EXPLORING RELAPSE IN THE HUMAN LABORATORY: NOTES FROM A SYMPOSIUM

Andrew R. Craig[1], Ryan T. Kimball[2], Valdeep Saini[3], Sean W. Smith[1], & William E. Sullivan[1]

[1]SUNY Upstate Medical University
[2]University of Saint Joseph
[3]Brock University

"Relapse" broadly refers to the recurrence of pre-intervention behavior patterns when some aspect of the intervention is changed. Because relapse poses a challenge to the long-term maintenance of behavior-analytic treatment effects, a considerable amount of basic, translational, and applied research has been dedicated to understanding why it happens and what can be done to prevent it. A growing proportion of that research is conducted with humans in laboratory settings. Human-laboratory analyses of relapse, however, come packaged with nuances that may not be immediately obvious to readers or researchers who aim to establish new lines of related research. This project is a symposium of sorts that focuses specifically on these nuances. Four researchers were asked to reflect on their experiences conducting laboratory analyses of relapse with human participants. The goal of this project was to provide information that may be helpful to researchers who may be interested in developing lines of human-laboratory research on relapse. This information included idiosyncratic factors researchers consider when studying relapse of human behavior in the laboratory as well as the strengths and weaknesses of various laboratory methods for doing so. The researchers' perspectives are synthesized in a post-symposium discussion. We encourage further development of a tight-knit community of human-laboratory relapse researchers to help overcome barriers to research in this context.

Keywords: human laboratory, human operant, relapse, resurgence, renewal, reinstatement

Behavior-analytic interventions aim to modify behavior. The goal may, on the one hand, be to increase the frequency of socially appropriate, adaptive behavior. On the other hand, the goal of an intervention may be to reduce the frequency of socially inappropriate, maladaptive behavior. An intervention may even work toward both of these goals simultaneously. Functional communication training, for example, establishes prosocial communication as a replacement for topographies of challenging behavior like aggression, self-injury, and property destruction (Greer et al., 2016). Whatever the short-term aim of an intervention, the ultimate goal is for treatment effects to maintain over time. Unfortunately, behavior change often is difficult to sustain: Various environmental circumstances may cause the behaviors we want to see more of to decrease and the behaviors we want to see less of to increase (e.g., Briggs et al., 2018; Kranak & Falligant, 2023; Muething et al., 2020). Reducing the availability of alternative reinforcement may produce relapse that is termed "resurgence." Changing the context in which treatment is arranged (e.g., the physical context in which treatment occurs or the individual administering treatment protocols) may result in relapse that is termed "renewal" of pre-intervention behavior patterns. "Reinstatement" is a form of relapse that may occur if, following a period of time without the reinforcer that previously maintained behavior, that reinforcer or stimuli correlated with it are re-presented. This list is not exhaustive (for a more thorough review of sources of relapse, see Wathen & Podlesnik, 2018), but it may provide some insights into the varied challenges that face

Author Note: Address correspondence to: Andrew R. Craig (email: craig.andrew.ryan@gmail.com), Golisano Center for Special Needs; SUNY Upstate Medical University, Syracuse, NY.

Authors names in the byline are listed in alphabetical order by last name. All authors contributed equally to this work. The authors encourage researchers to contact them about collaborating on future human-operant research projects

Other Author Information

Kimball: rkimball@usj.edu

Saini: vsaini@brocku.ca

Smith: smithse@upstate.edu

Sullivan: sullivaw@upstate.edu

practitioners in the effort to produce durable behavior change.

Relapse is a clinically relevant outcome for a host of problematic human behavior such as aggression, property destruction, self-injury, and alcohol and substance misuse. Inasmuch, a wealth of basic, translational, and applied analyses has been dedicated to understanding the circumstances under which behavior is likely to relapse and the variables that affect relapse when it occurs (for review, see Kimball et al., 2023; Nevin et al., 2017; Podlesnik & Kelley, 2015; Shahan & Craig, 2017). These programs of research offer a strong and timely example of how research that is conducted in basic, translational, and applied settings may evolve in a coordinated manner that is beneficial for all those involved. For example, studies that have translated work on relapse from the basic and translational laboratories into clinical practice have made breakthroughs in terms of refining strategies to reduce post-treatment resurgence of problem behavior in children (e.g., Fisher et al., 2018, 2019). Moreover, clinical problems related to resurgence have inspired translational and basic research that has provided new insights into behavior process (e.g., Brown et al., 2020; Nevin et al., 2016; Sweeney & Shahan, 2013).

A growing proportion of the relapse literature has been conducted in the human laboratory. This research setting may be particularly well suited for translational research aimed at extending outcomes initially identified using nonhuman animal subjects into human populations. Before translating technologies developed in the basic laboratory into applications with socially significant behavior, prudent and important intermediary steps are to ensure cross-species generality of the effects of that technology and to identify experimental parameters that are likely to have desired effects in humans. Practical reasons likely also contribute to the recent increased focus on human-laboratory research on relapse. Relative to animal-laboratory or clinical research, human-laboratory research often requires fewer resources like space, highly trained personnel, money, and specialized equipment. Moreover, it may be possible to collect an entire dataset during one or a few visits to the human laboratory, whereas datasets may take weeks or months to collect in other research settings.

Although the human laboratory offers a research setting that may seem on the surface to be particularly approachable to a wide range of investigators who are interested in relapse, human-laboratory research is not without its nuances.

