated number of other accounts that use that exact password (Khern-am-nuai et al., 2017). This nudge helps people map a password choice alternative to incentives associated with their desires for privacy.	When consumers consider the purchase of home-heating products, provide them with more understandable assessments of the products' energy use (e.g., in terms of expected utility bills) (Campbell et al., 2014). This nudge helps people map each alternative to cost reduction incentives.
Default	22	The default privacy settings in many social network services encourage more appropriate self-disclosure behaviours (Tschersich & Botha, 2013). This nudge helps people "choose" settings that agree with what the design architect believes are appropriate.	A slider on a website that allows users to select the dollar amount they would like to contribute as a carbon offset payment after purchasing a flight has a high default value (Székely et al., 2016). This nudge encourages people to choose higher carbon offset contributions.
Structuring complex choices	12	A decision-aid system guides users through the process of scheduling unfinished work during free periods in the next day. This aims to avoid overwork in the current day by providing the following day as an alternative within which to distribute resources (i.e., work and time) (Klesel et al., 2016).	Contacts are categorized at various levels of granularity to guide individuals to set up customized privacy settings within an online social network and share only certain types of content with different groups of contacts (e.g., family, colleagues, acquaintances, etc.). The various levels of groupings offered allow users to systematically distribute privacy settings in a more granular way (Knijnenburg & Kobsa, 2014).

OPPORTUNITIES AND CHALLENGES IN IS NUDGE RESEARCH

As we have demonstrated here, IS researchers have shown interest in and have begun to implement nudges in their work; however, the research program remains piecemeal and fragmented. Next we address some of the challenges and opportunities that we identified through the course of this review that can guide future IS nudge researchers. This discussion is organized by the research stream to which projects contribute, opportunities identified through our exploration of the nudge construct's definition, and opportunities identified through the typological analysis of the nudge construct.

Understudied areas of research for IS nudges

Through our research stream analysis, we identified a number of areas of IS research in which nudges have been investigated; primarily, Privacy, Green IS, and Health (see Table 4). However, there remain many areas of IS research in which nudges may be applicable but where they have not yet been investigated. For example, the *MISQ* research curations have identified nine major areas of ongoing IS research (Bush & Rai, 2019). Six of these did not appear in any of the research streams identified in our card-sorting study: information systems alignment, information systems sourcing[1], IS use, IT workforce, knowledge management, and trust. Thus, these may serve as fruitful areas of exploration for future IS nudge researchers. In Table 7 we have suggested some potential nudge research questions that could be explored in each of these areas, along with references from the curation as resources to use for investigating these particular

[1] Note that a category titled "Crowdsourcing" did emerge in the card sorting study. This represents a subset of the research curation IS Sourcing.

Table 7. Sample research questions or directions for so far unstudied areas of IS research.

Research Topic	Sample Research Questions/Directions
Information Systems Alignment	• Can nudges implemented in the IS planning process (Segars & Grover, 1998) shift IS strategies such that they result in increased alignment with organizational strategies? • Can nudges implemented in the decision-making structure of IT governance (Wu et al., 2015) change the intellectual dimension of strategic alignment and thereby the impact of IT governance on organizational performance?
Information Systems Sourcing	• Can nudges implemented in the choice problem presentation impact a client or supplier's sourcing decisions? • Can nudges implemented in the contract structure of a sourcing relationship change the degree of hierarchical elements and/or the division of risks and incentives that are eventually agreed upon between the client and the supplier? • Are there pre-existing nudges in contracts or choice problem presentations that can explain the present-day state of IS sourcing for a firm or business unit?
IS Use	• Can nudges be used to encourage or discourage use of an IS and/or individual features of IS? • How might nudge as a concept extend leading theories of IS Use (e.g. as a mediator, moderator, independent variable, etc.)? • Are there pre-existing nudges in IS that can explain previously confusing findings regarding use of that IS?
IT Workforce	• Did/do pre-existing nudges in IT job descriptions and/or application materials contribute to which skills are perceived to be important for the job described? • Can nudges implemented in governance elements (e.g. recognition, feedback, communication) change worker frustration and retention?
Knowledge Management	• Can nudges implemented in knowledge management systems increase overall individual contributions from workers and/or improve their quality? • Are there pre-existing nudges in different knowledge management systems that can explain previously confusing findings regarding participation rates and quality of the knowledge collected there?
Trust	• Does trust serve as a mediator or moderator in the nudge-behaviour relationship described in nudge literature? • Can nudges implemented in technology increase users' trust of the system?

questions. This is not intended to be a comprehensive roadmap for future IS nudge research but rather represents possible areas for future study in the current main streams of IS.

Understudied nudge definition elements

We found in our review that nudge IS researchers have overwhelmingly focused on nudges as improving individuals' lives, in line with the original conceptualization from Thaler and Sunstein (2009). However, there are no definition elements that prevent nudges from being neutral toward individuals and/or beneficial toward other entities, e.g. organizations, firms, business units, or departments. In addition, there are no definitional elements that prevent nudges (e.g., that exist in extant IS) from being harmful to individuals, organizations, etc. These potential organizational impacts from nudges have been understudied so far and represent a promising avenue of research for organizational IS scholars.

Understudied nudge types

After applying the nudge typology, we found that over half the nudges studied in our sample set of papers were of the increasing salience of incentives type. An additional quarter of the nudges were understanding mapping nudges. Therefore, only 11% and 6% of the nudges studied were default and structuring complex choice nudges, respectively. These understudied nudge types represent a promising area of future research for IS nudge researchers.

Default nudges investigated in other areas of research have proven to be highly effective in many settings. For example, organ donation rates are twice as high when the choice is presented with a default of participating in organ donation as opposed to a choice with no default or with the default of nonparticipation (Johnson & Goldstein, 2003). Defaults also represent a rich area for theorizing, as there are many competing explanations for how and why defaults affect Human behavior (Samuelson & Zeckhauser, 1988). Because they are easily implemented in many online choice environments, defaults are an excellent subject of both academic research and practice implementation.

Most of the empirical work we reviewed took the form of laboratory experiments or surveys. We speculate that in such settings, it may be challenging to implement structuring complex choice nudges, because it may require prohibitive training of research participants to prepare them to make a complex choice in the first place. Nevertheless, this nudge type could be meaningful for researchers and practitioners investigating and making complex choices. Structuring complex choices nudges could be important in design science research in the development of systems to achieve desired outcomes for users making complex and context-specific decisions.

Incorporating the IT artifact as giving feedback

Finally, we indicated earlier that Thaler and Sunstein's (2009) providing feedback nudge category should not be included in our general nudge typology because, rather than being a fundamentally different kind of nudge, feedback provides alternative ways in which other nudges can be implemented. Instead, whether a nudge gives feedback to the decision-maker is a characteristic that can be evaluated for all nudges, and is integral to the IS study of nudges.

Nudges are not inherently IS-related and can be implemented in both online and offline environments – in fact, scholars have called for research identifying how online and offline nudging differ (Meske & Amojo, 2020). However, only nudges in online environments can provide personalized feedback to individual users or groups of users in a real-time and scalable way. This is critical for nudge research, because personalized nudges have been posited to be more effective (Goldstein et al., 2008).

IS-to-human feedback is defined as “the communication of the state of the… [IS]… as a response to user actions, to inform the user about the conversation state of the system as a conversation participant, or as a result of some noteworthy event of which the user needs to be apprised” (Renaud & Cooper, 2000). We can further distinguish this concept as either immediate feedback or archival feedback (Renaud & Cooper, 2000). Immediate feedback (1) informs the user about the current system state (e.g., received user input, working on user input, or has a problem), (2) explains unusual occurrences, and (3) provides context-sensitive assistance (Foley & van Dam, 1982; Savage-Knepshield & Belkin, 1999; Suchman, 1987). Of particular interest for personalized nudges is immediate feedback that is smart and that which is adaptive (Goldstein et al., 2008). Smart feedback provides the user with nudges based on user-specific information, such as demographic variables. For example, based on a user entering his or her age and income, the IS can provide a range of retirement plan investment options, making sure that the “most appropriate” given the age and income data is the default option (Goldstein et al., 2008). Adaptive feedback provides the user with nudges that dynamically change based on the real-time sequence of choices made by the user. For example, web-based car configurators employ multiple steps, with earlier user choices leading to (and potentially limiting) options displayed in each subsequent step (Goldstein et al., 2008). Each step can have its own nudge. For example, some IS configurators provide a default configuration that starts out fully loaded (includes all available options) and allow users to eliminate the options they don’t want. Other configurators provide a default configuration that is stripped down (includes no options) and allow users to add the options they want. The fully loaded default systematically results in more expensive cars being chosen (Goldstein et al., 2008).

Archival feedback provides mental aids to help a user reconstruct the past circumstances (including their prior decisions and actions) that have led to the current state of the user-IS interaction (Draper, 1986; D. Norman, 2013; Renaud & Cooper, 2000). Of particular interest for personalized nudges is archival feedback that is persistent (Goldstein et al., 2008). With persistent nudges, the assumption is that a user's past decisions and actions are a good predictor of future decisions and actions (Goldstein et al., 2008). Persistent nudges are thus based on a user's past choices that were associated with the past interactions the user had with the IS. For example, hotels provide a persistent nudge when their online reservation systems make the default a smoking room for individuals who have requested them in the past (Goldstein et al., 2008). Table 8 provides IS feedback nudge examples for each category of nudge in our typology. This exercise helps illuminate how nudges are relevant to IS research, and how IS provide a novel and important lens for the study of nudges.

Table 8. Examples of nudge personalization via IS feedback.

	Immediate IS Feedback		Archival IS Feedback
Nudge Type	**Smart** (Provides the user with nudges based on user-specific information.)	**Adaptive** (Provides the user with nudges that dynamically change based on the real-time sequence of choices made by the user.)	**Persistent** (Provides current nudges based on a user's past choices that were associated with past interactions that the user had with the IS.)
Increasing salience of incentives. Makes certain incentive values associated with some attributes of choice alternatives more <u>prominent or noticeable</u>.	Presenting Facebook users who are typing a new post with the profile pictures of five people who follow them reminds the individuals of who will be able to see the post. This reminder can increase the salience of social norms pertaining to the kinds of information appropriate to post and has been found to prevent unintended disclosures (Wang et al., 2014).	In the UK, an LED device on a shopping cart keeps track of the average distance the items in the cart have travelled in order to reach the store (ranging from local product, to somewhere in Europe, to from other parts of the world). This is updated each time an item is put in the cart, and is compared to a social norm of average mileage (Kalnikaite et al., 2011). Shoppers tended to select items that were more locally sourced.	Default privacy settings can be set in Flickr.com that apply to all new photo and video uploads; these settings can be changed later for individual photos and videos. The salience of these settings is increased by Fickr.com because it labels each photo and video with its current setting (e.g., anyone can see, only friends and family can see, etc.) (Acquisti et al., 2017).
Understanding mapping. Makes information about one or more choice alternatives <u>more understandable</u>.	An IS uses individual's grocery receipt data to determine the individual's nutritional scorecard, which uses bar charts to display target, excess, and insufficient nutrients (Wayman & Madhvanath, 2015).	Individuals typically don't understand the relationships among password choice and strength. Password meters, which indicate the current strength (in terms of color and/or words) after each character has been entered, have been shown to result in stronger passwords (Egelman et al., 2013).	An IS that provides users a warning while they are typing a password, informing them of the similarity of the password they are entering to previous passwords they have used, and how easily a hypothetical hacker could crack the current password due to this similarity. (This is adapted from the example investigated in Khern-am-nuai et al., 2017.)

Default. A choice alternative that will be selected if the chooser does nothing**.**	Age and income information entered by the user help determine investment allocations for new employees who are joining retirement plans (Goldstein et al., 2008).	In the Chevrolet configurator website, the early choice of a Camaro coupe model results in the 1SS option being the default configuration (at $37,995) with other choice options (e.g., the 1LS at $25995) being available; accepting the default leads to the next page with an exterior color of blue and interior color of black as defaults, with other color options available (Chevrolet, 2020).	Airlines make an aisle seat the default for customers who have requested them in the past (Johnson & Goldstein, 2013).
Structuring complex choices. Choice alternatives presented in an organized way.	Take age, income, and risk preference data entered by the user into account when organizing and displaying the investment options to new employees who are joining retirement plans (Goldstein et al., 2008).	Rather than present a user with a comprehensive list of automobile models and model-option choices, web-based automobile configurators, structure user choices in a hierarchical fashion with early user choices informing the way in which subsequent choices are structured. Thus, choosing the Camaro coupe on the Chevrolet website results in a list of eight engine & transmission packages, the choice of which leads to exterior and interior color options, etc. (Chevrolet, 2020).	An IS may have different ways in which it interacts with users, depending on the user's skill level: task and IS interface novice (e.g., bank customer making an initial cellphone check deposit) and expert 'power' users (who are thoroughly familiar with the task and IS interface) (Shneiderman et al., 2017). Persistent feedback, then, structures the current dialogue in a way that is consistent with the skill level of the user during his or her last dialogue with the IS.

CONCLUSION

In order to identify how nudges have been applied in IS research we used a very open search procedure to collect 91 papers investigating nudges in technology, and then conducted three different analyses. First, we utilized a card sorting study to analyses the areas of IS research to which each study contributed. Second, we coded each article to understand how nudge is being defined and conceptualized across IS research. Finally, we coded 190 valid nudges from the sample set using a typology from extant literature that we significantly defined, developed, and limited to be orthogonal, explanatory, and comprehensive. We demonstrated that 1) nudge research so far has been fragmented and piecemeal, 2) the altered NUDGES typology that we define here can successfully describe and define the nudges found in IS literature and, more importantly, identify theoretical explanations for their effects, and 3) clarity in the definition and type of nudge utilized can explain previously confusing and unexpected empirical results in IS research. We went on to provide a number of future research directions for IS nudge research based on these analyses, and described how IS researchers can incorporate the IT artefact in their nudge work. We believe that our work here will be helpful to future IS researchers because it provides a cogent definition and typology of nudges and associated theoretical and empirical suggestions for future IS nudge research.

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ESSAY #2: WHY DO INFORMATION SYSTEMS USERS SELECT DEFAULT OPTIONS? ADDING ORDER TO CURRENT THEORIES

ABSTRACT. Nudges are aspects of the way a choice is presented that impact decision-makers' behavior without limiting their available options. Frequently implemented using Information Systems (IS), a default nudge is one that "selects" an option when the decision-maker does not make a choice. Dozens of theories can explain why individuals stick with a default option even when it is suboptimal. Although IS scholars have studied the default nudge extensively, many have investigated it with little or no theoretical explanation or have employed a theory that is not contextually applicable – which is paradoxical considering the abundance of theories available. Therefore, the research program now needs to answer the question: *How can default theories be organized to enable researchers to explain why individuals tend to select default options when those options are not necessarily the optimal choice?* We address this question by developing a typology of default nudge theories situated in an overarching decision-making framework and informed by concepts from neoclassical and behavioral economics. We also elaborate on the efficacy of our typology to inform predictions about default nudges, explain unexpected results in past studies, and guide the development and testing of new default nudges.

INTRODUCTION

Information systems (IS) influence the decision-makers who use them, whether this influence is intended by the IS designer or not. One way that IS can influence users even when providing all appropriate information for a choice problem is through nudges (Thaler & Sunstein, 2009). Nudges are aspects of the way a choice is presented that affect decision-makers' behavior without limiting their options. One popular nudge involves a default option, which is the resulting choice if the decision-maker does nothing. Individuals choosing among alternatives tend to accept the default option (*The Behavioural Insights Team*, 2017), as demonstrated in contexts including pension enrollment (Service, 2015) and organ donation (Johnson & Goldstein, 2003), independent of whether or not the default is the best choice for them.

As the use of ubiquitous digital and mobile tools and platforms increases both at work and at home, understanding the influences that nudges in IS can have on individuals' online choice-making becomes increasingly important. IS scholars have displayed an interest in nudging and have generated a large number of nudge-related publications in a short amount of time (Collier, 2018), but have done little to advance the question of *why* individuals tend to select default options when those options are not necessarily the optimal choice (e.g., Dogruel et al., 2017; Székely et al., 2016), focusing instead on empirical implementation of defaults in various information systems contexts.

This is not to say that there are no theories of why nudges influence individuals' behavior. Rather, the problem comes from the fact that there are too many unrelated theories being employed. For example, there are dozens of unrelated theories that could be used in the IS literature to describe why individuals tend to choose an alternative that is the default choice (Dinner et al., 2011; Johnson & Goldstein, 2003; Samuelson & Zeckhauser, 1988). Therefore, it is still not clear which theory is at play in any given context; that is, an overabundance of theory has contributed, paradoxically, to the lack of theory in IS default nudge research that we observe.

Our research question is thus: “How can default theories be organized to enable researchers to explain why individuals tend to select default options when those options are not necessarily the optimal choice?” To address this research question, we start by defining nudge and associated concepts based on a foundation of neoclassical and behavioral economics and then develop a typology of default theoretical explanations organized in a general decision-making framework. We demonstrate that this theory-based typology can (1) improve researchers’ predictions and explanations regarding default IS nudges, (2) help researchers reconcile inconsistent results currently found in the IS default nudge literature (Bart P. Knijnenburg, 2017; Langley et al., 2015; Stryja et al., 2017), (3) help researchers create new types of default nudges, and (4) inform researchers and practitioners about how to implement effective default nudges. In these ways, our typology contributes to the overarching theoretical goals of adapting the nudge concept to the IS field from its original field of behavioral economics and psychology (Markus & Saunders, 2007) and building a more coherent and integrated IS research program (Zmud, 1998).

Though there are other kinds of nudges, we focus on IS default nudges because (1) defaults examined in non-IS research have been very effective (Johnson & Goldstein, 2013), (2) defaults are a rich area for theorizing due to the many competing explanations for the ways in which they influence individuals’ choices (Samuelson & Zeckhauser, 1988), and (3) defaults are easily implemented in IS choice environments.

Note that we do not get mired in issues concerning how to nudge individuals into choosing the “right” or “best” alternative because these value judgments are difficult to ascertain and because nudges may be used for purposes other than selecting the "best" alternative. Instead, we focus on identifying and understanding the underlying theoretical nudge mechanisms that affect the choices that individuals make.

WHAT IS A NUDGE

A nudge is "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" (Thaler & Sunstein, 2009). Although this definition is frequently referenced in the literature, significant misunderstanding exists regarding what a nudge actually is (Hausman and Welch 2010). One possible way to address this problem is to develop a theoretical understanding of nudges by also taking into account a largely ignored definitional distinction between who will respond to a nudge and who will not. In accord with this idea, Thaler and Sunstein (2009, p. 8) note that: "a nudge is any factor that significantly alters the behavior of Humans, even though it would be ignored by Econs." Econs are idealized neoclassical economically rational individuals while Humans are individuals with decision-making biases that have been revealed by behavioral economics and social psychology researchers.

Tension between neoclassical economics and behavioral economics provides a solid foundation for theoretically-based nudge research. Table 9 provides examples that compare decision-making by Econs to that of Humans. As illustrated, neoclassical economic assumptions indicate that Econs have unlimited memory and calculative ability, have well-ordered utility functions that consider only their stable a priori preferences without attention to emotions, have mental models without systematic errors, and choose using consistent calculations based on utility maximization, which focuses on the accumulation of wealth.[2] In contrast, in violation of

[2] Neoclassical economists were not of one mind concerning utility maximization (Lecouteux 2013). For example, Jevons ([1871] 1965) and Mill ([1882] 2009) focused on the accumulation of wealth while Edgeworth ([1881] 1967) and Pantaleoni ([1889]

neoclassical economic assumptions, Humans have limited memory and calculative ability, have utility functions that are not well ordered and that include the consideration of emotions such as regret as well as irrelevant factors such as commitment to past decisions, have mental models that include systematic errors, and choose using rules of thumb and heuristics that are not based on utility maximization. Nudges, then, work to influence a Human's decision-making by taking advantage of or mitigating these Human decision-making idiosyncrasies and therefore cannot affect an Econ's decision-making.

Table 9. Econs vs. Humans

Assumption Categories	**Decision-Making by Econs**	**Decision-Making by Humans**
Physical Restrictions	• **Memory:** Short (working) and long term memory are unlimited (Thaler & Sunstein, 2009)**.** • **Cognitive Effort**: Choice process is relatively effort-free and does not take appreciable time (Hansen, 2016)	• **Memory:** Short (working) and long term memory are limited,(Thaler & Sunstein, 2009). • **Cognitive Effort:** Choice process can be effortful and time-consuming (Becker, 1976)
Utility Function	• **Irregularities:** o Consistency: any collection A always have the same utility over a collection B; (Becker, 1976). o Transitivity: if A is preferred to B, and B to C, then A must be preferred to C. (Becker, 1976). o Stability: Values are formed a priori and are stable throughout the decision process (Barr et al., 2012). • **Irrelevancies**: Only factors relevant to economic incentives, such as financial or other material costs and benefits, are considered (Thaler & Sunstein, 2009, Lecouteux 2013).	• **Irregularities:** o Consistency: Choices may not be consistent because choices are made by invoking external references (Hicks, 1956; Sen, 1993). o Transitivity: If A is preferred to B, and B to C, then C may be preferred to A. This can happen, for example, when preferences are being formed as part of the decision process (Barr et al., 2012; Hansson & Grune-Yanoff, 2018). o Stability: Values can be formed as part of the decision process and may change during the process (Barr et al., 2012). • **Irrelevancies**: Factors irrelevant to economic incentives, such as commitment to past decisions and emotions (happiness, regret, and disappointment) are considered (Loewenstein, 2000; Thaler & Sunstein, 2009).
Mental Model Errors	All calculations and evaluations are done without errors and with perfect precision (Thaler & Sunstein, 2009). Estimations and forecasts can be wrong but not systematically biased (Thaler & Sunstein, 2009). Mental Models (schema) are reasonable reflections of reality (Hansen, 2016).	Calculations and evaluations can be erroneous and imprecise (Thaler & Sunstein, 2009). Estimations and forecasts can include systematic bias. (Thaler & Sunstein, 2009). Mental Models (schema) can include erroneous constructs, relationships, and systematic errors (Hansen, 2016).

1898) focused on the satisfaction of individuals' interests. We will adopt the accumulation of wealth focus because it provides a much more specific and consistent point of Econ – Human comparison.

Non-Rational Choice Strategy	Chooses based on consistent calculations that maximize the individual's utility (Becker, 1976; Thaler & Sunstein, 2009).	Chooses using rules of thumb, guesses, and heuristics that may, for example, be inconsistent and satisfice rather than maximize utility (Gigerenzer & Brighton, 2009).

Researchers appear to recognize the importance of the Human decision-making idiosyncrasies. For example, building on the work of Mongin and Cozic (2014) and Hausman and Welch (2010), Hansen (2016 p. 170) offers the following nudge definition that is in accord with this view. A nudge is "[1]… a function of the choice architecture that [2]… alters people's behavior in a predictable way, [and] that is …[3] …[made possible] because of cognitive boundaries, biases, routines, and habits in individual and social decision-making…and which …[4] works by making use of those boundaries, biases, routines, and habits as integral parts of the choice architecture". There are two aspects of this definition with which we disagree. First, Hansen proposes that nudges encourage Humans' non-rational behavior by taking advantage of the limits of Humans' cognition. However, this would prevent employing nudges to mitigate Humans' non-rational decision-making. Take the case where individuals were provided with information about one or more choice alternatives in a more understandable form, which thereby enabled Humans to make more rational decisions; such information would not be classified as a nudge by Hansen. However, this conflicts with what was intended by Thaler and Sunstein (2009) when they proposed the "Understanding Mapping" nudges. Therefore, we include as nudges those aspects of the choice architecture that affect Humans' behavior while not affecting Econs' behavior, independent of whether the Humans' behavior comes closer to or further away from the Econs' behavior.

Our second disagreement involves limiting a nudge to a function of the choice architecture. A choice architecture consists of the way a choice is displayed to a decision-maker. For example, in an information system the choice architecture would typically involve that which is displayed on a computer screen. However, as described in detail later, we find that the existence and effectiveness of nudges can be affected by aspects of the choice context, which includes the choice architecture, and in addition includes characteristics of the task (e.g., time allowed for the choice), characteristics of the decision-maker (e.g., knowledge regarding aspects of the choice), prior period issues associated with the decision maker (e.g., was the status quo chosen by the decision-maker in an earlier period), and prior period issues associated with the choice architecture (e.g., are the current choice alternatives constrained by prior decision-maker choices).

NECESSARY CONDITIONS FOR NUDGES

Next, we offer some necessary conditions for nudges that are based on the Human versus Econ rule. These conditions are summarized in Table 10.

Choice Alternatives

A nudge cannot exclude nor add any rationally-relevant choice alternatives. In contrast, a nudge can add any irrational or irrelevant choice alternatives because they would be ignored by an Econ (Hansen, 2016). For example, having an individual click into a dropdown menu to see some important choice options does not exclude a decision-maker from seeing all rationally-relevant choice alternatives. In contrast, requiring that a decision-maker purchase a software upgrade to be able to see some important choice alternatives effectively excludes those choice alternatives from the current choice task. Knowing when alternatives are effectively excluded requires an understanding of the choice context, which includes the choice architecture, the individual decision-maker, and the choice task.

Economic Incentives

Economic incentives include prices, social sanctions, time, cognitive effort, etc. A nudge cannot significantly alter these incentives, since such alterations could influence an Econ's choices (Hansen, 2016; Thaler & Sunstein, 2009). The cost an Econ incurs or the value an Econ receives must be reasonably similar with and without a nudge. This ensures that the nudge can affect a Human's choice but would not alter an Econ's choice. Take the case of a decision-maker being provided with a list of alternatives on a computer screen, where one has just had a price reduction from $200 to $199.99. This one-cent reduction may influence an Econ's choice, suggesting that even such a minor price reduction should not be considered a nudge. However, the marginal effect on an Econ's choice behavior from this one-cent reduction should be relatively small when compared to the other attributes of the item. Humans' choices, on the other hand, display significantly greater changes than could be reasonably explained by the reduction in a Human's utility associated with a one-cent price reduction (Melina, 2011).

This appears to happen for at least two reasons. The first is that the experimental participants read from left to right, so that the most significant digits of a price "resonates with [them]… the most" (Melina 2011). Humans would thus tend to perceive the one-cent reduction as being much larger, in this case as much as $100. As a result, if an Econ and a Human have equivalent utility functions, the one-cent price reduction would have a much greater influence on a Human's choice behavior as compared to an Econ's choice behavior (Melina 2011). The second reason is that Humans typically interpret a price ending in 9 as being on sale, and act accordingly (Anderson & Simester, 2003). Thus, while such a one-cent price reduction would have an insignificant effect on Econs' choice behavior, the larger effect on Humans' choice behavior is considered a nudge effect. Compare this one-cent price reduction to a $25 reduction from a price of $100. Ceteris paribus, we would expect the $25 reduction to influence both Humans' and Econs' choices to the same degree, and therefore the reduction could not be a nudge.

Preference Strength

For nudges to be effective Humans cannot have an alternative for which they have a firm preference. The following conditions can reduce the potential for an individual to have a firmly preferred alternative. (1) The Human is ambivalent or lacks familiarity with the available choices (Acquisti et al., 2017). (2) The Human forms or changes preferences during the decision-making process (Barr et al., 2012; Dinner et al., 2011). (3) Humans are too distracted to reflect on their preferences (Meske & Potthoff, 2017). (4) The choice problem complexity obscures a preferred alternative (Thaler & Sunstein, 2009). None of these conditions would hold for Econs because their preferences are established prior to, and are consistent within, the decision-making process (Barr et al., 2012), and their superior and consistent decision-making capabilities preclude problems associated with distraction and problem complexity (Thaler & Sunstein, 2009).

Factually Correct Choice Architecture

Though Humans may not believe that the entity providing them with the choice architecture has his or her best interests in mind, Humans must believe that the information presented to them is at least factually correct. For example, it is unreasonable to expect a Human to choose to purchase an item from one of many vendors if he or she does not believe that the prices offered by each vendor will be honored by that vendor.

Experimental Condition

The effectiveness of a nudge associated with a specific option can be determined experimentally by the degree to which it changes the likelihood that a Human would choose the option while not affecting the likelihood that an Econ would choose the option. For example, an Econ's choice would not be affected by whether an option was the default or another alternative: if it was economically superior/inferior it would be chosen/not chosen in either case. In contrast, a Human would be more likely to choose the default, independent of its economic superiority or inferiority. Thus, if one is interested in determining the degree to which individuals behave more like Humans or Econs during a default nudge experiment, the default option must be economically inferior to at least one other alternative. However, as described above, we define nudges as being able to move Humans' behavior closer to or further away from an Econs' behavior. Therefore, when implemented in a real world context, default nudges can be employed to encourage Humans to choose the default even when it is economically superior and would also be chosen by an Econ.

Table 10. Necessary Conditions for Nudges

Category	Necessary Condition
Choice Alternatives	A nudge cannot exclude or add any rationally relevant choice alternatives; though irrational and/or irrelevant choice alternatives may be added.
Economic Incentives	A nudge cannot significantly change economic incentives (in terms of time, trouble, social sanctions, costs, etc.) that affect wealth, because such changes could affect an Econ's choices.
Preference Strength	Nudges require that a Human has no strongly preferred alternative. This can occur in any of the following conditions. o Preference uncertainty due to ambivalence or lack of familiarity with the available choices o Preferences formed or altered during the choice process. o Humans are distracted or otherwise occupied o The choice problem is complex and thereby obscures a preferred alternative.
Factually Correct	Humans believe that choice architecture is factually correct.
Nudge Experiment	If one is interested in determining the degree to which individuals behave more like Humans or Econs during a default nudge experiment, the default option must be economically inferior to at least one other alternative

IS DEFAULT NUDGE TYPOLOGY

Reviewing the IS nudge research, Collier (2018) found that a lack of theoretical foundation has inhibited the area's research progress. They found problems that included over 20 different definitions for IS nudges, mixed and unexplainable empirical results, and piecemeal and fragmented research streams. In addition, a number of nudge categorizations have emerged in literature, but none have differentiated among the multiple theoretical reasons that decision-makers stick to a default option (e.g., Acquisti et al., 2017; Datta & Mullainathan, 2014; Dimitrova et al., 2017; Dolan et al., 2012; Johnson et al., 2012; Michie et al., 2011; Mirsch et al., 2017; Münscher et al., 2016; Oinas-Kukkonen & Harjumaa, 2008; Promann & Brunswicker, 2017; Szaszi et al., 2018). Therefore, as a first step toward organizing theory for IS nudge research, we develop a theoretically-based typology for IS default nudges.

Though Thaler and Sunstein (2009) offered a nudge taxonomy, they did not include taxonomic category definitions, rules for differentiating among categories, or theory to help understand the ways in which each nudge category could influence choice behavior. We begin our theoretical exploration of their default nudge category by adopting their fundamental rule as an axiom:

> A nudge is an aspect of the choice architecture that can influence Humans' choices while not influencing Econs' choices.

As described earlier, Humans' non-rational choice of a default option (i.e., the option selected if a chooser does nothing) can occur as a result of Humans' cognitive biases in decision-making, which can be understood in terms of violations of neoclassical economic decision-making assumptions. Using this assumption violation scheme allows us to employ Econ decision-making as a prescriptive lens to better understand non-rational decision-making by Humans. To that end, we use the categories of assumption violation associated with the utility function irregularities and irrelevancies, mental model errors, and non-rational choice strategies that are presented in Table 10 as important categories in our Table 11 IS Default Nudge Typology. We do not include the cognitive effort and memory restrictions from Table 1 because Human limitations in this regard are manifest through the other neoclassical economic assumption violations. For example, using heuristics instead of utility maximization to determine preferences typically results from Human attempts to reduce their cognitive effort and short term memory requirements (Shah & Oppenheimer, 2008).

To further characterize and complete our typology, we add a theoretically-grounded descriptive Human decision-making model (described in detail next) consisting of four fundamental systems. This results in Table 11 that is divided into sections that are related to each decision-making system and processes within each system. In addition, each system-process pair is linked to each of the four assumption violation categories. In this way, the placement of each nudge and potential nudge mechanism provides insight into which Human decision-making system and which process within that system can result in what type of neoclassical economic assumption violation. This enables a deeper understanding of Human's non-rational decision-making processes that can lead to their non-rational acceptance of IS default nudges. As such, it can help researchers and practitioners develop as yet unidentified IS default nudges as well as more accurately predict the effects of currently identified IS default nudges.

Descriptive Decision-Making Model

While older decision-making models proposed that most human behaviors result from conscious decision processes, researchers have come to believe that most of our daily behaviors and decisions are guided by processes that operate outside of conscious awareness, with "consciousness … occasionally [intervening]… to override, regulate, redirect, and otherwise alter the stream of behavior— often at a distance, with [non-conscious]… processes filling in" (Baumeister & Bargh, 2014, pp. 36–37). As such, we find it reasonable to employ a non-conscious decision-making model as the foundation for our typology. It has been found that non-conscious decision-making components are very similar to those associated with conscious decision-making (Bargh et al., 2012), which makes our use of this model reasonable for nudges that may also involve conscious thought.

Bargh and Morsella proposed four distinct mental systems that are involved in non-conscious decision-making, having to do with Perception, Evaluation, Motivation, and Emotion. These systems are distinct in that they are "dissociable…[having] different operating characteristics and qualities and are not reducible to each other" (Bargh & Morsella, 2010, p. 93). The following description is largely based on Bargh and Morsella (2010), Bargh, et al. (2012), and Baumeister and Bargh (2014), and provides simplified information processing-oriented descriptions of these systems. Figure 2 illustrates this simplified model. References below to model paths include only the Figure letters. For example, inputs from the Environmental Stimuli to the Perception System are referred to below as [b].

Perception system. The Perception System receives inputs from Environmental Stimuli [b] as well as attention focus sent by the Motivation System [e] and employs the following processes. **Attention** is focused on Environmental Stimuli that are important to currently active goals based on Motivation System input. **Internal meaning** is activated for the different Environmental Stimuli, resulting in a mental model that includes knowledge, assumptions, and expectancies. This model is derived from processes such as stereotype and trait concept activation, embodiment (associations between physical and social/psychological concepts) based on phylogenetic (e.g. social warmth and coldness related to physical warmth and coldness), ontogenetic (e.g. psychological distance related to spatial distance), and semantic (e.g. physical hardness associated with difficulty) metaphorical effects, and effects on self-construal and self-concept. **Imitative behavioral tendencies** are created based on perceptions of descriptive norms among the environmental stimuli. Outputs of the Perception System include the mental model that is sent to the Evaluation System [f] and the imitative behavioral tendencies, along with their executive control structures, that direct behavior [g].

Emotion system. Inputs to the Emotion System include Environmental Stimuli [a], attention focus sent by the Motivation System [d], and Emotion Regulation of, e.g., anger, sent by the Motivation System [d]. The Emotion System process include the focus of **attention** on Environmental Stimuli that are important to currently active goals based on Motivation System input, **simulations** of potential behaviors within the environmental context and how they result in anticipated outcomes and associated emotion (e.g., anger) and attitudes (e.g. efficacy and confidence) based on prior analogous experiences, and control exerted over emotion via **emotion regulation** based on Motivation System input. The Emotion System outputs emotion (e.g. fear, anger, happiness, and liking) sent to the Motivation System [c] and attitudes (e.g. feelings of efficacy and confidence associated with the emotions) sent to the Motivation System [c].

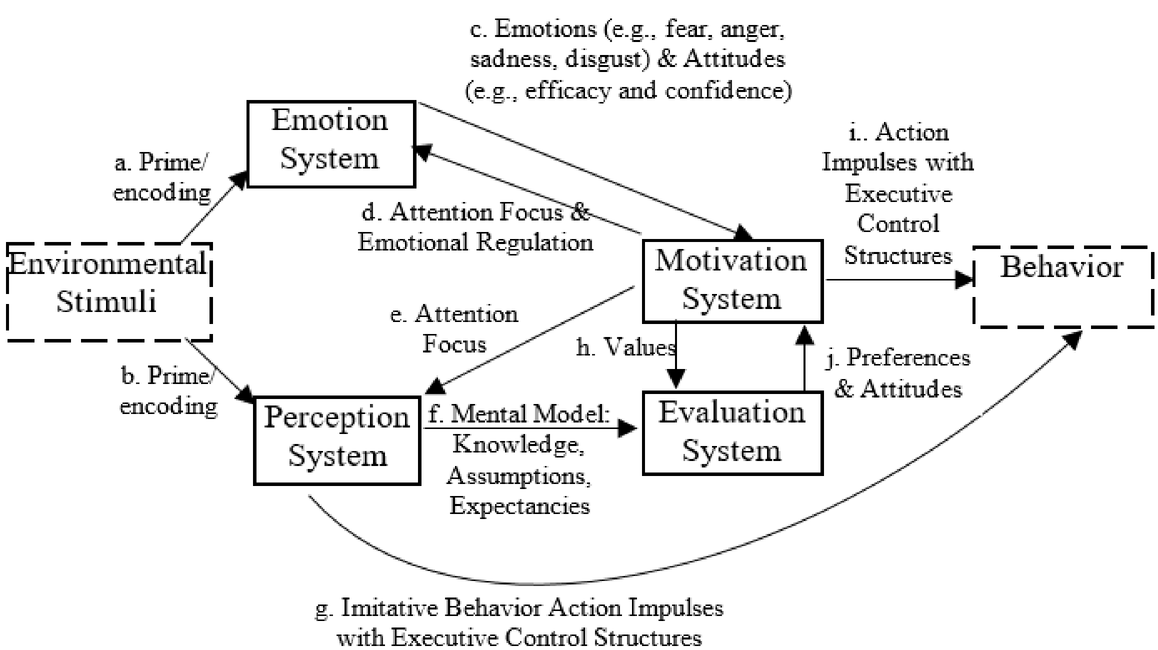
Evaluation system. The Evaluation System takes as inputs mental models (including knowledge, assumptions, and expectancies) from the Perception System [f] and values from the Motivation System [h]. The system enacts a process of **evaluating** the effects of potential behaviors on values in light of the mental model associated with the context. Outputs include the preferences and attitudes associated with alternative behaviors produced by this process, which are sent to the Motivation System [j].

Motivation system. Inputs to the Motivation System include emotions (e.g. fear, anger, happiness, and liking) and attitudes (e.g. efficacy and confidence) from the Emotion System [c] as well as preferences and attitudes associated with alternative behaviors from the Evaluation System [j]. The Motivation System **develops values** that are used by the Evaluation System. The

Motivation System also **reconciles** preferences and attitudes from the Evaluation System with emotions and attitudes from the Emotion system to result in goals (i.e., desired end states and the means to achieve those states and associated action impulses with executive control structures to direct behavior toward the goals), emotion regulation, and attention focus in accord with current goals. Outputs from the Motivation System are attention focus sent to both the Emotion System [d] and the Perception System [e], values sent to the Evaluation System [h], emotion regulation (e.g. of anger) sent to the Emotion System [d], and action impulses and associated executive control structures which direct behavior [i].

Figure 2. Non-Conscious Decision-Making Model

(Based on Bargh and Morsella 2009; Bargh, et al. 2012; Baumeister and Bargh 2014)



Populating the Typology

We populate Table 11 with two sets of theoretical findings. The first set is not italicized, and consists of theoretical mechanisms currently used by IS default nudge researchers to better understand why Humans choose default options when they are not optimal. The second set is italicized, and consists of additional theoretical decision-making biases found in the behavioral economics and social psychology literatures, and suggested by Samson (2014) to be important for behavioral economic researchers. We include these other findings because they have the potential to apply to default nudges, and we shall return to this idea later. Along with nudge and bias definitions, Table 11 indicates the choice context conditions 1) that are necessary in order for the nudge mechanisms to influence Human decision-making and 2) that have been found to make the mechanisms more effective. We also propose some necessary and effectiveness conditions for bias mechanisms if they were to be implemented as IS default nudges.

