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EDITORIAL

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Why and How Online Experiments Can Benefit Information Systems Research

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Abstract

Online experiments have become an important methodology in the study of human behavior. While social scientists have been quick to capitalize on the benefits of online experiments, information systems (IS) researchers seem to be among the laggards in taking advantage of this emerging paradigm, despite having the research motivations and technological capabilities to be among the leaders. A major reason for this gap is probably the secondary role traditionally attributed in IS research to experimental methods, as repeatedly demonstrated in methodological reviews of work published in major IS publication outlets. The purpose of this editorial is to encourage IS researchers interested in online behavior to adopt online experiments as a primary methodology, which may substitute for traditional lab experiments and complement nonexperimental methods. This purpose is pursued by analyzing why IS research has lagged behind neighboring disciplines in adopting experimental methods, what IS research can benefit from utilizing online experiments, and how IS research can reap these benefits. The prescriptive analysis is structured around key considerations that should be taken into account in using online experiments to study online behavior.

Keywords: Online Experiments, Online Behavior, Internal Validity, External Validity, IS Research

Dorothy E. Leidner was the accepting senior editor. This editorial was submitted on April 18, 2022 and underwent one revision.

1 Introduction

Experiments have been an important method of scientific inquiry since the introduction of the hypothetico-deductive model, which advocates the formulation of testable hypotheses that can be subjected to falsification through empirical observation (Popper, 1959). Their importance has been fostered by the ability of controlled experiments to manipulate the independent variables of interest while controlling for extraneous variance, thereby providing the most rigorous basis for causal inference among all empirical methods. Consequently, experiments have been widely adopted as a rigorous method of empirical investigation in disciplines that study human behavior, such as psychology, economics, and marketing (Falk & Heckman, 2009; Gupta et al., 2018; Viglia et al., 2021).

Parallel to the way the internet has transformed our lives in the past three decades, it has also expanded the boundaries of time and place for experimental research. Whereas experiments were generally limited to physical setups in the 20th century, researchers have leveraged new digital capabilities to conduct experiments that require no physical interaction with participants. These virtual experimental interactions, commonly referred to as online experiments, are not only more efficient than lab experiments, in the sense that data are collected more quickly and inexpensively, but also more externally valid, in the sense that populations of users and situations are better represented. Online experiments, commonly defined as experiments conducted in online environments (Barchard & Williams, 2008; Grootswagers, 2020; Prissé & Jorrat, 2022), are especially useful for studying online behavior. Because people have been gradually moving online to interact, consume, learn, work, and basically engage in any human activity, online experiments have arguably become a more valid way to observe human behavior. The advantages of online experiments have motivated social scientists to forsake their physical labs in favor of virtual ones. Simply put, many researchers have moved online because this is where their objects of investigation are found. For example, psychologists are studying online prosocial behavior (e.g., Sharps & Schroeder, 2019; Zlatev et al., 2020), economists are investigating online market behavior (e.g., Dinerstein et al., 2018; Edelman et al., 2017), and marketing researchers are examining online advertising (e.g., Hoban & Bucklin, 2015; van der Lans et al., 2021).

Although IS researchers have been conducting online experiments in recent years (e.g., Chen et al., 2022; Heimbach & Hinz, 2018; Kummer & Mendling, 2021; Sanyal et al., 2021), the opportunities brought about by this experimental revolution seem to have had a less profound impact on IS researchers, who have lagged in jumping on the online experiment bandwagon. A major reason for this is likely the inferior starting point of experiments, in general, in the IS community. Although some early experiments, such as the Minnesota experiments (Dickson et al., 1977), had a significant impact on the development of the field, the following decades were not characterized by massive adoption of such experimental methodology, despite demonstrated benefits to theory development and knowledge accumulation in neighboring disciplines. Literature reviews have repeatedly shown that experiments were not among the popular methodologies in IS research (Chen & Hirschheim, 2004; Claver et al., 2000; Farhoomand & Drury, 1999; Mingers, 2003; Riedl & Rueckel, 2011). A recent literature review demonstrated that behavioral experiments of any type have remained an underutilized methodology in IS, as reflected in the small number of experimental studies published in the top eight IS journals (i.e., the Senior Scholars' Basket of journals) (Cahenzli et al., 2021). Focusing on economic experiments, Gupta et al. (2018) noted that "the IS domain has been largely lagging in the use of the methodology" (p. 604). To provide some comparative evidence, I searched for the term "online experiment" in articles published in top psychology, marketing, economics, and IS journals. Most frequently in psychology and marketing journals, this term appeared in articles published in *Psychological Science* (30 articles), *Journal of Personality and Social Psychology* (25), *Journal of Consumer Research* (32), and *Journal of the Academy of Marketing Science* (30). In economics, this term appeared most frequently in dedicated experimental journals, specifically *Journal of Experimental and Behavioral Economics* (40) and *Experimental Economics* (33). In contrast, this term was much less frequent in articles published in IS journals: *Information Systems Research* (11), *Journal of the Association for Information Systems* (6), and *MIS Quarterly* (5).