Human behavior is complex and susceptible to extra-experimental influences, like history effects or participants' self-imposed rules, to which researchers rarely have access and over which they rarely have control. This complexity may affect human-laboratory data in unexpected ways, thus requiring careful and thoughtful experimental analysis to circumvent issues that otherwise may be disastrous for a study. Moreover, a casual survey of the literature on human-laboratory analyses of relapse or any other behavior process is likely to reveal striking heterogeneity of the procedures that different groups of researchers use. Human-laboratory analyses of relapse may take place in a controlled laboratory setting or in participants' natural environments; may involve participants manipulating physical objects like microswitches, pressing buttons on a computer keyboard, or pressing objects on a touch screen; and may involve delivering point, monetary, tangible, or edible reinforcers (e.g., Fuhrman et al., 2022; Lambert et al., 2015; Saini et al., 2021; Robinson & Kelley, 2020; Thrailkill, 2023). The variables that impact researchers' decision making concerning the procedures they use may not be made clear to readers and may further be obfuscated by procedural variation between (and sometimes even within) research groups. Publication bias may also complicate consumption of the literature on relapse in the human laboratory. The procedures that generate publishable data often are built on the backs of data sets and procedures shoved in the file drawer, never to see the light of day.[1]

Readers who are interested in developing novel lines of relapse research in the human laboratory may have experienced some discomfort reading the previous paragraph.

1 Estimation of how often data from human-laboratory analyses of relapse end up in the file drawer is difficult, and research on this topic is needed. Anecdotally, however, each of the contributing authors are able to report that they have added several such datasets to their respective file drawers.

"Given the complexities of human behavior and the nuances of human-laboratory research," they might wonder, "where do I start?" One strategy for overcoming barriers to human-laboratory research on relapse is for those who have boots on the ground to have open and frank conversations about their experiences with research in this setting. Such conversations may help new researchers avoid pitfalls others have experienced, identify and adopt laboratory practices that others have found critical for success, and ultimately develop fertile programs of research.

To this end, the present paper offers a symposium of sorts on this topic that includes perspectives on human-laboratory research on relapse from four researchers who have extensive experience working in this research setting: Drs. Valdeep Saini, William Sullivan, Ryan Kimball, and Sean Smith. I (Dr. Andrew Craig) will serve as the chair and discussant of this symposium. I asked each of these researchers to share their thoughts about human-laboratory research on relapse. I gave them the following prompt:

> "I think there should be a lot of flexibility for all of you to tell the stories you want to tell. Think of this like a symposium. What is the talk you would present if asked to talk about your experiences as a human-operant researcher?"

In the Discussion, I will highlight themes that emerge from the researchers' responses to this prompt.

A Note on the Development of This Symposium

As in the case of many other joint scientific ventures, the group participating in this symposium came together based on mutual interests and some degree of serendipity. In their individual contributions below, each researcher will begin by presenting background on their training to provide context about how and why they became involved in human-laboratory research. Synthesized across researchers, these background sections will clarify points of overlap in the researchers' training and professional appointments.

As for myself (still Andrew Craig), my graduate training at Utah State University focused on basic laboratory analyses of resistance to change and relapse using rat and pigeon subjects. After graduating, I was fortunate enough to have the opportunity to learn more about how these behavioral outcomes manifest in treatments for severe behavior disorders as a postdoctoral researcher at the University of Nebraska Medical Center's Munroe-Meyer Institute. Because I had a foothold on both sides of the basic-to-applied continuum, I developed strong interests in human-laboratory analyses of resistance to change and relapse to facilitate programs of bidirectional translational research. I continue lines of basic, applied, and translational research as an Assistant Professor of Behavior Analysis Studies, Pediatrics, and Neuroscience and Physiology at SUNY Upstate Medical University.

PERSPECTIVES FROM DR. VALDEEP SAINI

My research has primarily focused on identifying general relations across species, and identifying variables that are influenced by, or observed only in, humans. Because the pursuit of general relations often requires inter-species replication, amongst other types of replication, my research has traversed the broad spectrum of animal and human behavior. I don't consider myself either a basic or applied researcher, but instead view experiments through the lens that Baer et al. (1968) provided: two separate but interrelated domains of a unified science of behavior. Much of my doctoral (University of Nebraska Medical Center's Munroe-Meyer Institute) and post-doctoral (SUNY Upstate Medical University) training was largely influenced by exploring the limit of Baer et al.'s assertion, and this is something that I pass on to my own trainees at Brock University as well. My laboratory focuses on the processes that lead to applied technologies, which I believe is achieved through a bidirectional process in which applied research and basic studies are designed to investigate the behavioral processes involved in complex problems.

Human-laboratory research is well suited for identifying general relations, and between 2016 and 2021 I was fortunate to work with a number of skilled colleagues who studied relapse processes through the lens of human-operant research. Below, I outline why I see this approach to the study of behavior as advantageous, and then identify a few unique findings from our work that may have implications for the generality of relapse as a process and associated models.

One type of translational research in behavior analysis refers to the process of taking findings from basic scientific research and applying them to develop real-world practical interventions, strategies, or techniques that can improve human behavior and societal well-being. An advantage of this type of translational research over purely basic or purely applied research is that it allows a bridge to exist between theoretical and empirical research conducted in laboratory settings, and the practical implementation of these findings to address specific issues or problems in society. The human-operant laboratory is particularly well-suited for studying translational research.