Appendix A contains detailed rationales for the placement of the mechanisms within the typology. However, there are a few important issues to consider briefly here that involve our use of a descriptive Human decision-making model. First, there is nothing in Econ decision-making that is like the Human's imitative behavioral tendencies within the Perception System that directly influence behavior, since all of an Econ's behavior must involve some kind of utility considerations within the Evaluation System. Second, Econs possess Emotion Systems. Neoclassical economists did not propose that individuals lacked emotions, merely that emotions were not employed in the rational economic decision-making process. The Human and Econ therefore both are presumed to have active Emotion Systems, employing similar simulation processing within their systems. However, Econs and Humans differ regarding emotions in terms of their Motivation System processing: when making rational economic choices, Econs ignore the emotions to arrive at goals while Humans reconcile emotions with the preferences from the Evaluation System in order to arrive at goals. Third, holding all else constant (i.e., Econ-like) placement of a mechanism involves identifying the **one** decision-making process within the **one** decision-making system that, if altered as suggested by the default nudge mechanism, would increase the likelihood that the Human would accept the default choice.

There seems to be some confusion in the literature regarding the names of nudges and biases (Münscher et al., 2016). At times they appear to represent a choice context characteristic that leads to a Human's behavior (see, e.g., framing: "a controlled presentation of a decision problem considering different framing methods regarding one decision problem", Mirsch et al., 2017, p. 640). At other times they appear to refer to the cognitive mechanism that leads to a Human's behavior (see, e.g. framing heuristic: "people would prefer alternatives that are framed as gains over those framed as losses, even when the two alternatives are equivalent", Wang et al., 2014, p. 2368). We favor the cognitive mechanism approach, but additionally employ the characteristic label when it aids our understanding. For example, as described in Table 11, the default nudge associated with an individual being distracted (choice context characteristic) is based on a Human's overweighting of the costs of his or her cognitive effort (cognitive mechanism) for the choice task compared to the benefit from attending to the concurrent "distracting" issues. We therefore label it "Decision Choice Costs – Distracted". In addition the Human bias associated with the influence of a decoy alternative (choice context characteristic) results from a Human evaluating an alternative relative to a reference point (here, the decoy alternative) rather than relative to his or her absolute utility value (cognitive mechanism). We therefore label it "Reference Point – Decoy".

By design, it must be possible for all default IS nudge mechanisms to fit in the typology: each must involve a Human's decision-making process within a decision-making system and must violate a neoclassical economic assumption. One notes the sparsity of mechanism placement within Table 11, as evidenced by the many shaded rows. This is largely due to the fact that each neoclassical economic assumption tends to be related to only one decision-making process. For example:

- Utility Function issues typically come from the Develop Values process within the Motivation System. Utility Function Irregularities relate to problems associated with a Human’s economic values (e.g., valuing alternatives relative to a reference like the status quo rather than employing absolute preferences). Utility Function Irrelevancies relate to Humans employing non-economic values (e.g., valuing consistency in decisions across time independent of their economic consequences), employing economic values inappropriately (e.g., over-weighting the cognitive costs associated with the choice process), or considering emotions (such as future regret) when choosing.
- Mental Model Errors typically come from the Perception System’s Attention Focus process that directs attention to specific aspects of the environment (e.g., seeking confirming cues and ignoring disconfirming cues) or the Internal Meaning Activation-Mental Model process that derives meaning from the environmental cues for the Human.
- Non-Rational Choice Strategies typically are associated with the Evaluation process within the Evaluation System.

In addition, note that the Emotion System and its processes are not included in Table 11. This is due to the inappropriateness of Emotion System output for Econs’ decision-making. In order for a mechanism to be placed in a typology cell, it must involve a decision-making process that is performed by a Human in a manner differently from the way it would be performed by an Econ. Both Humans and Econs are assumed to have reasonable Emotion Systems that generate a range of emotions in response to their environments. However, while the outputs of this system are attended to and reconciled by Humans' Motivation System, they are ignored by Econs' Motivation System. Therefore, there are no neoclassical economic assumptions related to, for example, the veracity of the Emotion System processes because all emotions are ignored during rational decision-making by Econs.

Finally, the Internal Meaning Activation-Imitative Behavioral Tendencies process within the Perception System plays a role in promoting a Human's imitative behavior, resulting in the lone cell entry for Perception System processes that lead to Utility Function Irrelevancies. This reflects a feature of the non-conscious decision-making model that directly links individuals' automatic impulses to imitate others from the Perception System to behavior, circumventing processing by a Human's Evaluation and the Motivation Systems. Note that this circumvention does not preclude a further consideration of the imitative behavior on a Human's economic incentives via processing through the Evaluation and Motivation Systems. In such cases, a Human would have an initial imitative impulse that would then be enhanced (increasing the likelihood of imitation) or reduced (decreasing the likelihood of imitation) depending on the potential effects of the behavior on the Human's utility.

Structure versus Content Default Mechanisms

A default mechanism can be structurally or content oriented. When a mechanism depends on structure, Humans tend to accept the default option merely because it is the default, unrelated to what the default option represents. For example, people tend to choose the default even when it is a random option (Johnson and Goldstein 2013). As noted in the fifth Table 11 column, structural mechanisms include Consistency, Decision Choice Costs (including Cognitive Miser, Distracted, and Reanalysis), Implicit Preference Advice, Implicit Behavioral Norms, Habit, and

Implicit Inequity Advice.[3] In contrast, all other Table 11 default mechanisms rely on what the default and alternative choices represent, and thereby depend on the descriptions of what the options actually are (their content). For example, the Reference Point–Status Quo mechanism would result in Humans choosing whichever alternative was described as maintaining the status quo, whether that alternative was the default option or an alternative option.

[3] Reference Point – Anchoring is also structural, but results in the choice of an alternative other than the default.

Table 11. IS Default Nudge Typology

(*Non-Italics have been used as defaults in the IS literature. *Italics come from Samson (2014) in the Behavioral Economics literature and are potential defaults*)

Decision-Making System	Decision-Making Process	Neoclassical Economic Assumption Violation	Necessary & Effectiveness Contextual Conditions for Default Choice Mechanism*	Depiction: Default Mechanism is Dependent on Structure or Content.	Nudge/Potential Nudge Description*
Perception System					
	Attention Focus Process				
		Utility Function Irregularities			
		Utility Function Irrelevances			
		Mental Model Errors	*Necessary: Individuals a priori judgements are in accord with the default alternative to the exclusion of other alternatives.*	Content	***Confirmation – Information Seeking.*** *"Confirmation occurs when people … evaluate information in a way that fits with their existing thinking and preconceptions. … For example, a consumer who likes a particular brand and researches a new purchase may be motivated to seek out customer reviews on the internet that favor that brand. Confirmation bias has also been … evident in a reliance on information that is encountered early in a process (Nickerson, 1998)." (Samson 2014)*
		Non-Rational Choice Strategy			
	Internal Meaning Activation – Mental Model				
		Utility Function Irregularities			
		Utility Function Irrelevances			
		Mental Model Errors	*Necessary: If the availability related to the default option decreases the perceived likelihood of an associated positive outcome then explicitly describe the actual likelihood.*	Content	***Availability****. "Availability serves as a mental shortcut if the possibility of an event occurring is perceived as higher simply because an example comes to mind easily (Tversky & Kahneman, 1974); Readily available information in memory is also used when we make similarity-based judgments, as evident in the representativeness heuristic." (Samson 2014)*
			Necessary: Individuals a priori judgements are in accord with the default alternative to the exclusion of other alternatives.	Content	***Confirmation – Information Evaluating.*** *"Confirmation occurs when people seek out … information in a way that fits with their existing thinking and preconceptions. … For example, a consumer who likes a particular brand and researches a new purchase may be motivated to seek out customer reviews on the internet that*

				favor that brand. Confirmation bias has also been … evident in a reliance on information that is encountered early in a process (Nickerson, 1998).” (Samson 2014)
		Necessary: Describe default option in favorable current and future terms based on the individual's current visceral state (e.g., emotion, pain, hunger), e.g., default for future (e.g., next week) delivery of food for a choice made just before lunch should appeal to the benefit of satisfying current hunger.	Content	***Empathy Gap (Hot-Cold).*** *"It is difficult for humans to predict how they will behave in the future. A hot-cold empathy gap occurs when people underestimate the influence of visceral states (e.g. being angry, in pain, or hungry) on their behavior or preferences. When people are calm and comfortable, they have trouble appreciating the power of "hot" affective states--like fear, hunger, exhaustion, or thirst. In medical decision-making, for example, a hot-to-cold empathy gap may lead to undesirable treatment choices when cancer patients are asked to choose between treatment options right after being told about their diagnosis. Even low rates of adherence to drug regimens among people with bipolar disorder could be explained partly by something akin to a cold-to-hot empathy gap, while in a manic phase, patients have difficulty remembering what it is like to be depressed and stop taking their medication (Loewenstein, 2005).” (Samson 2014)*
		Necessary: Describe default as part of a larger entity, event, etc. toward which the individual has a positive attitude.	Content	***Halo****. "A global evaluation of a person sometimes influences people's perception of that person's other unrelated attributes. For example, a friendly person may be considered to have a nice physical appearance, whereas a cold person may be evaluated as less appealing (Nisbett & Wilson, 1977)… A study on the 'health halo' found that consumers tend to choose drinks, side dishes' and desserts with higher calorific content at fast-food restaurants that claim to be healthy (e.g. Subway) compared to others (e.g. McDonald's) (Chandon & Wansink, 2007).” (Samson 2014)*
		Necessary: Default does NOT maintain the status quo. *Necessary: Default option description should address the fact that it is better than the status quo, which did not account for problems that “were predictable” earlier.*	Content	***Hindsight****. "It happens when being given new information changes our recollection from an original thought to something different (Mazzoni & Vannucci, 2007). This bias can lead to distorted judgments about the probability of an event's occurrence, because the outcome of an event is perceived as if it had been predictable. It may also lead to distorted memory for judgments of factual knowledge.” (Samson 2014)*
		Necessary: Costs associated with the default option are described as part of the individual's current income account, while costs of	Content	***Mental Accounting****. "…people treat [assets] … as less fungible than they really are, [categorizing them] … as belonging to current wealth, current income, or future income. Marginal propensity to consume (MPC: The proportion of a rise in disposable income that is consumed) is highest for money in the*

		alternatives are described as coming from the future income account.		*current income account and lowest for money in the future income account (Thaler, 1990). Consider unexpected gains: Small windfalls (e.g. a $50 lottery win) are generally treated as 'current income' that is likely to be spent, whereas large windfalls (e.g. a $5,000 bonus at work) are considered 'wealth' (Thaler, 2008)." (Samson 2014)*
		Necessary: Include positive events in the default description but not in the alternatives' descriptions.	Content	***Optimism**. "People tend to overestimate the probability of positive events and underestimate the probability of negative events… For example, we may underestimate our risk of being in a car accident or getting cancer relative to other people. A number of factors can explain unrealistic optimism, including self-serving biases, perceived control, being in a good mood, etc. A possible cognitive factor that has been identified in optimism bias is the representativeness heuristic (Shepperd, Carroll, Grace & Terry, 2002)." (Samson 2014)*
		Necessary: In default, highlight the decision-maker's role in a future accomplishment while alternatives highlight the roles others must play in that future accomplishment.	Content	***Overconfidence**. "People's subjective confidence in their own ability is greater than their objective (actual) performance… Overconfidence is similar to optimism bias when confidence judgments are made relative to other people. A big range of issues have been attributed to overconfidence, including the high rates of entrepreneurs who enter a market despite the low chances of success (Moore & Healy, 2008)." (Samson 2014)*
		Necessary: Default maintains status quo. *Necessary: Status quo is at least satisficing.* *Necessary: Describe non-default alternatives in terms of average (expected returns, experiences, etc.) that do not compare favorably with the status quo peak or ending experiences.*	Content	***Peak-End**. "Our memory of past experience (pleasant or unpleasant) does not correspond to an average level of positive or negative feelings but to the most extreme point and the end of the episode (Kahneman & Tversky, 1999). … These prototypical moments are related to the judgments made when people apply a representativeness heuristic (Frederickson & Kahneman, 1993)." (Samson 2014)*
		Necessary: If the representativeness of the default option decreases the perceived likelihood of an associated positive outcome then explicitly describe the actual likelihood.	Content	***Representativeness**. "Is used when we judge the probability that an object or event A belongs to class B by looking at the degree to which A resembles B. When we do this, we neglect information about the general probability of B occurring (its base rate) (Kahneman & Tversky, 1972)." (Samson 2014)*

	Necessary: In the default description, highlight the improbable outcomes associated with the default.	Content	***Subjective Evaluations of Probabilities**. "People over-weight small probabilities, which explains lottery gambling—a small expense with the possibility of a big win." (Samson 2014)*
Non-Rational Choice Strategy			

Internal Meaning Activation – Imitative Behavioral Tendencies

Utility Function Irregularities			
Utility Function Irrelevances	Necessary: Default is interpreted as a description what everyone is doing. Necessary: Individual does not distrust that the default accurately reflects the descriptive norm. Effectiveness: Individual is from collectivist rather than individualistic culture.	Structure	**Implicit Behavioral Norms (also Herd Behavior).** Defaults may be perceived as an indication of how others behave or how one ought to behave. It can be interpreted as the socially approved form of action (Everett et al., 2015), providing evidence of both injunctive and descriptive norms and may even change normative expectations (Davidai et al., 2012). Norms as an informational influence has been termed Social Proof, and occurs in ambiguous situations where we are uncertain about how to behave and look to others for information or cues. Research suggests that receiving information about how others behave (social proof) leads to greater compliance among people from collectivist (rather than individualist) cultures (Cialdini, Wosinska, Barrett, Butner, & Gornik-Durose, 1999) (Samson 2014).
Mental Model Errors			
Non-Rational Choice Strategy			

Evaluation System

Evaluation

Utility Function Irregularities			
Utility Function Irrelevances			
Mental Model Errors			
Non-Rational Choice Strategy	*Necessary: Associate default choice with a habit cue, such as making the architecture look like those for software download default acceptance.*	Structure	***Habit**. "Habit is an automatic and rigid pattern of behavior in specific situations, which is usually acquired through repetition and develops through associative learning, when actions become paired repeatedly with a context or an event (Dolan et al., 2010). 'Habit loops' involve a cue that triggers an action, the actual behavior, and a reward. For example, habitual drinkers may come home after work (the cue), drink a beer (the behavior), and feel relaxed (the reward) (Duhigg, 2012). Behaviors may initially serve to attain a particular goal, but once the action is automatic and habitual, the goal loses its importance. For example, popcorn may habitually be eaten in the cinema despite the fact that it is stale*

			(Wood & Neal, 2009). Habits can also be associated with status quo bias." (Samson 2014). A Habit nudge will typically evolve from other nudges. For example, when we load software, we are confronted with a window that asks us to accept the terms of service. Few of us take the time to read the terms before we "automatically" allow the default acceptance. This may happen initially as the result of an Implicit Preference Advice nudge. However, over time the Habit nudge may "take over" and we might accept such defaults even when we do not necessarily trust the entity asking for acceptance.
	Necessary: Default is interpreted as advice from the entity that is providing the web page, and suggests that the default is the best or most appropriate alternative. Necessary: Individual does not distrust the advice.	Structure	**Implicit Preference Advice**. Defaults may be perceived as advice from others regarding the best alternative (Dinner et al., 2011; McKenzie et al., 2006); this is likely to be more important when: ▪ Values of those who offer advice match those of the Human (Gigerenzer & Brighton, 2009). ▪ Messenger Effect – a Human's attitude toward the endorsed option depends in part on his or her opinion of the messenger (Kassin, 1983).

Motivation System

Develop Values

Utility Function Irregularities: **Irregular Economic Values**	*Necessary: Emphasize default's positive rather than negative attributes.* *Necessary: Emphasize non-defaults' negative rather than positive attributes.*	Content	***Framing – Attribute**. Individuals more likely to take action in response to positive (e.g. beef that is 95% lean) rather than negative (e.g., 5% fat) attribute descriptions. (Levin, Schneider, & Gaeth, 1998).*
	*Necessary: Emphasize negative outcomes from **NOT** choosing default rather than positive outcomes for choosing default.* *Necessary: Emphasize positive outcomes for non-default options.*	Content	***Framing – Goal.** Individuals more likely to act when negative outcomes are emphasized (e.g. imposing a $5 penalty) as compared to positive outcomes (e.g. offering a $5 reward) (Levin, Schneider, & Gaeth, 1998).*
	Necessary: Describe default benefit likelihoods in terms of losses (e.g., fewer lives lost)	Content	***Framing – Risk.** People are risk averse when an action is described in terms of gains (e.g. the opportunity to save 90 out of 100 lives) and risk seeking when an action is described in terms of*

	rather than gains (e.g., more lives saved) *Necessary: Describe non-default benefit likelihoods in terms of gains rather than losses.*		*losses (e.g. the risk of losing 10 out of 100 lives) (Kahneman & Tversky, 1979).*
	Necessary: Explains the selection of an alternative **other than** the default. Necessary: Default must not be a categorical variable.	Structure	**Reference Point – Anchoring**. Anchoring and adjustment can help explain the selection of an alternative **other than** the default. The default option becomes an anchoring reference point that affects the alternative selected (Acquisti et al., 2017; Chapman & Johnson, 1994; Dhingra et al., 2012; Dinner et al., 2011; Jacowitz & Kahneman, 1995). Anchoring assumes that some values are closer to each other, such as those that exist on a continuum like item weight. This would not necessarily be the case for categorical values, such as item color (e.g. red, blue, green).
	Necessary: Asymmetrically dominated non-default choice favors default option. *Necessary: Default must dominate decoy.*	Content	***Reference Point – Decoy.*** *"Choices often occur relative to what is on offer rather than based on absolute preferences. The decoy effect is technically known as an 'asymmetrically dominated choice' and occurs when people's preference for one option over another changes as a result of adding a third (similar but less attractive) option. For example, people are more likely to choose an elegant pen over $6 in cash if there is a third option in the form of a less elegant pen (Bateman, Munro, & Poe, 2008)." (Samson 2014)*
	Necessary: Default maintains status quo. Necessary: Status quo is at least satisficing.	Content	**Reference Point – Status Quo**. (also **Reference Point – Endowment)** Individuals are likely to choose the status quo as the reference point from which gains and losses are determined (Dinner et al., 2011) and thus potential gains from choices other than the status quo are discounted. This choice of status quo may be due to Humans' feelings that they own the status quo (i.e., endowment: Johnson & Goldstein, 2003).
Utility Function Irrelevances**: Non-Economic Values**	Necessary: Default maintains status quo. Necessary: Status Quo must be chosen in a prior period by the decision-maker. Necessary: Status Quo is at least satisficing.	Structure	**Consistency**. The Human drive for consistency can be a theoretical mechanism encouraging status quo selection when the current state was chosen earlier by the individual. When the status quo is the default, Humans may choose it for the following reasons. (1) To avoid seeming like their original choice was incorrect (Samuelson & Zeckhauser, 1988). (2) To avoid conflicting cognitions causing cognitive dissonance (Festinger, 1962; Samuelson & Zeckhauser, 1988). A Human tends to discard or mentally suppress information that indicates a past decision was in error because that

			information would conflict with his or her self-image as a good decision-maker (Samuelson & Zeckhauser 1988). (3) To stick with a status quo that maintains a past choice made by them because, with uncertain preferences, they may believe their past behavior that results in their current state should also be reflected in their current preferences (Bem, 1972; Samuelson & Zeckhauser, 1988). (4) To maintain a consistent and positive self-image (Cialdini, 2008) by keeping commitments and avoid reputational damage (if they are made publicly) (Festinger, 1957).
	Necessary: Default option provides more variety in the future (e.g., in goods received) than alternatives.	Content	***Diversification****. "People seek more variety when they choose multiple items for future consumption simultaneously than when they make choices sequentially, i.e. on an 'in the moment' basis. Diversification is non-optimal when people overestimate their need for diversity (Read & Loewenstein, 1995)... For example, before going on vacation I may upload classical, rock and pop music to my MP3 player, but on the actual trip I may mostly end up listening to my favorite rock music." (Samson 2014).*
	Necessary: Emphasize individual's role in developing the default as a viable option from which to choose.	Content	***IKEA****. "Invested labor leads to inflated product valuation (Norton, Mochon, & Ariely, 2012). … The effect has a range of possible explanations, such as positive feelings (including feelings of competence) that come with the successful completion of a task, a focus on the product's positive attributes, and the relationship between effort and liking. The effort heuristic is another concept that proposes a link between perceived effort and valuation (Kruger, Wirtz, Van Boven, & Altermatt, 2004)." (Samson 2014)*
	Necessary: Default is interpreted as advice from the individual or entity that is providing the web page suggesting that the default is the equitable option. *Necessary: Individual does not distrust the advice.*	Structure	***Implicit Inequity Advice****. People prefer fairness and resist inequalities. In some instances …people are willing to forego a gain, in order to prevent another person from receiving a superior reward." (Samson 2014). For example, interpreting the default as the equitable option can occur in cases where an individual can choose the level of payment for a good (e.g., choosing among tips or choosing how much to pay in a "pay what you want" context).*
	Necessary: If default option is viewed as morally bad, the individual must be given the opportunity to do something morally good prior to making the choice.	Content	***Licensing****. "People allow themselves to do something bad (e.g. immoral) after doing something good (e.g. moral) first (Merritt, Effron & Monin, 2010)." (Samson 2014).*

	Necessary: Acceptance of default choice is interpreted as part of quid pro quo due to an earlier exchange.	Content	***Reciprocity**. "A social norm that involves in-kind exchanges between people—responding to another's action with another equivalent action. It is usually positive (e.g. returning a favor), but it can also be negative (e.g. punishing a negative action) (Fehr & Gaechter, 2000). … Charities often take advantage of reciprocity when including small gifts in solicitation letters, while supermarkets try to get people to buy by offering free samples." (Samson 2014).*
Utility Function Irrelevances: **Inappropriate Economic Values**	Necessary: Individuals overweight the value of their cognitive effort for this choice task compared to the benefit of attending to the choice task. Effectiveness: More likely when the choice stakes are small Effectiveness: More likely with a greater number or complexity of choices	Structure	**Decision Choice Costs.** The potential physical and cognitive costs associated with the process of choosing a non-default alternative **appear to** (but actually don't) outweigh the potential benefits of choosing an alternative (Dinner et al., 2011; Sunstein & Thaler, 2003; Tversky & Kahneman, 1974). This is more likely when the stakes are small (Dinner et al., 2011; McKenzie et al., 2006) or with a greater number or complexity of choices (Choice Overload: Samson 2014; Iyengar & Lepper, 2000).
	Necessary: Individuals severely overweight the value of their cognitive effort for this choice task compared to the benefit of attending to the choice task. Effectiveness: This is especially likely to occur when preferences are difficult to determine	Structure	**Decision Choice Costs - Cognitive Miser**. Humans may not engage with the choice process at all. Individuals choose the default alternative without attempting to compare its costs and benefits, but rather in order to minimize cognitive choice costs (minimum effort over time, Dolan et al., 2012; "path of least resistance," Lehner et al., 2016). This is especially likely to occur when preferences are uncertain or difficult to determine (Acquisti et al., 2017; C. J. Anderson, 2003; Dinner et al., 2011; Kahneman et al., 1991; Kahneman & Miller, 1986).
	Necessary: Individuals overweight the value their cognitive effort for this choice task compared to the benefit of attending to concurrent (distracting) issues. Effectiveness: Lack of choice importance	Structure	**Decision Choice Costs – Distracted.** Humans may not engage with the choice process at all. A lack of choice process engagement can occur when individuals are so distracted or thoughtless that they aren't reflecting on their own preferences (the "yeah, whatever" heuristic) (Meske & Potthoff, 2017; Thaler & Sunstein, 2009).

	Necessary: Default maintains status quo. Necessary: Status quo is at least satisficing.	Structure	**Decision Choice Costs – Reanalysis**. The costs associated with the process of reanalyzing a previously made decision can **appear to** (but actually don't) outweigh the potential benefits of choosing an alternative other than the default; these are decision reanalysis costs (Samuelson & Zeckhauser, 1988) and are relevant when the default is maintaining the status quo.
	Necessary: If the default option has negative effects on the individual in the future, the default description should emphasize the fact that the negative effects felt by the individual will actually be reduced in the future.	Content	***Hedonic Adaptation****. People get used to changes in life experiences… [For example] the happiness that comes with the ownership of a new gadget or salary raise will wane over time, even the negative effect of life events such as bereavement or disability on subjective well-being tends to level off, to some extent (Frederick & Loewenstein, 1999). When this happens, people return to a relatively stable baseline of happiness." (Samson 2014)*
	Necessary: Default maintains status quo. Necessary: Status quo is at least satisficing. Necessary: Focus on default current benefits.	Content	**Hyperbolic Discounting**. Individuals tend to severely discount the benefits of a potential change on their immediate future (Thaler, 1981). As a result, when the status quo is at least satisfying and is represented by the default, it tends to be chosen in one of two ways. (1) The default may be selected (Dolan et al., 2012; O'Donoghue & Rabin, 1999) or (2) the choice process is postponed because what the individual is doing now seems more important than whatever he or she will be doing in the immediate future (Thaler & Benartzi, 2004).
	Necessary: Emphasize default's benefits in terms of current tastes and preferences	Content	***Projection****. "People's assumption that their tastes or preferences will remain the same over time. For example, people may overestimate the positive impact of a career promotion due to an under-appreciation of (hedonic) adaptation, put above-optimal variety in their planning for future consumption (see diversification bias), or underestimate the future selling price of an item by not taking into account the endowment effect. Differences between present and future valuations should be particularly underappreciated for durable goods, where satisfaction levels are likely to fluctuate over time. Finally, consumers' under-appreciation of habit formation (associated with higher consumption levels over time) may lead to projection bias in planning for the future, such as retirement savings (Loewenstein, O'Donoghue, & Rabin, 2003)." (Samson 2014)*
	Necessary: Default maintains status quo.	Content	**Sunk Cost.** Individuals commit the sunk cost fallacy when they consider previously expended resources (time, money or effort)

	Necessary: Status quo is at least satisficing Necessary: Decision-maker is aware of past expenses surrounding the achievement of the status quo		when determining whether to continue a behavior (Arkes & Blumer, 1985). Humans may include sunk costs in their utility calculations, which is an irrelevant factor, in order to justify previous commitments to a (possibly failing) course of action (Samuelson & Zeckhauser, 1988).
	Necessary: In default description, emphasize current and very near future benefits; describe costs as occurring in the future.	Content	***Time Discounting**. "Present rewards are weighted more heavily than future ones. Once rewards are very distant in time, they cease to be valuable. Delay discounting can be explained by impulsivity and a tendency for immediate gratification, and it is particularly evident for addictions such as nicotine (Bickel, Odum, & Madden, 1999). Hyperbolic discounting theory suggests that discounting is not time-consistent; it is neither linear nor occurs at a constant rate. It is usually studied by asking people questions such as "Would you rather receive £100 today or £120 a month from today?" or "Would you rather receive £100 a year from today or £120 a year and one month from today?" Results show that people are happier to wait an extra month for a larger reward when it is in the distant future. In hyperbolic discounting, values placed on rewards decrease very rapidly for small delay periods and then fall more slowly for longer delays (Laibson, 1997)." (Samson 2014)*
Mental Model Errors			
Non-Rational Choice Strategy			

Reconcile Preferences & Attitudes with Emotions

Utility Function Irregularities			
Utility Function Irrelevance: **Emotions**	*Necessary: Default maintains status quo. Necessary: Status quo is at least satisficing. Necessary: In contrast to other options, the default option does **NOT** include opening an additional partition in a partitioned pool of resources.*	Content	***Partitioning**. "The rate of consumption can be decreased by physically partitioning resources into smaller units, for example cookies wrapped individually or money divided into several envelopes. When a resource is divided into smaller units (e.g. several packs of chips), opening a partitioned pool of resources incurs a psychological transgression cost, such as feelings of guilt (Cheema & Soman, 2008)." (Samson 2014)*
	Necessary: Default maintains status quo. Necessary: Status quo is at least satisficing	Content	**Regret Avoidance (also Omission)**. Humans may include regret avoidance in their utility function and choose options that reduce their potential for later regret (Samuelson & Zeckhauser, 1988). Humans tend to feel stronger regret for bad outcomes that are the consequences of new actions than similar bad outcomes resulting from inaction (Kahneman & Tversky, 1982). Thus, Humans are

				more likely to avoid choosing by sticking with the default when it maintains the status quo, especially if the status quo is in accord with social norms (Samuelson & Zeckhauser, 1988). Also Omission bias: Changing the status quo requires an act, but keeping the status quo requires only an omission, which is a failure to act. Humans favor harmful omissions over equally harmful commissions (Spranca et al., 1991), possibly because of the belief that actors do not cause the outcomes of their omissions (Ritov & Baron, 1992).
	Mental Model Errors			
	Non-Rational Choice Strategy			

APPLYING THE IS DEFAULT NUDGE TYPOLOGY

We next apply the typology to demonstrate its usefulness in (1) implementing an effective IS default nudge architecture, (2) creating new kinds of IS default nudges, and (3) better understanding IS nudge empirical results. To this end, we will use our Table 11 typology along with the Table 10 general nudge necessary conditions in our discussions.

Implementing an IS Default Nudge

The first step in creating a default nudge experiment is to explore Table 11and determine which non-conscious decision-making system and which process within that system we are interested in manipulating. For example, if we are interested in influencing the Motivational System's development of non-economic values, we would explore the nudge options in the Motivation System section of Table 11 and within the Utility Function Irrelevancies: Non-Economic Values rows, since non-economic values are irrelevant to economic incentives. Within those rows, we are presented with one nudge that has been used (Consistency) and five biases that have yet to be used. Let's say that we are interested in taking advantage of the Human drive for decision consistency in order to reduce unreliable decisions made by employees. This unreliability is common because many decision-makers' judgments are "…strongly influenced by irrelevant factors, such as their current mood, the time since their last meal, and the weather…[and]…often contradict their own prior judgments when given the same data on different occasions" (Kahneman et al., 2016, p. 40). We may thus want to encourage decision-making consistency by taking advantage of the Consistency nudge mechanism, and making the default choice equivalent to prior choices made by the decision-maker.

Meeting necessary conditions. We would next see in Table 11 that the first two necessary conditions for the Consistency nudge are that the default must maintain the status quo and the status quo must be known to have been chosen in a prior period by a typical decision-maker in the defined context.[4] In addition to these conditions, the necessary conditions for nudges must hold, relating to choice alternatives, economic incentives, preference strength, factual correctness, and nudge experiment.

Precluding structural nudges. However, merely having the default choice alternative maintain the status quo that was chosen by the decision-maker in the prior period and meeting all of the necessary conditions is not enough for a researcher who is attempting to focus specifically on a Consistency nudge. The researcher must control for participants' non-rational acceptance of the default option for reasons other than decision-making consistency. The next step in this regard is to make sure that the necessary conditions are **not** met for mechanisms noted as Structural rather than Content in Table 11, because structural mechanisms are potential confounds for any default nudge mechanism. The following are examples of such choice architecture design components to reduce the potential influences of structural mechanisms that might lead to default choice. (1) The default alternative should be described as not necessarily representative of that which is typically chosen by other decision-makers, thus precluding the potential for an Implicit Behavioral Norm nudge. (2) Data should be gathered concerning the degree to which the participants view the choice architecture as similar to those in which they would automatically accept the default option thereby enabling the statistical control for Habit nudges. (3) The default should be explicitly identified as not representing advice, thus precluding the potential for both an Implicit Preference Advice nudge and an Implicit Inequity Advice nudge. (4) Data should be gathered concerning the degree to which the participants value their cognitive choice effort and concerning the participants' value of the potential benefits of being

[4] Or, personalization through feedback, as described later, can adjust the default to reflect the option that was chosen in a prior period by that specific decision-maker.

involved in the choice task compared, for example, to other concurrent activities, thereby enabling the statistical control for Decision Choice Costs (including Cognitive Miser, Distracted and Reanalysis) nudges.

Precluding content nudges**.** The potential for all content nudges should also be controlled. As with the structural mechanisms, researchers can include controls by focusing on each mechanism's necessary conditions and excluding them in the experimental design or gathering data for post hoc statistical control. For example, default and alternative choice descriptions should all be framed in the same way, thus controlling for Framing – Attribute, Goal, and Risk. And, data should be gathered regarding the degree to which participants had a priori preferences for the default option so that Confirmation-Information Seeking and Confirmation-Information Evaluating can be statistically controlled.

In principle, all content nudges should be controlled. However, there are a number of content nudges that require very specialized descriptions and contexts, and as such may not require specific controls. In this case, such nudges might include Empathy Gap (Hot-Cold) that refers to visceral states; Halo that refers to the default as part of a larger entity or event; Mental Accounting that refers to current vs future income accounts; Overconfidence that refers to the decision-maker's role in accomplishments; Diversification that requires future variety; Licensing that requires prior good behavior; Reciprocity that requires quid pro quo; and Partitioning that requires the opening of additional partitions. Finally, the involvement of status quo as a necessary condition should be addressed. Consistency maintains status quo, so any mechanisms that require that the default does not maintain the status quo, such as Hindsight, can be ignored.

At this point the nudge experimental design has controlled for, or has the potential to statistically control for, all of the potentially confounding nudges in Table 11 except for

Reference Point-Status Quo. The only difference in necessary conditions is that Consistency requires that the status quo be chosen in a prior period by the decision-maker while Reference Point-Status Quo allows for the status quo to have been chosen in the prior period by the decision-maker or someone else. However, there are other important differences between the mechanisms. With Reference Point-Status Quo, the potential benefits due to a change from the status quo can be perceived to be half as valuable from the equivalent losses from the change (Tversky & Kahneman, 1992). In contrast, with the Consistency mechanism, the value resulting from a change from the status quo is all psychologically negative, in terms of the effects on the decision-maker's self-image, cognitive dissonance, etc. The following, drawing from an existing IS default nudge study, provides an example of how one might address this Consistency versus Reference Point–Status Quo issue.

Differentiating Competing Theoretical Explanations in an Example Extant Study

Knijnenburg et al. (2013), studied the influence of different versions of a website auto-completion tool on information disclosure. A **remove** version automatically filled all fields of a Web form but provided a "Remove" button next to each field allowing the user to delete the information in that field. This was proposed as a nudge with the provision of full information as the default option. An **add** version left all fields blank but provided an "Add" button next to each field to automatically populate the specific field information. This was proposed as a nudge with the provision of no information as the default option. The authors predicted that participants would tend to choose the defaults for each version, and thereby provide more information disclosure in the **remove** as compared to the **add** version.

In fact, the authors found no difference in information disclosure between the two versions, with an average of 90% of the fields disclosed in both. This suggests that the **remove** nudge worked (participants chose the default alternative 90% of the time) while the **add** nudge did not work (participants chose the non-default alternative 90% of the time). The question at issue is why participants would accept the remove default and reject the add default in a similar context. Looking beyond the immediate choice architecture to the choice context, what happened becomes clear. The authors indicated that immediately before being assigned to the **add** or **remove** treatment, participants disclosed “a wide range of personal information (general contact information, personal interests, job skills, and health record)” that would be used during the experiment to fill in web-based forms (Knijnenburg et al., 2013, p. 6). During this part of the experiment, participants could have refused to provide any of the data, but all chose to enter around 90% of the data. Therefore, the thought that they put into whether to provide information to the auto-fill tool and their subsequent acts of disclosing information to the tool established a prior state of 90% disclosure for participants in both treatments.

Examining Table 11, it appears that the Consistency and the Reference Point-Status Quo nudge descriptions can reasonably explain the users’ reactions to the **remove** version: the default enabled the acceptance of the status quo of relatively full disclosure, and this state was chosen by the decision-makers in the prior period. Accepting the default was thus in line with the Consistency nudge because, for example, it reduced the potential cognitive dissonance that would be associated with inconsistent decision-making. Accepting the default was also in line with the Reference Point-Status Quo nudge because the potential benefits from reducing information disclosure were significantly discounted compared to the potential loss of the status quo. In contrast, the **add** version did not meet the necessary conditions for either nudge mechanism because the default option did not maintain the status quo. Indeed, the add version default nudge was unsuccessful, with participants filling in 90% of the information.

We are left with two potential explanations for the Knijnenburg et al (2013) results. If the researchers were interested in disentangling the explanations, they could have added two parallel treatments in which the computer system's auto-fill tool did not ask the participants to disclose information, but rather obtained the information from various places on the web. (For example, a lot of the information is available from the participants' Facebook pages.) When the participants were told about the tool being populated with 90% of their personal information, this would have set the status quo at 90% disclosure, though the status quo would not have been created by them. This would fulfill the necessary condition for the Reference Point–Status quo mechanism but not that for the Consistency mechanism, because the participants were not directly involved with the decision to create the status quo. The experimental results thus could not be attributed to the Consistency mechanism, and could be compared to the existing experiment to gain insight into the two different nudge mechanisms.

These discussions demonstrate a couple of issues regarding the implementation of IS default nudges. First, one may need to look beyond the immediate choice architecture to the complete choice context, which can include prior periods, when attempting to implement effective IS default nudges.[5]   Second, it is a relatively complex process to design IS default nudge experiments with results that can be related to a single nudge mechanism. Being able to isolate the theoretical mechanism associated with each nudge is important because it will increase our ability to differentiate between choice contexts that enhance and contexts that reduce the effectiveness of an IS default nudge. It will also enable us to examine interactions among different mechanisms so that the effectiveness of IS default nudges can be increased by,

[5] Other examples of multi-period necessary conditions include a Licensing default nudge (that can influence Human choice when the default is viewed as morally bad to the decision maker), which has the necessary condition that the decision maker must have behaved in a morally good manner prior to making the decision to accept a morally bad default, and a Reciprocity default nudge that requires that the decision maker be involved in an earlier exchange in which he or she received something for which a quid pro quo in the form of choosing the default option would be appropriate.

e.g., employing complementary nudges. For example, we may find that the framing of a default option differently in this period than the way it was framed in the prior period when it was chosen might reduce decision-makers' need for decision-making consistency across periods, which can be more rational (Econ-like) when the decision context this period is significantly different than the prior period.

Creating New Types of Default Nudges

There are at least two ways that new types of IS default nudges can be created. The first is to employ bias mechanisms previously identified in behavioral economics, social psychology, and other areas of research that have not yet been used in IS research. The second is to add different kinds of feedback to currently employed nudge mechanisms.

Identifying New Nudge Mechanisms from Decision-Making Biases. The **non**-shaded rows within Table 11 represent areas with theoretical potential for IS default nudge mechanisms. The Table 11 descriptions in italics reflect the placement of Samson's (2014) list of behavioral economic and social psychology biases that have yet to be employed in the IS default nudge literature. We do not claim that Samson's list is comprehensive; for example Wikipedia lists over 100 such biases ("List of Cognitive Biases," 2020). However, Samson's purpose was to include biases with potential behavioral economic value, and we therefore believe it to be reasonably representative in that regard. As illustrated, IS default researchers have employed 10 mechanisms that can be placed within the Motivation System pertaining to Utility Function violations. However, Samson identified 13 additional mechanisms that can be placed in these rows and that are IS default nudge candidates. In addition, Samson identified 12 mechanisms that we find are related to the Mental Model Errors within the Perception System in our typology. IS researchers thus have at least 25 new bias mechanisms that may be able to be exploited by default nudges. As a first step in this regard, we have included in Table 11 some necessary conditions for employing the candidate mechanisms. For example, the Diversification mechanism proposes that the default option must provide more variety in the future (e.g., in goods received) than the alternative options. As indicated above, the 25 new nudge mechanisms are a relatively small subset of Human decision-making biases with potential for default nudge implementation. IS default researchers can thus avail themselves of the expanding Human decision-making bias findings to identify more potential nudges.