The fact that IS research has not fully benefited from the evolution of online experiments is striking for two main reasons. First, this evolution would not be possible without advances in information technologies, which IS researchers are arguably best positioned to predict, analyze, and understand. The shift of human behavior from physical to virtual is a phenomenon that should interest IS researchers at least as much as other social scientists. Second, IS researchers possess a unique set of technical skills, allowing them to construct environments for online experiments (e.g., websites and mobile apps) that are often superior to those employed by other social scientists in that they are more realistic, functionally richer, better controlled, and more able to capture fine-grained data on user behavior. Therefore, although IS researchers should have been among the early adopters of online experiments, they seem to instead be among the laggards in taking advantage of this emerging experimental paradigm.

This editorial aims at encouraging researchers to realize the potential of online experiments for IS research. To achieve this aim, in the following section, I discuss the insufficient use of all types of experiments in IS research, paying particular attention to the reasons for such low adoption. Then, I highlight the potential benefits of online experiments, both generally and specifically for IS research. Finally, based on a comparative analysis of different experimental setups, I outline key considerations that can guide IS researchers toward getting the most from online experiments.

2 Why Has IS Research Lagged Behind?

IS research has been slow to adopt experiments as a method for testing research hypotheses. This observation pertains to all types of experiments, which are commonly classified as lab, field, or natural experiments. Generally, "all experiments involve at least a treatment, an outcome measure, units of assignment, and some comparison from which change can be inferred and hopefully attributed to the treatment" (Cook & Campbell, 1979, p. 5). Lab experiments are conducted in highly constrained conditions that give researchers full control over the experiment. Field experiments take place in real-world settings, often without participants' awareness of the experiment. Natural experiments are also conducted in real-world settings, but researchers have no control over the assignment of participants to conditions. Due to the absence of random assignment, which is critical for inferring treatment-caused change, natural experiments are considered quasi-experiments (Cook & Campbell, 1979). Given the focus of this editorial on controlled experiments, greater attention is devoted here to lab and field experiments than to natural experiments.

Literature reviews of the methodologies employed in IS research have repeatedly demonstrated the low popularity of experimental methods. Evidently, lab experiments have been employed much less frequently than surveys and case studies in articles published in major IS publication outlets. The reviews show that lab experiments were used in about 7.5% of articles published between 1981-1997 (Claver et al., 2000), 10% of articles published between 1985-1996 (Farhoomand & Drury, 1999), and 18% of articles published between 1991-2001 (Chen & Hirschheim, 2004). The share of field experiments in these methodological reviews was between 1% (Claver et al., 2000) and 2% (Chen & Hirschheim, 2004; Farhoomand & Drury, 1999). Furthermore, these reviews found an increasing trend for both surveys and case studies, but not for experiments (Farhoomand & Drury, 1999). Only later, Riedl and Rueckel (2011) integrated the results of 20 metastudies on research methods to identify an upward tendency in the reliance on surveys, case studies, and lab experiments during 1968-2006. This integrative study revealed an average adoption rate of 10% for lab experiments and 3% for field experiments. A recent literature review by Cahenzli et al. (2021) showed that behavioral experiments of any type were uncommon between 1988 and 2018 in the eight IS journals included in the Senior Scholars' Basket. The number of articles in each journal that used behavioral experiments during this period ranged from 50 in *Information Systems Research* to 0 in *Journal of Strategic Information Systems*.

The natural question at this point is why experimental methods have been less popular in IS than in related disciplines like psychology, economics, and marketing. Teng and Galletta (1991) claimed that "this is probably due to the relative difficulty of conceiving and designing meaningful experiments in MIS research" (p. 56). Riedl and Rueckel (2011) suggested that the low adoption rate of experiments was due to the immaturity of the IS discipline, "since experiments allow for testing the theories generated during the previous decades" (p. 7). In a critique of laboratory research in IS, Introna and Whitley (2000) concluded that lab experiments should be "actively discouraged." They argued that because of the inability of researchers to determine whether the "style of coping in the experiment is a style of coping with the world or a style of coping with the requirements and constraints of the experiment," "most laboratory experiments in information systems research have neither internal nor external validity" (p. 161).