A unique advantage of human-laboratory research is the ability to conduct focused research in the experimental analysis of human behavior (EAHB). This subfield of behavior analysis focuses on the systematic study of human behavior using experimental methods derived from basic research. In human-operant EAHB experiments, researchers conduct controlled experiments to understand the principles and determinants of human behavior, with an emphasis on studying variables that may be uniquely human (e.g., complex verbal behavior, decision making). Human-operant EAHB experiments are ideal because of the rigorous and scientific approach to understanding dependent variables specific to humans, which may otherwise be impossible in basic studies, and contraindicated, unethical, or impractical in applied contexts.

Although human-laboratory research is ideal for research translation and EAHB experiments, this approach is not without its own limitations. Although in most cases, the principles of behavior have good inter-species generality, there are situations in which the introduction of humans as subjects increases the complexity of the variables under study, or provides novel explanations for responding that are unique to humans. This has led some to suggest that principles and processes studied in nonhuman experiments may be different than those studied in the human-operant laboratory. That is, controlled human-laboratory experiments may be studying different characteristics of behavior and underlying processes than what is studied in the basic laboratory (e.g., see "resurgence vs extinction-induced variability" below). As a result, findings from human-laboratory settings may not always accurately reflect the basic models they are designed to replicate or the real-life situations they are designed to better understand. Therefore, human-operant experiments may inadvertently introduce findings that are not parsimonious with the existing literature base.

A second limitation of human-operant research is the extent to which controlled histories of human behavior can be established. Unlike nonhuman studies where experimenters have more rigorous control over the environment, human laboratory experiments cannot be conducted independent of participant ontogeny. As a result, many human-laboratory experiments could be confounded by ontogeny (e.g., see "response persistence during extinction" below). The inability to control extra-experimental histories poses its own unique challenge centered around the extent to which these studies can serve as an appropriate bridge between highly controlled basic studies where ontogeny is systematically established and applied research where ontogeny and dependent variables are socially significant.

Resurgence vs Extinction-Induced Variability

A character feature of many basic and human-laboratory studies of resurgence is the inclusion of control stimuli which allows the subject to engage in a response option that has no established conditioning history within an experiment. The purpose of this control response is to distinguish between resurgence and extinction-induced variability that could occur during resurgence tests that employ extinction. Responding toward stimuli that have a previous reinforcement history during extinction would be indicative of resurgence whereas responding toward control stimuli, that have no reinforcement history, would be indicative of extinction-induced variability. Response generalization might be considered a form of relapse different from resurgence where responding that is topographically similar to the topography reinforced begins to emerge as a result of extinction-induced variability (Mackintosh, 1955). Interestingly, in a review of the use of control responses in resurgence research, Lattal and Oliver (2020) reported that 6 of 6 studies that have used human participants (including laboratory studies) have shown some responding toward the control stimulus in at least one participant whereas 13 of 14 reviewed studies using nonhuman animals as subjects have shown no or minimal responding toward the control stimulus. This raises the question of whether resurgence observed in human studies is fundamentally the same process as resurgence observed in nonhuman studies.

It is possible that human participants may be more susceptible to generalization effects given the higher rates of responding toward control stimuli. No study that has included human participants has directly compared extinction responding with and without the presence of a control response to determine if the addition of such a response affects patterns of resurgence. However, Cox et al. (2019) found that increasing the number of control responses increases variability across response options, suggesting that as response alternatives increase, so too does responding toward those alternatives, which could be conceptualized as a form of response generalization. The role of control responses in distinguishing between resurgence and extinction-induced variability in human-laboratory studies and how this relates to basic studies that use control responses should be the focus of future research on resurgence.

Further complicating the matter is the absence of control stimuli in applied research. To the best of our knowledge, there have been no applied studies that have included control responses as part of a resurgence evaluation. The absence of control responses in this domain could be concerning given the different patterns of responding toward control responses across basic and human-laboratory studies. That is, control responding is not observed in basic studies, suggesting resurgence, but is observed during human-laboratory studies, suggesting extinction-induced variability. It is unclear if applied studies of resurgence are indeed demonstrating resurgence effects (as in basic studies) or extinction-induced variability (as in human-laboratory studies). Interestingly, however, Sullivan et al. (2020) demonstrated that nontargeted challenging behavior may co-occur with targeted challenging behavior during resurgence tests in children, raising further questions about the degree to which reported outcomes in clinical settings provide the full picture of relapse in those settings (i.e., there may be many more alternative responses that are induced which aren't accounted for or explicitly described). Further correspondence and integration of procedures across basic, translational, and applied domains is warranted to resolve discrepant patterns of responding observed across studies.

Response Persistence During Extinction

In basic studies of relapse, a characteristic feature of responding during relapse tests is the immediate reemergence of a previously reduced target response, with a reduction in relapsed responding across successive sessions of extinction (Podlesnik et al., 2023; Shahan et al., 2020). In other words, the rate of relapsed responding appears to decrease over time. This pattern of responding is also consistently observed in applied research (Perrin et al., 2022; Saini & Mitteer, 2020). Interestingly, one phenomenon that appears to be unique to human-laboratory studies of relapse is persistent responding across successive sessions of extinction (e.g., Bolívar et al., 2017; King & Hayes, 2016; Kuroda et al., 2016; Saini et al., 2021; Sweeney & Shahan, 2016), which has led some to suggest that responding during extinction tests of relapse in such studies could be controlled by variables different than those observed in basic and applied research (Finch et al., 2022).