For example, though Samson (2014) provides many findings related to the Motivation System's Develop Values process, only one bias can be related to the Reconcile Preferences and Attitudes with Emotions process. This process involves integrating emotions into the Human's decision-making, which is an increasing area of research (Lerner et al., 2015) and a potentially rich area for IS default nudge research. This research suggests that both emotions integral to the choice being made (e.g., fear of flying can lead to driving though death rates for driving are higher: Gigerenzer, 2004) and emotions incidental to the choice (e.g., anger from one situation motivates blaming others in unrelated situations: Quigley & Tedeschi, 1996) can bias decisions.

In addition, Table 11 offers only the Implicit Behavioral Norms mechanism in the row related to Internal Meaning Activation-Imitative Behavior within the Perception System. However, there is much to learn from research on social norms and imitative behavior that can aid IS researchers to develop norm-oriented default nudges. For example, a meta-analysis by Melnyk et al (2019) found that descriptive social norms are much more effective in changing behavior than injunctive social norms.[6] Descriptive norms appear to act as "social proof" that

[6] Social Norms are "rules and standards that are understood by members of a group, and that guide and/or constrain social behavior without the force of laws" (Cialdini & Trost, 1998, p. 152). "Descriptive norms related to what other people do themselves and injunctive norms to what other people think one should do" (Melnyk et al., 2019).

affects behavior in a largely instinctive manner: this “tendency of people to instinctively copy … the behavior of others has evolutionary benefits and is an adaptive strategy for learning...Thus, often, consumers follow the behavior of others automatically and unwittingly” (Melnyk et al., 2019, p. 6). This explanation supports our typology’s placement of descriptive behavioral norm mechanisms within the Perception System’s Internal Meaning Activation process that results in imitative behavioral tendencies. In addition, Melnyk et al. found that the effects of descriptive norms acted directly on behavior without being mediated by behavioral intentions; this supports our typology’s direct link of imitative tendencies to behavior without going through processing of the Evaluation and Motivation systems. This is in contrast to injunctive norms that were found to affect behavior largely indirectly through, e.g., intentions, rather than directly (Melnyk et al., 2019).

Potential insights from this literature for IS default nudge research include the following. (1) The Implicit Behavioral Norms mechanism might be made more effective if the default description explicitly stated that the default option was chosen because it reflects the choice of many individuals. This would make explicit the descriptive norm character of the default (Melnyk et al., 2019). (2) A concrete specification of behavior is more effective than a more abstract specification (Melnyk et al., 2019). Thus, the default description should make clear that it is the specific default alternative that has been typically chosen by others as opposed to some more general description of others choosing an alternative similar to the default alternative. (3) The more the group being described is perceived by the decision-maker as sharing similar values, opinions, and attitudes, the more influence the descriptive norm will have on the decision-maker’s behavior (Melnyk et al., 2019). Thus, rather than having the default description indicate that “most people” choose the default alternative, it should specifically indicate that a group closely related to the decision maker (e.g., same political party) choose the default alternative. We could thus use this research stream to create an Explicit Behavioral Norm mechanism that would have (1) above as a necessary condition and (2) and (3) as effectiveness conditions.

Adding Feedback to Extant Nudges. A second method for creating new default nudges is to provide different kinds of feedback for a current nudge mechanism. This is especially true for IS choice architectures, because feedback facilitates the ability of the defaults to be more personalized (Goldstein et al., 2008) in a scalable and real-time way that cannot be achieved outside of IS. Thaler and Sunstein (2009) suggest that providing feedback is one of their six nudge categories. However, we believe that it is fundamentally different from their other five nudges, in that feedback provides alternative ways in which any of the other nudges can be implemented.

"The best way to help Humans improve their performance is to provide feedback. Well-designed systems tell people when they are doing well and when they are making mistakes" (Thaler & Sunstein, 2009, p. 92). Many users tend to treat IS as interactive participants (Suchman, 1987), and a reasonable definition of IS-to-human feedback would thus be "the communication of the state of the …[IS]…as a response to user actions, to inform the user about the conversation state of the system as a conversation participant, or as a result of some noteworthy event of which the user needs to be apprised" (Renaud & Cooper, 2000, p. 3). One can then envision both immediate and archival types of feedback (Renaud & Cooper, 2000).

Immediate feedback can (1) inform the user about the current system state (e.g., the IS has received user input, is working on user input, or has a problem), (2) explain unusual occurrences, and (3) provide context-sensitive assistance (Foley & van Dam, 1982; Savage-

Knepshield & Belkin, 1999; Suchman, 1987). Of particular interest for personalized IS default nudges is immediate feedback that is also smart and adaptive (Goldstein et al., 2008). Smart feedback provides the user with default nudges that are based on user-specific information, such as demographic variables. For example, based on a user entering his or her age and income, the IS can provide a range of retirement plan investment options, making sure that the "most appropriate" given the age and income data is the default option (Goldstein et al., 2008). Adaptive feedback provides the user with nudges that dynamically change based on the real-time sequence of choices made by the user. For example, web-based car configurators employ multiple steps, with earlier user choices leading to (and potentially limiting) options displayed in each subsequent step (Goldstein et al., 2008). Each step can have its own default nudge. For example, some IS configurators provide a default configuration that starts out fully loaded (includes all available options) and allow users to eliminate the options they don't want. Other configurators provide a default configuration that is stripped down (includes no options) and allow users to add the options they want. The fully loaded default systematically results in more expensive cars being chosen (Goldstein et al., 2008).

Thus, all of the nudges described in Table 11 have the potential to become more effective when personalized through IS feedback. For example, take the nudge offered by Knijnenburg et al. (2013) that we described above as a Consistency (or Reference Point-Status Quo) default nudge. The non-feedback **remove** default nudge automatically populated all web site fields with personal information (name, address, etc.) based on information entered by the individual during an earlier period, and provided the individual with the option to remove information from any of the populated fields. An archival feedback version of this would be to have the auto-fill tool automatically populate all web page fields with personal information (e.g., name and address) except for fields that the individual has typically excluded when using the tool in the past (e.g., credit card number). An immediate smart feedback version would be to have the auto-fill tool set up in an earlier period with three types of information disclosure: full, no payment, and none. In response to a web page asking for information, the auto-fill tool first asks the user to indicate which type of information disclosure is desired, and then populates the fields accordingly. Finally, an immediate adaptive feedback version would be to automatically populate a few web page fields with personal information (e.g., name and address). When the user enters information in a non-populated field, the tool then enters information that is typically associated with that field. For example, when the individual enters a credit card name, the card's number, expiration date, and CVV are entered by the tool.

Understanding Empirical Results

Our typology can be used to understand results of IS default nudge research that were previously unexplained. This understanding comes with significant effort because, as listed in Table 11, there are at least 38 mechanisms that can result in the single behavior of choosing the default rather than an alternative option. However, to further demonstrate the extent of such understanding and effort, the following discussions examine an empirical work by Momsen and Stoerk (2014).

Momsen and Stoerk evaluated seven nudges intended to increase the number of participants who selected a renewable energy contract over a conventional energy contract. Only one of the seven was a default nudge, and only the default nudge had a significant impact on users' selecting the renewable energy contract. Our typology can help explain why only this nudge was effective.

In Momsen and Stoerk's experimental problem, participants were asked to imagine that they had just moved to a new area and needed to choose between two energy contracts: one that was 100% conventional energy costing 30€/month and one that was part conventional and part renewable energy costing 45€/month. Participants were given an income of 800€/month and a budget indicating that all the monthly income had been allocated for various expenses in the participant's previous living situation. The six insignificant nudges clearly presented the prices of the renewable and conventional energy contracts, ensuring that participants could reflect on their price-related preferences when making their decisions.

Meeting general necessary conditions. We first determine if these nudges satisfy the Table 10 necessary conditions for nudges. The six insignificant nudges provided the same economic incentives for the same two choice alternatives, satisfying the Choice Alternatives and the Incentives Conditions. In addition, the scenario was known by the individuals to be made up by the researchers, so that the Factually Correct necessary condition was met. However, the different prices of the two energy contracts would likely have resulted in firm a priori preferences regarding a 50% differential in the cost of electricity, which violates the Preference Strength necessary condition. This violation was likely the reason that the six nudges were not effective. The Nudge Experiment condition was met in that each of the six nudges were attempting to get participants to choose the economically more expensive (i.e., economically inferior) contract.

In contrast to the clear depiction of the two energy contract prices by the six nonsignificant nudges, the default nudge clearly presented the price only for the renewable energy contract, hiding the conventional contract in such way that its price could only be viewed after clicking into a drop-down menu. Since clicking the drop-down menu was not physically or cognitively prohibitive, this choice architecture would not have stopped an Econ from finding and comparing the prices of the two contracts. Thus the Choice Alternatives general condition was met. As with the six insignificant nudges, both choice alternatives had the same economic incentives and the scenario was known to be made up by the researchers, so that the Incentives and the Factually Correct necessary conditions were met. In addition, the Nudge Experiment necessary condition was met because the default option was 50% more expensive than the alternative. Since the 50% price differential still existed, the Preference Strength necessary condition would only have been met for those individuals who did not take the time and cognitive energy to click into the dropdown menu. Therefore we are looking for default nudge mechanisms that would have led a Human to accept the default contract without first viewing the price of the conventional contract.

Examining structural nudges. Structural nudges might have led Humans to accept the default without examining the alternative choice because they work for reasons unrelated to what the default and alternative options represent. In Table 11, structural mechanisms that result in default choice include Consistency, Decision Choice Costs (including Reanalysis, Distracted, and Cognitive Miser), Implicit Preference Advice, Implicit Behavioral Norms, Implicit Inequity Advice, and Habit.

- **Consistency**. The Consistency necessary conditions require that the default choice maintains the status quo that was chosen in an earlier period by the Human. However, the scenario description does not indicate what kind of contract the participants had chosen in their prior location. Thus, these conditions were not met.

- **Decision Choice Costs**. The Decision Choice Cost-Reanalysis mechanism requires that the default maintains the status quo, which was not the case. The Distracted mechanism requires that Humans were in the middle of doing other (more important) activities, which was not part of the experimental design. The Cognitive Miser mechanism may be the case, though the associated effectiveness condition (preferences are difficult to determine) was not fulfilled. The Decision Choice Cost mechanism that is not associated with reanalysis, distracted, or cognitive miser has two effectiveness conditions. The greater number or complexity of choices condition was not met. However, the small choice stakes may have been met if the Humans did not feel invested in the experimental task. In the absence of further information regarding the value individuals placed on their cognitive efforts and the degree they were invested in the experimental task, we keep Decision Choice Costs as a candidate mechanism for explaining the default nudge's effectiveness.
- **Implicit Advice**. Implicit Preference Advice and Implicit Equity Advice mechanisms require that the default be interpreted as the best or the most equitable alternative according to the entity providing the web page and that the Human does not distrust the advice. Since the experimental manipulation was clearly contrived by the researchers and obviously did not reflect an actual scenario or choice, these conditions were not met.
- **Implicit Behavioral Norms**. One necessary condition for this mechanism is that the Human interprets the default as describing what individuals typically do. The second condition is that the Human does not distrust the default's depiction of this

behavior. Since the experimental manipulation was clearly contrived by the researchers and obviously did not reflect an actual scenario or behavior, these conditions were not met.

- **Habit.** This mechanism requires that the Human associate the default choice with a habit cue, such as making the architecture look like those for software download default acceptance. This is unlikely because the choice architecture took the format of a textual survey.

Examining content nudges. At this point, we have one viable structural nudge candidate for a mechanism: Decision Choice Cost. Our analysis moves to an examination of content nudges that might prevent a Human from clicking the dropdown menu. One decision-making process might be Attention Focus within the Perception System that directed attention away from the dropdown information. This could have led to a Mental Model Error consisting of the exclusion of the conventional contract price. The only potential nudge mechanism listed in Table 11's Attention Focus process within the Perception System and linked to Mental Model Error is Confirmation-Information Seeking. For this mechanism to result in an effective nudge, the necessary conditions in Table 11 suggest that the participants must have had a priori preferences that were in accord with the default alternative to the exclusion of other alternatives. In fact the experiment primed participants to favor renewable over conventional energy in one of the other nudge treatments, but not for the default nudge. Unfortunately, the researchers did not report whether participants had a bias toward renewable energy prior to the experimental treatments. We will thus keep Confirmation-Information Seeking as a potential nudge candidate.

The result of our analyses is that we have two candidate default nudge mechanisms that could explain why the default manipulation was effective: Decision Cognitive Cost and Confirmation-Information Seeking. If Momsen and Stoerk were specifically interested in the role that the Decision Cognitive Cost mechanism played in the default's effectiveness, they could have collected data concerning, e.g., participants' distraction, choice importance, and cognitive cost importance. In addition, they could have reduced the potential for Confirmation-Information Seeking by surveying participants on their a priori preferences regarding conventional versus renewable energy, and using these data as a statistical control.

DISCUSSION & CONCLUSION

In the IS literature, there are many unrelated theories on why default nudges work on individuals. Here, we posit that the availability of so many theories has paradoxically contributed to a lack of theory in IS default nudge research. For example, we note that many IS researchers simply predict that individuals will stick with the default without providing an explanation as to why this behavior occurs (e.g. Dogruel et al., 2017; Klesel et al., 2016; Székely et al., 2016) or cite several theoretical explanations but do not tailor their experimental designs to be able to test any specific theory (e.g. Djurica & Figl, 2017). We suggest that the IS default nudge research program would benefit from additional structure and organization to the available theories to make them more usable by researchers.

This inspired us to investigate how the many default theories can be organized to help IS researchers understand their differences and properly incorporate them to explain why individuals select default options in specific IS contexts. To this end, we developed a theory-based typology. We found it reasonable to do so especially because a typology can consist of multiple theories that have causal arguments explaining the internal consistency of the underlying processes within each ideal type (Doty & Glick, 1994). While our typology expands the set of default nudge theories by introducing theories that have not been used in previous IS research, it simultaneously provides structure such that researchers can easily exclude theories that will not be relevant for a given context. Through use of this tool, scholars can actually take advantage of the many available theories by excluding those that will not be relevant and controlling for those that may confound results. As illustrated in Table 12, our typology has six dimensions, each with a varying number of characteristics that help define each ideal type of theory. The Decision-Making System, and Decision-Making Process dimensions have characteristics that are mutually exclusive because a nudge mechanism cannot directly affect more than one decision-making process, and each decision-making process is defined within a specific decision-making system. The Neoclassical Assumption Violation dimension has characteristics that are mutually exclusive; if a single mechanism appears to violate more than one assumption, it can likely be divided into multiple mechanisms. The Contextual Conditions dimension contains characteristics that in the aggregate for a mechanism are mutually exclusive. That is, the set of necessary and effectiveness conditions for a mechanism should be unique to that mechanism; if a single mechanism can be triggered by more than one set of conditions this likely indicates that there is more than one psychological mechanism in play. The Depiction dimension includes the structure or description characteristics, though we allow for mechanisms for which there is an interaction of structure and description. The Personalized Feedback dimension allows for either no feedback, or one or a combination of archival, smart immediate, and adaptive immediate feedback. A specific nudge mechanism, then, is assigned to a typology category that is designated by its associated characteristic(s) for each of the six dimensions. (Examples of such designations are provided in Appendix A.)

Table 12. Typology Theoretical Organization

Typology Dimension	Dimension Characteristics
1. Decision-Making System	Perception, Evaluation, Motivation
2. Decision-Making Process	Perception: Attention Focus, Internal Meaning Activation – Mental Model, Internal Meaning Activation – Imitative Behavioral Tendencies; Evaluation: Evaluation; Motivation: Develop Values, Reconcile Preferences & Attitudes with Emotions
3. Neoclassical Economic Assumption Violation	Utility Function Irregularities, Utility Function Irrelevancies – Non-Economic Values, Utility Function Irrelevancies – Irregular Economic Values, Utility Function Irrelevancies – Inappropriate Economic Values, Utility Function Irrelevancies – Emotions, Mental Model Errors, Non-Rational Choice Strategy
4. Contextual Conditions	Various combinations of Necessary & Effectiveness
5. Depiction	Structure or Description
6. Personalized Feedback	None or Archival, Smart Immediate &/or Adaptive Immediate

The effectiveness of our typology is demonstrated by its accord with the following typological effectiveness attributes (Nickerson et al., 2013).

- **Categories are mutually exclusive**, such that an object in the domain cannot be simultaneously classified in more than one category (Bailey, 1994; Bowker & Star, 1999). All characteristics within each of our typology's dimensions are defined such that they are mutually exclusive, given our current level of understanding of the decision-making process. For example, one mechanism that employs archival but not smart immediate nor adaptive immediate feedback would be categorized as a different mechanism if it employs all three types of feedback.
- **Categories are complete** in that they cover all objects in the domain (Bailey, 1994; Bowker & Star, 1999). Our typology is based on the twin foundations of Human decision-making systems and processes and neoclassical economic assumption violations. Since nudges are defined as mechanisms that concurrently result from Human

decision-making **and** that violate neoclassical economic assumptions, all nudges must be able to be placed within our typology. Mechanisms that cannot be placed are not nudges.

- **Categories explain the nature of objects** (Bailey, 1994). Once a mechanism is placed in the appropriate characteristic within each of the six dimensions, we understand: (dimensions 1 & 2) what Human decision-making activities are at play, (dimension 3) how these activities diverge from rational thought, (dimension 4) what choice contexts are responsible for this divergence, (dimension 5) whether the divergence is due to the choice option description and/or due to inferences that made by the Human regarding why the choice architecture employed that option as the default, and (dimension 6) the degree of personalization required to make the mechanism effective.
- **Categories are not static**, in that they should be able to include additional dimensions and characteristics when, for example, it becomes useful to distinguish among objects formerly categorized together or brand new objects are identified (Bailey, 1994). For example, this dynamism is possible with our typology in the following ways. Characteristics of the decision-making system and decision-making process dimensions can expand and change in line with the advances in psychological and neuropsychological research. In addition, neoclassical assumption characteristics can change by, e.g., dividing one characteristic into sub-characteristics when it aids in discriminating among mechanisms. Also, the variety of contextual necessary and effectiveness conditions are not bounded.

However, the sine qua non for typological effectiveness is in its utility. We developed our typology to help order a rather chaotic theoretical nudge domain, in which there is an expanding set of independent explanatory theories for why Humans choose default options that are suboptimal, but in which there is little to help researchers understand the relationships among those theories. Our typology integrates and extends literature from multiple disciplines and greatly improves our understanding of why default options influence decision-makers. We compile over 30 theoretical explanations for why a decision-maker might select a default option and demonstrate that this integration of theory can 1) improve researchers' and practitioners' predictions for existing or planned default nudges, 2) explain previously unexplainable and unexpected results from default nudge experimentation, 3) facilitate the creation of new and previously unknown theoretically-informed default nudges, and 4) inform researchers and practitioners about how to implement effective default nudges and default nudge experiments.

We organized these theoretical explanations within an overarching framework of decision-making to produce an integrated tool for theory selection and implementation that can help IS researchers adapt the nudge concept from its original field of psychology and behavioral economics (Markus & Saunders, 2007) and contextualize it in the IS field (Whetten, 1989). This integration across literatures afforded us a novel way of comparing and differentiating default nudge theories, contributing a level of understanding that future researchers can utilize to inform theory-based default nudge work (Corley & Gioia, 2011). In the same way that researchers can utilize the typology to design better experiments, practitioners can utilize the typology to design nudges that can be expected to be successful in their specific context.

By identifying the boundary conditions of the various theoretical explanations, our integration of theory additionally led us to clarify aspects of the default nudge construct, including associated necessary conditions, the distinction between description and structural nudges, the necessity of examining the entire choice context and not just the immediate IS-screen choice architecture when studying IS default nudges, and the importance of various types of feedback for personalization. Thus, the typology we present here provides a structure to compare, contrast, and build on empirical studies (Whetten, 1989) conducted across a variety of IS contexts. This will contribute to the development of a coherent research program on IS default nudges.

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APPENDIX A. PROCEDURE FOR PLACING DEFAULT NUDGE THEORETICAL MECHANISMS WITHIN THE TYPOLOGY

The procedure for placing a default nudge theoretical mechanism within the typology is as follows. First, determine which decision-making process within which decision-making system is appropriate in the following manner.

(1) Assume that all processes within the individual's four decision-making systems work in a neoclassically rational manner (like those of an Econ). Note that there is nothing in Econ processing that is like the imitative behavioral tendencies within the Perception System that directly influence behavior, since all of an Econ's behavior must involve some kind of Evaluation System activity. Also note that the Emotion System is included in an Econ's decision-making. Neoclassical economists did not propose that individuals lacked emotions, merely that emotions were not employed in the rational economic decision-making process. The Human and Econ therefore both are presumed to have active Emotion Systems, employing the same simulation processing within their systems. However, Econs and Humans differ regarding emotions in terms of their Motivation System processing: when making rational economic choices, Econs ignore the emotions to arrive at goals while Humans reconcile emotions with the preferences from the Evaluation System in order to arrive at goals.

(2) Holding all else constant (i.e., Econ-like) identify the **one** process within the **one** system that, if altered as suggested by the default nudge mechanism, would increase the likelihood that the Human would accept the default choice. [7]

For example, the Regret Avoidance nudge proposes that Humans perceive that choosing an alternative other than the default requires an act with a result that is caused by the Human. In contrast, not choosing (i.e., accepting the default) does not require an act that can be linked to the Human. In addition, the Human evaluates negative consequences that have been caused by him or her to have greater negative value than the same consequences that were not caused by him or her. Thus, choosing an alternative other than the default has the potential for the Human to feel greater regret, and therefore increases the likelihood that the Human will accept the default.

Following the placement steps above, we presume that the Human's Perception System processes environmental stimuli in an Econ-like manner, developing a mental model that includes information that distinguishes between default and alternative choices. This mental model is sent to the Evaluation System, where normal Econ-like processing occurs using values from the Motivation System to derive behavioral preferences. These preferences may favor any one of the choice alternatives. The Human's Emotion System processes environmental stimuli normally, and simulations reveal a greater potential for regret if the default is not accepted. Thus far, the Human is processing information as an Econ would, in an economically rational manner. An Econ's Motivation System would ignore input from the Emotion System. In contrast, this is where the nudge mechanism makes the Human take on non-Econ qualities, with the Motivation System reconciling emotions from the Emotion System with preferences from the Evaluation System. It is within this reconciliation process that the nudge will increase the likelihood that the Human will accept the default choice. Therefore, the Regret Avoidance nudge is placed in the Reconcile Preferences & Attitudes with Emotions process within the Motivation System.

[7] Except for Reference Point-Anchoring, which increases the likelihood of choosing an alternative that is close to the default option.

The next step is to identify which neoclassical economic assumption is being violated within the decision-making system and process that has made the Human's processing diverge from an Econ's processing. With Regret Avoidance, it is the consideration of an emotion when emotions should be ignored. Thus, the violation occurs in terms of considering a factor that is irrelevant to economic incentives, and the nudge is placed within Utility Function Irrelevancies.

Placement of the 38 theoretical default and potential default mechanisms within the typology resulted in seven nudge categories. In order to reduce the complexity of the following descriptions, only decision-making systems and processes that are closely associated with each mechanism are described. For example, when describing the development of inappropriate values within the Motivation System, we omit descriptions related to the Perception System's creation of a mental model that will later be evaluated in light of the inappropriate values.

- **Mental Model Errors Resulting from the Attention Focus and Internal Meaning Activation Processes within the Perception System.** These theoretical default nudge mechanisms assume that errors are introduced into the individual's mental model by either the Internal Meaning Activation process or the Attention Focus process within the Perception System, and are thus placed in the associated typology section. All other decision-making systems and processes are assumed to be unchanged and Econ-like for the Human. All nudge mechanisms are linked to Mental Model Errors assumption violations, since they assume that Humans' mental models include systematic errors.
    - Availability. To make it more likely that the default option is chosen, the default's and alternative choice's descriptions take advantage of the way that individuals evaluate the probability of an event as being more likely because an example comes to mind easily. The Perception System develops the mental model that includes these inappropriate probabilities.
    - Confirmation – Information Evaluation. To make it more likely that the default option is chosen, the default's and alternative choice descriptions take advantage of the way that individuals evaluate information in a way that fits with their existing thinking and preconceptions. The Perception System develops the mental model that includes these inappropriate evaluations.
    - Confirmation – Information Seeking. To make it more likely that the default option is chosen, the default's and alternative choice's descriptions take advantage of the way that individuals seek out information in a way that fits with their existing thinking and preconceptions. The Perception System develops the mental model that includes these inappropriate biases.
    - Empathy Gap (Hot-Cold). To make it more likely that the default option is chosen, the default's (future impact) description is based on the individual's current visceral state in contrast to alternatives that are described based on other (future) visceral states. This takes advantage of the way individuals assume their current visceral state will be unchanged in the future. The Perception System develops the mental model that includes these inappropriate evaluations for the default option.
    - Halo. To make it more likely that the default option is chosen, the default's description relates it to an attractive entity or event while the alternatives' descriptions relate them to other less attractive entities or events. This takes advantage of the way individuals associate attributes of surrounding entities or events to an object or event. The

Perception System develops the mental model that associates these attributes to the default and alternative options.

- Hindsight. Taking advantage of the way individuals believe that important issues in the past were predictable in the past, the default's description makes arguments against keeping the status quo. In order for it to be more likely that the default option is chosen, the default option should **not** maintain the status quo. The Perception System develops the mental model that includes these inappropriate beliefs regarding the status quo.
- Mental Accounting. To make it more likely that the default option is chosen, the default's and alternative choice's descriptions take advantage of the way that individuals categorize costs into current income and future income accounts, e.g., describing costs associated with the default as connected to current income and costs associated with alternatives as connected to future income. The Perception System develops the mental model that includes this inappropriate cost categorization scheme.
- Optimism. To make it more likely that the default option is chosen, the default and alternative choice descriptions take advantage of the way that individuals overestimate the probability of positive events and underestimate the probability of negative events, e.g. by including potential positive events in the description of the default but not the alternatives. The Perception System develops the mental model that includes these inappropriate probabilities.
- Overconfidence. To make it more likely that the default option is chosen, the default's description takes advantage of the way that individuals are more confident than they should be regarding their ability to make things happen in the future. For example, the default description may highlight the decision-maker's role in a future accomplishment while alternatives highlight the roles others must play in that future accomplishment. The Perception System develops the mental model that includes these inappropriate expectations.
- Peak-End. To make it more likely that the default option is chosen, the default's description takes advantage of the way that individuals evaluate the benefits associated with past experiences as being related to the peak experience or the last experience. The Perception System develops the mental model that includes these inappropriate evaluations.
- Representativeness. To make it more likely that the default option is chosen, the default's description takes advantage of the way that individuals estimate the probability that event/object A is in class B by how representative A is of B. The Perception System develops the mental model that includes these inappropriate probabilities.
- Subjective Evaluations of Probabilities. To make it more likely that the default option is chosen, the default's description takes advantage of the way that individuals over-weight small probabilities, e.g. by highlighting improbable outcomes associated with the default. The Perception System develops the mental model that includes these inappropriate probabilities.

- **Inappropriate Economic Values Resulting from the Develop Values Process within the Motivation System**. These theoretical default nudge mechanisms assume that values coming from the Develop Values process within the Motivation System are inappropriate in that they involve economic incentives but are systematically biased such that they don't reflect an Econ's values. All other decision-making systems and processes are assumed to be unchanged and Econ-like for the Human. Since the resulting values are not appropriate for rational decision-making (i.e., are inappropriate for an Econ), they are linked to the Utility Function Irrelevance assumption violations.

- Decision Choice Costs. The values provided by the Motivation System over-weight the individual's cognitive decision-making effort. These values are then used by the Evaluation System to derive behavioral preferences based on the mental model relationships. This results in a cursory evaluation of the costs and benefits of choosing, and in a premature termination of the choice process, thereby increasing the likelihood of accepting the default option.
- Decision Choice Costs – Cognitive Miser. The values provided by the Motivation System severely over-weight the individual's cognitive decision-making effort. These values are then used by the Evaluation System to derive behavioral preferences based on the mental model relationships. This results in the individual choosing not to engage in the choice process, and thereby accept the default option.
- Decision Choice Costs - Distracted. The values provided by the Motivation System over-weight decision-making cognitive effort and under-weight the potential benefits associated the current choice task. These values are then used by the Evaluation System to derive behavioral preferences based on the mental model relationships, resulting in an overvaluation of the benefits of attending to current activities, which leads to the decision not to engage in the choice process for this task, and thereby accept the default option.
- Decision Choice Costs – Reanalysis. The values provided by the Motivation System over-weight cognitive effort associated with the current choice task. These values are then used by the Evaluation System to derive behavioral preferences based on the mental model relationships. This results in a cursory evaluation of the costs and benefits of reanalysis and choosing, and results in a premature termination of the choice process, and thereby an acceptance of the default option.
- Hedonic Adaptation. The values provided by the Motivation System inflate future pleasure that is forecast from a current event. These values are then used by the Evaluation System to derive behavioral preferences based on the mental model relationships. The default choice description takes advantage of the inflated forecast making it more likely that the default option is chosen.
- Hyperbolic Discounting. The values provided by the Motivation System severely discount gains that might be received in the immediate future. These values are then used by the Evaluation System to derive behavioral preferences based on the mental model relationships. The default and alternative choice descriptions take advantage of Human's severe discounting of gains that might be received in the immediate future as the result of choosing an alternative other than the status quo to make it more likely that the default option is chosen; the default choice represents the status quo.
- Projection. The values provided by the Motivation System assume that current values will remain the same over time. These values are then used by the Evaluation System to derive behavioral preferences based on the mental model relationships. The default and alternative choice descriptions take advantage of this assumption by Humans to make it more likely that the default option is chosen.

    - Sunk Costs. The values provided by the Motivation System are greater than zero for sunk costs when making decisions about future behaviors. These values are then used by the Evaluation System to derive behavioral preferences based on the mental model relationships. The default description takes advantage of this valuation by Humans to make it more likely that the default option is chosen.
    - Time Discounting. The values provided by the Motivation System diminish the importance of a reward over time. These values are then used by the Evaluation System to derive behavioral preferences based on the mental model relationships. The default and alternative choice descriptions take advantage of this reduction by Humans to make it more likely that the default option is chosen.
- **Irregular Economic Values Resulting from the Develop Values Process within the Motivation System**. These theoretical default nudge mechanisms assume that values coming from the Develop Values process within the Motivation System involve economic incentives but the values do not follow the neoclassical economic assumptions that map an individual's perceptions (of a good's attributes, of events, of costs, of benefits, etc.) to the individual's utility, including problems associated with the utility function's consistency, transitivity, and stability. Such values preclude neoclassical utility optimization. All other decision-making systems and processes are assumed to be unchanged and Econ-like for the Human. Thus, the mechanisms are linked to Utility Function Irregularities assumption violations.
    - Framing – Attribute. The values provided by the Motivation System inappropriately place larger values on positive than on the equivalent negative attributes of alternatives. These values are used by the Evaluation System to derive behavioral preferences based on the mental model relationships. The default and alternative choice descriptions take advantage of these valuations by Humans to make it more likely that the default option is chosen.
    - Framing – Goal. The values provided by the Motivation System weight negative outcomes more highly than the equivalent positive outcomes. These values are used by the Evaluation System to derive behavioral preferences based on the mental model relationships. The default and alternative choice descriptions take advantage of these valuations by Humans to make it more likely that the default option is chosen.
    - Framing – Risk. The values provided by the Motivation System associate more weight to risk-seeking in relation to losses (negative outcomes) and to risk-aversion in relation to gains (positive outcomes). These values are used by the Evaluation System to derive behavioral preferences based on the mental model relationships. The default and alternative choice descriptions take advantage of these valuations by Humans to make it more likely that the default option is chosen.
    - Reference Point - Anchoring. Rather than assessing value in the abstract, values provided by the Motivation System evaluate alternatives relative to a reference point. In this case, the reference point is the default option. These values are then used by the Evaluation System to derive behavioral preferences based on the mental model relationships. The alternative choice descriptions take advantage of this relative valuation by Humans to make it more likely that a non-default option that is close to the default is chosen.
    - Reference Point - Decoy. Rather than assessing value in the abstract, values provided by the Motivation System evaluate alternatives relative to a reference point. In this case,

the reference point is another alternative choice (the decoy) that is asymmetrically dominated by the default choice. This valuation approach is then used by the Evaluation System to derive behavioral preferences based on the mental model relationships. The default and alternative choice descriptions take advantage of this relative valuation by Humans to make it more likely that the default option is chosen.
    - Reference Point – Status Quo. Rather than valuing gains and losses in the abstract, values provided by the Motivation System require that gains and losses be evaluated relative to a reference point, which in this case is the status quo, with gains having less value than equivalent losses. These values are then used by the Evaluation System to derive behavioral preferences based on the mental model relationships. The default and alternative choice descriptions take advantage of this relative valuation by Humans to make it more likely that the default option is chosen.
- **Non-Economic Values Resulting from the Develop Values Process within the Motivation System**. These theoretical default nudge mechanisms assume that values coming from the Develop Values process within the Motivation System are not associated with economic incentives. All other decision-making systems and processes are assumed to be unchanged and Econ-like for the Human. Since the resulting values are not relevant for rational decision-making (i.e., are inappropriate for an Econ), they are linked to the Utility Function Irrelevance assumption violations.
    - Consistency. The values provided by the Motivation System place a significant negative valuation on cognitive dissonance, etc. associated with making different choices over time. These values are used by the Evaluation System to derive behavioral preferences based on the mental model relationships. This makes it more likely that humans choose the default when it represents the status quo and when the Human was involved in choosing the current state in an earlier period.
    - Diversification. The values provided by the Motivation System place a significant positive valuation on the choice of variety for future consumption. This valuation is used by the Evaluation System to derive behavioral preferences based on the mental model relationships. The default and alternative choice descriptions take advantage of this valuation by Humans to make it more likely that the default option is chosen.
    - IKEA. The values provided by the Motivation System place a significant positive valuation on outcomes that come from the Human's own efforts. This valuation is used by the Evaluation System to derive behavioral preferences based on the mental model relationships. The default and alternative choice descriptions take advantage of this valuation by Humans to make it more likely that the default option is chosen.
    - Implicit Inequity Advice. The values provided by the Motivation System place a significant positive valuation on fairness independent of its economic utility. This valuation is used by the Evaluation System to derive behavioral preferences based on the mental model relationships. The default and alternative choice descriptions take advantage of this valuation by Humans to make it more likely that the default option is chosen.
    - Licensing. The values provided by the Motivation System place a significant positive valuation on Humans behaving in a negative manner after they have behaved in a positive manner. This valuation is used by the Evaluation System to derive behavioral preferences based on the mental model relationships. If the default involves behaving

in a negative manner, the default description takes advantage of this valuation by providing Humans the opportunity to exhibit good behavior prior to accepting the default option.

  - Reciprocity. The values provided by the Motivation System place a significant positive valuation on Humans responding to another's action with an equivalent (good response to good or bad response to bad) action. This valuation is used by the Evaluation System to derive behavioral preferences based on the mental model relationships. The default's description takes advantage of this valuation by providing Humans the opportunity to exhibit reciprocation when they accept the default choice.
- **Non-Rational Choice Strategies Employed in the Evaluation process within the Evaluation System**. These theoretical default nudge mechanisms assume that the Evaluation process within the Evaluation System involves something other than Econ-like utility maximization strategies. All other decision-making systems and processes are assumed to be unchanged and Econ-like for the Humans. Thus, these mechanisms are linked to the Non-Rational Choice Strategies assumption violation.
  - Habit. The values provided by the Motivation System place a significant positive valuation on responding to a habit trigger in a specific situation with specific goals. The goals consist of a rigid pattern of behavior in the form of action impulses complete with executive control structure(s). This valuation is used by the Evaluation System to derive behavioral preferences for these goals based on the mental model relationships. The default's description takes advantage of this valuation to increase the likelihood of Humans accepting the default option.
  - Implicit Preference Advice. The values provided by the Motivation System place a significant positive valuation on advice provided by others (when the Human trusts, or at least does not distrust the others) regarding which alternative should be preferred. The Perception System's mental model interprets the default option as advice from others regarding the most appropriate alternative. This valuation of advice is used by the Evaluation System to derive behavioral preferences based on the mental model relationships. This increases the likelihood that Humans will accept the default option.
- **Reconcile Preferences and Attitudes with Emotions Process within the Motivation System**. Econs have active Emotion Systems, but their Motivation System ignores emotions during rational decision-making. In contrast, these theoretical default nudge mechanisms assume that Human's Motivation Systems reconcile emotions from their Emotion Systems with the preferences from their Evaluation Systems in order to arrive at goals. Since emotions are irrelevant to Econs, these mechanisms are linked to the Utility Function Irrelevance assumption violations.
  - Partitioning. Humans experience guilt when they "open" another partition from a partitioned good. This emotion is captured by their Emotion System and sent to the Motivation System, where it is reconciled with preferences coming from the Evaluation System. The default description takes advantage of the way that Humans experience this guilt, thereby increasing the likelihood that the default option will be chosen.
  - Regret Avoidance. See the detailed regret avoidance description at the beginning of this appendix. The default description takes advantage of the way that Humans perceive that choosing other than the default requires an act with a result that is caused by the Human. In this way, any negative consequences are associated with the Human, which

can lead to regret. Humans try to avoid regret, thereby increasing the likelihood that the default option will be chosen.

- **Internal Meaning Activation - Imitative Behavior Process within the Perception System.** These theoretical default nudge mechanisms assume that Imitative Behavioral Tendencies within the Internal Meaning Activation process in the Perception System are activated for Humans, and that these tendencies directly influence behavior, thereby increasing the likelihood that the default option will be chosen. Such behavioral tendencies are not activated for Econs. All other decision-making systems and processes are assumed to be unchanged and Econ-like for the individual. The mechanisms that exploit these tendencies are irrelevant to Econs because they are irrelevant to economic incentives. The mechanisms are thus linked to the Utility Function Irrelevance assumption violations.
    - Implicit Behavioral Norms. The default is interpreted by the Human as a description of how individuals typically behave or typically should behave. In accord with Humans' imitative behavioral norm imperative the Internal Meaning Activation (Imitative Behavioral Tendencies) process within the Perception System directly affects behavior, thereby increasing the likelihood that the default option will be chosen.

ESSAY #3: NUDGING ONLINE CHARITABLE GIVING: THE ROLE OF THE IT ARTIFACT AND SOCIAL VALUE ORIENTATION

ABSTRACT

Charitable giving is a major industry in the United States and is increasingly conducted via online platforms. However, charitable giving is understudied in information systems research and cannot be explained with traditional rational theoretical models. In this work, we conduct an online field study to investigate charitable giving online by utilizing nudges, or aspects of a decision-making environment that influence individuals' decisions non-rationally, personalized to individuals' social value orientations, or motivational preferences for resource distribution. Our results show that utilizing the IT artifact to present live, animated social information as a nudge can better establish a social norm than similar static data, but may not translate effectively into norm adherence. We find that individuals who are more self-regarding may actually donate just as much as more other-regarding individuals in online platforms that are not utilized mainly for charitable giving. Default options matter for donations, but customization of defaults is complicated. These findings contribute to our understanding of how nudges influence charitable giving online and inform practice regarding the selection and implementation of online nudges to maximize charitable donations.

INTRODUCTION

Behavioral economics tells us that elements of an environment can influence the decisions that individuals make, even when those elements have no rational impact on the decision outcomes (Thaler et al., 2013). Nudges are one such element. Defined as aspects of choice architecture that predictably alter people's behavior without forbidding any options or significantly changing their economic incentives (Thaler & Sunstein, 2009), nudges have been used in practice (*The Behavioural Insights Team*, 2017) and research (Johnson et al., 2012) to influence many behaviors and outcomes. Traditionally, nudges have been studied in live face-to-face settings. Although nudges are ubiquitous in information systems, the IS field has lagged in studying these non-rational effects on online decision-makers, particularly with a theoretical focus (essay 1, this dissertation), even though nudges tend to be much more malleable and scalable online than in non-virtual settings. Thus, the focus of this study is to investigate the efficacy of nudges in IS.