These views suggest that there is probably no single explanation for the low adoption of experiments in IS. First, IS research was originally motivated to study "the application of computers within organizations" (Hirschheim & Klein, 2012, p. 193). Therefore, IS studies from the previous century often focused on the organization as their unit of analysis. Clearly, experiments are a less effective way to study organizations, given that researchers can rarely control the assignment of organizations to different conditions. Organizations are less susceptible to the stringent control needed in controlled experiments. Accordingly, natural experiments remain the most viable experimental method available to IS researchers interested in organizational phenomena. Second, IS researchers frequently adopt a sociotechnical viewpoint to study the interactions among a gamut of social and technical factors (Bostrom & Heinen, 1977; Sarker et al., 2019). Such an inclusive approach fundamentally contradicts the experimental approach, which seeks to maximize internal validity by minimizing all variance beyond that resulting from the manipulation of a small set of independent variables. Essentially, sociotechnical approaches require significantly more breadth than that desirable in experiments, which, at most, investigate interactions among three or four variables. Third, IS researchers seem to be inclined toward constructing relatively complex research models, which often incorporate mediation as a mechanism for understanding the antecedents and consequences of IS. Experimental methods are less suitable for testing mediation, which involves estimating the relationships among endogenous (mediating and outcome) variables, whereas the strength of experiments lies in attributing causality to exogenous (independent) variables. Although experiments can be used to study research models that incorporate mediation, as is frequently done in marketing (Kim et al., 2018), the more complex the model becomes, the less advantageous the experiments are in testing it. For complex models, observational methods that assume all variables are endogenous offer similar analytical benefits with lower execution costs.

The literature offers additional explanations. Similar to strategic management research (Schwenk, 1982), IS research is frequently interested in understanding the behavior of senior managers. However, participants in lab experiments are often university students, who may not be good proxies for managers (Compeau et al., 2012; Wade & Tingling, 2005). Therefore, low population validity is likely another contributing factor to the negative disposition toward lab experiments of researchers interested in the behavior of managers. Another possible explanation is that some IS researchers lack the mastery of experimental design needed to run rigorous experiments. IS researchers may have graduated from schools that placed less emphasis on experimental methods, and experimental design courses are not always included in IS curricula (Adelman, 1991;

Mettler et al., 2014). Therefore, the IS community has been less prepared to take advantage of developments in experimental methods relative to scientific communities that are better versed in the effective use of experimental methods to study human behavior.

3 Why IS Research Can Benefit

The advent of the internet in the mid-1990s has changed human behavior dramatically, as people have moved online to perform many of the activities they had previously completed physically. The COVID-19 pandemic and consequent social distancing have considerably facilitated this shift from physical to virtual (Fink, 2020). However, this eventual shift was not necessarily evident in the instruments and procedures originally employed by researchers to study behavior. Just as TV broadcasts initially started as radio broadcasts with pictures, online studies began as virtual reflections of traditional research activities (e.g., the first online questionnaires were on-screen pen-and-paper questionnaires) (Wade & Tingling, 2005). It took a few years for behavioral researchers to understand the potential benefits of adapting their methods to the features and capabilities of the new medium. This pattern was true for all research methodologies, including observational research (Kozinets, 2002), surveys (Stanton & Rogelberg, 2001), and experiments (Wade & Tingling, 2005). Naturally, researchers studying novel online settings such as electronic markets, social networks, and crowdsourcing had to move online to observe the phenomena of interest. However, some researchers also chose to move online for methodological reasons. For instance, relative to mail surveys, online surveys offer the benefits of lower administration costs, faster response times, and greater process automation.

Relative to lab experiments, conducting experiments online primarily offers the benefits of greater efficiency and external validity, particularly in terms of population and ecological validity. Fewer resources are needed in online experiments because there is no need to set up a physical lab with up-to-date computing equipment, there is no need for research staff to run the experiment, and there is no need to recruit and coordinate participants who must travel to the lab. Considerable time is saved because participants can perform the experimental tasks in parallel (there is no physical capacity limitation), using their own devices in their natural environments. Considerable funds are thus saved because payments to participants can be lower given their lower participation costs. Population validity is enhanced because participants can be sampled from the global population rather than only from the population that can physically travel to the lab. Ecological validity is enhanced because the experiment better represents real-world situations.

These advantages have become more pronounced following the introduction of online labor (i.e., crowdsourcing) platforms such as Amazon Mechanical Turk (MTurk) and Prolific, which enable paying "workers" for performing online tasks. Such participant-recruitment platforms are complemented by experiment-hosting platforms, such as Gorilla, which provide configurable environments for building and running online experiments. Running experiments on such online platforms requires no expensive lab, advanced equipment, supervisory staff, participant recruitment, coordination, or travel. Experiments with hundreds of participants can be performed within a few hours instead of taking several full days, and the total payment to participants can be hundreds instead of thousands of dollars (of course, payment costs are naturally much lower if student participants are receiving course credit for their participation in physical or online experiments). Such online platforms allow researchers to sample from a global population, using various criteria (e.g., age, background, and country), instead of sampling university students, for example, who seldom represent the population of interest. Consequently, through using such online platforms, researchers can effortlessly obtain larger samples, which thereby increase statistical power, allowing them to rely more heavily on between-subjects designs and avoid sequence effects arising from within-subjects designs. The exposure of participants to multiple conditions in within-subjects designs, which may lead to confounding due to such factors as learning, fatigue, and knowledge of hypotheses, can be avoided when the sample size can be easily increased. Such benefits can also be realized without adversely affecting data quality, as online experiments have been shown to yield results consistent with those obtained in lab experiments (Arechar et al., 2018; Dandurand et al., 2008; Horton et al., 2011; Prissé & Jorrat, 2022).