In a typical three-phase resurgence paradigm, Saini et al. (2021, Experiment 1) required participants to respond on an iPad where they could interact with target, alternative, and control buttons displayed on the screen. The experimenters varied the number of baseline sessions for some participants, and also increased the number of sessions in the extinction phase for some participants to determine how these different histories would affect the occurrence of resurgence. Figure 1 displays results of their study and demonstrates the persistence of responding during extinction for all participants, regardless of the experimental manipulation made. Saini et al. (2021, Experiment 2) reproduced these results when participants were required to engage in the same task using physical stimuli (response buttons on a table) as opposed to responding on the iPad. This second experiment eliminates the possibility of the type of stimuli (high tech versus

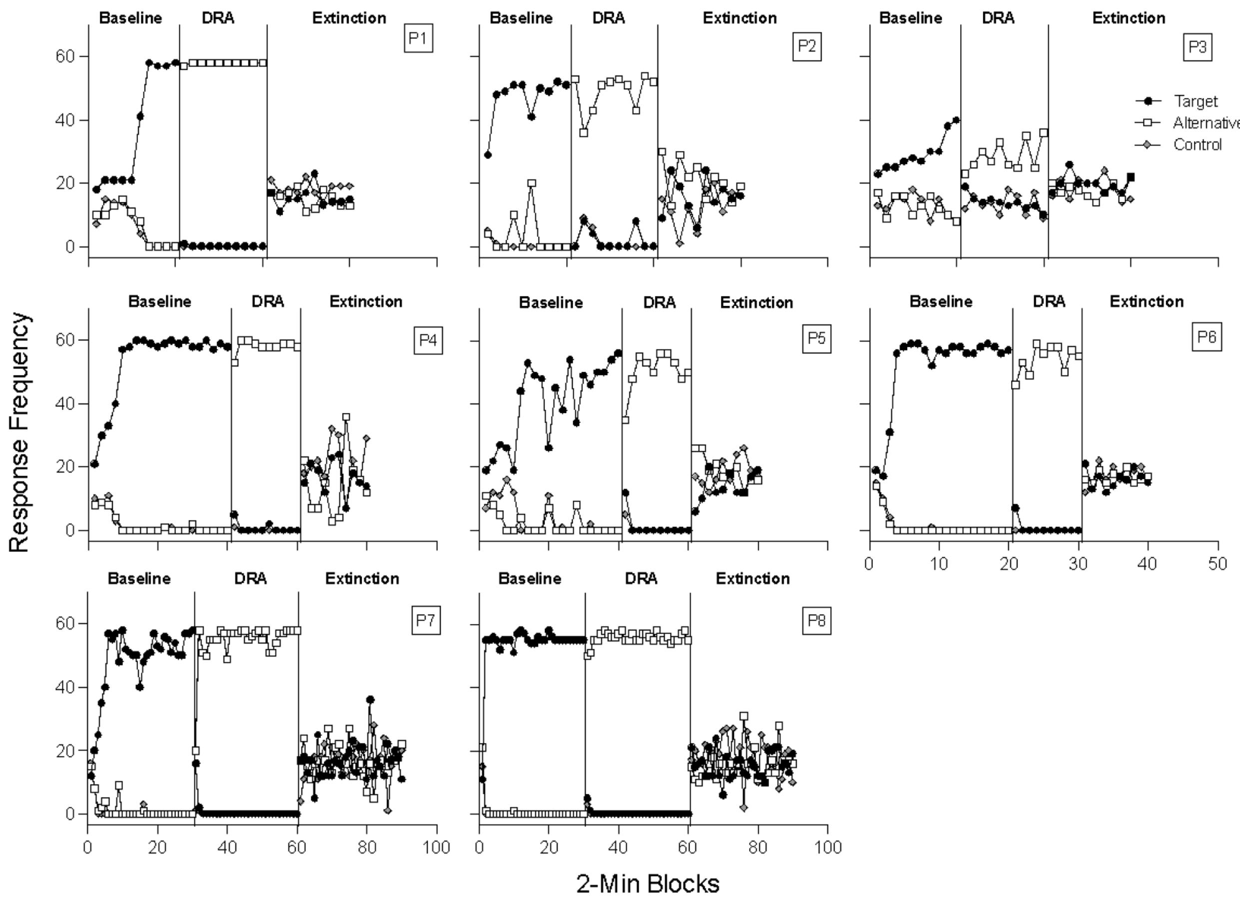

Figure 1. Results from Experiment 1 of Saini et al. (2021)

low tech) affects resurgence in human-operant studies, and suggest that such a pattern may be governed by different behavioral processes than those observed in basic-laboratory studies.