To conduct a theory-driven investigation of nudges, we first must consider the context in which they are implemented. For this investigation, we selected an online charitable giving context. Americans donated nearly $450 billion to charity in 2019 (Giving USA, 2020), an amount equal to approximately 2% of the American GDP. These charitable donations are partially credited for outcomes such as reduced poverty (*Facts & Statistics About World Poverty & Charitable Donations*, n.d.), improved management of land and oceans to combat climate change (Kaiser, 2020), and many other outcomes. Charitable donations are increasingly collected online, are voluntary, and cannot be explained with neoclassical rational decision-making models (Khalil, 2004). For these reasons, online charitable giving is a good context for online nudge investigation.

Recently, charitable organizations have been using technology in creative ways to attempt to increase donations. This effort has included some nudges; in particular, default nudges. Default nudges are choices that will be selected if the decision-maker does not take other action (Thaler & Sunstein, 2009) and usually result in individuals "sticking" with the default option rather than selecting something else, for a variety of theoretical reasons (essay 2, this dissertation; Samuelson & Zeckhauser, 1988). Scholars theorize that default options should increase online donations, but results are mixed and suffer from a curvilinear effect such that while some decision-makers do donate more when a default is employed, others donate less and total donations are not increased (Altmann et al., 2019). We argue that the effectiveness of default nudges can be improved by varying the default amount based on the individual user – something that is easily achieved with the IT artifact, but which to our knowledge has not yet been investigated in research. We draw on the theoretical construct of social value orientation to facilitate this variation in default level. Social value orientation (SVO) is a motivational orientation that "captures the preferences people have for allocating resources to themselves versus others" (Bieleke et al., 2020, p. 2) and has been shown to predict prosocial behavior such as charitable donations (Bekkers, 2007; Van Lange et al., 2007).

Another way that researchers have investigated charitable giving has been by varying the social information (for example, the donations made by others) available to potential donors (Croson et al., 2009; Martin & Randal, 2008). To our knowledge, this has only been investigated in face-to-face settings so far, where results have been sometimes difficult to understand (Martin & Randal, 2008). Online contexts allow for the collection and display of social information in a scalable, malleable, and real-time way. Specifically, we predict that animation available from the IT artifact will increase the proximity of a norm presented with social information (Salvy et al., 2014). Proximal norms have been shown to have a stronger effect on behavior than distal norms in face-to-face contexts (Lewis & Paladino, 2008) but, to our knowledge, have not yet been investigated in online contexts. We will investigate the role of proximal and distal social information in individuals' online charitable giving decisions, particularly how it interacts with individuals who have different levels of SVO and how its efficacy is altered by addition of the IT artifact via animation.

Finally, charitable organizations have extended their reach beyond traditional charitable giving platforms to non-charity-related online spaces such as social media (*How Nonprofits Can Use Social Media to Boost Donations | DMI*, 2018). This widens the organizations' net of potential donors, but we can also expect that the individuals encountered on non-charity-related platforms are likely different in important ways from the individuals encountered on charity-specific platforms. Particularly, we would expect that individuals who seek out donation opportunities are likely higher in SVO than the general population. We conduct this study on a non-charity-related platform and investigate the role of nudges and IT artifact capabilities in determining online donation amounts and likelihood of donations.

In summary, we investigate nudges in IS, specifically in an online charitable giving context but on a platform that is not dedicated to charitable giving. We examine how nudge efficacy is affected by 1) varying the default amount based on an individual's level of SVO and 2) providing social information about other users on the platform. We find that, counterintuitively, individuals with lower levels of SVO donate just as much as individuals with higher levels of SVO on a non-charity dedicated platform. The level of default is important, particularly for determining an individual's likelihood of donation, but can be complex to interpret. Social information when aided by the IT artifact can also be an important determinant of likelihood of donation over social information lacking animation, but only for individuals with specific levels of SVO. These results are important for research on nudges in charitable giving, optimal default settings, and IT-artifact-aided social information. In practice, our findings can guide charitable organizations utilizing nudges and non-charity-focused platforms (e.g. social media) to maximize donations.

The rest of this paper proceeds as follows. First, we review the relevant literature and develop theory and predictions for the study. Second, we provide an overview of the methods utilized and then report results of the study. Finally, we discuss those results, highlight contributions and limitations, and conclude.

BACKGROUND AND HYPOTHESIS DEVELOPMENT

Charitable Giving

Americans donated nearly $450 billion in 2019 – an amount equivalent to roughly 2% of the American GDP (Giving USA, 2020). Individuals have increasingly preferred to make those donations online in recent years, with approximately 10% of donations ($45 billion) contributed via an online platform in 2019 (Giving USA, 2020).

A number of dependent variables are important in the study of charitable giving. First and foremost, donation amount is the amount that the charity receives from a donor. This may be investigated as average donation per donor or average donation per potential donor (Martin & Randal, 2008). Actual donations are important since they indicate cash in hand for charities immediately. Likelihood of donation is an important dependent variable as it can build a charity's "warm list" of past donors that can then be utilized for future donations, even if the past donation was small (Harbaugh et al., 2007). Satisfaction with the donation opportunity is also important, as it may determine an individual's future willingness to engage with the organization or donating in general (Harbaugh et al., 2007).

Charitable giving cannot be explained with neoclassical rational models wherein individuals are motivated to maximize their own gain (Becker, 1976). However, there are multiple theories of altruism that attempt to explain why individuals would contribute to charity. A model of pure altruism assumes that some individuals have an inherent drive to contribute resources to better the world (Harbaugh et al., 2007). We know, however, that not all acts of kindness are exclusively the result of an internal drive for charity. Individuals may contribute out of egoistic drive – offering altruistic assistance because they expect future benefit – or egocentric drive – offering altruistic assistance because the individual receives some immediate benefit (Khalil, 2004). Future benefits might include reciprocity, social standing, or tax benefits. Immediate benefits can include vicarious pleasure or a "warm glow" (Andreoni, 1990).

We posit here that there are other reasons that individuals donate, or reasons they select the donation amounts they do. One of these is the way the choice environment is structured and the functions presented in that environment, particularly nudges. Nudges have been investigated in some face-to-face studies and these findings can inform our understanding of their functionality online, but variation in nudge presentation exists online that does not exist face-to-face. Thus, studying the online implementation of nudges in charitable giving can help us to better understand how to increase their efficacy.

Many studies of charitable giving have been conducted in face-to-face settings. We know from these studies that giving is affected by its cost (the effective price of giving), the method of solicitation, the revealing of donors' identities, explicit suggestions or requests, and information about the behavior of others (Edwards & List, 2014; Feldhaus et al., 2019; Martin & Randal, 2008). However, there are limitations to face-to-face studies that can be solved by moving the studies online. For example, while suggested donation amounts can be implemented in face-to-face settings, it is difficult to implement a default option – an option that is chosen unless the decision-maker makes a different active choice – encouraging a positive donation. A default option such as this is a specific type of nudge.

Nudges

In our previous work (essays 1 and 2 of this dissertation) we have elaborated on the definition and theory of the nudge construct. We define a nudge as a function of the choice architecture that alters people's behavior in a predictable way, made possible because of cognitive boundaries, biases, routines, and habits in individual and social decision-making, but which does not add or remove any rationally relevant choice options or change the incentives of any options (Hansen, 2016; Hausman & Welch, 2010; Mongin & Cozic, 2014; Thaler & Sunstein, 2009).

A useful heuristic for determining whether something is a nudge is that a nudge is anything that affects the behavior of humans but would not be expected to influence the behavior of hyper-rational beings that adhere to traditional neoclassical decision-making models (Thaler & Sunstein, 2009). Using this heuristic, we can identify a few exclusionary conditions for nudges, namely that they:

1. Cannot exclude nor add any rationally-relevant choice alternatives (Hansen, 2016)
2. Cannot significantly alter any economic incentives, such as prices, social sanctions, time, cognitive effort, etc. (Hansen, 2016; Thaler & Sunstein, 2009).

By considering the fact that rationality can vary within humans, we can also identify some conditions under which nudges would be expected to be effective, including:

1. Preference strength: For nudges to be effective, Humans cannot have an alternative for which they have a firm preference. This lack of firm preference occurs when an individual is ambivalent or lacks familiarity with the choices (Acquisti et al., 2017), forms or changes his or her preferences during the decision-making process (Barr et al., 2012; Dinner et al., 2011), is distracted (Meske & Potthoff, 2017), or when the choice problem complexity obscures a preferred alternative (Thaler & Sunstein, 2009).

2. Factually correct choice architecture: For a nudge to be effective, the individual must believe that the information presented to them in the choice architecture is factually correct.

A number of typologies exist to differentiate types of nudges (Acquisti et al., 2017; Datta & Mullainathan, 2014; Dimitrova et al., 2017; Dolan et al., 2012; Johnson et al., 2012; Michie et al., 2011; Mirsch et al., 2017; Münscher et al., 2016; Oinas-Kukkonen & Harjumaa, 2008; Promann & Brunswicker, 2017; Szaszi et al., 2018). Many build on the original typology suggested by Thaler and Sunstein, which includes five types, presented in Table 13 (adapted from a similar table in essay 1 of this dissertation). We will examine two types of nudges in this work: an increasing salience of incentives nudge and a default nudge.

Social Norms

Norms are social patterns that govern behavior (Morris et al., 2015). These include descriptive norms, or norms about what other individuals do, and injunctive norms, or norms about what other individuals think one should do. Knowledge of social norm information influences behavior because individuals tend to be motivated to act in accordance with the norms that they perceive (Croson et al., 2009; Everett et al., 2015). Presenting social norm information to individuals is a type of nudge; specifically, it increases the salience of incentives[8] related to adhering to the social norm and predictably changes people's behavior to adhere to the norm, but does not change the incentives of the situation or add/remove any rationally relevant options.

[8] Incentives of adhering to a social norm might include better group acceptance, avoidance of sanctions related to non-conforming behavior, and ensuring a "safe" behavior in times of uncertainty (Morris et al., 2015)

Notably, individuals are motivated to adhere to social norms and therefore avoid deviation from the norm – in either direction. For example, Schultz et al. (Schultz et al., 2018) utilized social norm information to encourage energy conservation by informing individuals about the neighborhood's average energy consumption. This had the expected effect of reducing energy usage by households that were above this average, but had an undesired "boomerang effect" such that individuals consuming less energy than the average actually *increased* their energy usage to align with the descriptive norm. Social norms are one theoretical explanation for the "sticky" phenomenon of default options: individuals may perceive that a default is selected because it is what most people choose (descriptive norm) or because it is what most people or some authority figure thinks is the best option (injunctive norm) (Everett et al., 2015). Social norms have been shown to have a stronger effect when paired with a default option (Everett et al., 2015).

The effects of social information on individuals' donation behaviors has been investigated in prior research, but as far as we are aware, the investigation has been limited to face-to-face interactions. For example, Martin and Randal (2008) studied how changing the composition of bills and coins in a transparent donation box of an art gallery affected individuals' decisions to donate and found that donations tended to mirror the original composition of the box: when the box was empty, individuals donated less, for example. A study like this is constrained by location, the type of people who walk in, the cash they have available in the moment, the individuals who entered at the same time, etc. Information systems facilitate a much more malleable, generalizable context of donation and allow for easier varying of important attributes such as defaults and proximity.

Table 13. Thaler and Sunstein's typology of nudges

Nudge Type	**Defining Characteristics**	**Example**
Increasing salience of incentives	Makes certain incentive values associated with some attributes of choice alternatives more prominent or noticeable	While Facebook users are typing a new post, presenting them with the profile pictures of five random people who will be able to view the post, thus increasing the salience of the social norms pertaining to the kind of information that is appropriate to post given one's audience (Wang et al., 2014)
Understanding mapping	Makes information about one or more choice alternatives more understandable relative to incentives.	When users are typing a password, providing them with a warning that evaluates the strength of the password in terms of the time a hypothetical hacker would require to crack it, thus mapping the password choice alternatives to incentives associated with a user's desire for privacy (Khern-am-nuai et al., 2017).
Default	A choice alternative that will be selected if the chooser does nothing.	Social network services contain default privacy settings, meaning users end up with the settings chosen by the designer unless they opt to change them (Tschersich & Botha, 2013).
Giving feedback[9]	A (typically real-time) process by which one of the other types of nudges is conveyed to an individual in response to some action by that individual.	Note that the first two examples here (increasing salience of incentives and understanding mapping) are both delivered by feedback mechanisms.
Expecting error[9]	Anticipates and attempts to prevent error-prone behaviors in a given context.	A pop-up when a user attempts to close an unsaved document can prevent unintentional loss of unsaved work.
Structuring complex choices	Choice alternatives are presented in an organized way.	Contacts are categorized at various levels of granularity to guide individuals to set up customized privacy settings in a social network (Knijnenburg & Kobsa, 2014)

[9] Note that in essay #1 of this dissertation, we discuss how both the giving feedback and expecting error categories present orthogonality problems when using this typology

Effects of social norms are theorized to vary based on their proximity to the decision-maker. The concept of proximal vs. distal social norms has been applied in studies about drinking behavior (Salvy et al., 2014). Individuals who experienced more proximal social norms (being in the presence of others who are consuming) were more likely to drink more than individuals who experienced more distal social norms (hearing about drunk teenagers from someone else the day after a party) (Salvy et al., 2014). Proximal norms were shown to produce stronger relationships with drinking behavior than distal norms (Lewis & Paladino, 2008). Individuals are more likely to be influenced by descriptive norms that are derived from the setting they are currently occupying in other contexts as well, such as vegetable selection (Thomas et al., 2017).

Previous researchers have defined proximity as being in the same space and time with others (Salvy et al., 2014) and investigation has been limited to face-to-face contexts. However, we can also manipulate proximity in online platforms. We posit that manipulating spatial – being on the same platform as other users – and temporal – acting at the same time as other users – will have a similar effect to the spatial and temporal proximity manipulated in face-to-face settings. That is, increased proximity of the social norm is expected to increase its effect on users' behavior.

Hypothesis 1: Users will a) donate more and b) be more likely to donate when exposed to a positive donation social norm that is more proximal to them compared to a social norm that is more distal. Both norms will influence behavior more than no social information presented.

Default Nudges

As described in Table 13, default nudges are options that will be selected if the decision-maker does not make a different active choice. Decision-makers tend to stick with a default option, even when it is suboptimal. Dozens of theories have been suggested to explain this phenomenon (sometimes called the status quo bias) which we review and summarize in essay two of this dissertation (Samuelson & Zeckhauser, 1988). Default options are easily implemented and manipulated in IS and are ubiquitous: for example, there are over 30 default options in just one group of commands on the Microsoft Word ribbon.

It is worth noting that default nudges to encourage action (as opposed to inaction) are more easily implemented in IS than any other setting. For example, a letter mailed to encourage a charitable donation may have a suggested donation value selected for the recipient, but the decision-maker is still required to actually provide the funds and mail back the form. Online, a default value can be suggested and actually be donated if the decision-maker does nothing other than progress through the system, particularly given web browsers that save and auto-populate individuals' payment methods. For these reasons, we selected default nudges as one nudge of choice for this investigation.

Essay two of this dissertation does a deep dive into the theoretical reasons that default nudges affect behavior. In this context, we are aiming to test the implicit behavioral norms (herd behavior) explanation of why a default affects behavior. This theory posits that defaults are perceived as an indication either of how other people behave or how one ought to behave – in other words, the socially approved form of action (Everett et al., 2015). We hope to strengthen this effect by coupling it with explicit social information that others are donating the default amount as described earlier. We utilize Amazon Mechanical Turk (AMT) for the study. Because AMT is not traditionally a charitable giving platform, the socially approved donation to make may be ambiguous, making this a stronger context in which to test this explanation (Samson, 2014). Specifically, AMT is a platform typically used to earn money, meaning we will expect users to aim to maximize their earnings while on the platform. However, the use of a default in the donation opportunity will present users with a socially acceptable donation amount in this ambiguous setting, meaning they will tend to donate more when faced with a default than when it is not present. Thus, we predict:

Hypothesis 2: Participants will a) donate more and b) be more likely to donate in conditions that include a default than conditions that require an active choice.

In Appendix A: Default Theories – Tested and Controlled, we have replicated the table from essay two describing different theoretical explanations of default nudges, with an additional column describing how the other default theories (other than imitative behavioral tendencies) are controlled in this study. Based on this analysis, we also expect to see effects of habit (Dolan et al., 2012; Samson, 2014; Wood & Neal, 2009) from individuals who tend to donate often (although these individuals should be split evenly across conditions due to random assignment, and the effect should be attenuated due to donation opportunities in AMT being rare – although not unheard of – compared to donation-focused platforms). It is also possible that individuals will donate out of reciprocity (Fehr & Gachter, 2000; Samson, 2014) or confirmation (Samson, 2014) based on an individual's opinion of the charities offered. We attenuate that effect by offering multiple, high-quality charities.

Defaults have been studied in charitable giving in the past. As expected, defaults do affect individuals' donation decisions (Altmann et al., 2019). However, the effect is complicated. Researchers observe a curvilinear effect such that while some individuals donate more when faced with a default, others donate less and there is no effect on total donations or average donations (Altmann et al., 2019). Scholars theorize that this is because a "one-size-fits-all" nudge is less effective than personalized nudges would be (Altmann et al., 2019; Egelman & Peer, 2015). This aligns with our theorizing of the nudge construct: nudges are less effective when individuals have strong preferences, and we can predict some preferences based on individuals' states and traits. A personal characteristic of particular interest to predict individual's preferences regarding charitable giving is social value orientation (SVO).

Social Value Orientation

Social Value Orientation (SVO) is a motivational orientation (Van Lange, 1999) capturing the preferences people have for allocating resources to themselves versus to others (Bieleke et al., 2020). SVO "extends the rational self-interest postulate by assuming that individuals tend to pursue broader goals than self-interest" (Van Lange, 1999, p. 337). This extension is necessary in the study of charitable giving, since altruistic donation cannot be explained in a purely rational model of decision-making, and fits with our non-rational theoretical grounding of nudges.

SVO is a continuous construct ranging from more prosocial (placing higher value on resource allocation to others) to less prosocial/more individualistic (placing higher value on resource allocation to oneself) (Ackermann et al., 2016). Individuals with prosocial value orientations are more likely to engage in prosocial behaviors than individuals with more individualistic value orientations (Bekkers, 2007; Van Lange et al., 2007). Differences in SVO reflect different motivations for charitable giving, with prosocials motivated by benefits to others and individualists motivated by personal gain (Ackermann et al., 2016). Based on these preferences, we can derive that individuals with higher (more prosocial/less individualistic) SVOs will have stronger preferences to donate to charity when compared to individuals with lower (less prosocial/more individualistic) SVOs. In other words, a default encouraging higher charitable donations (as opposed to lower) will align more closely with the preferences of a higher SVO individual. This preference alignment will allow the default nudge to be effective, where a preference misalignment would result in less effectiveness. Therefore, we predict:

Hypothesis 3: Default nudges that are personalized to an individual's SVO (that is, higher defaults for prosocial individuals) will result in a) higher average donations and b) higher likelihood of donation compared to general defaults or active choice conditions.

Individuals with extremely low (very individualistic) SVOs would not be expected to donate at all given that they have a strong preference for maximizing their own resources (Murphy & Ackermann, 2014). However, SVO is a continuum, and individuals who are individualistic but not extremely so may be expected to donate under some circumstances. We expect, therefore that defaults encouraging much more modest charitable donations will align more closely with the preferences of a lower SVO individual, increasing the effectiveness of the default at soliciting donations.

Hypothesis 4: Default nudges that are personalized to an individual's SVO (that is, lower defaults for moderately individualistic individuals) will result in a) higher average donations and b) higher likelihood of donation compared to general defaults or active choice conditions.

Capitalizing on this group of low-SVO individuals represents an opportunity for charitable organizations to increase total donations and potential donor lists. This is particularly the case as organizations expand beyond traditional charitable giving platforms to platforms that are not built for charitable giving (e.g. social media), removing the need for individuals to seek out opportunities to donate (as prosocial individuals are much more likely to seek such opportunities than individualists).

This capability of the IT artifact to reach individuals who may otherwise not have opted in to a donation opportunity provides a rich area for theorizing. Because prosocial individuals are more likely to donate to charity in general (Van Lange et al., 2007) we can expect that they donate more overall than individualistic individuals and therefore can infer two attributes of prosocial individuals. First, they are more likely than their individualistic counterparts to have preferred mechanisms by which they donate. These might be preferences regarding preferred or trusted 1) organizations to which to donate (e.g. specific charitable causes, types of organizations, sizes of organizations, ratings on charitable organization websites, etc.), 2) timing or incentives for donation (e.g. only donating when the donation is matched or only donating at certain times of the year relative to holidays or personal budgeting), 3) methods of donating (e.g. only donating items rather than money, only donating via specific websites or campaigns), etc. Second, they are more likely than their individualistic counterparts to be “tapped out”; in other words, to have already donated or committed all resources they are willing/able to and therefore be unable or unwilling to donate when an unexpected opportunity arises. Therefore, we predict:

Hypothesis 5: When an unexpected donation opportunity arises on a platform not intended for charitable donations, prosocial individuals will a) donate no more and b) be no more likely to donate than individualistic individuals.

Other Important Constructs

In addition to the main constructs we have described here, it is important to consider that there are many more possible influences on the relationships we are interested in. While no research models can account for all possible influences, we include the following control variables that we expect to account for some variation in our relevant relationships, based on extant literature.

First, an individual's willingness to donate to any cause will be influenced by their level of disposable income. We would expect that individuals who struggle to meet their own needs with their earnings will be unable or unwilling to donate regardless of any of the other influences we have hypothesized here.

Like with most behaviors, past prosocial behavior is expected to be a good predictor of future prosocial behavior (Saunders et al., 2016) because people are influenced by habit and assume that what has worked in the past will continue to work in the future. Therefore, we collect past charitable giving behavior.

Previous literature has identified several constructs that have been shown to predict prosocial behaviors such as charitable donation. As we have described, individuals differ on their motivations regarding distribution of resources between themselves and others. While we are primarily interested in Social Value Orientation, two similar but distinct constructs we take into account are Self- and Other-Interest, which describes the pursuit of gains in socially valued domains (self-interest) and the pursuit of gains for others in socially valued domains (other-interest) (Gerbasi & Prentice, 2013). We expect, as shown in previous literature, that both of these constructs will influence an individual's motivation to donate or abstain from donation since donation can offer an opportunity to pursue gains for others in socially valued domains but may threaten an individual's ability to pursue gains for oneself.

Another way scholars have predicted individuals' propensity for prosocial behavior is through measurement of stable, individual-level traits such as the Big Five personality traits (Venable et al., 2005). The Big Five personality traits include openness, conscientiousness, extraversion, agreeableness, and neuroticism (Costa & McCrae, 1992). Openness, or openness to experience, reflects an individual's level of imagination, sensitivity to art and beauty, emotional complexity, intellectual curiosity, behavioral flexibility, and dogmatism in attitudes and values (Costa & McCrae, 1992). Openness can impact prosocial motivation and behavior because one's ability to imagine can affect their ability to empathize with those in need, which can influence an individual's desire or willingness to help. Conscientiousness reflects an individual's level of scrupulousness, organization, and diligence (Costa & McCrae, 1992). An individual high in conscientiousness is well-organized and highly diligent, which may influence prosocial behavior as charitable giving may require remembering of deadlines, having organized finances, etc. Extraversion is a dimension that reflects sociability, activity, and a tendency to experience positive emotions such as joy and pleasure (Costa & McCrae, 1992). Extraversion relates to an individual's ability to connect with others (Costa & McCrae, 1992) and therefore, like openness, may influence an individual's ability to empathize and desire to help others. Agreeableness is also related to sociability and reflects an individual's level of trust in others, their sympathy for others, and level of cooperation with others (Costa & McCrae, 1992). Agreeableness is important for predicting prosocial behavior through individual's trust in people and charitable organization as well as their sympathy for individuals in need. Finally, neuroticism reflects an individual's tendency to experience psychological distress (Costa & McCrae, 1992). Individuals who are high in neuroticism can likely be induced to feel distress via pleas from charitable organizations and may aim to reduce that distress by engaging in prosocial behavior. Thus, each of the Big Five personality traits can be important for predicting prosocial behavior.

Finally, research shows that individuals' preferences and behavior are influenced by their current visceral state, or internal feeling states (Steinmetz et al., 2018), including preferences and behaviors related to charitable giving (Harel & Kogut, 2015). Current visceral state is classified in five types: temperature (hot/cold), thirst, hunger, tired, and awake. Research has hypothesized that individuals experiencing a negative state (e.g. hunger) would be more willing to give to reduce that negative state in others (charitable donation to feed the hungry), but have empirically found that a satisfied and comfortable decision-maker is more generous, possibly because they (Harel & Kogut, 2015). Thus, we measure to control for individuals' current visceral states.

METHODS

Participants

We recruited U.S.-based participants for our study via Amazon Mechanical Turk (AMT), an online platform that connects a distributed workforce with discrete tasks in exchange for payment (*Amazon Mechanical Turk*, n.d.). AMT has been used widely in research and has been shown to provide samples that are more diverse than samples of college students (Gandullia et al., 2020; Saunders et al., 2016) with a similar level of quality compared to experts and lab subjects (O'Grady et al., 2019).

A total of 336 individuals participated in the study over four rounds of data collection and one pilot study (pilot: 20; round 1: 102; round 2: 101, round 3: 59; round 4: 79). After removing incomplete responses and individuals who failed attention checks, we retained 306 valid responses. However, due to a problem understanding one of our experimental manipulations, 133 participants were removed for a sample size of 173. We then removed two outliers that caused our statistical models to have problems coming to a solution; thus, our final utilized sample size was 171. 83.6% of participants were aged 20-40, 36.26% reported their gender as female, 56.14% reported having a Bachelor's degree, and 77.77% reported their race as white. Full descriptive statistics of the sample are presented in Appendix D.

Procedure

We took the following measures to ensure high-quality data from AMT. First, participants were paid a highly competitive wage: $2 for approximately 10-15 minutes of work, equivalent to an $8-12 hourly wage. Valid participants also had the option to receive up to a $1 bonus, bringing their hourly wage to $12-18. In 2010, AMT workers were willing to accept an hourly rate of $1.38 (Horton & Chilton, 2010). While this has likely increased in the last decade, we are confident that the pay for our AMT task was competitive and encouraged high-quality responses. We also utilized an AMT qualification to ensure that workers could only participate in the study once. The AMT task description clearly stated that attention was required, and participants' attention was verified with multiple attention check questions.

Once recruited via AMT, participants were redirected to the experiment hosted via oTree (Chen et al., 2016). oTree is a Python-based open-source platform for web-based interactive tasks that has been used in hundreds of academic studies (*OTree*, n.d.). We utilized oTree because it provided the capability to customize screens based on the scoring of an individual's previous answers; thus, we were able to facilitate real-time customization to individuals' SVO scores.[10]

In the survey, participants agreed to a consent and then answered various questions including demographics, income (Wunderlich et al., 2019), past donation behavior (Saunders et al., 2016), the Big Five Inventory-10 measure of personality (Rammstedt & John, 2007), the Self- and Other-Interest Inventory (Gerbasi & Prentice, 2013), and current visceral state (Steinmetz et al., 2018). The measure of interest was the slider measure of SVO (Murphy et al., 2011). All measurement items are included in Appendix B. To implement Likert-scale items, we adapted the otreeutil package (Konrad, 2019).

Once they finished the survey, participants who passed the attention check questions[11] were then informed that they had qualified for a $1 bonus and were given an opportunity to donate some, all, or none of that bonus to charity. To increase participants' trust that charities would actually receive these donations, we offered to send participants a link to a website with the donation totals and receipts from the charities, a practice similar to what was implemented by O'Grady et al. (2019)[12]. We also replicated O'Grady et al.'s method for offering charities. We utilized a list of nine[13] popular and highly-rated charities from three categories: environmental, domestic (U.S.) aid, and international aid. Each participant saw three charities, one randomly selected from each category. It was on this screen that we implemented the default nudge and

[10] While Qualtrics provides options to customize the flow of a survey, it did not support the complex math required to compute an individual's level of SVO based on their answers to the slider questions.

[11] Participants who failed the attention check questions were informed that they had failed an attention check question and the survey ended for them prior to the donation opportunity.

[12] See https://donationstudy.weebly.com

[13] The nine charities were: The Nature Conservancy, World Wildlife Fund, Natural Resource Defense Council, Disabled American Veterans, American Red Cross, St. Jude Children's Research Hospital, Doctors Without Borders, United Nations Children's Fund, and Save the Children.

social information manipulations, described next. Once individuals made their donation decisions, they answered a few follow-up questions and the survey concluded. All donations selected by participants were actually donated to the selected charities, and any amount not donated by the individuals was actually paid to them as a bonus in addition to their AMT payment.

Conditions[14]

Immediately after consenting to participate in the research, participants were randomly assigned to one of the conditions described in the following section. Regardless of condition, all participants saw the following description:

"Congratulations! Based on your attentiveness and responses, you have qualified for a $1 bonus in addition to your Amazon Mechanical Turk payment.

You have the opportunity to retain this entire $1 bonus or donate any portion of it to a charity of your choice from the list below. If you choose to donate, you can receive access to a website that tracks all donations and displays receipts for the donations."

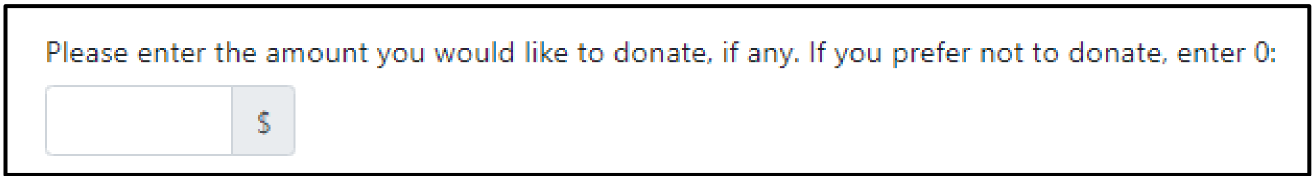
Default conditions

Based on our theory that defaults should be more effective when they are personalized to an individual's level of SVO, we had three conditions that varied the presence and level of the default: control, general, and personal. When present, defaults were implemented using slider bars that could be manipulated by the users. The values of all of the defaults are presented in Table 14.

[14] All conditions possible are replicated in Appendix C. Complete details on the experimental design are reported in Appendix H.

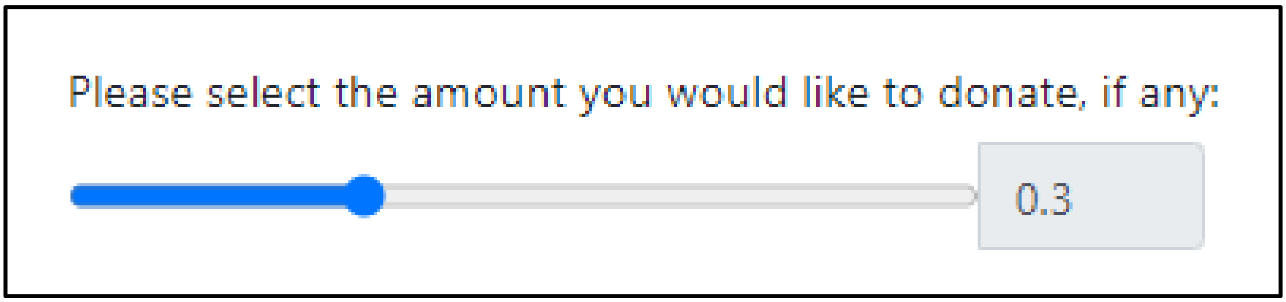
1. Control. The control condition had no default and required an "active choice"; in other words, the participant had to type in the amount they would like to donate (they could type in 0 to abstain from the donation).

Figure 3. Control condition donation opportunity.



2. General. The general condition utilized a generalized default that was the same for all participants who were assigned to the general condition.

Figure 4. General condition donation opportunity.



3. Personalized. The personalized condition utilized a personalized default that was low for participants with individualistic SVOs (defined as a slider angle less than 22.45, Murphy & Ackermann, 2014) and high for participants with prosocial SVOs (defined as a slider angle greater than or equal to 22.45).

Figure 5. Personalized condition donation opportunity for individualistic participants in data collection rounds 2-4.

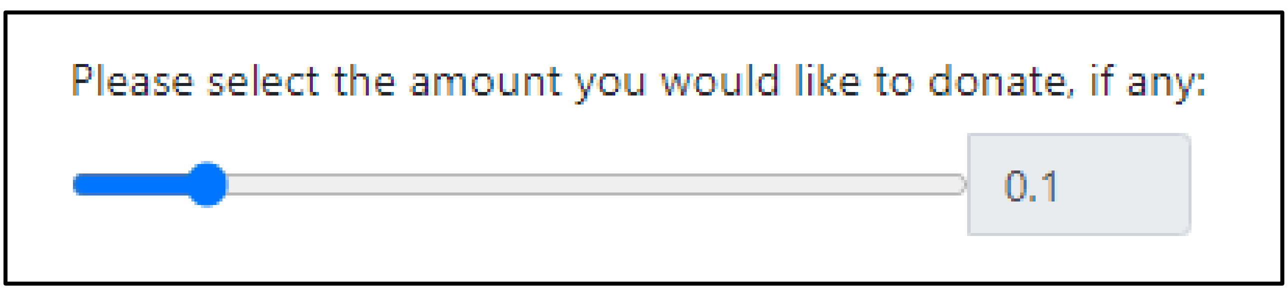


Figure 6. Personalized condition donation opportunity for prosocial participants in data collection rounds 2-4.

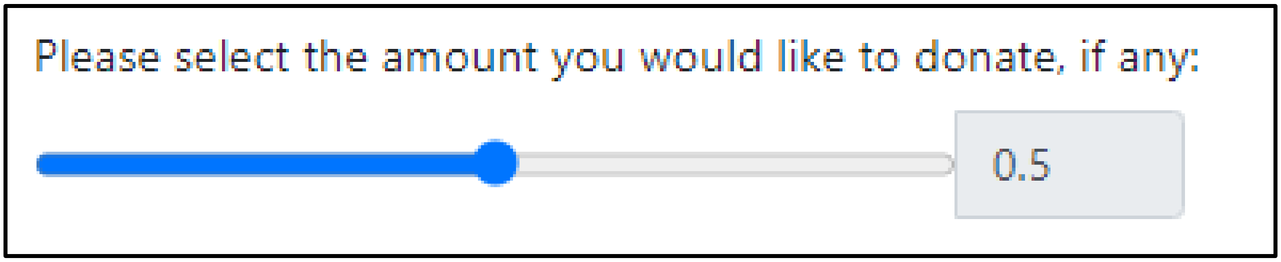


Table 14. Default values by data collection round

	Pilot Study & Round 1	Rounds 2-4
General Default	$0.50	$0.30
Personalized Low Default	$0.25	$0.10
Personalized High Default	$0.75	$0.50

Social information conditions

In addition to the default manipulation, we also varied the social information available to participants. Participants were randomly assigned to one of three conditions regarding social information: no data, static data, and live data.

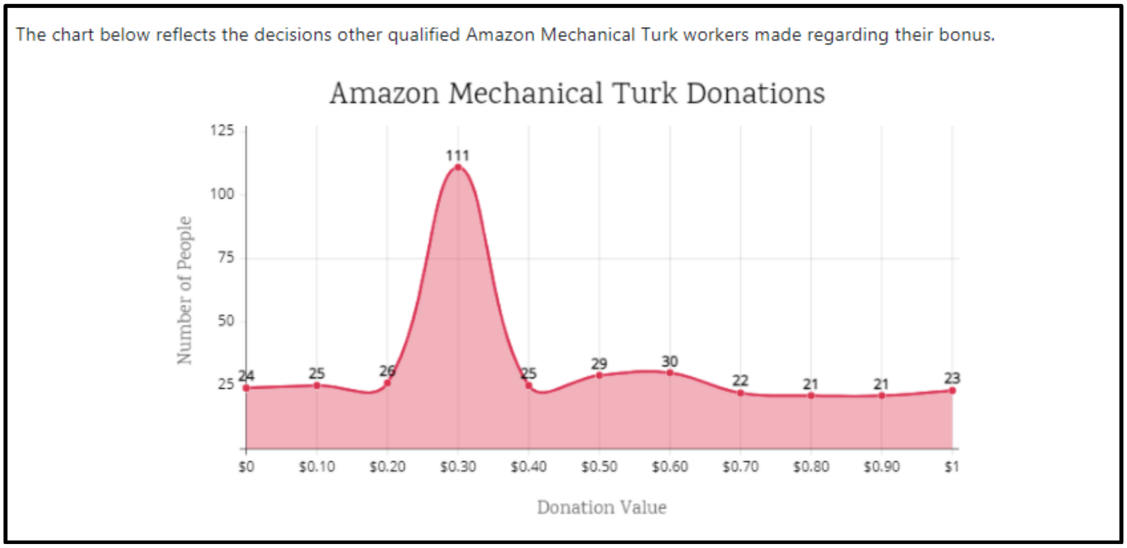
1. No data. Participants assigned to this condition did not receive any information about the donations of others.
2. Static data. Participants assigned to this condition saw a static chart that ostensibly displayed the donation decisions made by other individuals who had taken the survey at some undisclosed previous time.
3. Live data. Participants assigned to this condition saw an animated, live chart that ostensibly displayed the donation decisions currently being made by other individual taking the survey.

The purpose of the charts was to communicate a social norm about what other participants typically or are currently donating in this situation[15]. The decisions ostensibly

[15] Based on manipulation check information that we collected, participants struggled to understand the charts presenting social norm data. Details on this challenge and the steps we took to mitigate it are presented in Appendix E.

presented in the charts reflected a social norm to stick with the default (when present) or to donate some amount (in the active choice condition). Thus, if a user saw a $0.30 default and was in either the static or live data condition, he or she saw a chart indicating that most other donors donated/were donating $0.30, as in Figure 7.

Figure 7. Example of static data reflecting a descriptive social norm to donate $0.30.



We took the following measures to make data treatments as similar as possible:

1. Live data treatments were all gif files with the same number and length of frames.
2. Static data treatments were the final frame of the gifs used for live data treatments.
3. All treatments reflected the decisions of 300-350 individuals.

Examples of all conditions are reproduced in Appendix B[16].

Conditions combined

Our study, therefore, was a 3 (default condition) by 3 (type of social information) between-subjects study. Crossing both manipulations, participants were assigned to one of the following nine conditions presented in Table 15:

[16] Note that we cannot produce the effect of animation in print, so the examples are limited to the default condition with and without data.

Table 15. The nine possible conditions of the study.

		No Data	*Static Data*	*Live Data*
Default condition	*Control (Active Choice/no default)*	Control + none	Control + static	Control + live
	General	General + none	General + static	General + live
	Personalized	Personal + none	Personal + static	Personal + live

Operationalization

Demographics

We collect demographic information for two purposes: 1) to understand our sample and 2) to control for demographic variables that might affect charitable giving. Individuals report their age, gender, level of education, and employment status. These are all values that are reasonable to be collected via self-report survey items. We speculate that all of these demographic variables could have an impact on the relationships we are interested in. We know that as individuals age and increase their levels of education, their preferences and motivations change due to maturation through these processes. Likewise, we know that there are sometimes marked differences among genders regarding beliefs, preferences, and behaviors. We expect that employment status will also impact the relationships of interest, since one's employment status can sometimes impact their willingness and ability to spend and donate money as it implies whether the individual expects to receive more money in earnings in the future.

Income

We ask participants to self-report their annual household income from a drop-down list (see the measure in Appendix B). Individuals should be equipped to report their own income, however, there may be differences in how participants interpreted "household" income. We use income as a proxy for the more abstract construct of ability to donate to charity. Income is an imperfect proxy for this, as we do not take into account other factors that affect this such as living expenses. Income is likely to be one important factor when determining individuals' willingness to pay or donate.