Such technological and methodological advances could allow IS researchers to close the gap in the adoption of experiments, as IS researchers are ideally positioned to capitalize on these particular advances. The internet is fundamentally a technological innovation. As such, IS researchers are positioned to predict, analyze, and understand the implications of this innovation for human behavior better than their colleagues in less technology-savvy disciplines. Given their interest in the behavior of computer users, IS researchers should have a strong motivation to move online in pursuit of their research interests. Further, IS researchers possess the technical knowledge and skills to develop websites and mobile apps that can serve as highly valid environments for online experiments. Field and natural experiments offer greater ecological validity, given their real-world nature, but at the cost of lower control. While lab experiments are highly controlled, the tasks performed by participants are often artificial and synthetic, making them markedly different from real-world tasks. The familiarity of IS researchers with web and mobile technologies can allow them to develop online environments for experiments that are highly realistic, interactive, and detailed, without sacrificing control over the manipulation of independent variables and the measurement of dependent variables. Instead of asking participants to project how they might behave under different conditions, such online environments allow researchers to observe the real behavior of participants under given conditions. For instance, instead of measuring the intention to download (Chen et al., in press) and login to (Krasnova et al., 2014) mobile apps in hypothetical scenarios, participants can be asked to download (Fink & Geldman, 2017) and login to (Steinbart et al., 2016) real mobile apps developed for experimental purposes. IS researchers are likely more capable than, for example, their social science colleagues of developing such realistic environments for online experiments. Therefore, IS researchers have the capacity to close the experimental gap with neighboring disciplines and even gain a methodological advantage that could strengthen the distinctiveness of IS research.

Nevertheless, IS research has continued to lag behind reference disciplines in the adoption of experimental methods (Gupta et al., 2018), which have remained underutilized in IS research (Cahenzli et al., 2021). Against this background, the aim of this editorial is to offer guidance to IS researchers on how online experiments can advance the state of the art in IS research.

4 How IS Research Can Benefit

Before discussing the specifics of how IS research can benefit from online experiments, clearer definitions are needed. Fundamentally, all types of experiments can be performed online (Karahanna et al., 2018). A broad perspective may suggest that lab, field, and natural experiments can all be considered online experiments if participants perform tasks online during the experiment (e.g., participants engage in e-commerce, social networking, online learning, or online dating). However, a narrower definition of online experiments may be needed to facilitate their effective use in IS research. An "online lab experiment" can be defined as an experiment in which participants perform tasks online while being situated in a physical lab (Jung et al., 2017). In such a setting, participants use either computing devices existing in the lab or their own devices (e.g., smartphones, tablets, or laptops) to access the online environment in which the experimental tasks are performed. An "online field experiment" can be defined as an experiment in which participants perform real tasks online in their natural environments. Because the present prescriptive analysis focuses on controlled experiments, natural experiments are excluded, although they can similarly be conducted online. These definitions set the boundaries for defining an "online experiment" more narrowly as an experiment in which participants perform experimental tasks online in their natural environments. Online experiments are different from online lab experiments because tasks are performed off-site by remote participants in their natural environments rather than by on-site participants in a physical lab. Likewise, online experiments are different from online field experiments because tasks are artificial and designed for experimental purposes rather than real-world tasks, and because participants generally know that they are taking part in an experiment (e.g., they have expressed their informed consent to participate). Table 1 highlights the similarities and differences among these three experimental setups.[1]

As presented in Table 1, the key advantage of an online lab experiment is the researcher's full control over the task and external environment. For instance, the researcher controls whether participants are alone or in the presence of others during task execution. Similarly, the researcher can ensure that participants are not multitasking during the experiment. Such control is impractical unless there is physical interaction with participants. Therefore, an online lab experiment affords the highest level of internal validity, confirming that the observed variance in dependent variables is caused by the experimental manipulations rather than by unobserved factors. The key disadvantage of an online lab experiment is the need for significant resources, as lab experiments are costly and time-consuming. The key advantage of an online field experiment is high external validity, particularly ecological validity, as participants perform real tasks in real contexts. Its key disadvantage is limited control over the experiment due to the reliance on a mediating organization that owns the online environment.[2]

[1] Karahanna et al. (2018) similarly analyzed different experimental setups and suggested that lab, field, and natural experiments can have online variants. The term "online experiment" here can be mapped to their online variant for lab experiments.