Observations of response persistence across successive sessions of extinction during relapse testing poses an interpretive challenge for human-operant experiments and brings into question the generality of findings from basic and applied research. Although the exact reason for such a difference has not been examined empirically, there may be at least two interpretations of these findings. First, Lattal and Oliver (2020) noted that a participant's extra-experimental history with technology could influence the results of relapse studies that rely on computer interfaces and online tasks. Indeed, as technological advances have permitted novel methods of arranging human-operant studies of relapse, a trend to rely on such methods has emerged (Ritchey et al., 2021; Saini & Roane, 2018). It is possible that the vast majority of participants who contribute to human-laboratory studies contact schedules of intermittent reinforcement when manipulating these stimuli outside of the laboratory setting (e.g., a touch screen failing to sense an interaction or a phone not turning on or unlocking which requires the user to engage in a response multiple time before reinforcement occurs). These unintended schedule effects may promote response persistence within laboratory settings. Moreover, participants may also have prior experience with the types of tasks being required of them based on an extra-experimental reinforcement history, such as playing a computer game to earn points. As described above, Saini et al. (2021) demonstrated that persistence during extinction is also observed in human-operant studies that use low-technology stimuli (e.g., pressing a button), which could indicate that this phenomenon is not directly related to the types of stimuli used but other aspects of ontogeny.

An alternative explanation for persistence during extinction, which may account for the observations obtained from studies using low-technology stimuli, is sensitivity to the laboratory setting and rule-governance associated with task completion (Cox et al., 2019). It is possible that the extra-experimental history affecting response persistence is related to rule-governance, and not any unique aspects of high- and low-technology stimuli. In human-laboratory studies, participants are often asked to complete a task from an authority figure (experimenter) for some duration of time and are encouraged to perform their best on the task. Verbal statements about the experiment combined with the experimental setting could set the occasion for rule following, which is then observed as continued responding during extinction. Said another way, persistence during extinction in human-laboratory studies of relapse could be a function of verbal mediation. As a result, human-laboratory studies could be confounded by rule-governance as responding observed during supposed “relapse tests” may not be a function of prior experimental conditioning, as is observed in basic and applied studies.

PERSPECTIVES FROM DR. WILLIAM SULLIVAN

I began my career in behavior analysis as an undergraduate research assistant at West Virginia University. I then obtained my Ph.D. in school psychology, emphasizing behavior analysis and translational research, at Syracuse University. Following graduate school, I continued my training at SUNY Upstate Medical University, where I completed my predoctoral internship and postdoctoral fellowship. At Upstate, I received rigorous and comprehensive training in providing evidence-based care for individuals with intellectual and developmental disabilities (IDD) who engage in severe destructive behavior (e.g., self-injurious behavior, aggression) and conducting research across the translational continuum.

Currently, I serve as the Director of Outpatient Behavioral Services at the Golisano Center for Special Needs and an Assistant Professor within the Departments of Pediatrics and Behavior Analysis Studies at SUNY Upstate Medical University. As a scientist-practitioner, my passion for bi-directional translational research is driven by my endeavor to improve treatments for severe destructive behavior displayed by individuals with IDD. Primarily, I have been interested in examining relapse phenomena under tightly controlled conditions that more closely approximate clinical practice, relative to the basic laboratory, to better inform clinical application.

"The importance of a science of behavior derives largely from the possibility of an eventual extension to human affairs" (Skinner, 1938, p. 441). Fundamental to this pursuit is the notion that the same behavioral processes governing the behavior of nonhuman animals in the basic laboratory also similarly affect socially significant human behavior. To answer questions regarding interspecies generality, translational research is needed and has been defined as investigations concerning fundamental principles and everyday problems (Mace & Critchfield, 2010). Translational research focusing specifically on replicating findings from the basic laboratory with humans is one critical form of translation along the continuum from bench to bedside. The human-operant laboratory is particularly well-suited for this type of research because investigators can conduct tightly controlled experiments that systematically replicate the procedures used in the basic laboratory to evaluate their effects on human behavior. Ultimately, human-operant research of this kind can provide evidence that the behavioral processes shown to control the behavior of nonhuman animals also apply to human behavior and thus may be leveraged to benefit humanity more generally.

Although there have been numerous replications of the effects of basic behavioral principles across species, experimental settings, and applications (e.g., differential reinforcement, stimulus control), some essential patterns of responding in nonhuman animals have not been reliably produced with humans. For example, it has been shown that human response patterns differ considerably from other organisms under some basic schedules of reinforcement and when encountering a programmed change in contingencies (Hayes et al., 1989). In the paragraphs below, I will outline some of these discrepant findings and discuss the implications regarding the behavioral processes being studied in human-operant research.

Discrepant Findings Between Basic- and Human-Operant Laboratories

One of the earliest examples of differences in response patterns observed with humans relative to nonhuman animals is performance under fixed-interval (FI) schedules. In 1962, for example, Harold Weiner conducted a series of human-operant experiments with adult males who pressed buttons to earn point reinforcement. The study aimed to evaluate the effects of response cost on human responding maintained by VI and FI schedules. In Experiment 2, specifically, Weiner found that participants displayed constant rates of responding under FI schedules, deviating from the typical "scalloped" pattern observed with nonhuman animals. Once he added a response-cost contingency, the participants' response rates were immediately reduced and approximated a flat scalloping pattern.

Then, in 1969, Weiner demonstrated that patterns of human responding under FI schedules could be experimentally controlled by exposing participants to low- or high-rates of reinforcement before introducing FI schedules. Psychiatric nursing assistants served as participants, and those with a history of responding under ratio schedules produced high and stable rates of responding when exposed to FI schedules. Those with a history of responding under schedules that produced low response rates (i.e., differential reinforcement of low-rate behavior) continued to respond at low rates under FI schedules. Thus, response patterns persisted when contingencies changed to FI schedules, demonstrating an insensitivity to the programmed contingency change.