Self- and Other-Interest Inventory (SOII)

The Self- and Other-Interest Inventory (SOII) measures individuals' motivation to act in one's own interest (self-interest: the pursuit of gains in socially valued domains, including material goods, social status, recognition, academic or occupational achievement, and happiness) and motivation to act in another's interest (other-interest: the pursuit of gains for others in socially valued domains, including material goods, social status, recognition, academic or occupational achievement, and happiness.) (Gerbasi & Prentice, 2013). These are conceptualized as independent constructs and are each measured with a 9-item subscale of the SOII (reliabilities of the scales are reported in a later section; the items can be found in Appendix B). The nine items are combined by taking the average (adding all items and dividing by nine) in both cases. The SOII measures these motivations at the level of self-beliefs; thus, self-reported survey items are a reasonable way to collect this information. We will refer to these two constructs as, "Self- and Other-Interest Inventory: Self-Interest Score" and "Self- and Other-Interest Inventory: Other-Interest Score" and may occasionally use the acronym SOII (Self- and Other-Interest Inventory), SI (self-interest), and OI (other-interest) to conserve space.

Personality

We utilize the Big Five Inventory 10 (BFI-10) to measure personality (Rammstedt & John, 2007). This scale presents two items per Big Five personality facet (openness, conscientiousness, extraversion, agreeableness, and neuroticism) for a total of 10 items. We present the reliability measures for each personality facet in a later section. Each set of two items is combined into a single measure of that personality facet by taking the average (adding the score of both items divided by two). Note that some items are reverse-coded prior to this combination. The BFI-10 has been shown to perform nearly as well as other, longer measures of personality while requiring only a few minutes of participants' time (Rammstedt & John, 2007). To get a full picture of an individual's personality, other measures may be employed (e.g. behavioral observation, asking close others about an individual's personality) but self-report personality tests have been demonstrated to accurately measure personality for the purpose of predicting behavior. We will refer to each trait as "BFI-10" plus the trait of interest, for example: "BFI-10: Extraversion."

Past Donation Behavior

We use two variables to measure past donation behavior. We ask individuals to report 1) the amount of their past donations and 2) the frequency with which they have donated in the past. We will refer to these constructs as "Past Donations – Monthly" and "Past Donations – Frequency" respectively. These measures (presented in Appendix B) are adapted from Saunders et al. 2016. An ideal measure of past donation behavior would be actual activity (for example, donation receipts or records), but given the challenge of collecting that information, a self-report survey item is also reasonable. Note that this item in particular may suffer from social desirability bias such that individuals may be motivated to inflate their past donations to appear more socially desirable.

Current Visceral State

There are five variables within the umbrella of current visceral state: temperature, thirst, hunger, tired, and awake (Steinmetz et al., 2018). We utilize these each as an independent variable; they are not combined into an overall measure of current visceral state. This is a measure of individuals' internal feeling states, thus, self-report survey items are the most valid way to collect this information. We will refer to each of these as "Current Visceral State" plus the state being discussed, e.g. "Current Visceral State – Hunger."

Social Value Orientation

We utilize the slider measure of Social Value Orientation (Murphy et al., 2011). The slider measure of Social Value Orientation (SVO) has the benefit of producing a continuous measure of SVO, while most other measures produce a categorical label for the decision-maker (Murphy et al., 2011). A continuous measure aligns more closely with our theoretical understanding of SVO as a continuum of motivational preferences.

The SVO slider measure is made up of six items which take the form of a resource allocation choice over a well-defined continuum of joint payoffs (these items are presented in Appendix B). These "decomposed games" represent the interconnections between the four points on the SVO allocation plane corresponding to the idealized social orientations reported in the literature: altruistic, prosocial, individualistic, and competitive (Murphy & Ackermann, 2014). For full details of the SVO framework, refer to Murphy & Ackermann 2014.

Individuals respond to the six decomposed game items of the SVO slider measure (see the items in Appendix B) and their selected allocations can be used to calculate an SVO slider angle as a measure of SVO (Murphy et al., 2011). According to Murphy et al., 2011:

"The mean allocation for self ($\bar{A}_s$) is computed as is the mean allocation for the other ($\bar{A}_o$). Then 50 is subtracted from each of these means in order to "shift" the base of the resulting angle to the center of the circle (50, 50) rather than having its base start at the Cartesian origin. Finally,

the inverse tangent of the ratio between these means is computed, resulting in a single index of a person's SVO."
Thus, the equation for calculating an individual's SVO slider angle is as follows in Figure 8.

Figure 8. Equation to calculate SVO slider angle

$$\text{SVO}^\circ = \arctan\left(\frac{(\bar{A}_o - 50)}{(\bar{A}_s - 50)}\right)$$

This equation results in a slider angle in degrees for each participant, which can range from -16.26° (perfectly individualistic) to 61.39° (perfectly prosocial). We utilize Murphy et al. 2011's cutoff of 22.45° to categorize individuals as either individualistic (22.45° and less) or prosocial (greater than 22.45°). For full details on the SVO slider measure and the calculation of SVO slider angles, refer to Murphy et al. 2011. We will refer to this continuous construct as "SVO Slider Angle." At times, we also refer to an individual's categorization as either prosocial or individualistic, which we will term, "SVO Categorization," the levels of which we interchangeably refer to as low SVO/individualistic and high SVO/prosocial.

Categorical Variable Codings

In the results reported in the next major section, we utilize dummy variables to handle categorical variables in our statistical analyses. This will be described in detail in the Results section and Table 16 can be used throughout the section to understand how categorical variables were handled. Note that we use different variable codings for hypothesis 3b, and a different categorical variables codings table is presented there.

Table 16. Categorical variables' codings

Categorical Variables Codings

			Parameter coding					
		Frequency	(1)	(2)	(3)	(4)	(5)	(6)
Education	LessThanHighSchool	2	.000	.000	.000	.000	.000	.000

	HighSchoolGrad	22	1.000	.000	.000	.000	.000	.000
	SomeCollege	20	.000	1.000	.000	.000	.000	.000
	Associate	16	.000	.000	1.000	.000	.000	.000
	Bachelor	96	.000	.000	.000	1.000	.000	.000
	Master	16	.000	.000	.000	.000	1.000	.000
	Doctor	1	.000	.000	.000	.000	.000	1.000
Employment Status	FullTime	127	.000	.000	.000			
	PartTime	23	1.000	.000	.000			
	Retired	4	.000	1.000	.000			
	Unemployed	19	.000	.000	1.000			
Gender	female	62	.000	.000				
	male	110	1.000	.000				
	did not disclose	1	.000	1.000				
Data Treatment	none	95	.000	.000				
	static	34	1.000	.000				
	live	44	.000	1.000				
Default Treatment	none	52	.000	.000				
	general	56	1.000	.000				
	personal	65	.000	1.000				

Attention Checks

We utilized two attention checks drawn from literature (they are presented in full in Appendix B). In the first, individuals were shown a passage with some facts about forests. Embedded within the passage was the statement, “Please answer 100 trees.” Below the passage was a picture of a forest. The question was, “Roughly how many trees are in this photo of a deciduous forest?” Participants who answered 100 trees were considered to have displayed an appropriate degree of attention. This attention check question is from O’Grady et al 2019.

Second, participants saw a Likert-style question that asked, “How much do you agree with this statement?” with the corresponding statement, “I am participating in an online study currently.” Participants could select from 7 Likert answers (1-very strongly disagree, 7-very strongly agree). If participants answered agree, strongly agree, or very strongly agree, they were considered to have displayed an appropriate degree of attention. This attention check question is from Curran and Hauser 2019.

RESULTS

Measurement Reliability

For constructs that were measured with multiple scale items, we conducted reliability analyses in SPSS. These constructs include Self- and Other-Interest and the Big Five Inventory 10 measure of personality. For each scale, we report Cronbach's alpha, which is a measure of internal consistency that indicates how closely related a set of items are as a group. A high Cronbach's alpha reflects that the items in the scale are closely related and the measure is reliable. A rule of thumb for interpreting Cronbach's alpha is: >0.9 = Excellent, 0.8-0.9 = Good, 0.7-0.8 = Acceptable, 0.6-0.7 = Questionable, 0.5-0.6 = Poor, and < 0.5 = Unacceptable (Gliem & Gliem, 2003). For reliable measures, we also provide validity information in the form of correlations among measurement items (Gliner et al., 2009).

Self- and Other-Interest Inventory (SOII) (Gerbasi & Prentice, 2013)

Self-Interest Subscale

For the self-interest subscale of the SOII, Cronbach's alpha = .886, which is considered high (Cortina, 1993; Gliner et al., 2009) and supports the reliability of the self-interest subscale of the SOII.

Table 17. Reliability statistics for self-interest subscale of SOII.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.886	.885	9

Other-Interest Subscale

For the other-interest subscale of the SOII, Cronbach's alpha = .905, which is considered high (Cortina, 1993; Gliner et al., 2009) and indicates that the other-interest subscale of the SOII is reliable.

Table 18. Reliability statistics for other-interest subscale of SOII.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.905	.907	9

Big Five Inventory 10 (BFI-10) (Rammstedt & John, 2007)

Extraversion

For the extraversion subscale of the BFI-10, Cronbach's alpha = .563, which is considered poor (Cortina, 1993; Gliner et al., 2009) and indicates that the extraversion subscale of the BFI-10 is not reliable for this sample. Thus, we are unable to utilize extraversion as a covariate in our analyses.

Table 19. Reliability statistics for extraversion subscale of the BFI-10.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.563	.579	2

Agreeableness

For the agreeableness subscale of the BFI-10, alpha = .106, which is considered unacceptable (Cortina, 1993; Gliner et al., 2009) and indicates that the agreeableness subscale of the BFI-10 is not reliable for this sample. Thus, we are unable to use agreeableness as a covariate in our analyses.

Table 20. Reliability statistics for the agreeableness subscale of the BFI-10.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.106	.106	2

The two agreeableness items from the BFI-10 scale are not significantly correlated, indicating a lack of support for validity of the measure.

Conscientiousness

For the conscientiousness subscale of the BFI-10, alpha = .515, which is considered poor (Cortina, 1993; Gliner et al., 2009) and indicates that the conscientiousness subscale of the BFI-10 is not reliable for this sample. Thus, we are unable to use conscientiousness as a covariate in our analyses.

Table 21. Reliability statistics for the conscientiousness subscale of the BFI-10.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.515	.543	2

The two measures of conscientiousness from the Big Five Inventory-10 are significantly positively correlated at r=0.372. This indicates some support for validity of the measure, although it is not high enough to indicate that the two items are measuring the same construct.

Neuroticism

For the neuroticism subscale of the BFI-10, alpha = .657, which is considered questionable (Cortina, 1993; Gliner et al., 2009) and indicates that the neuroticism subscale of the BFI-10 may not be reliable for this sample. Thus, we do not utilize neuroticism in our analyses.

Table 22. Reliability statistics for the neuroticism subscale of the BFI-10.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.657	.665	2

The two measurement items for neuroticism in the Big Five Inventory 10 are significantly positively correlated at r=0.498. This provides some support for validity of the scale but is not high enough to indicate that the items are measuring the same construct.

Openness

For the openness subscale of the BFI-10, alpha = .381, which is considered unacceptable (Cortina, 1993; Gliner et al., 2009) and indicates that the openness subscale of the BFI-10 is not reliable for this sample. Thus, we are unable to utilize openness in our analyses.

Table 23. Reliability statistics for the openness subscale of the BFI-10.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.381	.389	2

The two items of the Big Five Inventory 10 that measure openness are significantly positively correlated at r=0.242. This indicates some support for validity, but the correlation is not high enough to indicate that the items are measuring the same construct.

Convergent and Discriminant Validity

Only the two subscales of the Self- and Other-Interest Inventory demonstrated acceptable reliability. Therefore, we go on to evaluate the convergent and discriminant validity of these two subscales. Convergent validity describes how well the items of a scale measure the construct they are intended to measure, while discriminant validity describes the degree to which the items of a scale do not measure (i.e. discriminate from) other constructs they are not intended to measure (Gliner et al., 2009).

We utilized confirmatory factor analysis (CFA) to investigate whether the two subscales of the SOII measure their respective constructs (self-interest and other-interest) with acceptable convergent and discriminant validity. We use CFA rather than exploratory factor analysis (EFA) because self- and other-interest are theorized to be two constructs in extant literature; we are not exploring data to understand how many factors are represented.

An important consideration with factor analysis is the factor rotation that will be utilized. Factor rotation helps us interpret factor loadings and falls into two general types: orthogonal rotation and oblique rotation (Institute for Digital Research & Education, n.d.). Orthogonal rotation assumes factors are independent while oblique rotation assumes factors are correlated. To assess the correlation between the two subscales we are analyzing, we first ran a factor analysis with the direct oblimin method and examined the resulting component correlation matrix, presented next:

Table 24. Component Correlation Matrix of oblimin factor analysis of SOII

Component Correlation Matrix

Component	1	2
1	1.000	.510
2	.510	1.000

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

We find that the two factors are correlated at r=.510, meaning the appropriate rotation method is an oblique rotation. We then run a factor analysis with the promax rotation, which is an oblique rotation.

The output of the factor analysis includes a correlation matrix, presented in Table 26. We see here that the items of the self- and other-interest subscales are all correlated with each other with values ranging from r=.0116 to r=0.776. The mean correlation is 0.415 and the median correlation is 0.423, indicating that most of these items are correlated with each other. However, we also note that most self-interest items correlate more highly with each other (mean correlation among self-interest items = 0.461) compared to the correlation between self-interest and other-interest items (mean correlation = 0.348). The same is true for other-interest items (mean correlation among other-interest items = 0.519).

We evaluated the Kaiser-Meyer-Olkin (KMO) Measure of sampling adequacy and the Bartlett's Test of Sphericity to determine whether our data is suitable for factor analysis. KMO is a statistic that indicates the proportion of variance in the variables that might be caused by underlying factors and indicates that factor analysis may be useful when the statistics is greater than 0.50 and closer to 1. Bartlett's test of sphericity tests the hypothesis that the correlation matrix is an identity matrix and, when significant, indicates that factor analysis can be useful (*IBM Docs*, 2021).

The KMO is 0.898, which is greater than the generally accepted threshold of 0.5, and the Bartlett's test of Sphericity is significant, so we know factor analysis may be useful with this data.

Table 25. KMO and Bartlett's Test for factor analysis of SOII subscales

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.898
Bartlett's Test of Sphericity	Approx. Chi-Square	1994.909
	df	153
	Sig.	.000

The pattern matrix presents the factor loadings of our factor analysis with promax rotation (*Pattern Matrix and Structure Matrix Definition in SPSS FACTOR Output*, 2020). We can utilize these factor loadings to evaluate both convergent and discriminant validity.

Table 26. Correlation matrix of items in the Self- and Other-Interest Inventory (SOII)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. SOII: Self-Interest Item #1	1.000																	
2. SOII: Self-Interest Item #2	.360	1.000																
3. SOII: Self-Interest Item #3	.599	.264	1.000															
4. SOII: Self-Interest Item #4	.424	.772	.336	1.000														
5. SOII: Self-Interest Item #5	.480	.678	.418	.688	1.000													
6. SOII: Self-Interest Item #6	.728	.434	.605	.464	.616	1.000												
7. SOII: Self-Interest Item #7	.571	.393	.421	.484	.582	.593	1.000											
8. SOII: Self-Interest Item #8	.429	.312	.350	.219	.252	.351	.344	1.000										
9. SOII: Self-Interest Item #9	.491	.398	.410	.345	.395	.503	.465	.427	1.000									
10. SOII: Other-Interest Item #1	.530	.441	.452	.508	.526	.421	.309	.250	.376	1.000								
11. SOII: Other-Interest Item #2	.390	.470	.270	.459	.309	.324	.328	.188	.363	.492	1.000							
12. SOII: Other-Interest Item #3	.447	.251	.314	.243	.205	.423	.231	.252	.353	.492	.448	1.000						
13. SOII: Other-Interest Item #4	.512	.496	.312	.537	.466	.439	.441	.249	.397	.619	.624	.481	1.000					
14. SOII: Other-Interest Item #5	.497	.544	.339	.566	.701	.494	.437	.123	.404	.721	.463	.392	.589	1.000				
15. SOII: Other-Interest Item #6	.369	.301	.329	.246	.318	.472	.258	.180	.404	.503	.521	.496	.537	.472	1.000			
16. SOII: Other-Interest Item #7	.416	.398	.363	.471	.507	.436	.323	.161	.273	.776	.471	.514	.590	.653	.514	1.000		
17. SOII: Other-Interest Item #8	.372	.282	.259	.258	.256	.303	.139	.301	.196	.553	.486	.541	.607	.406	.488	.572	1.000	
18. SOII: Other-Interest Item #9	.343	.227	.150	.170	.151	.343	.211	.116	.335	.375	.433	.626	.453	.350	.562	.434	.433	1.000

Note: all correlations are significant at p < .05 except for those that are shaded, which all have p<= .065

Table 27. Factor loadings of the SOII subscales.

Pattern Matrix [a]

	Component 1	Component 2
SOII: Self-Interest Item #1	**.663**	.155
SOII: Self-Interest Item #2	**.735**	-.002
SOII: Self-Interest Item #3	**.644**	.002
SOII: Self-Interest Item #4	**.801**	-.047
SOII: Self-Interest Item #5	**.921**	-.137
SOII: Self-Interest Item #6	**.756**	.059
SOII: Self-Interest Item #7	**.864**	-.192
SOII: Self-Interest Item #8	**.514**	-.049
SOII: Self-Interest Item #9	**.582**	.092
SOII: Other-Interest Item #1	.292	**.597**
SOII: Other-Interest Item #2	.122	**.637**
SOII: Other-Interest Item #3	-.111	**.839**
SOII: Other-Interest Item #4	.264	**.622**
SOII: Other-Interest Item #5	.503	**.365**
SOII: Other-Interest Item #6	-.017	**.773**
SOII: Other-Interest Item #7	.171	**.680**
SOII: Other-Interest Item #8	-.151	**.862**
SOII: Other-Interest Item #9	-.239	**.876**

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 3 iterations.

Our measurement items load well onto the expected two factors, with factor loadings for all self-interest items having loadings greater than 0.5 on one construct and factor loadings for all other-interest items having loadings greater than 0.5 on the other construct. With the exception of Other-Interest Item #5, no item has a factor loading greater than 0.3 on the opposite construct. This serves as evidence that the two subscales are, indeed, measuring two constructs.

Average variance extracted (AVE) provides a measure of convergent validity. AVE compares the amount of variance captured by a construct vs. the amount of variance captured by error. The AVE of the self-interest subscale was 0.533 and the AVE of the other-interest subscale was 0.506. While an AVE of 0.7 is considered good, an AVE of 0.5 is considered acceptable (Alarcón et al., 2015). Thus, we have evidence for acceptable convergent validity for both the self- and other-interest subscales of the SOII.

A rule of thumb for evaluating discriminant validity with AVE is that the positive square root of the AVE for each of the latent variables should be higher than the highest correlation with any other variable (Alarcón et al., 2015). The positive square root of the AVE for the self-interest construct is 0.73 and the positive square root of the AVE for the other-interest construct is 0.71. By referring back to the data presented here, we can indeed confirm that our data meets this rule of thumb and therefore demonstrates acceptable discriminant validity.

Manipulation check: social norm proximity

It is a limitation of our work that we did not additionally include a manipulation check to confirm that participants perceived the animated data to be a more proximal social norm than the static data.

Manipulation check: data treatment interpretation

For this analysis, we retained only individuals who correctly answered the mode of the data presented to them when asked the question, "How much were most other donors donating while you were making your decision?" (in the live treatment) or "How much had most other donors donated when you were making your decision?" (in the static treatment). Thus, the answer to the question was perfectly correlated with the mode of the data ($r = 1$, $p<.001$) and there is support for the idea that individuals in the analyses understood the social norm data presented to them.

Table 28. Correlations of data treatment and data treatment manipulation check question for only individuals included in the analysis.

Correlations

		1	2
1. Answer to the "how much were other donors donating" question	Pearson Correlation	1	1.000**
	Sig. (2-tailed)		.000
	N	78	78
2. Mode of the data presented to the participant	Pearson Correlation	1.000**	1
	Sig. (2-tailed)	.000	
	N	78	173

**. Correlation is significant at the 0.01 level (2-tailed).

When all participants are included, these two variables are still correlated ($r = .211$, $p = .006$).

Table 29. Correlations of data treatment and data treatment manipulation check question for all participants.

Correlations

		1	2
1. Answer to the "how much were other donors donating" question	Pearson Correlation	1	.211**
	Sig. (2-tailed)		.006
	N	171	171
2. Mode of the data presented to the participant	Pearson Correlation	.211**	1
	Sig. (2-tailed)	.006	
	N	171	306

**. Correlation is significant at the 0.01 level (2-tailed).

Hypotheses Evaluations

Our predictions regarding donation amount include one continuous dependent variable (donation amount) utilizing scores on one of two categorical independent variables with three levels each (default: none, general, personalized; and data: none, static, live) implemented between-subjects. Based on this design, the recommended statistical tests to test our hypotheses are one-way ANOVA and independent samples t-tests (Campbell & Stanley, 1963; Gliner et al., 2009). We utilized and report both tests here. A one-way ANOVA tests the main effect of each independent variable on the dependent variable as well as testing for an interaction effect between the independent variables. We also report the results of ANCOVA, which also takes into account the control variables we collected. ANOVA and ANCOVA tell us whether the variables of interest are associated with a change in the dependent variable, but do not tell us the direction of that relationship. Thus, when a relationship is significant in ANOVA/ANCOVA, we follow up the test with independent t-tests to determine the direction of the relationship. Independent samples t-tests compare the means of two groups and investigate whether those means differ significantly and in what direction, but do not incorporate any control variables. Thus, the combination of tests helps for a thorough investigation of donation amount.

Likelihood of donation is a binary variable, assigned either 1 (when an individual makes a positive donation) or 0 (when an individual abstains from donating). Our hypotheses predict likelihood of donation based on either default treatment or data treatment; thus, we are predicting a binary dependent variable utilizing one of two three-level independent variables. To test these hypotheses, we utilize logistic regression. The results of the hypotheses tests are described next.

Results: Hypothesis 1

In Hypothesis 1, we predicted that users would be more likely to donate and would donate more when exposed to a positive donation social norm that was more proximal to them compared to one that was more distal or no information at all.

Donation Amount. First, we ran an ANOVA with donation amount as the dependent variable and data treatment as a three-level fixed factor. The resulting model indicates a significant effect of data treatment ($p = .012$).

Table 30. Details of H1 Donation Amount ANOVA

Between-Subjects Factors

		Value Label	N
Data Treatment	1	none	94
	2	static	33
	3	live	44

Tests of Between-Subjects Effects

Dependent Variable: Donation Amount

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[b]
Corrected Model	1.061[a]	2	.530	4.517	.012	.051	9.034	.764
Intercept	8.059	1	8.059	68.640	<.001	.290	68.640	1.000
Data Treatment	1.061	2	.530	4.517	.012	.051	9.034	.764
Error	19.725	168	.117					
Total	33.468	171						
Corrected Total	20.785	170						

a. R Squared = .051 (Adjusted R Squared = .040)

b. Computed using alpha = .05

Next, we re-ran the model as an ANCOVA including default treatment and our reliable controls (demographics: gender, education, employment status, age, and income, plus SVO, Self- and Other-Interest, past donation amounts and frequency, all five aspects of current visceral state) as covariates with data treatment as a fixed factor. Categorical covariates with more than two levels (default treatment, gender, education, and employment status) were dummy coded such that n dummy variables were created for each variable, where n is equal to the level of the variable. For example, there are three levels of gender (female, male, and did not disclose), so three dummy variables were created. When adding these categorical variables to the model, we included n-1 dummy variables and excluded the nth dummy variable, thus utilizing the nth dummy variable as a reference category to which the others were compared and maintaining 1 degree of freedom for each included dummy variable. In this model, we see a significant effect for data treatment (p=.042). The model reports an R-squared of 0.326 and adjusted R-squared of 0.210.

Table 31. Details of H1 Donation Amount ANCOVA.

Tests of Between-Subjects Effects

Dependent Variable: Donation Amount

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[b]
Corrected Model	6.786[a]	25	.271	2.812	<.001	.326	70.288	1.000
Intercept	.068	1	.068	.704	.403	.005	.704	.133
Default Treatment_1 (active choice)	.131	1	.131	1.358	.246	.009	1.358	.212
Default Treatment_2 (general default)	9.755E-5	1	9.755E-5	.001	.975	.000	.001	.050
Gender_1 (female)	.364	1	.364	3.771	.054	.025	3.771	.488
Education_1 (less than high school)	.055	1	.055	.572	.451	.004	.572	.117
Education_2 (high school grad)	.801	1	.801	8.297	.005	.054	8.297	.816
Education_3 (some college)	.567	1	.567	5.876	.017	.039	5.876	.673
Education_4 (associate degree)	.123	1	.123	1.276	.261	.009	1.276	.202
Education_5 (bachelor degree)	.227	1	.227	2.346	.128	.016	2.346	.331
Employment_Status_1 (full time)	.054	1	.054	.560	.455	.004	.560	.115
Employment_Status_2 (part time)	.067	1	.067	.691	.407	.005	.691	.131
Employment_Status_3 (retired)	.002	1	.002	.016	.900	.000	.016	.052
Age	.081	1	.081	.843	.360	.006	.843	.149
Income	.036	1	.036	.375	.542	.003	.375	.093
SVO Slider Angle	.625	1	.625	6.476	.012	.043	6.476	.715
Self- and Other-Interest Inventory: Self-Interest Score	.414	1	.414	4.283	.040	.029	4.283	.538
Self- and Other-Interest Inventory: Other-Interest Score	.001	1	.001	.007	.935	.000	.007	.051
Past Donations Amount - Monthly	.846	1	.846	8.761	.004	.057	8.761	.837

Past Donations Amount - Frequency	.026	1	.026	.267	.606	.002	.267	.081
Current Visceral State - Temperature	.015	1	.015	.158	.691	.001	.158	.068
Current Visceral State - Thirst	.002	1	.002	.022	.881	.000	.022	.053
Current Visceral State - Hunger	.005	1	.005	.055	.815	.000	.055	.056
Current Visceral State - Tired	.255	1	.255	2.636	.107	.018	2.636	.364
Current Visceral State - Awake	.000	1	.000	.003	.954	.000	.003	.050
Data Treatment	.616	2	.308	3.191	.044	.042	6.381	.603
Error	13.999	145	.097					
Total	33.468	171						
Corrected Total	20.785	170						

a. R Squared = .326 (Adjusted R Squared = .210)

b. Computed using alpha = .05

Given the significant effect of data treatment in the ANOVA and ANCOVA, we go on to summarize the results of independent samples t-tests to investigate the direction of this relationship in Table 32. The full details of the t-tests are reported in Appendix F.

Table 32. Results of t-tests for H1

Comparison	Result – donation amount	Significance
none vs. static	No data (M=\$0.34) is associated with larger donations than static data (M=\$0.19)	Significant (p=.011)
none vs. live	No data (M=\$0.34) is associated with larger donations than live data (M=\$0.18)	Significant (p=.003)
static vs. live	No difference between static data (M=\$0.19) and live data (M=\$0.18)	Insignificant (p=.42)

Although we find a significant effect of our data treatments, the direction of the effect is opposite of what we predicted. In fact, participants who saw no data donated more than those who saw either static or live data.

Likelihood of Donation. To test H1b regarding likelihood of donation, we ran a logistic regression with block 1 containing just the data treatment and block 2 adding all of our reliable controls and the default treatment as covariates. We utilized the SPSS “categorical” command to identify our categorical variables (data treatment, default treatment, gender, education, and employment status) and create the necessary dummy variables (see the categorical variables’ coding below).

To interpret these variables, we first look at the first line labeled “Data Treatment”: this line tells us if the overall data treatment variable is statistically significant. In both models, we can see that data treatment is not significant (p>.05), indicating that there is no effect of data treatment on individuals’ likelihood of donations.

Table 33. Details of H1 likelihood of donation logistic regression

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	2.371	2	.306
	Block	2.371	2	.306
	Model	2.371	2	.306

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	228.277[a]	.014	.019

a. Estimation terminated at iteration number 3 because parameter estimates changed by less than .001.

Classification Table[a]

Observed			Predicted: Likelihood of Donation 0	Predicted: Likelihood of Donation 1	Predicted: Percentage Correct
Step 1	Likelihood of Donation	0	17	52	24.6
		1	16	86	84.3
	Overall Percentage				60.2

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Data Treatment			2.366	2	.306	
	Data Treatment(1) (no data)	-.629	.409	2.360	1	.124	.533
	Data Treatment(2) (static data)	-.200	.374	.286	1	.593	.819
	Constant	.568	.215	7.001	1	.008	1.765

a. Variable(s) entered on step 1: Data Treatment.

Block 2: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	45.161	23	.004
	Block	45.161	23	.004
	Model	47.532	25	.004

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	183.116[a]	.243	.328

a. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

Classification Table[a]

	Observed		Predicted		
			Likelihood of Donation		Percentage Correct
			0	1	
Step 1	Likelihood of Donation	0	35	34	50.7
		1	21	81	79.4
	Overall Percentage				67.8

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Data Treatment			2.972	2	.226	
	Data Treatment(1) (no data)	-.893	.518	2.971	1	.085	.409

	Data Treatment(2) (static data)	-.290	.466	.387	1	.534	.748
	Default Treatment			8.040	2	.018	
	Default Treatment(1) (active choice)	1.078	.511	4.452	1	.035	2.938
	Default Treatment(2) (general default)	1.396	.510	7.511	1	.006	4.041
	Gender_1 (female)	.411	.440	.873	1	.350	1.509
	education_numeric			7.977	5	.158	
	Education_1 (less than high school)	-.846	1.595	.282	1	.596	.429
	Education_2 (high school grad)	-.590	1.615	.134	1	.715	.554
	Education_3 (some college)	.313	1.623	.037	1	.847	1.368
	Education_4 (associate degree)	.673	1.552	.188	1	.664	1.960
	Education_5 (bachelor degree)	1.470	1.696	.752	1	.386	4.350
	Employment Status			2.796	3	.424	
	Employment_Status_1 (full time)	.904	.628	2.071	1	.150	2.470
	Employment_Status_2 (part time)	1.542	1.425	1.172	1	.279	4.675
	Employment_Status_3 (retired)	.443	.623	.505	1	.477	1.557
	Age	.000	.019	.000	1	.986	1.000
	Income	.000	.000	1.278	1	.258	1.000
	SVO Slider Angle	.024	.016	2.294	1	.130	1.024
	Self- and Other-Interest Inventory: Self-Interest Score	.664	.258	6.644	1	.010	1.943
	Self- and Other-Interest Inventory: Other-Interest Score	.094	.235	.160	1	.689	1.099
	Past Donations - Monthly Amount	.000	.000	.872	1	.350	1.000
	Past Donations - Frequency	.000	.001	.022	1	.881	1.000
	Current Visceral State - Temperature	.074	.153	.236	1	.627	1.077

Current Visceral State - Thirst	-.111	.159	.488	1	.485	.895
Current Visceral State - Hunger	.144	.150	.917	1	.338	1.154
Current Visceral State - Tired	.137	.156	.769	1	.380	1.146
Current Visceral State - Awake	-.072	.185	.152	1	.696	.930
Constant	-5.238	2.245	5.442	1	.020	.005

Results: Hypothesis 2

In H2, we predicted that participants would a) donate more and b) be more likely to donate in conditions that included a greater-than-zero default than conditions that don't have a default value and require an active choice.

Donation Amount. First, we ran an ANOVA with donation amount as the dependent variable and default treatment as a three-level (general, personal, or active choice) fixed factor. We find no significant effect of default treatment on donation amounts (p=.210).

Table 34. Details of H2 donation amount ANOVA

Between-Subjects Factors

		Value Label	N
Default Treatment	1	none	51
	2	general	55
	3	personal	65

Descriptive Statistics

Dependent Variable: Donation Amount

Default Treatment	Mean	Std. Deviation	N
none	.2275	.35047	51
general	.3396	.38731	55
personal	.2506	.31027	65
Total	.2723	.34967	171

Tests of Between-Subjects Effects

Dependent Variable: Donation Amount

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[b]
Corrected Model	.383[a]	2	.191	1.575	.210	.018	3.150	.331
Intercept	12.574	1	12.574	103.539	<.001	.381	103.539	1.000
Default Treatment	.383	2	.191	1.575	.210	.018	3.150	.331
Error	20.403	168	.121					
Total	33.468	171						
Corrected Total	20.785	170						

a. R Squared = .018 (Adjusted R Squared = .007)

b. Computed using alpha = .05

Next, we re-ran the model as an ANCOVA including data treatment and our reliable controls (demographics: gender, education, employment status, age, and income, plus SVO, Self- and Other-Interest, past donation amounts and frequency, all five aspects of current visceral state) as covariates with the three-level default treatment (general, personal, or active choice) as a fixed factor. Categorical covariates were handled as described in H1. In this model, we see no significant effects for default treatment (p=.410). Thus, we conclude there is no support for H2a.

Table 35. Details of H2 donation amount ANCOVA

Between-Subjects Factors

		Value Label	N
Default Treatment	1	none	51
	2	general	55
	3	personal	65

Descriptive Statistics

Dependent Variable: Donation Amount

Default Treatment	Mean	Std. Deviation	N

none	.2275	.35047	51
general	.3396	.38731	55
personal	.2506	.31027	65
Total	.2723	.34967	171

Tests of Between-Subjects Effects

Dependent Variable: Donation Amount

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[b]
Corrected Model	5.939[a]	23	.258	2.557	<.001	.286	58.803	.999
Intercept	.093	1	.093	.923	.338	.006	.923	.159
Data_1 (no data)	.780	1	.780	7.721	.006	.050	7.721	.788
Data_2 (static data)	.021	1	.021	.205	.651	.001	.205	.074
Gender_1 (female)	.512	1	.512	5.073	.026	.033	5.073	.609
Education_1 (less than high school)	.083	1	.083	.823	.366	.006	.823	.147
Education_2 (high school grad)	1.078	1	1.078	10.676	.001	.068	10.676	.901
Education_3 (some college)	.911	1	.911	9.024	.003	.058	9.024	.847
Education_4 (associate degree)	.281	1	.281	2.777	.098	.019	2.777	.381
Education_5 (bachelor degree)	.360	1	.360	3.564	.061	.024	3.564	.466
Employment_Status_1 (full time)	.045	1	.045	.444	.506	.003	.444	.101
Employment_Status_2 (part time)	.059	1	.059	.589	.444	.004	.589	.119
Employment_Status_3 (retired)	.000	1	.000	.004	.952	.000	.004	.050
Age	.099	1	.099	.982	.323	.007	.982	.166
Income	.019	1	.019	.191	.663	.001	.191	.072
SVO Slider Angle	.775	1	.775	7.669	.006	.050	7.669	.786
Self- and Other-Interest Inventory: Self-Interest Score	.430	1	.430	4.253	.041	.028	4.253	.535
Self- and Other-Interest Inventory: Other-Interest Score	.001	1	.001	.009	.926	.000	.009	.051
Past Donations Amount - Monthly	.002	1	.002	.023	.880	.000	.023	.053
Past Donations Amount - Frequency	.051	1	.051	.509	.477	.003	.509	.109
Current Visceral State - Temperature	.010	1	.010	.101	.751	.001	.101	.061
Current Visceral State - Thirst	.176	1	.176	1.743	.189	.012	1.743	.259
Current Visceral State - Hunger	.002	1	.002	.015	.903	.000	.015	.052
Default Treatment	.181	2	.090	.896	.410	.012	1.792	.202
Error	14.847	147	.101					

Total	33.468	171							
Corrected Total	20.785	170							

a. R Squared = .286 (Adjusted R Squared = .174)

b. Computed using alpha = .05

Likelihood of Donation. Next, we ran a logistic regression with block 1 containing just the three-level default treatment and block 2 adding all of our reliable controls and the data treatment as covariates. Once again, we classified appropriate variables as categorical for SPSS to create the necessary dummy variables. In block 1, default treatment is significant at p=.042. When controls are added in block 2, default treatment is significant at p=.018, indicating that default treatment has a significant effect on likelihood of donation. Given this significant effect, we can go on to interpret the other lines in the Block 2 – Variables in the Equation table. The betas in the remaining Default Treatment lines indicate differences between default treatments as compared to the reference level, which is active choice (no default value). Therefore, the coefficients next to Default Treatment (1) (1.078 – general default) and Default Treatment (2) (1.396 – personalized default) represent their differential impact on likelihood of donation compared to no default/active choice. Both coefficients are positive and significant (p=.035 and p=.006, respectively) so we can conclude that general and personal default are both associated with higher likelihood of donation than an active choice setting. Therefore, H2b is supported.

Table 36. Details of H2 likelihood of donation logistic regression

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	6.419	2	.040
	Block	6.419	2	.040

	Model	6.419	2	.040

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	224.229[a]	.037	.050

a. Estimation terminated at iteration number 3 because parameter estimates changed by less than .001.

Classification Table[a]

	Observed		Predicted: Likelihood of Donation 0	Predicted: Likelihood of Donation 1	Predicted: Percentage Correct
Step 1	Likelihood of Donation	0	28	41	40.6
		1	23	79	77.5
	Overall Percentage				62.6

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Default Treatment			6.337	2	.042	
	Default Treatment(1) active choice	.917	.402	5.201	1	.023	2.502
	Default Treatment(2) general default	.799	.383	4.357	1	.037	2.223
	Constant	-.197	.281	.489	1	.485	.821

a. Variable(s) entered on step 1: Default Treatment.

Block 2: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	41.113	23	.011
	Block	41.113	23	.011
	Model	47.532	25	.004

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	183.116[a]	.243	.328

a. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

Classification Table[a]

Observed			Predicted: Likelihood of Donation 0	Likelihood of Donation 1	Percentage Correct
Step 1	Likelihood of Donation	0	35	34	50.7
		1	21	81	79.4
	Overall Percentage				67.8

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Default Treatment			8.040	2	.018	
	Default Treatment(1) active choice	1.078	.511	4.452	1	.035	2.938
	Default Treatment(2) general default	1.396	.510	7.511	1	.006	4.041
	Data Treatment			2.972	2	.226	
	Data Treatment(1) no data	-.893	.518	2.971	1	.085	.409
	Data Treatment(2) static data	-.290	.466	.387	1	.534	.748
	Gender (1) female	.411	.440	.873	1	.350	1.509
	education_numeric			7.977	5	.158	
	Education_1 (less than high school)	-.846	1.595	.282	1	.596	.429
	Education_2 (high school grad)	-.590	1.615	.134	1	.715	.554
	Education_3 (some college)	.313	1.623	.037	1	.847	1.368
	Education_4 (associate degree)	.673	1.552	.188	1	.664	1.960
	Education_5 (bachelor degree)	1.470	1.696	.752	1	.386	4.350

employed_numeric			2.796	3	.424	
Employment_Status_1 (full time)	.904	.628	2.071	1	.150	2.470
Employment_Status_2 (part time)	1.542	1.425	1.172	1	.279	4.675
Employment_Status_3 (retired)	.443	.623	.505	1	.477	1.557
Age	.000	.019	.000	1	.986	1.000
Income	.000	.000	1.278	1	.258	1.000
SVO Slider Angle	.024	.016	2.294	1	.130	1.024
Self- and Other-Interest Inventory: Self-Interest Score	.664	.258	6.644	1	.010	1.943
Self- and Other-Interest Inventory: Other-Interest Score	.094	.235	.160	1	.689	1.099
Past Donations - Monthly Amount	.000	.000	.872	1	.350	1.000
Past Donations - Frequency	.000	.001	.022	1	.881	1.000
Current Visceral State - Temperature	.074	.153	.236	1	.627	1.077
Current Visceral State - Thirst	-.111	.159	.488	1	.485	.895
Current Visceral State - Hunger	.144	.150	.917	1	.338	1.154
Current Visceral State - Tired	.137	.156	.769	1	.380	1.146
Current Visceral State - Awake	-.072	.185	.152	1	.696	.930
Constant	-5.238	2.245	5.442	1	.020	.005

Results: Hypothesis 3

Donation Amount. In H3, we predicted that default nudges that were personalized to an individual's SVO (that is, higher defaults for prosocial individuals) would result in a) higher donations and b) higher likelihood of donation compared to general defaults or active choice conditions.