[2] An online field experiment can be more controlled if the researcher develops and runs the online environment (e.g., an online learning website).

An online experiment is sort of a hybrid setup. It can strike a better balance between internal and external validity. It offers a low-cost alternative to lab experiments, and it requires no collaboration with a third party. The following paragraphs highlight important considerations that researchers are advised to take into account in planning, designing, constructing, running, and analyzing online experiments. These considerations can just as well be used by reviewers and editors in evaluating online experimental studies. Table 2 provides a summary of these considerations, alongside questions that can guide their application.

Table 1. Characteristics of Different Experimental Setups

	Online lab experiment	**Online experiment**	**Online field experiment**
Defining characteristics	Participants perform ***experimental tasks*** online in a ***physical lab***	Participants perform ***experimental tasks*** online in their ***natural environments***	Participants perform ***real tasks*** online in their ***natural environments***
Nature of task	Artificial	Artificial	Real
Location of participants	Lab	Remote	Remote
Internal validity: control of task environment	High: task environment is fully controlled	High: task environment is fully controlled	Moderate: task environment can be controlled to the extent permitted by the environment owner
Internal validity: control of external environment	High: external environment is fully controlled	Moderate: external environment cannot be controlled; it can be indirectly observed via self-reports of participants	Low: external environment cannot be controlled
External validity: population validity	Low: participants are often university students	High: participants can be sampled from diverse populations, although they are limited to users of online labor platforms	Moderate: participants are limited to users of the real-world environment
External validity: ecological validity	Low: an artificial task in a lab environment	Moderate: an artificial task in a natural environment	High: a real task in a natural environment
Participant awareness	High: Participants are aware of the experiment	High-moderate: participants are commonly aware of the experiment	Low: participants are commonly unaware of the experiment
Demand characteristics	High: the task is performed in a lab and there is physical interaction with research staff	Moderate: no physical interaction with research staff	Low: no awareness of the experiment
Sample size	Relatively small: typically, several hundred participants	Medium: typically several hundred to several thousand participants	Large: limited only by the number of real users
Attrition	Low: participants seldom dropout	Moderate: can be substantial if the task is demanding	Low-moderate: consistent with real user behavior
Participant compensation	High: monetary compensation needs to be significant (unless course credit is given)	Low: monetary compensation can be relatively small	Unnecessary
Costs	High: costs of environment development, lab equipment, research staff, and participant recruitment and compensation	Moderate: costs of environment development and participant compensation	Low: most costs are incurred by the environment owner
Duration	Long: contingent on lab availability and capacity	Short: no capacity limitations	Short: no capacity limitations
Main advantage	High internal validity	Balance between internal and external validity	High external validity
Main disadvantage	Considerable resources are needed	Limited control over participants	Limited control over the experiment
Examples	Deng et al. (2022), Fink & Papismedov (in press), Huang et al. (2018)	Adjerid et al. (2018), Ananthakrishnan et al. (2020), Kummer & Mendling (2021)	Lee et al. (2020), Li et al. (2021), Sun et al. (2019)

Table 2. Key Considerations for Online Experiments

No.	Consideration	Guiding questions
#1	Choose the most effective experimental setup	• Is an online experiment the most suitable setup for answering the research question? • Is there an option to collaborate with a third party that runs an existing online environment? • Does the research team possess the resources to develop an online environment for real use? • Does the research context limit the development of a real online environment? • Is there a need to control the surroundings in which the experiment takes place?
#2	Aim for high ecological validity	• Are the experimental task and environment comparable to real-world tasks and environments in the specific context of interest? • Is the online environment overly simplistic and artificial? • Have the marginal costs and benefits of higher ecological validity been considered? • Does higher ecological validity introduce endogeneity concerns? • Are ethical standards maintained?
#3	Record user behavior	• Does the experimental environment collect all possible data on user behavior? • Are the clickstream data utilized to provide information about choices, durations, and search behavior? • Does the database record all information displayed during task execution? • Are self-reports of attitudes and intentions collected to complement behavioral data?
#4	Ensure the quality of behavioral data	• Are data quality safeguards introduced to mitigate agency problems? • Are attention check questions included to screen out inattentive participants? • Are qualification systems used to prescreen participants based on their past performance? • Are response patterns analyzed to detect low-quality data? • Is attrition controlled and mitigated?
#5	Adopt a multi-experiment approach	• Has a multi-experiment approach been considered? • Are the economies of scale of online experiments leveraged to replicate the fundamental effects and dynamically expand the research model? • Have opportunities to test additional variables, relationships, or situations been exhausted?
#6	Become familiar with available online platforms	• Are online labor platforms utilized to recruit participants? • Can the online environment for the experiment be constructed using general cloud infrastructures rather than specialized hosting platforms? • Is complete control over the experiment maintained? • Have the available options and their strengths and weaknesses been analyzed in light of research needs?
#7	Maximize experimental rigor	• Are all relevant control mechanisms employed to maximize experimental rigor? • Is random assignment of participants to conditions automatically executed by the online environment? • Are additional procedures needed to ensure the effectiveness of random assignment?