More recently, there has been a series of human-operant studies on resurgence, and when participants experienced extinction during resurgence testing, responding persisted (e.g., Bolívar et al., 2017; King & Hayes, 2016; Kuroda et al., 2016; Saini et al., 2021; Sweeney & Shahan, 2016). For example, in my collaborative work with colleagues in this symposium (Saini et al., 2021), we arranged a two-experiment human-operant investigation of resurgence with college participants who pressed buttons on an iPad (Experiment 1) or manual buttons (Experiment 2) to earn point reinforcement. Outcomes across both experiments showed that human-operant behavior failed to extinguish when we removed programmed reinforcement (see Figure 1). This outcome, and those noted above (i.e., Weiner, 1964, 1969), have led researchers to hypothesize about potential reasons as to why human response patterns fail to converge with the response patterns produced by other organisms (e.g., pigeons, rats).

One obvious and important distinction between humans and nonhuman animals is our capacity for language, which led Lowe (1979) to propose the "language hypothesis" to account for these differing response patterns. To investigate this hypothesis, Lowe et al. (1983) reinforced two human infants (9 and 10 months) using FI schedules. These infants' performance showed clear scalloping patterns similar to what is observed with other species. Lowe et al. concluded this was likely because the infants had not yet developed language. Then, in 1985, Bentall and colleagues conducted a developmental study that showed that as children age, their performance shifts from response patterns like nonhuman animals to those of adult humans by age seven. Again, this suggests that verbal processes begin to control our behavior (e.g., rule-governance) as we develop language and diverge from those processes controlling nonhuman animal behavior in the basic laboratory.

Rule-governed Behavior

From a behavior-analytic perspective, rule-governed behavior refers to behavior controlled by stimuli that specify a contingency (Skinner, 1966). This can be contrasted with behavior that is governed by the contingencies themselves. Thus, rule-governed behavior is not influenced by the organism experiencing the contingencies in its environment but by the rule exerting control over behavior through the specification of a contingency or by creating a socially mediated contingency. Over the years, there has been a plethora of research on the effects of rules on human-operant behavior, and Hayes (1993) outlined three general conclusions: (1) rules affect the impact of programmed contingencies, (2) rules alter how those contingencies are contacted, and (3) rules introduce social contingencies for rule-following.

Hayes et al. (1986), for example, required human participants to press buttons to move light through a matrix to earn points worth chances for money. Button presses were reinforced according to a multiple fixed-ratio

18/differential reinforcement of low rate 6-s schedule, with components alternating every 2 mins. In Experiment 1, four conditions were assessed where participants were provided (1) minimal instruction, (2) "Go Fast" instruction, (3) "Go Slow" instruction, or (4) instruction that sometimes responding rapidly would work and other times responding slowly would work. Outcomes showed that the instructions affected contact with the programmed contingencies within each component of the multiple schedule and subsequent performance. The authors also suspected that in some cases, responding appeared to result from added social contingencies related to the rules. To parse apart these potential effects, in Experiment 2, the authors presented and withdrew two lights that had been paired with the "Go Fast" and "Go Slow" rules. In one condition, only the "Go Fast" light was on. Only the "Go Slow" light was on in the second condition, and in the third condition, the lights alternated each minute, producing accurate rules only half the time. Participants completed three consecutive 32-min sessions, and within each condition, half of the subjects had all instruction lights turned off after the first session. The other half of the participants had instruction lights remain on throughout all three sessions.

The key outcomes from Hayes et al. (1986) relevant to this discussion involved comparing each condition when instruction lights were present for one or three sessions. Differences in responding during the second and third sessions between groups that experienced instruction lights during the first or all sessions would indicate that responding had been controlled by socially mediated consequences for rule-following. This pattern was observed and most pronounced for participants who only experienced alternating "Go Fast—Go Slow" instruction lights in the first session. That is, participants in this condition immediately showed expected response patterns given the schedule in effect when the lights were turned off. In contrast, the participants who had the lights on throughout the three sessions responded in accordance with the rule rather than the programmed contingencies.

Insensitivity to programmed contingencies in human-operant research may be because rules restrict the range of responses available to contact the programmed contingencies or because they may establish extra-experimental socially mediated contingencies for rule-following (Hayes et al., 1989). As adult humans, we have long reinforcement histories for following rules, and that history is likely to be carried forward in human-operant arrangements. Several experimental manipulations have been shown to help overcome those history effects and produce response patterns like those of nonhuman animals. For example, providing participants with a competing activity (e.g., Lowe et al., 1978), providing extensive experimental reinforcement histories (see Wanchisen & Tatham, 1991), or adding in additional contingencies (e.g., Weiner, 1962) may produce such response patterns. Although these manipulations might help produce response patterns in humans that mimic the response patterns observed in the basic laboratory with nonhuman animals, they inherently suggest that different processes control behavior across basic- and human-operant laboratories. Ultimately, this creates interpretive difficulties related to the generality of the processes being studied.

Conclusions

In human-operant research, Baron and Galizio (1983) suggested that the effects of rules introduced by the experimenter or self-imposed by the participant appear to be a significant factor in accounting for the response patterns observed in this type of research. As a community of human-operant researchers who believe a science of human behavior is possible, we must not be naïve to the fact that the behavior being studied in human-operant laboratories is likely under the influence of variables not present in the basic laboratory. And that is OK. This type of human-operant work is necessary to progress toward a more complete understanding of complex human behavior. For human-operant work seeking to examine basic processes or evaluate quantitative models developed in the basic laboratory, however, this poses serious interpretive problems. Yes, we can make experimental manipulations to produce response patterns with humans that "look" like the behavior of other organisms, but this is insufficient. We need to understand better the *interaction* among those basic operant and verbal processes to have a more complete translation between humans and other organisms.