To investigate H3, first we limited our dataset to only prosocial individuals and then ran an ANOVA with donation amount as the dependent variable and default treatment as a three-level (general, personal, or active choice) fixed factor. We found no significant effect of default treatment (p=.12).

Table 37. Details of H3 donation amount ANOVA.

Between-Subjects Factors

		Value Label	N
Default Treatment	1	none	19
	2	general	23
	3	personal	34

Descriptive Statistics

Dependent Variable: Donation Amount

Default Treatment	Mean	Std. Deviation	N
none	.1342	.25715	19
general	.2948	.37604	23
personal	.3238	.32259	34
Total	.2676	.33062	76

Tests of Between-Subjects Effects

Dependent Variable: Donation Amount

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[b]
Corrected Model	.463[a]	2	.231	2.182	.120	.056	4.365	.433
Intercept	4.515	1	4.515	42.609	<.001	.369	42.609	1.000
Default Treatment	.463	2	.231	2.182	.120	.056	4.365	.433
Error	7.735	73	.106					
Total	13.642	76						
Corrected Total	8.198	75						

a. R Squared = .056 (Adjusted R Squared = .031)

b. Computed using alpha = .05

Next, we re-ran the model as an ANCOVA including data treatment and our reliable controls (demographics: gender, education, employment status, age, and income, plus SVO, Self- and Other-Interest, past donation amounts and frequency, all five aspects of current visceral state) as covariates with the three-level default treatment (general, personal, or active choice) as a fixed factor, still with the limited dataset of only prosocial individuals. Categorical covariates were managed as described in H1. Once again, there is no significant effect of default treatment (p=.15). Therefore, we conclude that there is no support for H3a.

Table 38. Details of H3 donation amount ANCOVA

Between-Subjects Factors

		Value Label	N
Default Treatment	1	none	19
	2	general	23
	3	personal	34

Descriptive Statistics

Dependent Variable: Donation Amount

Default Treatment	Mean	Std. Deviation	N
none	.1342	.25715	19
general	.2948	.37604	23
personal	.3238	.32259	34
Total	.2676	.33062	76

Tests of Between-Subjects Effects

Dependent Variable: Donation Amount

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[b]
Corrected Model	2.982[a]	25	.119	1.143	.335	.364	28.582	.747
Intercept	.157	1	.157	1.506	.226	.029	1.506	.226
Data_1 (no data)	.002	1	.002	.022	.883	.000	.022	.052

Data_2 (static data)	.037	1	.037	.357	.553	.007	.357	.090
Gender_1 (female)	.481	1	.481	4.612	.037	.084	4.612	.558
Education_1 (less than high school)	.013	1	.013	.122	.728	.002	.122	.064
Education_2 (high school grad)	.075	1	.075	.722	.400	.014	.722	.133
Education_3 (some college)	.084	1	.084	.802	.375	.016	.802	.142
Education_4 (associate degree)	.000	1	.000	.004	.953	.000	.004	.050
Education_5 (bachelor degree)	.102	1	.102	.977	.328	.019	.977	.163
Employment_Status_1 (full time)	.039	1	.039	.372	.545	.007	.372	.092
Employment_Status_2 (part time)	.047	1	.047	.453	.504	.009	.453	.101
Employment_Status_3 (retired)	.033	1	.033	.315	.577	.006	.315	.085
Age	.034	1	.034	.327	.570	.006	.327	.087
Income	.012	1	.012	.118	.732	.002	.118	.063
SVO Slider Angle	.222	1	.222	2.129	.151	.041	2.129	.299
Self- and Other-Interest Inventory: Self-Interest Score	.000	1	.000	.002	.967	.000	.002	.050
Self- and Other-Interest Inventory: Other-Interest Score	.018	1	.018	.174	.678	.003	.174	.069
Past Donations Amount - Monthly	.163	1	.163	1.563	.217	.030	1.563	.232
Past Donations Amount - Frequency	.873	1	.873	8.366	.006	.143	8.366	.810
Current Visceral State - Temperature	.037	1	.037	.355	.554	.007	.355	.090
Current Visceral State - Thirst	.029	1	.029	.276	.601	.005	.276	.081
Current Visceral State - Hunger	.012	1	.012	.117	.734	.002	.117	.063
Current Visceral State - Tired	.021	1	.021	.205	.653	.004	.205	.073
Current Visceral State - Awake	.199	1	.199	1.907	.173	.037	1.907	.273
Default Treatment	.411	2	.206	1.970	.150	.073	3.941	.389
Error	5.216	50	.104					
Total	13.642	76						
Corrected Total	8.198	75						

a. R Squared = .364 (Adjusted R Squared = .046)

b. Computed using alpha = .05

Likelihood of Donation. We ran a logistic regression with block 1 containing just the three-level default treatment (general, personal, and active choice) and block 2 adding all of our reliable controls and the data treatment as covariates, limiting the dataset to prosocial individuals only (n=78). Once again, we noted appropriate variables as categorical and SPSS created the necessary dummy variables. This time, since we are interested in learning whether the personalized default (for high SVO individuals) was associated with higher likelihood of donations compared to active choice and a generalized default, we set the personalized default treatment as the reference to which other treatments were compared (see the variables' codings below in Table 39).

Table 39. Categorical variables' coding for H3 likelihood of donation logistic regression.

Categorical Variables Codings

			Parameter coding					
		Frequency	(1)	(2)	(3)	(4)	(5)	(6)
Education	LessThanHighSchool	2	.000	.000	.000	.000	.000	.000
	HighSchoolGrad	14	1.000	.000	.000	.000	.000	.000
	SomeCollege	11	.000	1.000	.000	.000	.000	.000
	Associate	9	.000	.000	1.000	.000	.000	.000
	Bachelor	33	.000	.000	.000	1.000	.000	.000
	Master	8	.000	.000	.000	.000	1.000	.000
	Doctor	1	.000	.000	.000	.000	.000	1.000
Employment Status	FullTime	45	.000	.000	.000			
	PartTime	17	1.000	.000	.000			
	Retired	2	.000	1.000	.000			
	Unemployed	14	.000	.000	1.000			
Gender	female	38	.000	.000				
	male	39	1.000	.000				
	did not disclose	1	.000	1.000				
Data Treatment	none	35	.000	.000				
	static	20	1.000	.000				
	live	23	.000	1.000				
Default Treatment	none	20	1.000	.000				
	general	24	.000	1.000				
	personal	34	.000	.000				

In block 1, default treatment is not significant (p=.111). When controls are added in block 2, default treatment is significant at p=.046, indicating that default treatment has a significant effect on likelihood of donation for prosocial individuals. Given this significant effect, we can go on to interpret the other lines in the Block 2 – Variables in the Equation table. The betas in the remaining Default Treatment lines indicate differences between default treatments as compared to the reference level, which in this case is the personalized treatment (see the variables' codings above). Therefore, the coefficients next to Default Treatment (1) (-2.708: active choice/no default) and Default Treatment (2) (0.209 – general default) represent their differential impact on likelihood of donation compared to a personalized default. The comparison between active choice and the personalized default is significant (p=.019). When combined with the negative beta, we can conclude that an active choice condition is associated with significantly lower likelihood of donation compared to a personalized default for high SVO individuals. However, the comparison between a general default and a personalized default is not significant (p=.830), indicating that there is no significant difference in likelihood of donations for high SVO individuals who saw a general default compared to those who saw a personalized default. Therefore, we conclude that there is mixed support for H3b.

Table 40. Details of H3 likelihood of donation logistic regression

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	4.578	2	.101
	Block	4.578	2	.101
	Model	4.578	2	.101

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	98.877[a]	.058	.079

a. Estimation terminated at iteration number 3 because parameter estimates changed by less than .001.

Classification Table[a]

Observed			Predicted: Likelihood of Donation 0	Predicted: Likelihood of Donation 1	Percentage Correct
Step 1	Likelihood of Donation	0	12	20	37.5
		1	7	37	84.1
	Overall Percentage				64.5

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Default Treatment			4.395	2	.111	
	Default Treatment(1) – active choice	-1.145	.596	3.694	1	.055	.318
	Default Treatment(2) – general default	.022	.566	.002	1	.968	1.023
	Constant	.606	.359	2.853	1	.091	1.833

a. Variable(s) entered on step 1: Default Treatment.

Block 2: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	36.529	23	.036
	Block	36.529	23	.036
	Model	41.108	25	.022

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	62.348[a]	.418	.562

Classification Table[a]

Observed			Predicted: Likelihood of Donation 0	Predicted: Likelihood of Donation 1	Percentage Correct
Step 1	Likelihood of Donation	0	24	8	75.0
		1	6	38	86.4
	Overall Percentage				81.6

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Default Treatment			6.167	2	.046	
	Default Treatment(1) active choice	-2.708	1.156	5.490	1	.019	.067
	Default Treatment(2) general default	.209	.973	.046	1	.830	1.233
	Data Treatment			.829	2	.661	
	Data Treatment(1) no data	-.766	.962	.633	1	.426	.465
	Data Treatment(2) static	-.662	.950	.485	1	.486	.516
	Gender_1 (female)	1.948	.982	3.933	1	.047	7.014
	Education			3.919	5	.561	
	Education_1 (less than high school)	-3.176	2.324	1.869	1	.172	.042
	Education_2 (high school grad)	-3.555	2.495	2.030	1	.154	.029
	Education_3 (some college)	-2.223	2.426	.840	1	.359	.108
	Education_4 (associate degree)	-3.034	2.311	1.723	1	.189	.048
	Education_5 (bachelor degree)	-1.116	2.466	.205	1	.651	.327
	Employment Status			1.829	3	.609	
	Employment_Status_1 (full time)	1.615	1.195	1.825	1	.177	5.026
	Employment_Status_2 (part time)	23.305	21902.054	.000	1	.999	13221019745.143

	Employment_Status_3 (retired)	.768	1.054	.531	1	.466	2.156
	Age	-.036	.036	1.010	1	.315	.965
	Income	.000	.000	1.004	1	.316	1.000
	SVO Slider Angle	-.179	.075	5.636	1	.018	.836
	Self- and Other-Interest Inventory: Self-Interest Score	-.097	.471	.042	1	.837	.908
	Self- and Other-Interest Inventory: Other-Interest Score	-.681	.459	2.204	1	.138	.506
	Past Donations - Monthly Amount	.000	.000	1.209	1	.272	1.000
	Past Donations - Frequency	.393	.120	10.785	1	.001	1.481
	Current Visceral State - Temperature	-.282	.437	.417	1	.518	.754
	Current Visceral State - Thirst	.593	.425	1.949	1	.163	1.809
	Current Visceral State - Hunger	-.061	.284	.046	1	.830	.941
	Current Visceral State - Tired	.199	.376	.281	1	.596	1.220
	Current Visceral State - Awake	.901	.518	3.028	1	.082	2.463
	Constant	6.606	5.140	1.652	1	.199	739.655

Results: Hypothesis 4

In H4, we predicted that default nudges that were personalized to an individual's SVO (that is, lower defaults for moderately individualistic individuals) would result in a) higher average donations and b) higher likelihood of donation compared to general defaults or active choice conditions.

Donation Amount. To test the effect of defaults on donation amount for low-SVO individuals, we replicated the analysis from Hypothesis 3 but for the subset of participants who were low-SVO rather than high-SVO. First, we ran an ANOVA with donation amount as the dependent variable and the three-level default treatment (general, personal, and active choice) as a fixed factor. Default treatment was marginally significant at p=.09.

Table 41. Details of H4 donation amount ANOVA.

Between-Subjects Factors

		Value Label	N
Default Treatment	1	none	32
	2	general	32
	3	personal	31

Tests of Between-Subjects Effects

Dependent Variable: Donation Amount

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.642[a]	2	.321	2.472	.090
Intercept	7.183	1	7.183	55.334	<.001
Default Treatment	.642	2	.321	2.472	.090
Error	11.943	92	.130		
Total	19.827	95			
Corrected Total	12.584	94			

a. R Squared = .051 (Adjusted R Squared = .030)

Next, we re-ran the model as an ANCOVA including data treatment and our reliable controls (demographics: gender, education, employment status, age, and income, plus SVO, Self- and Other-Interest, past donation amounts and frequency, all five aspects of current visceral state) as covariates with the three-level default treatment (general, personal, or active choice) as a fixed factor, still with the limited dataset of only prosocial individuals. Categorical covariates were managed as described in H1. There was no significant effect of default treatment (p=.863).

Thus, we determine that there is no effect of default treatment on the amount donated by low-SVO individuals and no support for H4a.

Table 42. Details of H4 donation amount ANCOVA.

Between-Subjects Factors

		Value Label	N
SVO categorization	1	low SVO	95
	2	high SVO	76

Descriptive Statistics

Dependent Variable: Donation Amount

SVO categorization	Mean	Std. Deviation	N
low SVO	.2761	.36589	95
high SVO	.2676	.33062	76
Total	.2723	.34967	171

Tests of Between-Subjects Effects

Dependent Variable: Donation Amount

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[b]
Corrected Model	6.467[a]	25	.259	2.620	<.001	.311	65.496	.999
Intercept	.047	1	.047	.478	.490	.003	.478	.106
Default Treatment_1 (active choice)	.141	1	.141	1.424	.235	.010	1.424	.220
Default Treatment_2 (general default)	2.228E-5	1	2.228E-5	.000	.988	.000	.000	.050
Data_1 (no data)	.546	1	.546	5.529	.020	.037	5.529	.646
Data_2 (static data)	.017	1	.017	.169	.681	.001	.169	.069
Gender_1 (female)	.359	1	.359	3.634	.059	.024	3.634	.474
Education_1 (less than high school)	.039	1	.039	.397	.530	.003	.397	.096
Education_2 (high school grad)	.663	1	.663	6.711	.011	.044	6.711	.730
Education_3 (some college)	.450	1	.450	4.558	.034	.030	4.558	.564
Education_4 (associate degree)	.086	1	.086	.876	.351	.006	.876	.153
Education_5 (bachelor degree)	.188	1	.188	1.905	.170	.013	1.905	.278

Employment_Status_1 (full time)	.053	1	.053	.533	.467	.004	.533	.112
Employment_Status_2 (part time)	.065	1	.065	.659	.418	.005	.659	.127
Employment_Status_3 (retired)	.003	1	.003	.028	.867	.000	.028	.053
Age	.066	1	.066	.672	.414	.005	.672	.129
Income	.047	1	.047	.479	.490	.003	.479	.106
SVO Slider Angle	.334	1	.334	3.378	.068	.023	3.378	.447
Self- and Other-Interest Inventory: Self-Interest Score	.000	1	.000	.004	.949	.000	.004	.050
Self- and Other-Interest Inventory: Other-Interest Score	.934	1	.934	9.458	.003	.061	9.458	.863
Past Donations Amount - Monthly	.053	1	.053	.541	.463	.004	.541	.113
Past Donations Amount - Frequency	.044	1	.044	.447	.505	.003	.447	.102
Current Visceral State - Temperature	.002	1	.002	.016	.898	.000	.016	.052
Current Visceral State - Thirst	.007	1	.007	.071	.790	.000	.071	.058
Current Visceral State - Hunger	.307	1	.307	3.108	.080	.021	3.108	.417
Current Visceral State - Tired	.002	1	.002	.017	.897	.000	.017	.052
SVO Categorization	.307	1	.307	3.104	.080	.021	3.104	.417
Error	14.318	145	.099					
Total	33.468	171						
Corrected Total	20.785	170						

a. R Squared = .311 (Adjusted R Squared = .192)

b. Computed using alpha = .05

Likelihood of Donation. We ran a logistic regression with block 1 containing just the three-level default treatment (general, personal, and active choice) and block 2 adding all of our reliable controls and the data treatment as covariates, limiting the dataset to individualistic participants only (n=95). Once again, we noted appropriate variables as categorical and SPSS created the necessary dummy variables. Like in hypothesis 3, since we are interested in learning whether the personalized default (for low SVO individuals this time) was associated with higher likelihood of donations compared to active choice and a generalized default, we set the personalized default treatment as the reference to which other treatments were compared (see the variables' coding below).

Table 43. Categorical variables' coding for H4 likelihood of donation logistic regression.

Categorical Variables Codings

		Frequency	Parameter coding (1)	(2)	(3)	(4)
Education	HighSchoolGrad	8	.000	.000	.000	.000
	SomeCollege	9	1.000	.000	.000	.000
	Associate	7	.000	1.000	.000	.000
	Bachelor	63	.000	.000	1.000	.000
	Master	8	.000	.000	.000	1.000
Employment Status	FullTime	82	.000	.000	.000	
	PartTime	6	1.000	.000	.000	
	Retired	2	.000	1.000	.000	
	Unemployed	5	.000	.000	1.000	
Data Treatment	none	60	.000	.000		
	static	14	1.000	.000		
	live	21	.000	1.000		
Default Treatment	none	32	1.000	.000		
	general	32	.000	1.000		
	personal	31	.000	.000		
Gender	female	24	.000			
	male	71	1.000			

In both blocks, the default treatment is not significant (p>.05); therefore, we conclude that likelihood of donation is not significantly different for low-SVO individuals experiencing different default treatments and H4b is not supported.

Table 44. Details of H4 likelihood of donation logistic regression

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	2.582	2	.275
	Block	2.582	2	.275
	Model	2.582	2	.275

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	124.435[a]	.027	.036

a. Estimation terminated at iteration number 3 because parameter estimates changed by less than .001.

Classification Table[a]

Observed			Predicted: Likelihood of Donation 0	Predicted: Likelihood of Donation 1	Percentage Correct
Step 1	Likelihood of Donation	0	0	37	.0
		1	0	58	100.0
	Overall Percentage				61.1

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Default Treatment			2.560	2	.278	
	Default Treatment (1) active choice	-.598	.516	1.344	1	.246	.550
	Default Treatment (2) general	.191	.535	.127	1	.722	1.210
	Constant	.598	.375	2.536	1	.111	1.818

Block 2: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	65.047	22	<.001
	Block	65.047	22	<.001
	Model	67.629	24	<.001

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	59.388[a]	.509	.691

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Classification Table[a]

Observed			Predicted: Likelihood of Donation 0	Predicted: Likelihood of Donation 1	Percentage Correct
Step 1	Likelihood of Donation	0	31	6	83.8
		1	5	53	91.4
	Overall Percentage				88.4

a. The cut value is .500

Variables in the Equation

	B	S.E.	Wald	df	Sig.	Exp(B)
Default Treatment			5.160	2	.076	
Default Treatment_1 (active choice)	-2.474	1.163	4.524	1	.033	.084
Default Treatment_2 (general default)	-.522	.984	.282	1	.595	.593
Data Treatment			3.795	2	.150	
Data Treatment (1) (no data)	-1.569	1.180	1.767	1	.184	.208
Data Treatment (2) (static data)	1.035	1.116	.861	1	.353	2.816
Gender_1 (female)	.075	1.129	.004	1	.947	1.078
Education			10.400	4	.034	
Education_1 (less than high school)	-1.205	2.416	.249	1	.618	.300
Education_2 (high school grad)	1.872	2.056	.829	1	.363	6.500
Education_3 (some college)	3.794	2.004	3.584	1	.058	44.432
Education_4 (associate degree)	5.144	3.158	2.653	1	.103	171.394
Employment Status			2.495	3	.476	
Employment_Status_1 (full time)	2.999	2.183	1.887	1	.170	20.063
Employment_Status_2 (part time)	-19.597	26001.637	.000	1	.999	.000
Employment_Status_3 (retired)	-.805	1.850	.189	1	.664	.447
Age	.053	.050	1.138	1	.286	1.054
Income	.000	.000	1.493	1	.222	1.000
SVO Slider Angle	.120	.056	4.584	1	.032	1.127

Self- and Other-Interest Inventory: Self-Interest Score	.636	.579	1.206	1	.272	1.889
Self- and Other-Interest Inventory: Other-Interest Score	.614	.548	1.255	1	.263	1.848
Past Donations - Monthly Amount	.002	.001	1.449	1	.229	1.002
Past Donations - Frequency	.000	.000	.113	1	.737	1.000
Current Visceral State - Temperature	.552	.349	2.510	1	.113	1.738
Current Visceral State - Thirst	-.603	.351	2.960	1	.085	.547
Current Visceral State - Hunger	.528	.298	3.129	1	.077	1.696
Current Visceral State - Tired	.393	.324	1.465	1	.226	1.481
Current Visceral State - Awake	-.592	.376	2.471	1	.116	.553
Constant	-10.356	4.251	5.934	1	.015	.000

Results: Hypothesis 5

In H5, we predicted that when an unexpected donation opportunity arises on a platform not intended for charitable donations, prosocial individuals would a) donate no more and b) be no more likely to donate than individualistic individuals.

Donation Amount. First, we ran an ANOVA with donation amount as the dependent variable and SVO classification as a two-level (high SVO, low SVO) fixed factor. SVO classification had no significant impact on donation amount (p=.875).

Table 45. Details of H5 donation amount ANOVA

Between-Subjects Factors

		Value Label	N
SVO categorization	1	low SVO	95
	2	high SVO	76

Descriptive Statistics

Dependent Variable: Donation Amount

SVO categorization	Mean	Std. Deviation	N
low SVO	.2761	.36589	95

high SVO	.2676	.33062	76
Total	.2723	.34967	171

Tests of Between-Subjects Effects

Dependent Variable: Donation Amount

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[b]
Corrected Model	.003[a]	1	.003	.025	.875	.000	.025	.053
Intercept	12.483	1	12.483	101.510	<.001	.375	101.510	1.000
SVO Categorization	.003	1	.003	.025	.875	.000	.025	.053
Error	20.782	169	.123					
Total	33.468	171						
Corrected Total	20.785	170						

a. R Squared = .000 (Adjusted R Squared = -.006)

b. Computed using alpha = .05

Next, we ran an ANCOVA with donation amount as the dependent variable, SVO classification as a fixed factor, and our reliable control variables included as covariates (excluding SVO slider angle, since SVO classification is the fixed factor), along with both default and data treatment. Categorical covariates were handled as described in H1. Once covariates are included, SVO classification becomes marginally significant at p = .08. Thus, H5a is supported: SVO categorization is not significantly associated with donation amount in our context of Amazon Mechanical Turk.

Table 46. Details of H5 donation amount ANCOVA

Between-Subjects Factors

		Value Label	N
SVO Categorization	1	low SVO	95
	2	high SVO	76

Descriptive Statistics

Dependent Variable: Donation Amount

SVO Categorization	Mean	Std. Deviation	N
low SVO	.2761	.36589	95
high SVO	.2676	.33062	76
Total	.2723	.34967	171

Tests of Between-Subjects Effects

Dependent Variable: Donation Amount

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[b]
Corrected Model	6.467[a]	25	.259	2.620	<.001	.311	65.496	.999
Intercept	.047	1	.047	.478	.490	.003	.478	.106
Data_1 (no data)	.546	1	.546	5.529	.020	.037	5.529	.646
Data_2 (static data)	.017	1	.017	.169	.681	.001	.169	.069
Default_1 (active choice)	.141	1	.141	1.424	.235	.010	1.424	.220
Default_2 (general default)	2.228E-5	1	2.228E-5	.000	.988	.000	.000	.050
Gender_1 (female)	.359	1	.359	3.634	.059	.024	3.634	.474
Education_1 (less than high school)	.039	1	.039	.397	.530	.003	.397	.096
Education_2 (high school grad)	.663	1	.663	6.711	.011	.044	6.711	.730
Education_3 (some college)	.450	1	.450	4.558	.034	.030	4.558	.564
Education_4 (associate degree)	.086	1	.086	.876	.351	.006	.876	.153
Education_5 (bachelor degree)	.188	1	.188	1.905	.170	.013	1.905	.278
Employment_Status_1 (full time)	.053	1	.053	.533	.467	.004	.533	.112
Employment_Status_2 (part time)	.065	1	.065	.659	.418	.005	.659	.127
Employment_Status_3 (retired)	.003	1	.003	.028	.867	.000	.028	.053
Age	.066	1	.066	.672	.414	.005	.672	.129
Income	.047	1	.047	.479	.490	.003	.479	.106
SVO Slider Angle	.334	1	.334	3.378	.068	.023	3.378	.447
Self- and Other-Interest Inventory: Self-Interest Score	.000	1	.000	.004	.949	.000	.004	.050
Self- and Other-Interest Inventory: Other-Interest Score	.934	1	.934	9.458	.003	.061	9.458	.863
Past Donations Amount - Monthly	.053	1	.053	.541	.463	.004	.541	.113
Past Donations Amount - Frequency	.044	1	.044	.447	.505	.003	.447	.102
Current Visceral State - Temperature	.002	1	.002	.016	.898	.000	.016	.052

Current Visceral State - Thirst	.007	1	.007	.071	.790	.000	.071	.058
Current Visceral State - Hunger	.307	1	.307	3.108	.080	.021	3.108	.417
Current Visceral State - Tired	.002	1	.002	.017	.897	.000	.017	.052
SVO Categorization	.307	1	.307	3.104	.080	.021	3.104	.417
Error	14.318	145	.099					
Total	33.468	171						
Corrected Total	20.785	170						

a. R Squared = .311 (Adjusted R Squared = .192)

b. Computed using alpha = .05

Likelihood of Donation. We ran a logistic regression to test the effect of SVO categorization on likelihood of donation. Once again, we noted appropriate variables as categorical and SPSS created the necessary dummy variables (see the categorical variables' coding in Table 16).

Block 1 of the logistic regression contained just the two-level SVO classification (prosocial and individualistic) and block 2 added all of our reliable controls (excluding SVO slider angle) and the data and default treatment as covariates. In both blocks, SVO classification was not significant, which provides support for H5b.

Table 47. Details of H5 likelihood of donation logistic regression.

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	.175	1	.676
	Block	.175	1	.676
	Model	.175	1	.676

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	230.473[a]	.001	.001

a. Estimation terminated at iteration number 3 because parameter estimates changed by less than .001.

Classification Table[a]

Observed			Predicted: Likelihood of Donation 0	Predicted: Likelihood of Donation 1	Percentage Correct
Step 1	Likelihood of Donation	0	0	69	.0
		1	0	102	100.0
	Overall Percentage				59.6

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	SVO Categorization	-.131	.313	.175	1	.676	.877
	Constant	.581	.481	1.459	1	.227	1.787

Block 2: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	46.348	24	.004
	Block	46.348	24	.004
	Model	46.522	25	.006

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	184.125[a]	.238	.322

a. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

Classification Table[a]

Observed	Predicted: Likelihood of Donation

			0	1	Percentage Correct
Step 1	Likelihood of Donation	0	35	34	50.7
		1	22	80	78.4
	Overall Percentage				67.3

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	SVO Categorization	.503	.437	1.326	1	.250	1.654
	Default Treatment			8.057	2	.018	
	Default Treatment(1) active choice	1.067	.507	4.431	1	.035	2.905
	Default Treatment(2) general	1.387	.506	7.520	1	.006	4.002
	Data Treatment			3.031	2	.220	
	Data Treatment(1) no data	-.915	.526	3.031	1	.082	.400
	Data Treatment(2) static	-.285	.462	.380	1	.538	.752
	Gender_1 (female)	.408	.439	.867	1	.352	1.504
	Education			7.134	5	.211	
	Education_1 (less than high school)	-.798	1.596	.250	1	.617	.450
	Education_2 (high school grad)	-.584	1.619	.130	1	.718	.558
	Education_3 (some college)	.306	1.626	.035	1	.851	1.358
	Education_4 (associate degree)	.599	1.553	.149	1	.700	1.821
	Education_5 (bachelor degree)	1.321	1.689	.612	1	.434	3.748
	Employment Status			2.549	3	.466	
	Employment_Status_1 (full time)	.857	.627	1.872	1	.171	2.357
	Employment_Status_2 (part time)	1.472	1.430	1.060	1	.303	4.358
	Employment_Status_3 (retired)	.417	.628	.442	1	.506	1.518
	Age	-.001	.019	.003	1	.958	.999
	Income	.000	.000	1.082	1	.298	1.000

Self- and Other-Interest Inventory: Self-Interest Score	.624	.251	6.161	1	.013	1.866
Self- and Other-Interest Inventory: Other-Interest Score	.092	.232	.158	1	.691	1.097
Past Donations - Monthly Amount	.000	.000	.958	1	.328	1.000
Past Donations - Frequency	.000	.001	.023	1	.881	1.000
Current Visceral State - Temperature	.094	.151	.386	1	.534	1.099
Current Visceral State - Thirst	-.108	.159	.468	1	.494	.897
Current Visceral State - Hunger	.140	.149	.877	1	.349	1.150
Current Visceral State - Tired	.146	.155	.887	1	.346	1.158
Current Visceral State - Awake	-.059	.185	.103	1	.749	.943
Constant	-5.407	2.343	5.325	1	.021	.004

Summary of Hypotheses Evaluations

In Table 48, we summarize the hypotheses tested and which are supported.

Table 48. Summary of hypotheses evaluations.

Hypothesis	Prediction	Supported?
H1a	Users would donate more when exposed to a positive donation social norm that was more proximal to them compared to one that was more distal or no information at all.	No – the opposite. Users donate less when exposed to our social norm data treatments than when experiencing no data.
H1b	Users would be more likely to donate when exposed to a positive donation social norm that was more proximal to them compared to one that was more distal or no information at all.	No
H2a	Participants would donate more in conditions that included a default than conditions that require an active choice.	No

H2b	Participants would be more likely to donate in conditions that included a default than conditions that require an active choice.	Supported
H3a	Default nudges that were personalized to an individual's SVO (that is, higher defaults for prosocial individuals) would result in higher donations compared to general defaults or active choice conditions.	No
H3b	Default nudges that were personalized to an individual's SVO (that is, higher defaults for prosocial individuals) would result in higher likelihood of donation compared to general defaults or active choice conditions.	Partial support: Personalized defaults for high SVO individuals are associated with higher likelihood of donation compared to active choice, but not compared to a general default.
H4a	Default nudges that were personalized to an individual's SVO (that is, lower defaults for moderately individualistic individuals) would result in higher average donations compared to general defaults or active choice conditions.	No
H4b	Default nudges that were personalized to an individual's SVO (that is, lower defaults for moderately individualistic individuals) would result in higher likelihood of donation compared to general defaults or active choice conditions.	No
H5a	When an unexpected donation opportunity arises on a platform not intended for charitable donations, prosocial individuals would donate no more than individualistic individuals.	Supported (SVO classification did not have a significant effect on donation amount)
H5b	When an unexpected donation opportunity arises on a platform not intended for charitable donations, prosocial individuals would be no more likely to donate than individualistic individuals.	Supported (SVO classification did not have a significant effect on likelihood of donation)

Internal and External Validity

Appendix G includes an in-depth analysis of the internal and external validity for this study. Here we present a summary of that analysis.

Internal Validity

Internal validity is defined as “the degree to which the researcher can infer that a relationship between independent and dependent variables is causal” (Gliner et al., 2009, p. 431) and can be summarized by two categories: equivalence of groups on participant characteristics and control of extraneous experience and environmental variables. We had high retention rates (306/336 or 91%) and the individuals who were removed exited the experiment before the manipulation, meaning the retention rate between experiencing the manipulation and measuring the dependent variable was 0 and the same for all groups. However, we had high attrition as a result of participants not understanding the data treatment. There were 211 individuals in the static (n=102) and live (n=109) treatments; only 78 of these demonstrated understanding of the d data they saw (retention rate of 37%). 95 participants were in a no data treatment. Therefore, the total valid participants for the study were those who were retained from the static and live data treatments (n=78) and all those from the no data treatment (n=95) for a total of n=173.

The study was conducted in a controlled online environment via Amazon Mechanical Turk and we took measures to make all treatments as similar to each other as possible; however, we cannot observe nor control any influences from individuals’ physical (non-online) environments. We do utilize random assignment to groups (however, some groups sizes are lower than the recommended 30 participants for random assignment) and include a no-treatment group for both default and data treatments. Therefore, we consider our equivalence of groups internal validity to be low and the control of experiences and environmental variables to be medium, for an overall internal validity rating of medium-low. As such, any conclusions from our study should be taken with caution.

External Validity

External validity “addresses the question of generalizability, to what populations, settings, treatment variables, and measurement variables can the observed effect be generalized” and can be summarized by two categories: population external validity and ecological external validity (Gliner et al., 2009, p. 430). We utilized Amazon Mechanical Turk to obtain a more representative sample than other typical sampling options such as college students (Gandullia et al., 2020; Saunders et al., 2016); however, we cannot guarantee that our sample is representative of our theoretical population of individuals who make decisions online. Our experiment required participants to make real donation decisions with real money through their own computer equipment presumably matching their typical work day as AMT workers. Based on these and other factors discussed in Appendix G, we rate the population external validity as medium and the ecological external validity as medium, for an overall external validity rating of medium.

DISCUSSION AND CONTRIBUTIONS

Our results indicate that use of the IT artifact to display social norm information regarding the decisions of other users can actually backfire and result in lower charitable donations compared to individuals who had no access to social norm information. Defaults result in higher likelihood of donation, but not higher donation amounts. Personalized defaults are not associated with higher donations or likelihoods compared to general defaults, although they do out-perform active choice conditions for high SVO individuals (but not low SVO individuals). Finally, there is no difference in donation amounts or likelihood of donation between high- and low-SVO individuals when an unexpected donation opportunity arises on a non-charitable-giving platform.

These findings make important contributions to our understanding of nudges. Most nudges have been studied in live, face-to-face settings, but nudges are much more flexible, scalable, and more easily personalized when implemented online. However, research so far has not investigated how different implementations of nudges online change their efficacy. This study begins to illuminate that incorporating the IT artifacts of animation and personalization may not be worthwhile efforts to increase donation amounts or likelihood of donations, but that the IT capability to implement charitable giving opportunities on non-charitable giving platforms is promising. We do demonstrate that default amounts – easily adjusted online – matter and should not be selected randomly. Our different findings regarding donation amounts and likelihood of donations (e.g. H2a vs. H2b) imply that charitable organizations should make different decisions with defaults depending on their current goal: to maximize immediate donations or increase their donor base by getting more individuals to donate any positive amount (increasing likelihood of donation).

We are not the first to examine the role of defaults in charitable giving. Altmann et al. found that defaults are important in determining individuals' online donation decisions and that default amounts matter, but personalization of defaults can be complicated (2019). Our study differs from theirs in that we investigated a platform that is not traditionally focused on charitable giving, while their context was limited to a donation-focused platform. We also test default personalization based on SVO, a theory-driven attribute, while Altmann et al. utilize a post-hoc analysis to determine which individual-level attributes (gender, type of donation, etc.) were associated with a tendency to stick with the default. Altmann et al. report a curvilinear effect of defaults on donations, such that while some individuals donate more when faced with a default, others donate less or abstain and aggregate donations are not affected. They therefore caution that “a strategy that attempts to boost donation revenues through higher defaults based on a simplistic notion that ‘defaults work’ might backfire for charitable organizations” (Altmann et al., 2019, p. 809). We actually find that defaults do tend to work: generalized defaults consistently outperformed the active choice condition in both donation amounts and likelihood of donation. However, we do concur with Altmann et al.’s findings that defaults that are too high can backfire, but there may be no downside to defaults that are too low. Our results help shed light on how to define “too high” and “too low” and can help guide researchers and practitioners to set appropriate default levels given the profile of the potential donor.

To our knowledge, social information has not been used in IS to affect online charitable giving decisions. However, researchers have studied the role of social information in non-online settings. Martin and Randal varied the amount and type of donations in a transparent donation box at an art gallery to see how the composition of existing donations affected individuals’ donation decisions (2008). The authors investigated four treatments that corresponded to four different social norms, presented in Table 49.

Table 49. Treatments and norms investigated in Martin and Randal 2008

Treatment	**Norm**
Empty box	Most people free-ride
50 cent treatment: box mostly filled with coins	Most people give
$5 treatment: box mostly filled with $5 bills	Some people give
$50 treatment: box filled with a few big bills	Very few people give

We utilized different treatments than Martin and Randal. Our treatments all reflected a social norm of donating a positive amount. When a default was present, the social norm presented was to donate the default amount; when participants were in an active choice condition, the social norm presented was to donate some positive amount. While our work is not a replication of theirs, we can draw interesting conclusions by comparing the two studies.

Because Martin and Randal utilized a live, face-to-face setting for their study, they had a number of confounding variables to deal with including how busy the art gallery was on a given day. They found that potential donors are less likely to donate on a busy day than on a day when the gallery is less busy. This is similar to our own puzzling findings that allowing AMT workers to perceive the “presence” of other workers via social information actually reduced donations. Both results may be explained by potential donors assuming that, with so many others around, surely there have been plenty of contributions.

In a live setting, Martin and Randal had to contend with what types of individuals happened to arrive at the art gallery during the study, how the contents of the donation box changed over time during the experiment, the number of individuals who were visiting, the exhibits currently on display, and dozens of other potentially confounding variables. In our online setting, these are much more easily controlled. We were able to standardize our social norm information so that every AMT worker received exactly the same information and was in exactly the same choice environment as the other workers in their condition. In this way, extending nudges into the digital space can offer much more controlled field experiments than those conducted in live settings. Our findings therefore contribute to research on charitable giving by demonstrating how a highly controlled but still realistic experiment can be conducted online.

Our findings have implications for practice in the industry of charitable giving. First, charitable organizations have begun expanding beyond their own websites and platforms to attract donors from other platforms (e.g. social media) (*How Nonprofits Can Use Social Media to Boost Donations | DMI*, 2018). It may be tempting during such an expansion to tailor marketing campaigns to high-SVO individuals who traditionally have donated more (Van Lange et al., 2007). However, based on the results of our study, charities may actually benefit more from targeting all individuals on a non-charitable-giving-focused platform since low-SVO individuals are just as likely to donate just as much as high-SVO individuals in this context.

The use of default nudges to encourage monetary payments is ubiquitous across IS platforms. In this study we specifically examined a charitable donation opportunity, but similar default options appear in other contexts. For example, e-commerce sites may suggest that individuals "round up" their purchase cost and donate the extra money or ask for donations to cover administrative website costs or carbon offsetting (Carattini & Blasch, 2020). All of these platforms have the capability to tailor the online experience to users or groups of users, and our study can help platform designers understand what will be helpful in increasing participation in these programs and which users to target.

LIMITATIONS AND FUTURE RESEARCH

Our research has a number of limitations, some of which can be addressed in future research.

First, our survey questions related to prosocial behaviors like donations may have suffered from social desirability bias, a phenomenon wherein participants are likely to inflate their participation in socially desirable behaviors and deflate their participation in socially undesirable behaviors (Chung & Monroe, 2003). This is partially mitigated by our use of the slider measure for SVO, which presents more as a game than as outright questions about one's level of altruism or generosity (Murphy et al., 2011). However, future research can continue to develop methods for measuring self- and other-regarding attributes in ways that are more robust against social desirability bias.

As discussed earlier, our social norm manipulation was difficult to understand and severely limited our sample sizes. The internal validity of the study was affected, and our conclusions should be taken with caution. Future research can replicate the study with much higher sample sizes and improved social norm communication.

We limited our participants to a maximum donation of $1. Considering participants earned $2 for participating in the research, this was a handsome bonus, but it may have limited our sensitivity to identify differences between very similar conditions. For example, a $0.10 personalized default is only $0.20 different from a $0.30 generalized default – the difference may not have been sufficient to affect behavior. Future research can investigate defaults with larger differences to capture more variation in behavior. We also note that the bonus offered to individuals in this study was "found money," which may impact what individuals decide to do with it as compared to money that they were expecting or previously endowed with (Ackert et al., 2006). We attempted to mitigate this risk by announcing the possibility of a bonus in the AMT task description, but our qualitative data indicates that some participants still considered the bonus to be found money. Future research may investigate asking for donations from an already endowed amount of money or from an expected rather than unexpected wage.

Some individuals (10 out of the 306 valid participants) expressed a lack of trust that donations would actually be forwarded on to the charities selected. These were evenly split between low (5) and high (5) SVO individuals and excluding them did not affect our results.