Consideration #1: Choose the most effective experimental setup. An online experiment, as defined above, is not necessarily the most suitable setup for studying online user behavior. In certain contingencies, online lab or field experiments may be more effective, in the sense of allowing the researcher to answer the research question of interest. If the researcher can collaborate with a third party that runs an online environment, such as a website or mobile app, and there is an opportunity to manipulate interesting independent variables, preferably through random assignment, and to observe dependent variables reflective of user behavior in a real-world setting, then an online field experiment will often be the most beneficial setup.

Field experiments are likely to be evaluated more favorably by reviewers and editors because of the real nature of the task and consequent high external validity. However, such collaborations with online providers are not easy to establish, as evident from the small number of field experiments in past decades (Chen & Hirschheim, 2004; Claver et al., 2000; Farhoomand & Drury, 1999; Riedl & Rueckel, 2011). Such collaborations have become more challenging due to growing concerns over user privacy and stricter organizational policies. An online field experiment may be a viable alternative, even in the absence of a collaborator, if the research team possesses the knowledge, skills, and resources to develop a real online environment for experimental purposes. The appeal of this alternative is also contingent on the specific context, as some contexts (e.g., online gaming and online learning) are more susceptible to the development of real online environments than others (e.g., online banking and online dating).

If an online field experiment is not a viable option, the researcher should consider whether it would be more effective to ask participants to complete the online experimental tasks in their natural environments or in a physical lab. Using remote participants is more efficient, but it can be less effective if there is a need to control the surroundings in which the experiment takes place. For instance, my research students are currently running several experiments that investigate the effects of interruptions on online decision-making. In this line of research, we differentiate between on-screen interruptions and interruptions that originate from external sources. In the case of on-screen interruptions, an online lab experiment offers no significant advantages. By contrast, in the case of external interruptions, it is practically impossible to manipulate the type and magnitude of such interruptions in participants' natural environments. Consequently, we study on-screen interruptions in online experiments and external interruptions in online lab experiments. Researchers are encouraged to be cognizant of cases in which online experiments are not the most effective setup, as online experiments are not a panacea for experimentally studying online behavior.

Consideration #2: Aim for high ecological validity. An important goal in developing the online environment for experimental tasks is high ecological validity. Ecological validity is a type of external validity and refers to "the appropriate generalization from the laboratory to real-life situations" (Graziano & Raulin, 2010, p. 164). Such generalization is high to the extent that the experimental task and environment are comparable to real-world tasks and environments in the specific context of interest. For example, if the experiment is designed to investigate online consumer behavior, then the task can be to choose a preferred product or service after comparing multiple alternatives with multiple attributes, and the online environment can simulate popular e-commerce environments (e.g., Amazon.com, eBay.com, or Hotels.com). If the experiment is designed to study online learning, then the task can be to acquire new knowledge by watching, reading, or listening to content, and the online environment can simulate popular e-learning environments (e.g., Google Classroom, Udemy, Coursera, or Zoom). Importantly, while researchers should aim for high ecological validity, they should not seek to maximize it. Artificial experimental environments need not provide the same user experience as real-world environments because the marginal costs of reaching this goal, particularly development costs, considerably outweigh the marginal benefits. Moreover, reaching this goal can be counterproductive if the rich functionality generates variance along multiple dimensions, which complicates the estimated models and introduces endogeneity concerns that increase the difficulty of inferring causality. Maximizing ecological validity may also compromise the ability to maintain ethical standards, such as the need for informed consent (Barchard & Williams, 2008; Mason & Suri, 2012). Therefore, researchers should pursue high ecological validity yet remain aware that more is not always better. This consideration is particularly important for IS researchers, given their technical advantage over other social scientists in constructing more realistic tasks and environments for online experiments. Whereas researchers in less technical disciplines may resort to relying on simplistic environments, asking participants to report what they are likely to do in various scenarios, IS researchers can allow participants to engage with environments that are considerably more realistic and authentic. For a research community that constantly seeks its uniqueness, the ability to design realistic online experiments can be an important advantage.