PERSPECTIVES FROM DR. RYAN KIMBALL

My human-operant research (e.g., Kimball et al., 2023) primarily focuses on studying the conditions in which relapse occurs, relapse-mitigation procedures, and the optimal approaches for responding to relapse after it has occurred. My interest in researching relapse stems from my fascination with extinction-related phenomena and my clinical background in the assessment and treatment of severe behavior (e.g., aggression, self-injury, property destruction). I entered the field of behavior analysis more than 11 years ago, and I was fortunate enough to get involved with human-operant research early while I was a master's student. I earned my bachelor's degree at West Virginia University, where I first encountered behavior analysis and gained some experience working with individuals with challenging behavior. Next, I gained a master's degree in Applied Behavior Analysis/Organizational Behavior Management at the Florida Institute of Technology. As a master's student working as a clinician in a clinic-based severe behavior program, I was first introduced to translational research, and briefly contributed to some unpublished human-operant research on the treatment relapse phenomenon of reinstatement. Finally, I earned my doctoral degree in Applied Behavior Analysis at the University of Nebraska Medical Center's Munroe-Meyer Institute while working in an intensive outpatient severe behavior program. During my time as a doctoral student, I decided I wanted to pursue a career in teaching and conducting translational research.

Several variables influence my approach to conducting human-operant research, such as the participant population I have access to, the operanda I have access to, a lack of funding for compensating research participants, and my past experiences with examining extinction-related phenomena through human-operant experiments. What follows are brief summaries of each of these influences on my human-operant work and the lessons that I have learned.

I am currently in my 5th year of service as a tenure-track Assistant Professor teaching in a master's degree program in Applied Behavior Analysis at the University of Saint Joseph, a small private institution in the Northeastern United States that prioritizes teaching over scholarship. I do not have any clinical responsibilities, and I do not have access to a clinical population (e.g., individuals who engage in severe behavior) that I might recruit from to conduct other forms of relapse research. Therefore, I only have access to recruiting college students for human-operant research. From a certain point of view, conducting human-operant research is really my only option. As a result, I craft my research questions while considering a few critical features of recruiting college students as research participants. For instance, in my experience, college students typically become fatigued rather quickly while completing experimental tasks, so I design my experiments to last less than 1 hr. Similarly, I typically design my experiments to last for only a single research visit with participants because I have historically had difficulty getting participants to return to complete the second part of a two-part experiment. A lesson I have learned from recruiting college students is that students typically express interest in participation at the beginning and end of a given semester, so I have had to learn to be patient and endure long periods without collecting new data sets.

The second variable that influences my approach to conducting human-operant research is the type of operanda I can access. Despite a few attempts at learning to code, I sadly do not have any programming skills. Thus, I have had to collaborate with other researchers with programming repertoires or who already have software ready to deploy for research. As a workaround for this issue, I have contemplated conducting research with low-tech operanda and manual data collection instead of high-tech operanda with automated data collection. For example, some researchers have found success with using low-tech responses such as microswitch presses or ball deposits in object-permanence boxes and manually collecting data with commonly used software programs like BDataPro (Bullock et al., 2017; Fuhrman et al., 2021). However, conducting that type of human-operant research requires a team of trained research assistants to help implement the experimental protocol and collect primary plus secondary data, which I do not have consistent access to currently.

The software I consistently use is a relatively simple but flexible program deployed on touchscreen tablet devices that I helped develop as a doctoral student. In short, participants respond by pressing shapes that move around the screen, and the program collects data on response frequency plus provides timestamps for when each response occurred. The only programmed consequences for responding available on the program are points added to a point counter and animated bursts of confetti on the screen when a participant's behavior meets the requirements of a reinforcement contingency. For any given experiment, I can change several aspects of the program, such as a) the number of response operanda available (i.e., shapes) on the screen, b) the schedules of reinforcement for pressing the shapes, c) the speed at which the shapes move around the screen, d) the type of shape (e.g., circle, square, triangle), e) the points available for completing each schedule , and f) the background color of the tablet screen. Other human-operant researchers have successfully used similar programs in published research on relapse (e.g., Finch et al., 2022; Romano & St. Peter, 2016).

The simplicity of the program I use for human-operant research impacts the design of my experiments. As an example, in my experiments, participants are pressing moving shapes on a screen for points for upwards of 50 min. My experimental tasks may be considered tedious and boring for college students who have access to very complex video games on their cell phones and tablet devices. Therefore, I program relatively dense schedules of reinforcement for responding (e.g., variable-interval [VI] 12 s) and program the shapes to move rapidly across the screen (e.g., 8 cm/s) in an attempt to maintain consistent rates of responding and participant attention (Madden & Perone, 1999). One lesson that I have learned through various unpublished experiments and pilot studies is that with this type of experimental task, participants tend to stop responding entirely or respond at extremely low rates with relatively lean schedules of reinforcement.