However, despite our best efforts to provide proof of donation, our results may be skewed by a lack of guarantee for the participants that their donation would actually be donated. Future studies may attenuate this by creating a real-time donation system.

We also concluded from our qualitative data that a common reason individuals elected not to donate was because they did not like any of the charities offered to them. It was a technological limitation of our research that we could not facilitate selection of all possible charities, but future research may incorporate a way for individuals to select from a wider range of possible charities and limit the individuals who opt out due to a lack of identification with the charities offered.

Past research tells us that high-SVO individuals should be more likely to donate and should donate more than low-SVO individuals when in charity-focused environments; however, we focused exclusively on an environment that is not traditionally utilized for charitable donations. Future research should directly compare behaviors in a charity-focused environment with behaviors in a non-charity-focused environment to further elaborate the boundary conditions of the SVO-donation relationship.

We see some evidence in our results that there may be an interaction effect between default level and the presence and type of data, but the study lacks sufficient power to detect such an effect. Future research should investigate how combinations of nudges impact decision-making compared to individual nudges.

Finally, this study was conducted in spring 2021, when many individuals continued to feel the negative financial effects of the economic downturn related to the COVID-19 pandemic.

Individuals may have been less included to donate due to these external challenges (Jones, 2020), making this a conservative test of our predictions.

Regarding other future research opportunities, we speculate here that high SVO individuals are less likely to donate in an unexpected platform because they are “tapped out” having donated more via other mechanisms. However, we do not see any significant difference between high SVO and low SVO individuals on past donation behavior. Future research could investigate what other reasons high SVO individuals may be hesitant to share in unexpected donation opportunities, if not because they share more in other times.

CONCLUSION

We can draw the following conclusions based on this study, although it should be noted that conclusions should be taken with caution given the internal validity of the study. The effort to utilize IT to provide users with live, animated data does not increase – and may actually even reduce – donation amounts or likelihood of donations. Many users do not understand the data presented to them without training, which makes this particularly challenging to implement in practice.

We contribute to literature and practice by identifying that use of unexpected platforms (such as online work platforms, social media, etc.) to collect charitable donations may be an effective way to solicit donations from individuals who would otherwise remain untapped for donations.

Overall, we can state that defaults increase donation amounts and likelihood of donation over no defaults. The default amount itself matters, but finding the optimal default amount to maximize donations is complex. Defaults can be implemented and changed easily in the IS medium and these changes can affect their efficacy. Future research should continue to investigate the conditions that affect individuals' charitable donation decisions online, particularly on platforms that are not focused on charitable giving.

APPENDIX A: DEFAULT THEORIES – TESTED AND CONTROLLED

Decision-Making System, Decision-Making Process, Economic Assumption Violation	Necessary & Effectiveness Contextual Conditions	Content vs. Structure	Nudge Description	Controlled or tested by
Perception System – Attention Focus Process – Mental Model Errors	*Necessary: Individuals' a priori judgements are in accord with the default alternative to the exclusion of other alternatives.*	Content	***Confirmation – Information Seeking.*** *"Confirmation occurs when people … evaluate information in a way that fits with their existing thinking and preconceptions. … For example, a consumer who likes a particular brand and researches a new purchase may be motivated to seek out customer reviews on the internet that favor that brand. Confirmation bias has also been … evident in a reliance on information that is encountered early in a process (Nickerson, 1998)." (Samson 2014)*	In our context, this may be an influence based on participants' preconceptions of donation in general and/or preconceptions of the charity available. Controlled by offering a variety of high-quality charities and collecting information on participants' charitable giving histories.
Perception System – Internal Meaning Activation – Mental Model – Mental Model Errors	*Necessary: If the availability related to the default option decreases the perceived likelihood of an associated positive outcome then explicitly describe the actual likelihood.*	Content	***Availability****. "Availability serves as a mental shortcut if the possibility of an event occurring is perceived as higher simply because an example comes to mind easily (Tversky & Kahneman, 1974); Readily available information in memory is also used when we make similarity-based judgments, as evident in the representativeness heuristic." (Samson 2014)*	Controlled because there is no positive outcome associated with the default choice for the decision-maker
Perception System – Internal Meaning Activation – Mental Model – Mental Model Errors	*Necessary: Individuals a priori judgements are in accord with the default alternative to*	Content	***Confirmation – Information Evaluating.*** *"Confirmation occurs when people seek out … information in a way that fits with their existing thinking and preconceptions. … For*	Controlled by offering a variety of charities to which to donate.

	the exclusion of other alternatives.		*example, a consumer who likes a particular brand and researches a new purchase may be motivated to seek out customer reviews on the internet that favor that brand. Confirmation bias has also been … evident in a reliance on information that is encountered early in a process (Nickerson, 1998)." (Samson 2014)*	
Perception System – Internal Meaning Activation – Mental Model – Mental Model Errors	*Necessary: Describe default option in favorable current and future terms based on the individual's <u>current</u> visceral state (e.g., emotion, pain, hunger), e.g., default for future (e.g., next week) delivery of food for a choice made just before lunch should appeal to the benefit of satisfying current hunger.*	Content	***Empathy Gap (Hot-Cold).*** *"It is difficult for humans to predict how they will behave in the future. A hot-cold empathy gap occurs when people underestimate the influence of visceral states (e.g. being angry, in pain, or hungry) on their behavior or preferences. When people are calm and comfortable, they have trouble appreciating the power of "hot" affective states--like fear, hunger, exhaustion, or thirst. In medical decision-making, for example, a hot-to-cold empathy gap may lead to undesirable treatment choices when cancer patients are asked to choose between treatment options right after being told about their diagnosis. Even low rates of adherence to drug regimens among people with bipolar disorder could be explained partly by something akin to a cold-to-hot empathy gap, while in a manic phase, patients have difficulty remembering what it is like to be depressed and stop taking their medication (Loewenstein, 2005)." (Samson 2014)*	Avoid causing any specific visceral state (e.g. no emotional language or media in charity descriptions) Collect information on current visceral state

Perception System – Internal Meaning Activation – Mental Model – Mental Model Errors	*Necessary: Describe default as part of a larger entity, event, etc. toward which the individual has a positive attitude.*	Content	***Halo**. "A global evaluation of a person sometimes influences people's perception of that person's other unrelated attributes. For example, a friendly person may be considered to have a nice physical appearance, whereas a cold person may be evaluated as less appealing (Nisbett & Wilson, 1977)… A study on the 'health halo' found that consumers tend to choose drinks, side dishes' and desserts with higher calorific content at fast-food restaurants that claim to be healthy (e.g. Subway) compared to others (e.g. McDonald's) (Chandon & Wansink, 2007)." (Samson 2014)*	It's possible that individuals' global evaluations of AMT, the survey, or the charities offered could affect their evaluation of the default opportunity; collected qualitative data to evaluate this and offered a variety of charities.
Perception System – Internal Meaning Activation – Mental Model – Mental Model Errors	*Necessary: Default does NOT maintain the status quo.* *Necessary: Default option description should address the fact that it is better than the status quo, which did not account for problems that "were predictable" earlier.*	Content	***Hindsight**. "It happens when being given new information changes our recollection from an original thought to something different (Mazzoni & Vannucci, 2007). This bias can lead to distorted judgments about the probability of an event's occurrence, because the outcome of an event is perceived as if it had been predictable. It may also lead to distorted memory for judgments of factual knowledge." (Samson 2014)*	Controlled because this is a new choice problem – decision-makers do not have problems that "were predictable" earlier and do not have a current status quo
Perception System – Internal Meaning Activation – Mental Model – Mental Model Errors	*Necessary: Costs associated with the default option are described as part of the individual's current income account, while costs of alternatives are described as*	Content	***Mental Accounting**. "…people treat [assets] … as less fungible than they really are, [categorizing them] … as belonging to current wealth, current income, or future income. Marginal propensity to consume (MPC: The proportion of a rise in disposable income that is consumed) is highest*	Controlled by avoiding discussion of how costs associated with the default (income given up to charity) are part of a current income. No costs associated with alternative (keeping money for self)

	coming from the future income account.		*for money in the current income account and lowest for money in the future income account (Thaler, 1990). Consider unexpected gains: Small windfalls (e.g. a $50 lottery win) are generally treated as 'current income' that is likely to be spent, whereas large windfalls (e.g. a $5,000 bonus at work) are considered 'wealth' (Thaler, 2008)." (Samson 2014)*	
Perception System – Internal Meaning Activation – Mental Model – Mental Model Errors	*Necessary: Include positive events in the default description but not in the alternatives' descriptions.*	Content	***Optimism**. "People tend to overestimate the probability of positive events and underestimate the probability of negative events… For example, we may underestimate our risk of being in a car accident or getting cancer relative to other people. A number of factors can explain unrealistic optimism, including self-serving biases, perceived control, being in a good mood, etc. A possible cognitive factor that has been identified in optimism bias is the representativeness heuristic (Shepperd, Carroll, Grace & Terry, 2002)." (Samson 2014)*	Controlled by avoiding mention of positive events in the description of either the default or the alternative
Perception System – Internal Meaning Activation – Mental Model – Mental Model Errors	*Necessary: In default, highlight the decision-maker's role in a future accomplishment while alternatives highlight the roles others must play in that future accomplishment.*	Content	***Overconfidence**. "People's subjective confidence in their own ability is greater than their objective (actual) performance… Overconfidence is similar to optimism bias when confidence judgments are made relative to other people. A big range of issues have been attributed to overconfidence, including the high rates of entrepreneurs who enter a*	Controlled because there are no future accomplishments for the decision-maker associated with the default selection

			market despite the low chances of success (Moore & Healy, 2008)." (Samson 2014)	
Perception System – Internal Meaning Activation – Mental Model – Mental Model Errors	*Necessary: Default maintains status quo. Necessary: Status quo is at least satisficing. Necessary: Describe non-default alternatives in terms of average (expected returns, experiences, etc.) that do not compare favorably with the status quo peak or ending experiences.*	Content	***Peak-End**. "Our memory of past experience (pleasant or unpleasant) does not correspond to an average level of positive or negative feelings but to the most extreme point and the end of the episode (Kahneman & Tversky, 1999). … These prototypical moments are related to the judgments made when people apply a representativeness heuristic (Frederickson & Kahneman, 1993)." (Samson 2014)*	Controlled because default does not maintain status quo (this is a new choice problem); unlikely that the default option (donating to charity) has big peaks or ending experiences
Perception System – Internal Meaning Activation – Mental Model – Mental Model Errors	*Necessary: If the representativeness of the default option decreases the perceived likelihood of an associated positive outcome then explicitly describe the actual likelihood.*	Content	***Representativeness**. "Is used when we judge the probability that an object or event A belongs to class B by looking at the degree to which A resembles B. When we do this, we neglect information about the general probability of B occurring (its base rate) (Kahneman & Tversky, 1972)." (Samson 2014)*	Controlled because the representativeness of the default option does not decrease the perceived likelihood of any positive outcome
Perception System – Internal Meaning Activation – Mental Model – Mental Model Errors	*Necessary: In the default description, highlight the improbable outcomes associated with the default.*	Content	***Subjective Evaluations of Probabilities**. "People over-weight small probabilities, which explains lottery gambling—a small expense with the possibility of a big win." (Samson 2014)*	Control by not highlighting any improbable outcomes associated with the default
Perception System – Internal Meaning Activation – Imitative Behavioral	Necessary: Default is interpreted as a description what everyone is doing.	Structure	**Implicit Behavioral Norms (also Herd Behavior).** Defaults may be perceived as an indication of how others behave or how one ought to	Tested by coupling some defaults with social information reflecting that most people select the default option.

Tendencies – Utility Function Irrelevances	Necessary: Individual does not distrust that the default accurately reflects the descriptive norm. Effectiveness: Individual is from collectivist rather than individualistic culture.		behave. It can be interpreted as the socially approved form of action (Everett et al., 2015), providing evidence of both injunctive and descriptive norms and may even change normative expectations (Davidai et al., 2012). Norms as an informational influence has been termed Social Proof, and occurs in ambiguous situations where we are uncertain about how to behave and look to others for information or cues. Research suggests that receiving information about how others behave (social proof) leads to greater compliance among people from collectivist (rather than individualist) cultures (Cialdini, Wosinska, Barrett, Butner, & Gornik-Durose, 1999) (Samson 2014).	
Evaluation System – Evaluation – Non-Rational Choice Strategy	*Necessary: Associate default choice with a habit cue, such as making the architecture look like those for software download default acceptance.*	Structure	***Habit****. "Habit is an automatic and rigid pattern of behavior in specific situations, which is usually acquired through repetition and develops through associative learning, when actions become paired repeatedly with a context or an event (Dolan et al., 2010). 'Habit loops' involve a cue that triggers an action, the actual behavior, and a reward. For example, habitual drinkers may come home after work (the cue), drink a beer (the behavior), and feel relaxed (the reward) (Duhigg, 2012). Behaviors may initially serve to attain a particular goal, but once the action is automatic and habitual, the goal loses its importance. For*	Controlled because, while donating online is not a totally novel experience, it's also not likely to be so well-known as to initiate a habitual response. This is particularly the case since AMT is not a charitable-donation-focused platform. Also collected information on how often/how much participants' donate to gauge how much this is a habitual action, as well as qualitative data about why individuals chose to donate.

			example, popcorn may habitually be eaten in the cinema despite the fact that it is stale (Wood & Neal, 2009). Habits can also be associated with status quo bias." (Samson 2014). A Habit nudge will typically evolve from other nudges. For example, when we load software, we are confronted with a window that asks us to accept the terms of service. Few of us take the time to read the terms before we "automatically" allow the default acceptance. This may happen initially as the result of an Implicit Preference Advice nudge. However, over time the Habit nudge may "take over" and we might accept such defaults even when we do not necessarily trust the entity asking for acceptance.	
Evaluation System – Evaluation – Non-Rational Choice Strategy	Necessary: Default is interpreted as advice from the entity that is providing the web page, and suggests that the default is the best or most appropriate alternative. Necessary: Individual does not distrust the advice.	Structure	**Implicit Preference Advice**. Defaults may be perceived as advice from others regarding the best alternative (Dinner et al., 2011; McKenzie et al., 2006); this is likely to be more important when: ▪ Values of those who offer advice match those of the Human (Gigerenzer & Brighton, 2009). ▪ Messenger Effect – a Human's attitude toward the endorsed option depends in part on his or her opinion of the messenger (Kassin, 1983).	Controlled because the default is not presented as a suggestion, and participants are informed that the survey is conducted as academic research, not on behalf of any charitable organization that might suggest a donation amount.

Motivation System – Develop Values Process – Utility Function Irregularities: Irregular Economic Values	*Necessary: Emphasize default's positive rather than negative attributes.* *Necessary: Emphasize non-defaults' negative rather than positive attributes.*	Content	***Framing – Attribute****. Individuals more likely to take action in response to positive (e.g. beef that is 95% lean) rather than negative (e.g., 5% fat) attribute descriptions. (Levin, Schneider, & Gaeth, 1998).*	Controlled by avoiding emphasis of negative or positive attributes of the default or other option.
Motivation System – Develop Values Process – Utility Function Irregularities: Irregular Economic Values	*Necessary: Emphasize negative outcomes from **NOT** choosing default rather than positive outcomes for choosing default.* *Necessary: Emphasize positive outcomes for non-default options.*	Content	***Framing – Goal.*** *Individuals more likely to act when negative outcomes are emphasized (e.g. imposing a $5 penalty) as compared to positive outcomes (e.g. offering a $5 reward) (Levin, Schneider, & Gaeth, 1998).*	Controlled by avoiding emphasis of negative or positive outcomes to the participant from either default or non-default choice
Motivation System – Develop Values Process – Utility Function Irregularities: Irregular Economic Values	*Necessary: Describe default benefit likelihoods in terms of losses (e.g., fewer lives lost) rather than gains (e.g., more lives saved)* *Necessary: Describe non-default benefit likelihoods in terms of gains rather than losses.*	Content	***Framing – Risk.*** *People are risk averse when an action is described in terms of gains (e.g. the opportunity to save 90 out of 100 lives) and risk seeking when an action is described in terms of losses (e.g. the risk of losing 10 out of 100 lives) (Kahneman & Tversky, 1979).*	Controlled by avoiding framing in gains and losses when describing the default option
Motivation System – Develop Values Process – Utility Function Irregularities: Irregular Economic Values	Necessary: Explains the selection of an alternative **other than** the default. Necessary: Default must not be a categorical variable.	Structure	**Reference Point – Anchoring**. Anchoring and adjustment can help explain the selection of an alternative **other than** the default. The default option becomes an anchoring reference point that affects the alternative selected (Acquisti et al.,	Controlled because the default is continuous (amount of money donated) and we are not explaining selection of a non-default option

			2017; Chapman & Johnson, 1994; Dhingra et al., 2012; Dinner et al., 2011; Jacowitz & Kahneman, 1995). Anchoring assumes that some values are closer to each other, such as those that exist on a continuum like item weight. This would not necessarily be the case for categorical values, such as item color (e.g. red, blue, green).	
Motivation System – Develop Values Process – Utility Function Irregularities: Irregular Economic Values	*Necessary: Asymmetrically dominated non-default choice favors default option.* *Necessary: Default must dominate decoy.*	Content	***Reference Point – Decoy.*** *"Choices often occur relative to what is on offer rather than based on absolute preferences. The decoy effect is technically known as an 'asymmetrically dominated choice' and occurs when people's preference for one option over another changes as a result of adding a third (similar but less attractive) option. For example, people are more likely to choose an elegant pen over $6 in cash if there is a third option in the form of a less elegant pen (Bateman, Munro, & Poe, 2008)." (Samson 2014)*	Controlled because no decoy option was offered
Motivation System – Develop Values Process – Utility Function Irregularities: Irregular Economic Values	Necessary: Default maintains status quo. Necessary: Status quo is at least satisficing.	Content	**Reference Point – Status Quo**. (also **Reference Point – Endowment)** Individuals are likely to choose the status quo as the reference point from which gains and losses are determined (Dinner et al., 2011) and thus potential gains from choices other than the status quo are discounted. This choice of status quo may be due to Humans' feelings that they own the status quo (i.e.,	Controlled because default does not maintain status quo (this is a new choice problem)

			endowment: Johnson & Goldstein, 2003).	
Motivation System – Develop Values Process – Utility Function Irregularities: Non-Economic Values	Necessary: Default maintains status quo. Necessary: Status Quo must be chosen in a prior period by the decision-maker. Necessary: Status Quo is at least satisficing.	Structure	**Consistency**. The Human drive for consistency can be a theoretical mechanism encouraging status quo selection when the current state was chosen earlier by the individual. When the status quo is the default, Humans may choose it for the following reasons. (1) To avoid seeming like their original choice was incorrect (Samuelson & Zeckhauser, 1988). (2) To avoid conflicting cognitions causing cognitive dissonance (Festinger, 1962; Samuelson & Zeckhauser, 1988). A Human tends to discard or mentally suppress information that indicates a past decision was in error because that information would conflict with his or her self-image as a good decision-maker (Samuelson & Zeckhauser 1988). (3) To stick with a status quo that maintains a past choice made by them because, with uncertain preferences, they may believe their past behavior that results in their current state should also be reflected in their current preferences (Bem, 1972; Samuelson & Zeckhauser, 1988). (4) To maintain a consistent and positive self-image (Cialdini, 2008) by keeping commitments and avoid reputational damage (if they are made publicly) (Festinger, 1957).	Controlled because default does not maintain status quo (this is a new choice problem) and the default was not selected in a prior period by the decision-maker
Motivation System – Develop Values	*Necessary: Default option provides more*	Content	***Diversification**. "People seek more variety when they choose multiple*	Controlled because the default option (donating to charity) does

Process – Utility Function Irregularities: Non-Economic Values	*variety in the future (e.g., in goods received) than alternatives.*		*items for future consumption simultaneously than when they make choices sequentially, i.e. on an 'in the moment' basis. Diversification is non-optimal when people overestimate their need for diversity (Read & Loewenstein, 1995)... For example, before going on vacation I may upload classical, rock and pop music to my MP3 player, but on the actual trip I may mostly end up listening to my favorite rock music." (Samson 2014).*	not provide more variety in the future
Motivation System – Develop Values Process – Utility Function Irregularities: Non-Economic Values	*Necessary: Emphasize individual's role in developing the default as a viable option from which to choose.*	Content	***IKEA**. "Invested labor leads to inflated product valuation (Norton, Mochon, & Ariely, 2012). … The effect has a range of possible explanations, such as positive feelings (including feelings of competence) that come with the successful completion of a task, a focus on the product's positive attributes, and the relationship between effort and liking. The effort heuristic is another concept that proposes a link between perceived effort and valuation (Kruger, Wirtz, Van Boven, & Altermatt, 2004)." (Samson 2014)*	Controlled because the participant did not invest labor in developing the default
Motivation System – Develop Values Process – Utility Function Irregularities: Non-Economic Values	*Necessary: Default is interpreted as advice from the individual or entity that is providing the web page suggesting that the default is the equitable option.*	Structure	***Implicit Inequity Advice**. People prefer fairness and resist inequalities. In some instances …people are willing to forego a gain, in order to prevent another person from receiving a superior reward." (Samson 2014). For example, interpreting the default as the equitable option can occur in cases where an individual can choose the*	Controlled because the default is not presented as advice from anyone and it is not implied that the suggested default is the "fair" option (although it may be interpreted this way by some participants, random assignment should help mitigate this influence)

	Necessary: Individual does not distrust the advice.		*level of payment for a good (e.g., choosing among tips or choosing how much to pay in a "pay what you want" context).*	
Motivation System – Develop Values Process – Utility Function Irregularities: Non-Economic Values	*Necessary: If default option is viewed as morally bad, the individual must be given the opportunity to do something morally good prior to making the choice.*	Content	***Licensing**. "People allow themselves to do something bad (e.g. immoral) after doing something good (e.g. moral) first (Merritt, Effron & Monin, 2010)." (Samson 2014).*	Controlled because the default option (donating to charity) is not morally bad
Motivation System – Develop Values Process – Utility Function Irregularities: Non-Economic Values	*Necessary: Acceptance of default choice is interpreted as part of quid pro quo due to an earlier exchange.*	Content	***Reciprocity**. "A social norm that involves in-kind exchanges between people—responding to another's action with another equivalent action. It is usually positive (e.g. returning a favor), but it can also be negative (e.g. punishing a negative action) (Fehr & Gaechter, 2000). … Charities often take advantage of reciprocity when including small gifts in solicitation letters, while supermarkets try to get people to buy by offering free samples." (Samson 2014).*	Controlled because the donation goes to charity, not to the researchers who are paying the participant. Participants may have experience with the charities we used, but random assignment and the variety of charities offered should prevent this from being a systematic effect in our data.
Motivation System – Develop Values Process – Utility Function Irregularities: Inappropriate Economic Values	Necessary: Individuals overweight the value of their cognitive effort for this choice task compared to the benefit of attending to the choice task. Effectiveness: More likely when the choice stakes are small	Structure	**Decision Choice Costs.** The potential physical and cognitive costs associated with the process of choosing a non-default alternative **appear to** (but actually don't) outweigh the potential benefits of choosing an alternative (Dinner et al., 2011; Sunstein & Thaler, 2003; Tversky & Kahneman, 1974). This is more likely when the stakes are small (Dinner et al., 2011; McKenzie et al., 2006) or	Controlled by: • Having people give up real money • Making the default and non-default almost equally easy to select (one click) • Limiting number and complexity of choices

	Effectiveness: More likely with a greater number or complexity of choices		with a greater number or complexity of choices (Choice Overload: Samson 2014; Iyengar & Lepper, 2000).	
Motivation System – Develop Values Process – Utility Function Irregularities: Inappropriate Economic Values	Necessary: Individuals severely overweight the value of their cognitive effort for this choice task compared to the benefit of attending to the choice task. Effectiveness: This is especially likely to occur when preferences are difficult to determine	Structure	**Decision Choice Costs - Cognitive Miser**. Humans may not engage with the choice process at all. Individuals choose the default alternative without attempting to compare its costs and benefits, but rather in order to minimize cognitive choice costs (minimum effort over time, Dolan et al., 2012; “path of least resistance,” Lehner et al., 2016). This is especially likely to occur when preferences are uncertain or difficult to determine (Acquisti et al., 2017; C. J. Anderson, 2003; Dinner et al., 2011; Kahneman et al., 1991; Kahneman & Miller, 1986).	Controlled by: • Having people give up real money, meaning avoiding engagement with the decision context is costly • Implementing attention check questions to ensure that disengaged participants are removed from the analysis
Motivation System – Develop Values Process – Utility Function Irregularities: Inappropriate Economic Values	Necessary: Individuals overweight the value their cognitive effort for this choice task compared to the benefit of attending to concurrent (distracting) issues. Effectiveness: Lack of choice importance	Structure	**Decision Choice Costs – Distracted.** Humans may not engage with the choice process at all. A lack of choice process engagement can occur when individuals are so distracted or thoughtless that they aren’t reflecting on their own preferences (the “yeah, whatever” heuristic) (Meske & Potthoff, 2017; Thaler & Sunstein, 2009).	Controlled by: • Having people give up real money, meaning avoiding engagement with the decision context is costly • Implementing attention check questions to ensure that distracted participants are removed from the analysis
Motivation System – Develop Values Process – Utility Function Irregularities:	Necessary: Default maintains status quo. Necessary: Status quo is at least satisficing.	Structure	**Decision Choice Costs – Reanalysis**. The costs associated with the process of reanalyzing a previously made decision can **appear to** (but actually don’t) outweigh the potential benefits of choosing an alternative	Controlled because default does not maintain status quo (this is a new choice problem)

Inappropriate Economic Values			other than the default; these are decision reanalysis costs (Samuelson & Zeckhauser, 1988) and are relevant when the default is maintaining the status quo.	
Motivation System – Develop Values Process – Utility Function Irregularities: Inappropriate Economic Values	*Necessary: If the default option has negative effects on the individual in the future, the default description should emphasize the fact that the negative effects felt by the individual will actually be reduced in the future.*	Content	***Hedonic Adaptation**. People get used to changes in life experiences… [For example] the happiness that comes with the ownership of a new gadget or salary raise will wane over time, even the negative effect of life events such as bereavement or disability on subjective well-being tends to level off, to some extent (Frederick & Loewenstein, 1999). When this happens, people return to a relatively stable baseline of happiness." (Samson 2014)*	Controlled because the default option (donating a small amount of money online) will not have long-lasting effects (positive or negative)
Motivation System – Develop Values Process – Utility Function Irregularities: Inappropriate Economic Values	Necessary: Default maintains status quo. Necessary: Status quo is at least satisficing. Necessary: Focus on default current benefits.	Content	**Hyperbolic Discounting**. Individuals tend to severely discount the benefits of a potential change on their immediate future (Thaler, 1981). As a result, when the status quo is at least satisfying and is represented by the default, it tends to be chosen in one of two ways. (1) The default may be selected (Dolan et al., 2012; O'Donoghue & Rabin, 1999) or (2) the choice process is postponed because what the individual is doing now seems more important than whatever he or she will be doing in the immediate future (Thaler & Benartzi, 2004).	Controlled because default does not maintain status quo (this is a new choice problem)
Motivation System – Develop Values Process – Utility	*Necessary: Emphasize default's benefits in*	Content	***Projection**. "People's assumption that their tastes or preferences will remain the same over time. For example,*	Controlled given that the costs and benefits of the action (donating a

Function Irregularities: Inappropriate Economic Values	*terms of current tastes and preferences*		*people may overestimate the positive impact of a career promotion due to an under-appreciation of (hedonic) adaptation, put above-optimal variety in their planning for future consumption (see diversification bias), or underestimate the future selling price of an item by not taking into account the endowment effect. Differences between present and future valuations should be particularly underappreciated for durable goods, where satisfaction levels are likely to fluctuate over time. Finally, consumers' under-appreciation of habit formation (associated with higher consumption levels over time) may lead to projection bias in planning for the future, such as retirement savings (Loewenstein, O'Donoghue, & Rabin, 2003)." (Samson 2014)*	small amount of money online) are unlikely to persist long in time
Motivation System – Develop Values Process – Utility Function Irregularities: Inappropriate Economic Values	Necessary: Default maintains status quo. Necessary: Status quo is at least satisficing Necessary: Decision-maker is aware of past expenses surrounding the achievement of the status quo	Content	**Sunk Cost.** Individuals commit the sunk cost fallacy when they consider previously expended resources (time, money or effort) when determining whether to continue a behavior (Arkes & Blumer, 1985). Humans may include sunk costs in their utility calculations, which is an irrelevant factor, in order to justify previous commitments to a (possibly failing) course of action (Samuelson & Zeckhauser, 1988).	Controlled because default does not maintain status quo (this is a new choice problem) and no past expenses have been utilized to achieve the status quo
Motivation System – Develop Values Process – Utility	*Necessary: In default description, emphasize current*	Content	***Time Discounting**. "Present rewards are weighted more heavily than future ones. Once rewards are very distant in*	Controlled by not emphasizing current and very near future

Function Irregularities: Inappropriate Economic Values	*and very near future benefits; describe costs as occurring in the future.*		*time, they cease to be valuable. Delay discounting can be explained by impulsivity and a tendency for immediate gratification, and it is particularly evident for addictions such as nicotine (Bickel, Odum, & Madden, 1999). Hyperbolic discounting theory suggests that discounting is not time-consistent; it is neither linear nor occurs at a constant rate. It is usually studied by asking people questions such as "Would you rather receive £100 today or £120 a month from today?" or "Would you rather receive £100 a year from today or £120 a year and one month from today?" Results show that people are happier to wait an extra month for a larger reward when it is in the distant future. In hyperbolic discounting, values placed on rewards decrease very rapidly for small delay periods and then fall more slowly for longer delays (Laibson, 1997)." (Samson 2014)*	benefits and describing costs as occurring in the future. Costs to the decision-maker are occurring now (giving up pay that otherwise would be received now)
Motivation System – Develop Values Process – Reconcile Preferences & Attitudes with Emotions - Utility Function Irrelevance: Emotions	*Necessary: Default maintains status quo.* *Necessary: Status quo is at least satisficing.* *Necessary: In contrast to other options, the default option does **NOT** include opening an additional partition in a partitioned pool of resources.*	Content	***Partitioning**. "The rate of consumption can be decreased by physically partitioning resources into smaller units, for example cookies wrapped individually or money divided into several envelopes. When a resource is divided into smaller units (e.g. several packs of chips), opening a partitioned pool of resources incurs a psychological transgression cost, such as feelings of guilt (Cheema & Soman, 2008)." (Samson 2014)*	Controlled because default does not maintain status quo (this is a new choice problem)

Motivation System – Develop Values Process – Reconcile Preferences & Attitudes with Emotions - Utility Function Irrelevance: Emotions	Necessary: Default maintains status quo. Necessary: Status quo is at least satisficing	Content	**Regret Avoidance (also Omission)**. Humans may include regret avoidance in their utility function and choose options that reduce their potential for later regret (Samuelson & Zeckhauser, 1988). Humans tend to feel stronger regret for bad outcomes that are the consequences of new actions than similar bad outcomes resulting from inaction (Kahneman & Tversky, 1982). Thus, Humans are more likely to avoid choosing by sticking with the default when it maintains the status quo, especially if the status quo is in accord with social norms (Samuelson & Zeckhauser, 1988). Also Omission bias: Changing the status quo requires an act, but keeping the status quo requires only an omission, which is a failure to act. Humans favor harmful omissions over equally harmful commissions (Spranca et al., 1991), possibly because of the belief that actors do not cause the outcomes of their omissions (Ritov & Baron, 1992).	Controlled because default does not maintain status quo (this is a new choice problem)

APPENDIX B: MEASUREMENT ITEMS

Demographics

What is your gender? (Dholakia, 2016)

- o Male
- o Female
- o Transgender
- o Other _______________
- o Prefer not to say

What is your age? _____

What is your nationality?

- o USA (1)
- o Other (please specify) (2) ____________________

What is your race/ethnic group?

- o Asian (1)
- o Black/African descent (2)
- o East Indian (3)
- o Hispanic/Latino (4)
- o Middle Eastern (5)
- o Native American (6)
- o Pacific Islander (7)
- o White/Caucasian (8)
- o Other (please specify) (9) ____________________

What is the highest degree or level of education you have completed?

- o Less than high school
- o High school graduate/GED
- o Completed some college
- o Associate's degree/two-year college
- o Bachelor's degree (four-year college)
- o Master’s or professional degree
- o Doctoral degree
- o Other (please specify)

Are you currently employed? Yes/No
If you are employed, are you working part time or full time? Part time/full time
What is your occupation? If you are unemployed or retired, please state accordingly.
____
How many years in total have you been working or have you worked? ____________

Income

What is your total **yearly gross** household income? We mean the amount that is a total of salary, wages, income from self-employment, annuity or pension. Please add any income from public aid sources, income from rent, lease, housing benefit, child benefit and other forms of income.
Options:
Less than $10,000;
$10,000-$19,000;
$20,000 - $29,000;
$30,000 - $39,000;
$40,000 - $49,000;
$50,000 - $59,000;
$60,000 - $69,000;
$70,000 - $79,000;
$80,000 - $89,000;
$90,000 - $99,000;
$100,000 - $199,000;
$200,000 - $299,000;
$300,000 - $399,000;
$400,000 - $499,000;
$500,000 or over

Self- and Other-Interest Inventory (SOII)

(Gerbasi & Prentice, 2013)
Instruction: Please indicate your level of agreement with the following statements:
7-point Likert scale: 1 – very strongly disagree, 7 – very strongly agree
Self-interest subscale:

1. I am constantly looking for ways to get ahead
2. Hearing others praise me is something I look forward to
3. Doing well in my pursuits is near the top of my priorities
4. I try to make sure others know about my successes
5. I look for opportunities to achieve higher social status
6. Success is important to me
7. Having a lot of money is one of my goals in life
8. I keep an eye out for my own interests
9. I am constantly looking out for what will make me happy

Other-interest subscale:

1. I am constantly looking for ways for my acquaintances to get ahead
2. Hearing others praise people I know is something I look forward to
3. I want to help people do well
4. I try to help my acquaintances by telling other people about their successes.
5. I look for opportunities to help people I know achieve higher social status
6. The success of my friends is important to me
7. I look out for ways for my friends to have more money

8. I keep an eye out for other's interests
9. It is important to me that others are happy.

Personality

Big Five Inventory-10 (BFI-10) - (Rammstedt & John, 2007)
Instruction: How well do the following statements describe your personality? (1- Disagree strongly, 2- Disagree a little, 3-Neither agree nor disagree, 4-Agree a little, 5-Agree strongly)
I see myself as someone who…

1. Is reserved
2. Is generally trusting
3. Tends to be lazy
4. Is relaxed, handles stress well
5. Has few artistic interests
6. Is outgoing, sociable
7. Tends to find fault with others
8. Does a thorough job
9. Gets nervous easily
10. Has an active imagination

Past Donation Behavior

Adapted from (Saunders et al., 2016)

1. How much do you typically donate each month? If you usually make bulk contributions once in a year, enter the estimated value of your contribution divided by 12.
2. How many times have you donated to charity in the last 12 months?
3. Imagine someone you know who has donated to charity. About how much do you think that person typically donates each month?
4. Imagine someone you know who has donated to charity. About how many times do you think that person donated to charity in the last 12 months?

Current Visceral State

(Steinmetz et al., 2018)
Please answer the following questions about how you currently feel. That is, how are you feeling **right now**?

How do you currently feel? 1 – very cold, 7 – very warm
How thirsty do you currently feel? 1 – not at all, 7 – very thirsty
How hungry do you currently feel? 1 – not at all, 7 – very hungry
How tired do you currently feel? 1 – not at all, 7 – very tired
How awake do you currently feel? 1- not at all, 7 – very awake

Social Value Orientation (SVO)

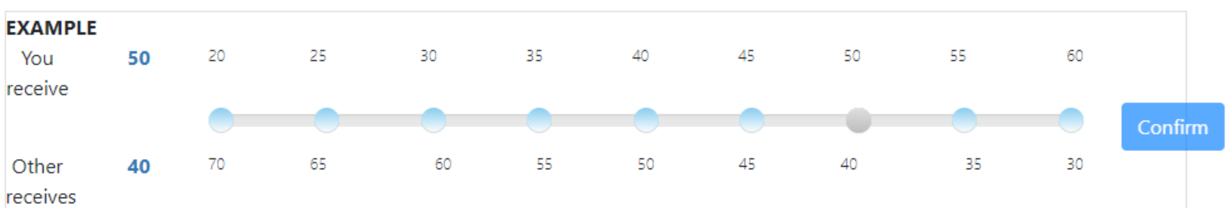
SVO slider measure (Murphy et al., 2011)

Instructions:
In this task, imagine that you have been randomly paired with another person, whom we will refer to as **the other**. This other person is someone you do not know and will remain mutually anonymous. All of your choices are completely confidential.

You will be making a series of decisions about allocating resources between you and this other person. For each of the following questions, please indicate the distribution you prefer most by **moving the slider along the scale to your preferred payoff allocation**.
You can only make one selection for each question.

Your decisions will yield money for both yourself and the other person. In the example below, a person has chosen to distribute money so that he/she receives $50, while the anonymous other person receives $40.

There are no right or wrong answers, this is all about personal preferences. After you have made your decision, **make it final by pressing the Confirm button to the right of the scale.** As you can see, your choices will influence both the amount of money you receive and the amount of money the other receives. When you have made all your decisions, **press the Continue button at the bottom of the screen** to complete this decision task. No actual money will be distributed after this task.



1

You receive	**85**	85	85	85	85	85	85	85	85	85	Confirm
Other receives	**50**	85	76	68	59	50	41	33	24	15	

2

You receive	**93**	85	87	89	91	93	94	96	98	100	Confirm
Other receives	**33**	15	19	24	28	33	37	41	46	50	

3

You receive	**68**	50	54	59	63	68	72	76	81	85	Confirm
Other receives	**93**	100	98	96	94	93	91	89	87	85	

4

You receive	**68**	50	54	59	63	68	72	76	81	85	Confirm
Other receives	**58**	100	89	79	68	58	47	36	26	15	

5

You receive	**75**	100	94	88	81	75	69	63	56	50	Confirm
Other receives	**75**	50	56	63	69	75	81	88	94	100	

6

You receive	**93**	100	98	96	94	93	91	89	87	85	Confirm
Other receives	**68**	50	54	59	63	68	72	76	81	85	

Continue

Attention Check Questions

Participants are shown the following passage:
Forests are complex ecosystems in which trees are the dominant flora. Forests occur whenever the ambient temperature rises above 10°C (50°F) in the warmer months. Precipitation annually has to typically exceed 8 inches. Depending on the local climate, different types of forests grow. This question is a test of your attention. Please answer 100 trees. Colder climates at higher latitudes are often dominated by conifers such as pines, spruces, and larches. These forests are called taiga or boreal forests. Moderate-latitude climates generally give rise to deciduous forests, which are primarily composed of species such as oak, elm, birch, maple, beech, and aspen.
Following the passage respondents are shown a picture of a deciduous forest and are asked: "Roughly how many trees are in this photo of a deciduous forest?" And are given the options: 99 or fewer; 100; 200; 300; 400; and 401 or more. (O'Grady et al., 2019):

How much do you agree with this statement? "I am participating in an online study currently" 1-very strongly disagree, 7-very strongly agree (valid answers were agree, strongly agree, or very strongly agree) (Curran & Hauser, 2019)

APPENDIX C: EXAMPLES OF TREATMENTS

Control + No Data

Congratulations - Bonus Received!

Congratulations! Based on your attentiveness and responses, you have qualified for a $1 bonus in addition to your Amazon Mechanical Turk payment. You must proceed through the rest of the survey to receive your bonus and your standard payment.

You have the opportunity to retain this entire $1 bonus or donate any portion of it to a charity of your choice from the list below. If you choose to donate, you can receive access to a website that tracks all donations and displays receipts for the donations.