Consideration #3: Record user behavior. Although participants' awareness that they are being studied is likely to introduce certain biases (e.g., demand characteristics), high ecological validity enables participants to exhibit their natural behavior, similar to how they choose products, play games, or interact with others in real online environments. Given the opportunity to observe user behavior, researchers should aim to collect as much data on user behavior as possible. This aim should guide the construction of the experimental environment. Researchers are encouraged to think broadly about the behavioral data that can be collected and to incorporate the functionality necessary to record these data into the experimental system. Such an approach reduces the likelihood of missed opportunities to collect data whose importance is recognized post hoc. The fundamental source of behavioral data is the clickstream generated during task performance. The clickstream can provide information about participants' choices, the time it took to make these choices (durations calculated from clickstream data are frequently overlooked as interesting variables), and the search behavior that preceded these choices. In an e-commerce environment, for instance, the clickstream can provide information about the alternatives viewed, the alternative chosen, and the decision time. Beyond the clickstream, it is also critical to meticulously record the information displayed to the participant during task execution. For instance, if the participant is asked to choose an alternative from a set of alternatives, it is vital to record all available alternatives and the order in which they were displayed, in addition to the chosen alternative. Failure to do so may result in low internal validity because of alternative explanations (e.g., ranking effects) that could otherwise be controlled. Importantly, this guideline does not suggest that researchers should refrain from collecting data about participants' feelings, attitudes, and intentions, as such data can be reflective of constructs that serve as key mediators, moderators, or outcomes in research models. Instead, it is suggested that self-reports of attitudes and intentions should complement behavioral data, rather than stand on their own due to difficulties in developing realistic online environments.

Consideration #4: Ensure the quality of behavioral data. An important downside of online experiments is the inability to directly observe participants. Although participant behavior can be recorded through various measures, researchers cannot ascertain whether participants are performing to the best of their abilities. For instance, participants may multitask or otherwise devote limited attention to the experiment. Participants may reduce cognitive effort by engaging in satisficing behavior, opting for the first minimally acceptable alternative that comes to mind in a manner that is not reflective of their real behavior in similar situations (Krosnick, 1991; Oppenheimer et al., 2009).

Particularly when participants are recruited on online labor platforms such as MTurk, they may be motivated to maximize income while minimizing effort. Although comparative studies have demonstrated that results obtained from MTurk are similar to those obtained from traditional samples (Chandler et al., 2014; Goodman et al., 2013; Paolacci et al., 2010), researchers need to be aware of this "agency problem" and seek to mitigate it by introducing data quality safeguards. An important safeguard is the inclusion of attention check questions, which screen out participants who are not paying close attention to instructions and tasks (Goodman et al., 2013; Paolacci et al., 2010; Peer et al., 2014). However, such questions may disrupt the natural flow of a study and filtering out participants after data collection may diminish sample size, lead to unbalanced groups, or introduce selection bias (Peer et al., 2014). Instead of screening many participants post hoc, researchers should prescreen participants by using the qualification systems of online platforms to recruit participants based on their past performance, such as using the MTurk approval rate to recruit only workers whose previous tasks were approved at least 95% of the time (Chandler et al., 2014; Peer et al., 2014).

Finally, researchers can detect low-quality data by analyzing response patterns, targeting responses characterized by a lack of variance or short response times (Mason & Suri, 2012). In so doing, researchers take advantage of the ability of online environments to record user behavior. Another potential problem related to low participant commitment is attrition (Arechar et al., 2018; Dandurand et al., 2008; Horton et al., 2011). Substantial dropout of participants during the experiment or endogenous dropout (i.e., unevenly distributed across conditions) can bias the results. Such attrition bias should be mitigated primarily by ensuring that tasks are not overly demanding and by creating incentives for participants to complete the experiment. Particularly in online experiments, researchers need to record attrition and demonstrate its lack of influence.

Consideration #5: Adopt a multi-experiment approach. The use of multiple experiments in a single paper appears to be less common in IS than in psychology and marketing. A multi-experiment approach allows the replication of fundamental effects while additional variables, interactions, or situations are tested. Notwithstanding these merits, IS researchers frequently draw conclusions on the basis of a single experiment, possibly due to the considerable resources needed to run multiple experiments on user behavior in a lab. Online experiments allow IS researchers to close this gap. Economically, relative to lab experiments, online experiments primarily reduce variable costs rather than fixed costs. Developing the online environment for an experiment bears roughly the same fixed costs, irrespective of whether the experiment takes place on-site or off-site. However, the variable costs of an additional participant or an additional experiment are significantly lower in the off-site setup. Therefore, similar to information goods (Shapiro & Varian, 1999), there are significant economies of scale in online experiments. IS researchers can leverage these economies of scale to gain the benefits of a multi-experiment approach. Specifically, IS researchers can strengthen the validity and robustness of their findings by replicating the fundamental effects of interest (Dennis et al., 2020) and can dynamically expand their research models to include additional variables, relationships, or situations. In so doing, IS researchers should be able to produce experimental papers with greater theoretical and empirical depth.