Please enter the amount you would like to donate right now of your $1 bonus, if any. If you prefer not to donate, enter 0:

[ ] $

Which charity would you like to receive your donation? You will have access to proof of the donation.

- ○ Doctors Without Borders
- ○ American Red Cross
- ○ National Resource Defense Council

Next

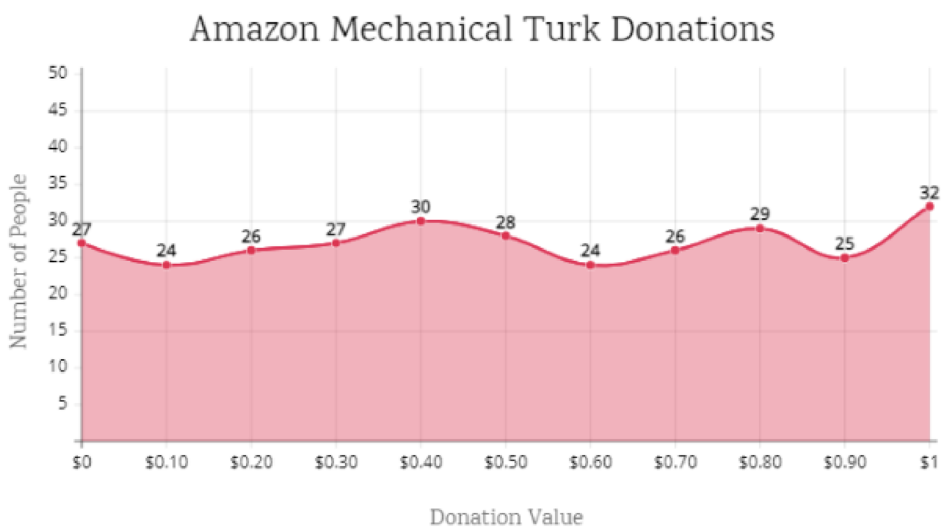
Control + Data

Congratulations - Bonus Received!

Congratulations! Based on your attentiveness and responses, you have qualified for a $1 bonus in addition to your Amazon Mechanical Turk payment.

You have the opportunity to retain this entire $1 bonus or donate any portion of it to a charity of your choice from the list below. If you choose to donate, you can receive access to a website that tracks all donations and displays receipts for the donations.

The chart below reflects the decisions other qualified Amazon Mechanical Turk workers made regarding their bonus.



Please enter the amount you would like to donate, if any. If you prefer not to donate, enter 0:

[ ] $

Which charity would you like to receive your donation? You will have access to proof of the donation.

- ○ Disabled American Veterans
- ○ United Nations Children's Fund (UNICEF)
- ○ The Nature Conservancy

Next

General + No Data

Congratulations - Bonus Received!

Congratulations! Based on your attentiveness and responses, you have qualified for a $1 bonus in addition to your Amazon Mechanical Turk payment. You must proceed through the rest of the survey to receive your bonus and your standard payment

You have the opportunity to retain this entire $1 bonus or donate any portion of it to a charity of your choice from the list below. If you choose to donate, you can receive access to a website that tracks all donations and displays receipts for the donations.

Please select the amount you would like to donate, if any:

0.3

Which charity would you like to receive your donation? You will have access to proof of the donation.

- ○ Save the Children
- ○ National Resource Defense Council
- ○ St. Jude Children's Hospital

Next

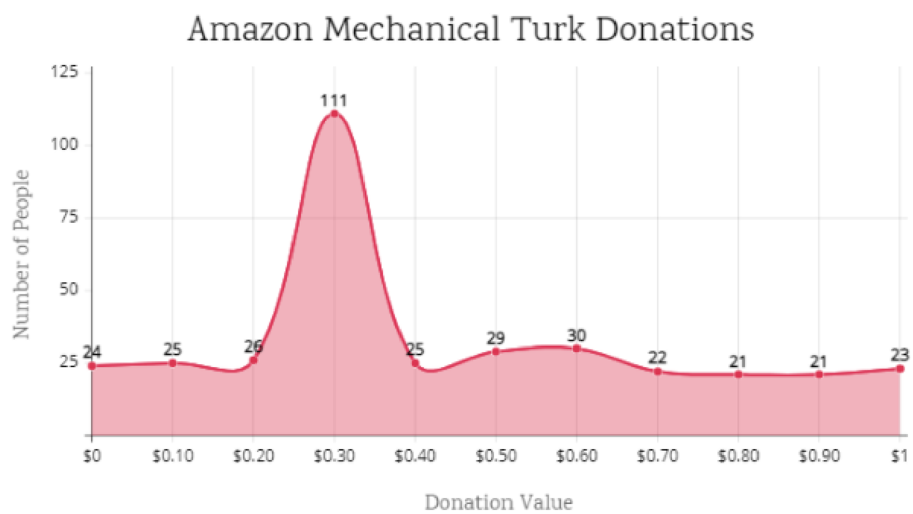
General + Data

Congratulations - Bonus Received!

Congratulations! Based on your attentiveness and responses, you have qualified for a $1 bonus in addition to your Amazon Mechanical Turk payment.

You have the opportunity to retain this entire $1 bonus or donate any portion of it to a charity of your choice from the list below. If you choose to donate, you can receive access to a website that tracks all donations and displays receipts for the donations.

The chart below reflects the decisions other qualified Amazon Mechanical Turk workers made regarding their bonus.



Please select the amount you would like to donate, if any:

0.3

Which charity would you like to receive your donation? You will have access to proof of the donation.

- Save the Children
- National Resource Defense Council
- Disabled American Veterans

Next

Personal High + No Data

Congratulations - Bonus Received!

Congratulations! Based on your attentiveness and responses, you have qualified for a $1 bonus in addition to your Amazon Mechanical Turk payment. You must proceed through the rest of the survey to receive your bonus and your standard payment

You have the opportunity to retain this entire $1 bonus or donate any portion of it to a charity of your choice from the list below. If you choose to donate, you can receive access to a website that tracks all donations and displays receipts for the donations.

Please select the amount you would like to donate, if any:

0.5

Which charity would you like to receive your donation? You will have access to proof of the donation.

- ○ United Nations Children's Fund (UNICEF)
- ○ St. Jude Children's Hospital
- ○ National Resource Defense Council

Next

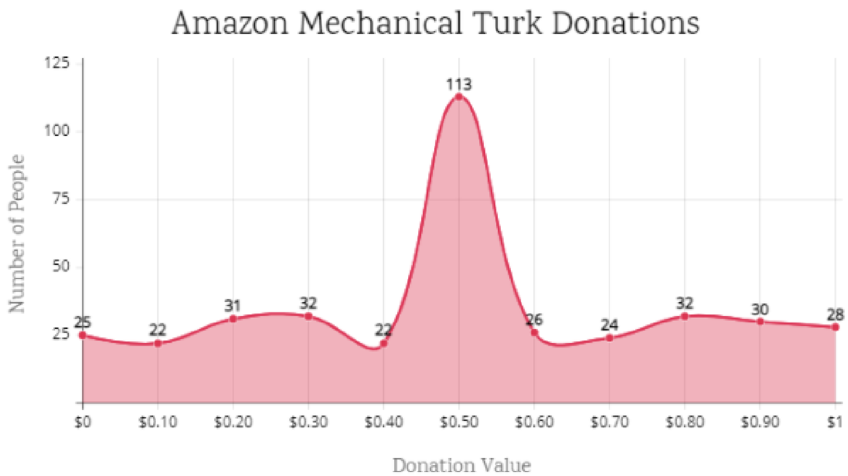
Personal High + Data

Congratulations - Bonus Received!

Congratulations! Based on your attentiveness and responses, you have qualified for a $1 bonus in addition to your Amazon Mechanical Turk payment.

You have the opportunity to retain this entire $1 bonus or donate any portion of it to a charity of your choice from the list below. If you choose to donate, you can receive access to a website that tracks all donations and displays receipts for the donations.

The chart below reflects the decisions other qualified Amazon Mechanical Turk workers made regarding their bonus.



Please select the amount you would like to donate, if any:

0.5

Which charity would you like to receive your donation? You will have access to proof of the donation.

○ American Red Cross

○ National Resource Defense Council

○ Doctors Without Borders

Next

Personal Low + No Data

Congratulations - Bonus Received!

Congratulations! Based on your attentiveness and responses, you have qualified for a $1 bonus in addition to your Amazon Mechanical Turk payment.

You have the opportunity to retain this entire $1 bonus or donate any portion of it to a charity of your choice from the list below. If you choose to donate, you can receive access to a website that tracks all donations and displays receipts for the donations.

Please select the amount you would like to donate, if any:

0.1

Which charity would you like to receive your donation? You will have access to proof of the donation.

- Save the Children
- Disabled American Veterans
- National Resource Defense Council

Next

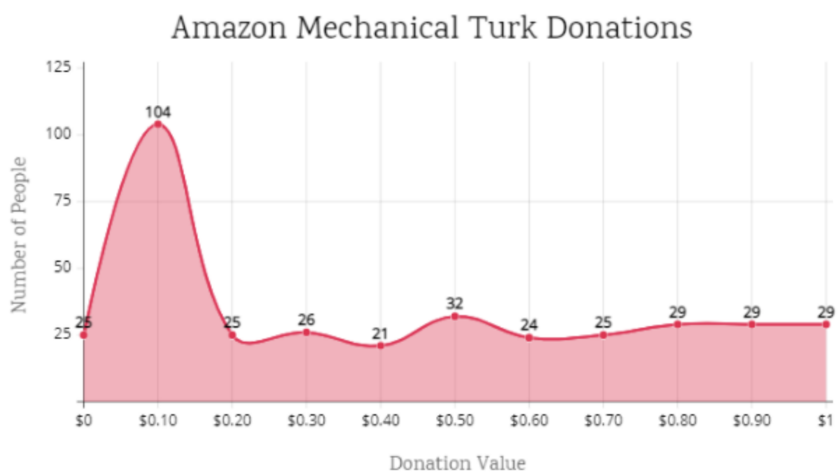
Personal Low + Data

Congratulations - Bonus Received!

Congratulations! Based on your attentiveness and responses, you have qualified for a $1 bonus in addition to your Amazon Mechanical Turk payment.

You have the opportunity to retain this entire $1 bonus or donate any portion of it to a charity of your choice from the list below. If you choose to donate, you can receive access to a website that tracks all donations and displays receipts for the donations.

The chart below reflects the decisions other qualified Amazon Mechanical Turk workers made regarding their bonus.



Please select the amount you would like to donate, if any:

0.1

Which charity would you like to receive your donation? You will have access to proof of the donation.

- The Nature Conservancy
- Disabled American Veterans
- Doctors Without Borders

Next

APPENDIX D: PARTICIPANT DESCRIPTIVE STATISTICS

Descriptive Statistics

	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Age	171	50	20	70	33.80	11.537	133.113	.913	.186	.472	.369
Years of Employment	171	45	0	45	13.74	10.128	102.572	1.008	.186	.449	.369
Income	171	298000	2000	300000	54687.13	38453.219	1478650068.799	2.167	.186	10.208	.369
Past Donations - Monthly Amount	171	25000.00	.00	25000.00	786.5722	3107.73100	9657991.970	5.909	.186	37.903	.369
Past Donations - Frequency	171	45000	0	45000	353.77	3524.325	12420869.071	12.223	.186	154.222	.369
Valid N (listwise)	171										

Gender

	N	%
female	62	36.3%
male	109	63.7%

Race

	N	%
Asian	8	4.7%
Black	15	8.8%
EastIndian	1	0.6%
HispanicLatino	4	2.3%
MiddleEastern	1	0.6%
NativeAmerican	6	3.5%
Other	2	1.2%
PacificIslander	1	0.6%
White	133	77.8%

Education

	N	%
LessThanHighSchool	2	1.2%
HighSchoolGrad	21	12.3%
SomeCollege	20	11.7%
Associate	16	9.4%

Bachelor	96	56.1%
Master	16	9.4%

Employment Status

	N	%
FullTime	126	73.7%
PartTime	22	12.9%
Retired	4	2.3%
Unemployed	19	11.1%

APPENDIX E: CHART TRAINING

We utilized a manipulation check question to ensure that individuals correctly perceived the social norm being presented via the chart we utilized. However, in the first round of data collection, we found that many participants (53/95; 56%) were unable to correctly answer a question about what other participants had donated in the manipulation. To combat this challenge, we implemented a training on the chart in subsequent data collection rounds.

The training presented an example chart (different from any utilized in the actual donation opportunity, but with similar characteristics), instructed the participant on how to read it, and asked two questions requiring the participant to understand the chart in order to answer. The training is presented below. In subsequent rounds, we continued to have challenges with participants understanding the chart despite the training (round 2: 60/92 or 65% correct; round 3: 27/54 or 50% correct; round 4: 32/50 or 64% correct).

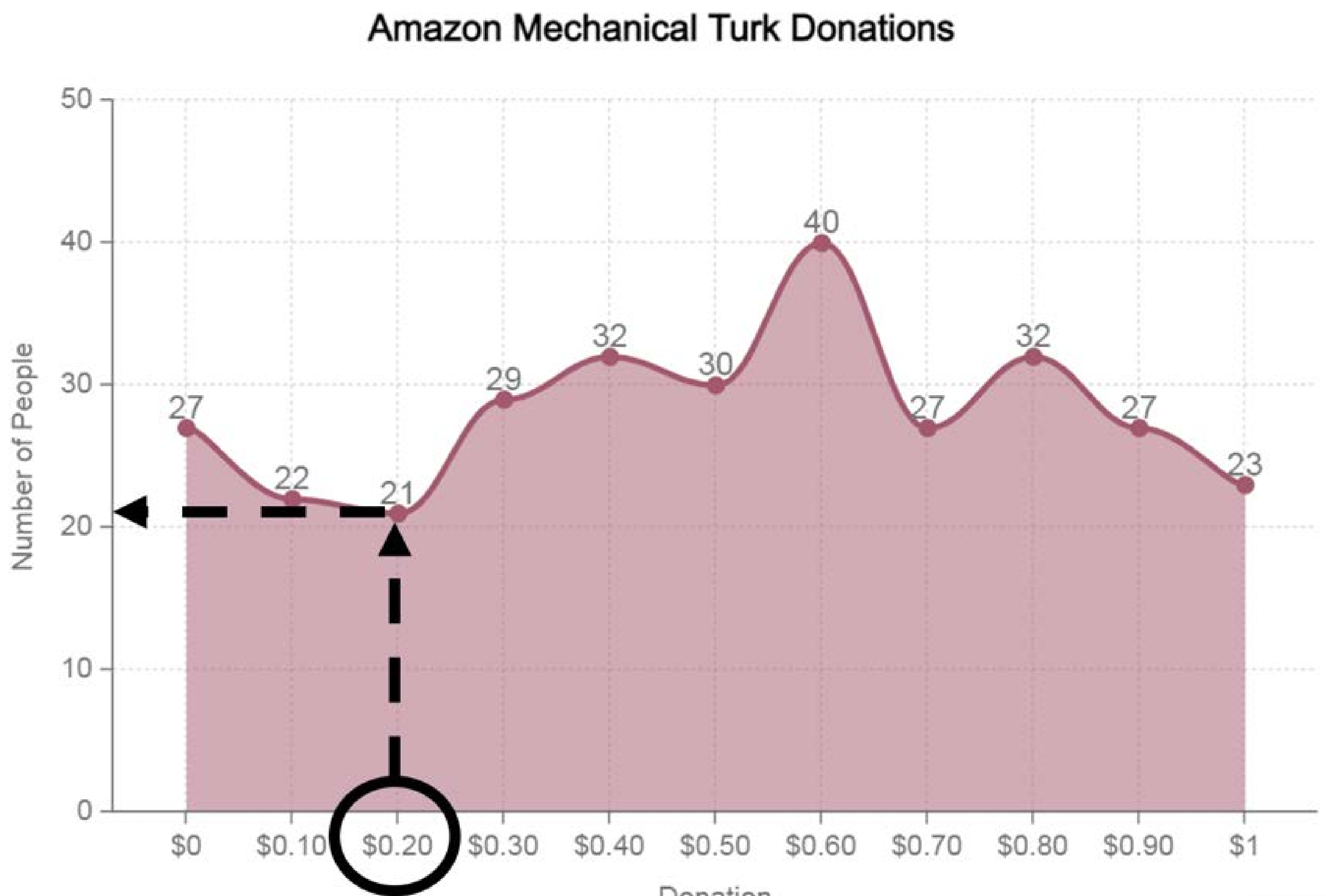
This may have been a limitation with the way participants were asked about the chart. We asked, “How much were most other donors donating while you were making your decision?” (live data condition) or “How much had most other donors donated when you were making your decision?” (static data condition). We were looking for participants to answer the mode of the data, when there was one, but it’s possible that participants instead replied with the mean of the data (always about $0.50). Future research can work on improving this test of comprehension. One suggestion for a potentially clearer measure is to ask participants, “What amount was frequently donated?”

Survey

Please read the instructions and evaluate this page carefully.

Amazon Mechanical Turk workers sometimes donate their bonuses to charity. This chart represents a fictional example of such donations. Note that the vertical axis represents the number of people who have donated, and the horizontal axis represents the amount they donated.

Find $0.20 on the horizontal access. By finding the corresponding data point, you can see that 21 individuals donated $0.20. Note that **more** people (29) donated $0.30 than donated $0.20 (21 people).


Amazon Mechanical Turk Donations
Number of People
0
10
20
30
40
50
Donation
$0
$0.10
$0.20
$0.30
$0.40
$0.50
$0.60
$0.70
$0.80
$0.90
$1
27
22
21
29
32
30
40
27
32
27
23

Use the chart to answer the following questions.

How many people donated $0.90 in this scenario?

27

How much did the most people donate in this scenario? In other words, what was the most popular donation amount selected?

$0.60

Next

APPENDIX F: FULL DETAILS OF H1 T-TESTS

None vs. Static

Group Statistics

	Data Treatment	N	Mean	Std. Deviation	Std. Error Mean
Donation Amount	none	94	.3435	.38338	.03954
	static	33	.1930	.29177	.05079

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Donation Amount	Equal variances assumed	8.360	.005	2.054	125	.021	.042	.15048	.07328	.00546	.29550
	Equal variances not assumed			2.338	73.286	.011	.022	.15048	.06437	.02220	.27876

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
Donation Amount	Cohen's d	.36214	.416	.015	.815
	Hedges' correction	.36433	.413	.015	.810
	Glass's delta	.29177	.516	.096	.928

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

None vs. Live

Group Statistics

	Data Treatment	N	Mean	Std. Deviation	Std. Error Mean
Donation Amount	none	94	.3435	.38338	.03954
	live	44	.1798	.27834	.04196

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Donation Amount	Equal variances assumed	16.836	<.001	2.535	136	.006	.012	.16374	.06458	.03602	.29145
	Equal variances not assumed			2.840	112.326	.003	.005	.16374	.05766	.04950	.27797

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
Donation Amount	Cohen's d	.35356	.463	.100	.824
	Hedges' correction	.35552	.461	.100	.820
	Glass's delta	.27834	.588	.206	.964

a. The denominator used in estimating the effect sizes.

Cohen's d uses the pooled standard deviation.

Hedges' correction uses the pooled standard deviation, plus a correction factor.

Glass's delta uses the sample standard deviation of the control group.

Static vs. Live

Group Statistics

	Data Treatment	N	Mean	Std. Deviation	Std. Error Mean
Donation Amount	static	33	.1930	.29177	.05079
	live	44	.1798	.27834	.04196

Independent Samples Test

Levene's Test for Equality of Variances		t-test for Equality of Means					
F	Sig.	t	df	Significance	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference

						One-Sided p	Two-Sided p			Lower	Upper
Donation Amount	Equal variances assumed	.674	.414	.203	75	.420	.840	.01326	.06543	-.11709	.14361
	Equal variances not assumed			.201	67.269	.421	.841	.01326	.06588	-.11823	.14475

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
Donation Amount	Cohen's d	.28415	.047	-.405	.498
	Hedges' correction	.28703	.046	-.401	.493
	Glass's delta	.27834	.048	-.404	.499

a. The denominator used in estimating the effect sizes.

Cohen's d uses the pooled standard deviation.

Hedges' correction uses the pooled standard deviation, plus a correction factor.

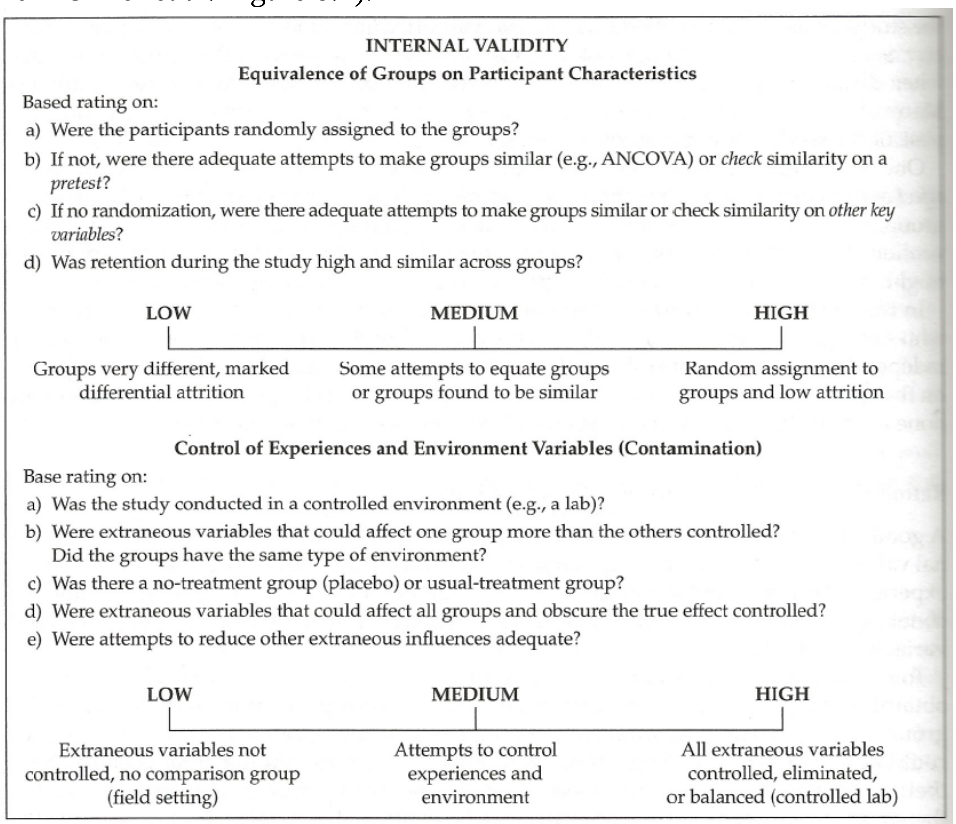
Glass's delta uses the sample standard deviation of the control group.

APPENDIX G: EVALUATION OF INTERNAL AND EXTERNAL VALIDITY

Our design is a 3x3 between-subjects design employing random assignment and a posttest with no pretest. Thus, it is a variation of Design #6 ("The Posttest Only Control Group Design") as described by Campbell and Stanley (1963). Campbell and Stanley recommend that use of the t-test is optimal with this design and that covariance analysis and blocking on "subject variables" can be used to increase the power of the significance test to be similar to that provided by a pretest in other designs.

Internal Validity

Gliner et al. classify internal validity issues into two main types: 1) equivalence of groups on participant characteristics and 2) control of extraneous experience and environmental variables (2009). They produce a method for rating the internal validity of a study, displayed in Figure X (replicated from Gliner et al. Figure 8.2).


INTERNAL VALIDITY

Equivalence of Groups on Participant Characteristics

Based rating on:

a) Were the participants randomly assigned to the groups?
b) If not, were there adequate attempts to make groups similar (e.g., ANCOVA) or *check* similarity on a *pretest*?
c) If no randomization, were there adequate attempts to make groups similar or check similarity on *other key variables*?
d) Was retention during the study high and similar across groups?

LOW — Groups very different, marked differential attrition
MEDIUM — Some attempts to equate groups or groups found to be similar
HIGH — Random assignment to groups and low attrition

Control of Experiences and Environment Variables (Contamination)

Base rating on:

a) Was the study conducted in a controlled environment (e.g., a lab)?
b) Were extraneous variables that could affect one group more than the others controlled? Did the groups have the same type of environment?
c) Was there a no-treatment group (placebo) or usual-treatment group?
d) Were extraneous variables that could affect all groups and obscure the true effect controlled?
e) Were attempts to reduce other extraneous influences adequate?

LOW — Extraneous variables not controlled, no comparison group (field setting)
MEDIUM — Attempts to control experiences and environment
HIGH — All extraneous variables controlled, eliminated, or balanced (controlled lab)

Equivalence of Groups on Participant Characteristics

Our participants were randomly assigned to the groups utilized. Retention across the study was high (306/336 or 91%). 30 participants were removed from the study for failing attention checks. This occurred prior to participants experiencing the experimental manipulation, so the retention rate between experiencing the manipulation and measuring the dependent variable was 0 and thus the same for all experimental groups.

As discussed elsewhere, we had a problem effectively communicating social norm information (our data treatment) to participants. Of the 306 participants who passed the attention checks and experienced the experimental manipulations, 211 saw a data treatment (102 saw static data and 109 saw live data) while 95 saw no data. Of the 211 who saw data, only 78 correctly answered the question intended to test understanding of the social norm data.

Table 50. Breakdown of data treatment manipulation check question.

	"What were other donors donating" manipulation check answer					
Data Treatment	***Correct***	***Incorrect***	***Empty***[17]	***Total***	***Total Non-Empty***	***% Correct***
None			95	95	0	N/A
Static	34	54	14	102	88	33%
Live	44	46	19	109	90	40%
Total	78	100	128	306	178	33%

To investigate whether the number of individuals who correctly answered the manipulation check question was significantly different in the static vs. live groups, we ran a t-test on a variable titled other_donors_correct, which was a binary variable assigned 1 if the participant correctly answered the manipulation check and 0 if not. Results of the t-test indicate that individuals who saw live data were more likely to answer the manipulation check correctly M_{live} = .49, SD = .503; M_{static} = .39, SD=.490), but this result is only marginally significant (p=.085).

Group Statistics

	numeric_data_treatment	N	Mean	Std. Deviation	Std. Error Mean
other_donors_correct	static	88	.39	.490	.052
	live	90	.49	.503	.053

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
other_donors_correct	Equal variances assumed	4.706	.031	-1.378	176	.085	.170	-.103	.074	-.249	.044
	Equal variances not assumed			-1.378	175.998	.085	.170	-.103	.074	-.249	.044

The attrition rate of 67% is high and weakens the internal validity of our study. However, the rate of attrition is not significantly different between treatment groups.

[17] Due to a limitation of oTree with the complexity of our survey flow, we could not require an answer to this question. Individuals who were in the no data treatment were not presented this question; thus, it is empty for all of those participants.

In Appendix X, we report descriptive statistics of all experimental groups on all measures we collected, to support the argument that the groups were not significantly different.

Control of Experiences and Environment Variables (Contamination)

The study was conducted in a controlled online environment via Amazon Mechanical Turk; however, we cannot observe nor control any influences from individuals' physical (non-online) environments. By utilizing random assignment, we do not anticipate any systematic effects of individuals' physical environments. All groups had the same online environment and we are not aware of any extraneous variables that could have affected one group more than the others. We utilized a no-treatment group for both default (active choice) and data (no data) treatments. We collected various control measures to address extraneous variables that could affect all groups and obscure the true effect controlled. We attempted to make all treatments as similar as possible to reduce extraneous influences.

Internal Validity Rating

Based on our evaluation, we consider our equivalence of groups internal validity to be medium and the control of experiences and environmental variables to be medium, for an overall internal validity rating of medium. See the table at the end of this section to see our specific evaluation of each of the eight threats to internal and external validity identified by Campbell and Stanley.

External Validity

Gliner et al. classify external validity issues into two main types: 1) population, involving how participants were selected to be in the study and 2) ecological, or whether the conditions, settings ,times, testers, or procedures are representative of natural conditions and can therefore be generalized to real-life outcomes (2009). They produce a method for rating the external validity of a study, displayed in Figure X (replicated from Gliner et al. Figure 9.3).

Population

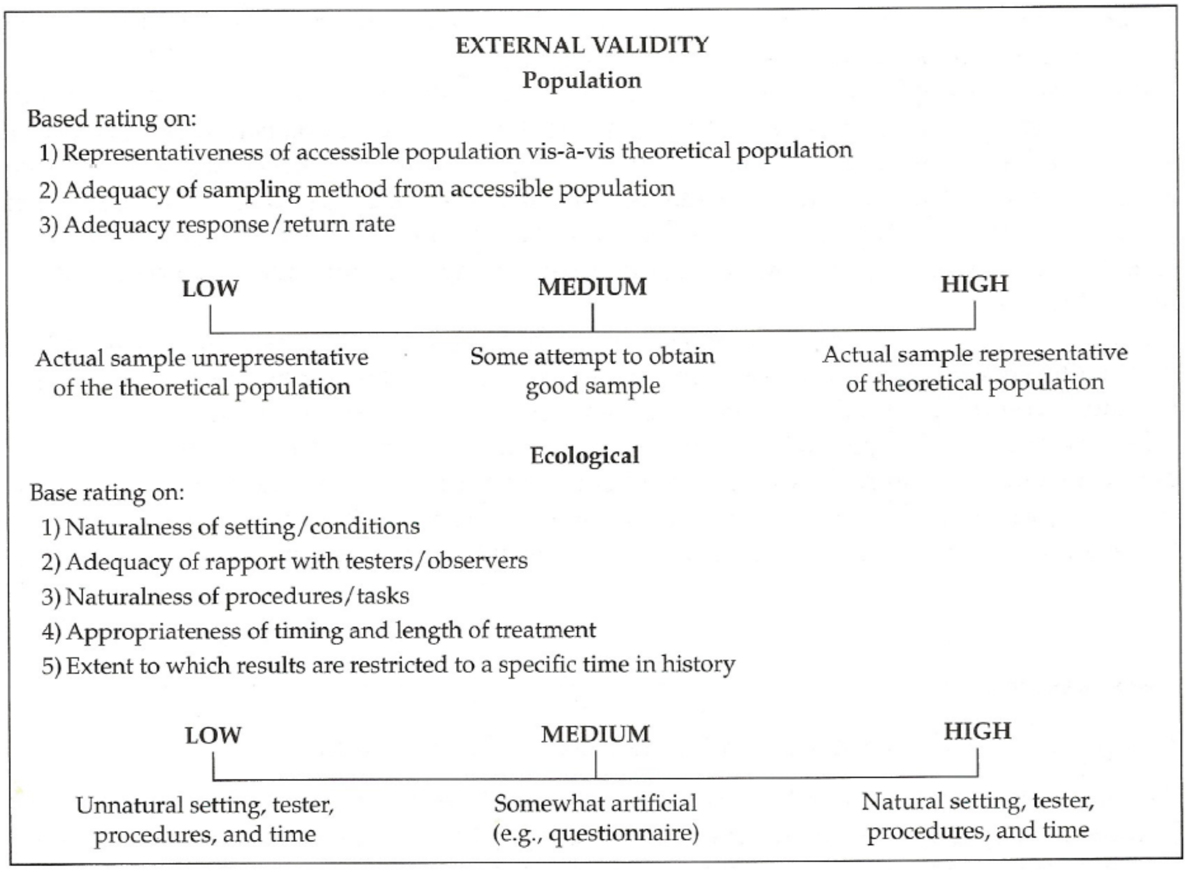
Our theoretical population is all individuals who make decisions online. We utilized Amazon Mechanical Turk (AMT) to sample from this population. AMT is praised for providing more representative samples than other typical sampling options such as college students (Gandullia et al., 2020; Saunders et al., 2016) with a similar level of quality compared to experts and lab subjects (O'Grady et al., 2019). In Appendix X, we provide descriptive statistics of the entire sample and demonstrate that there is diversity in demographic characteristics such as age, gender, income, race, etc. However, we cannot guarantee that our sample is representative of the theoretical population.

Ecological

We are interested in charitable giving decision-making online and replicate this in our setting and conditions. Participants elected to donate real money from their earnings, which is how charitable donations occur in real settings as well (Cherry et al., 2005). Participants had no interaction with the researchers. The survey questions involved in the task were not natural; however, the experimental manipulation of default options and social norm data were both natural in that they are similar to settings provided in the real world. Participants utilized their own computer equipment and accessed the study in a way that was presumably natural and typical for them in their work day as AMT workers. Participants had the option to spend as much time as desired in the experiment and nearly all participants were done with the experiment in under 30 minutes (most in under 15 minutes).

External Validity Rating

Based on our evaluation of external validity, we rate the population as medium and the ecological as medium, for an overall external validity rating of medium.



Detailed Evaluations of Threats to Internal and External Validity

While Gliner et al. classify two types each of internal and external validity, Campbell and Stanley produce specific threats to both types of validity. In the following table, we have described each threat and noted how they have been mitigated (where possible) and which threats remain limitations of our research.

Table of Campbell and Stanley's Eight Threats to Internal and External Validity

In Table X, we present the eight threats to internal and external validity provided by Campbell and Stanley (1963) and indicate how these threats are mitigated within our study and which threats remain limitations of the work.

#	**Extraneous variable**	**Description**	**Relevant for this study?**	**Mitigation**
1	History	specific events occurring between first and second measurement in addition to the experimental variable	No – we have no pretest (no first measurement)	History is mitigated by having no first measurement of our DV
2	Maturation	processes within the respondents operating as a function of the passage of time per se (not specific to the particular events) including growing older, growing hungrier, growing more tired, and the like	No – should be the same for all participants who were included. Also, nearly all participants were done with the experiment in under 30 minutes (most in under 15 minutes).	Maturation is mitigated because all participants spend about the same amount of time and effort in the study (in other words, additional time or effort resulting in maturation processes should not occur differentially for different experimental groups)
3	Testing	the effects of taking a test upon the scores of a second testing	No – we have no pretest	Testing is mitigated because we do not utilize multiple tests
4	Instrumentation	changes in the calibration of a measuring instrument	No – instrument and calculations were the same for all participants	Instrumentation is mitigated because there were no changes or calibrations to the measuring instruments during the study

5	Statistical regression	operating where groups have been selected on the basis of their extreme scores	No – groups were randomly assigned	Statistical regression is mitigated because groups were not selected on the basis of extreme scores
6	Selection	differential selection of respondents for the comparison groups can result in biases	No – groups were randomly assigned	Selection is mitigated because groups were randomly assigned. However, some groups are below the n=30 required for random assignment to be a full mitigation of this issue (due to our limited population because of the chart understanding issue)
7	Mortality	differential loss of respondents from the comparison groups	Yes	Mortality is less likely because groups were randomly assigned and the experimental procedure was very similar for all groups. It is a limitation of our study that the data treatment manipulation was difficult for participants to understand and resulted in the removal of participants from those groups. Our analysis shows that mortality from different treatment groups was not significantly different. Future research should continue to investigate how

				to better communicate social norm information and how to better evaluate understanding of social norm information.
8	Selection-maturation interaction	an interaction between differential selection of participants for the comparison groups and their rates of maturation	No – groups were randomly assigned	Selection-maturation is mitigated through random assignment and the fact that all groups experienced very similar treatments, meaning different rates of maturation were unlikely.
9	Reactive or interaction effect of testing	pretest might increase or decrease the respondents' sensitivity or responsiveness to the experimental variable and thus make the results obtained for a pretested population unrepresentative of the effects of the experimental variable on the unpretested universe from which the experimental respondents were selected	We did not have a pretest. Participants' reactivity to the donation opportunity may have been heightened by the nature of the other data collected, particularly the measure of Social Value Orientation.	While participants may have been particularly primed for a donation opportunity after filling out SVO information, all participants in all conditions filled out the same survey materials. Thus, this reactivity cannot explain any differences among groups. However, it may limit the generalizability of our results. It is worth noting that this concern is at least somewhat mitigated by having participants donate real money, rather than indicate their intention of donation.
10	Interaction of selection and the	the effects of X only hold for that unique population from	Maybe	Hopefully mitigated because AMT provides a varied

	experimental variable	which the experimental and control groups were jointly selected		sample, but we cannot guarantee that these results will generalize outside the AMT setting. Specifically, we cannot guarantee that the kind of person who chooses to be an AMT worker is representative of the kind of person who does not choose to be an AMT worker.
11	Reactive effects of experimental arrangements	which would preclude generalization about the effect of the experimental variable upon persons being exposed to it in a nonexperimental setting	Yes	We cannot guarantee that these results will generalize outside the AMT setting.
12	Multi-treatment interference	Likely to occur when multiple treatments are applied to the same respondents, because effects of prior treatments are usually not erasable. Particularly a problem for one-group designs of type 8 or 9	Each participant experienced only one default and one data treatment.	It is possible that there is an interaction between data and default, however. It is a limitation of the work that our sample size is underpowered to identify interactions between default and data treatments.

APPENDIX H: DETAILS ON EXPERIMENTAL DESIGN

Table 51. Descriptive statistics for donation amount DV for experimental groups

Default Nudge Conditions	*Normative Data Conditions*									
	No Data	*Static Normative Data (Temporally Distal) Low Salience*				*Live Normative Data (Temporally Proximal) High Salience*				**Comparison Row**
		No Mode	Low Mode	General Mode	High Mode	No Mode	Low Mode	General Mode	High Mode	
No default option	Mean $0.29 SD $0.37 N=36	Mean $0.02 SD $0.04 N=6	X	X	X	Mean $0.16 SD $0.32 N=10	X	X	X	**A**
Low Personalized Default = .1 or .25	Mean $0.35 SD $0.38 N=12	X	Mean $0.04 SD $0.05 N=7	X	X	X	Mean $0.08 SD $0.09 N=12	X	X	**B**
General Default = .3 or .5	Mean $0.43 SD $0.41 N=34	X	X	Mean $0.24 SD $0.35 N=10	X	X	X	Mean $0.18 SD $0.26 N=12	X	**C**
High Personalized Default = .75 or .5	Mean $0.27	X	X	X	Mean $0.37	X	X	X	Mean $0.34	**D**

	SD $0.32 N=13				SD $0.31 N=11				SD $0.36 N=10	
Comparison Column	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	

Table 52. Descriptive statistics for likelihood of donation DV for experimental groups

Default Nudge Conditions	*Normative Data Conditions*									
	No Data	*Static Normative Data (Temporally Distal) Low Salience*				*Live Normative Data (Temporally Proximal) High Salience*				**Comparison Row**
		No Mode	Low Mode	General Mode	High Mode	No Mode	Low Mode	General Mode	High Mode	
No default option	Mean 0.53 SD 0.51 N=36	Mean 0.17 SD 0.41 N=6	X	X	X	Mean 0.30 SD 0.48 N=10	X	X	X	**A**
Low Personalized Default = .1 or .25	Mean 0.67 SD 0.49 N=12	X	Mean 0.57 SD 0.53 N=7	X	X	X	Mean 0.67 SD 0.49 N=12	X	X	**B**
General Default = .3 or .5	Mean 0.74	X	X	Mean 0.40	X	X	X	Mean 0.67	X	**C**

	SD 0.45 N=34			SD 0.52 N=10				SD 0.49 N=12		
High Personalized Default = .75 or .5	Mean 0.62 SD 0.51 N=13	X	X	X	Mean 0.73 SD 0.47 N=11	X	X	X	Mean 0.60 SD 0.52 N=10	**D**
Comparison Column	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	

Because the social norm presented in our data always matched the default individuals saw (e.g. for a $0.30 default, participants saw social norm data indicating a donation mode of $0.30), there are many cells untested in what could be a different full factorial design (e.g. participants seeing a $0.30 default and a social norm indicating a donation mode of something other than $0.30). We elected to utilize this design to support our theoretical argument that individuals stick with a default because it reflects a social norm. A necessary condition for this theoretical explanation (outlined in essay 2) is that participants trust that the default does accurately depict a social norm. Thus matching the social norm data with the default seemed a reasonable choice. Future research can investigate how the effects change when participants see a social norm that is different from the selected default.

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