Consideration #6: Become familiar with available online platforms. Although it is possible to run online experiments with traditional participant samples such as university students, capitalizing on the benefits of online experiments largely depends on the utilization of online labor platforms, such as MTurk and Prolific, to recruit participants. Researchers may also wish to utilize experiment-hosting platforms, such as Gorilla, [3] to construct the online environment. However, experiment-hosting platforms may be less appealing to IS researchers than to other social scientists because IS researchers are likely to be knowledgeable and skilled in using general cloud infrastructures, such as Amazon Web Services (AWS), to develop online environments. Using such infrastructures can allow IS researchers to maintain complete control over the experiment rather than being constrained by the functionalities of an experiment-hosting platform. Irrespective of whether participant-recruitment platforms or experiment-hosting platforms are employed, researchers should become acquainted with the available options, their unique features, and their strengths

[3] A cloud-based platform that helps researchers create and deploy behavioral experiments online (https://gorilla.sc/).

and weaknesses. For instance, recent findings suggest that while Prolific is superior to MTurk in terms of data quality, MTurk is more widely used, probably due to lower costs and higher levels of familiarity (Peer et al., 2022). Given such differences, researchers should adopt a contingency approach and identify the online platform, or combination of platforms, that best fits their research needs.

Consideration #7: Maximize experimental rigor. Lastly, taking advantage of online experiments does not constrain researchers' ability to maximize experimental rigor. Therefore, researchers need not sacrifice any control mechanism in their toolbox to benefit from online experiments. For example, randomization is considered the most powerful tool in experiments because it can control for threats to internal and external validity, control for many variables simultaneously, and even control for unknown factors (Graziano & Raulin, 2010). Random assignment of participants ensures the equivalence of experimental groups, allowing researchers to conclude that variance in dependent variables is caused by the manipulations of independent variables and not by confounding variables. In most online behavioral studies, random assignment is automatically executed during the experiment by the online environment, such as when participants are randomly assigned by the system to different information displays. Therefore, random assignment is generally not constrained by where participants are located. In specific cases, particularly when random assignment needs to be controlled externally, additional procedures may be necessary to ensure the effectiveness of random assignment. For instance, if participants need to be randomly assigned to different devices (e.g., smartphones or desktops), it will be easier to ensure that participants are using the device assigned to them if they can be observed in the lab versus when they are remote. To accomplish that in an online experiment, technical procedures (e.g., a device-switching procedure) should be put in place to confirm that participants are indeed using the assigned device (Ilany-Tzur & Fink, 2019). Such additional procedures can allow researchers to maximize experimental rigor while capitalizing on the benefits of online experiments.

5 The Road Ahead

The shift in human behavior from physical to virtual is expected to intensify in the future. This trend is likely to make online experiments a valuable methodology for researchers interested in understanding human behavior, and certainly for those aiming at untangling causal relationships between context and behavior. Given that IS researchers are at the forefront of efforts to understand how digital technologies shape behavior, it will become challenging for researchers interested in user behavior to remain relevant to research and practice unless they master online experiments as a vehicle for empirically investigating online behavior. Online experiments, however, should be regarded as one of several important methodologies. When the variables of interest are not susceptible to manipulation, observational or survey methods may be preferred. Online experiments may also be less effective than online lab experiments when the external environment must be controlled and less effective than online field experiments when real-world environments can be manipulated. Therefore, while the greater adoption of online experiments is encouraged, they should not be regarded as the only viable methodology for studying online behavior.

If IS researchers do choose to use online experiments, the key considerations outlined above and summarized in Table 2 can enhance the effectiveness of such endeavors. These considerations may facilitate the ability of researchers to capitalize on the benefits of online experiments, including their ability to tap into the phenomenon of interest with greater ecological and population validity. Accordingly, online experiments can overcome the traditional trade-off between internal and external validity, where the ability to draw causal inferences needs to be sacrificed to better represent real-world situations. Online experiments can allow researchers to maintain the rigor of their empirical investigations while moving the research settings closer to the natural environments of online users.

To facilitate the adoption of online experiments, the IS community needs to ameliorate some of the barriers that have hindered the widespread adoption of experimental methods in IS research, as discussed in Section 2. Naturally, the community should not move in the direction of allowing methodological considerations to dominate the formulation of research questions; likewise, the basic characteristics of IS research, such as the frequent focus on the organization as the unit of analysis, need not change in the face of methodological advances. However, some barriers can be alleviated. For instance, knowledge of experimental design, particularly in online settings, should become integral to IS curricula at all levels. IS research students should be familiar with the principles of experimental design and with the technologies and platforms available to implement such principles in the study of online behavior. Undergraduate IS students need to acquire the knowledge and skills to design, run, and analyze online experiments because they are likely to encounter the use of such methods in industry to improve the usability and effectiveness of online platforms. Alleviating such barriers, while making IS researchers more aware of what they have to gain from online experiments, can enhance the uniqueness and contribution of IS research.

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