The third variable that influences my approach to conducting human-operant research is my lack of funding for conducting the research. In my experience, grant funding agencies rarely consider funding human-operant projects that do not involve socially significant behavior and do not immediately impact clinical practice. As a result, I have historically collaborated with undergraduate faculty at my university to offer students small amounts of extra credit if they participate in my research instead of providing monetary compensation (e.g., money or gift cards). One crucial detail to note is that participants in my experiments do not earn different amounts of extra credit based on their performance with the experimental task. That is, earning more points with the experimental task does not translate to earning more extra credit, and this procedural detail primarily stems from my university's Institutional Review Board policies. Unsurprisingly, when paired with the simplicity of the task, the lack of differential compensation for performance with the experimental task likely contributes to the variability in response rates across participants. Human-operant researchers operating under similar circumstances should also expect to observe robust variability in response rates across participants.

The fourth variable that has significantly influenced my approach to conducting human-operant research is my experience conducting experiments that include phases in which all responding is placed on extinction. By and large, contemporary research on relapse is built upon years of foundational research on the behavioral processes that govern behavior change during extinction (Bouton et al., 2012; Nevin & Wacker, 2013). As a result, many investigations of relapse include phases in which previously reinforced responding is placed on extinction. For example, consider a common preparation for studying resurgence. In Phase 1, target responding produces reinforcement. In Phase 2, the experimenter simultaneously places the target response on extinction while differentially reinforcing an alternative response (DRA). Finally, in Phase 3, both the target and alternative response produce no programmed consequences (i.e., extinction). Resurgence is often defined as the re-emergence of target responding in Phase 3 when the alternative response contacts extinction (Lattal et al., 2017). However, if target responding reemerges in Phase 3 but fails to extinguish or decrease to near-zero levels in Phase 2, researchers are left wondering if they are truly examining resurgence and if the programmed consequences for behavior in Phases 1 and 2 were ever actually reinforcers in the first place. Some researchers have documented this phenomenon in published research (Saini et al., 2021) and hypothesized that the lack of robust decreases in target responding in the face of extinction during Phase 3 could be

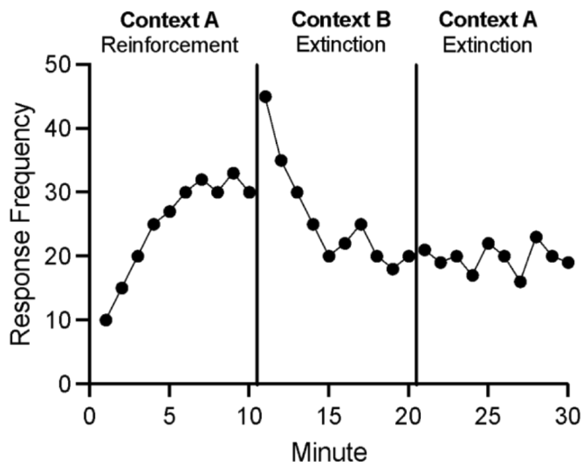

Figure 2. Target Responding that Fails to Extinguish in an ABA Renewal Arrangement. *Note:* This figure displays an example of target responding that does not significantly decrease in Context B and the renewal test in Context A despite repeatedly contacting extinction. A pattern of responding such as this makes it challenging to detect renewal.

due to unique learning histories of adults, rule governance, low response effort, and more. Unfortunately, I have observed this lack of extinguished target responding following relapse in Phase 3 not only in a few unpublished human-operant resurgence experiments, but also in similar evaluations with reinstatement and renewal. As an illustration, Figure 2 depicts an undesirable response pattern in which target responding fails to extinguish or significantly decrease during Phase 2 and 3 of an ABA renewal arrangement. I suspect many other human-operant researchers have also experienced this problem, but have not been able to disseminate their null findings due to the "file drawer problem" (Rosenthal, 1979).

While I certainly applaud the researchers seeking to identify why target responding fails to extinguish in human-operant relapse experiments, I have recently learned to avoid the issue altogether by crafting relapse investigations that do not include phases with programmed extinction for all responding. As an illustration, consider the relapse phenomenon of renewal, which occurs due to a change in context, such as the physical setting or treatment implementer (Podlesnik et al., 2017). During the treatment of severe behavior, behavior analysts commonly observe renewal when novel clinicians implement the intervention with the client, who usually receives services from another clinician, or treatment takes place in a different location (e.g., a transition from the clinic to the community; Muething et al., 2020). Many basic and translational researchers have historically programmed extinction alone to eliminate target responding in Phase 2 before testing for relapse

in Phase 3. For example, with an ABA renewal preparation, researchers reinforce target responding in Context A, extinguish that target response in Context B, and then test for the re-emergence of target responding in Context A despite the extinction contingency remaining in place (e.g., Kelley et al., 2015). To avoid the problem of target responding not decreasing in Context B and not extinguishing after re-emerging in the Context A renewal test, my research includes a DRA contingency in combination with extinction for target responding in Context B and the renewal test. In this way, I can still study the effects of context changes on a previously eliminated target response, but without worrying about the target response not decreasing to zero because the DRA contingency helps suppress target responding. Fortunately, designing my current line of human-operant experiments on renewal in this manner is also beneficial because the procedures align with scenarios that clinicians often encounter in practice. That is, clinicians rarely program extinction alone for challenging behavior during treatment. Instead, clinicians typically place challenging behavior on extinction while differentially reinforcing a functionally equivalent alternative response (e.g., Kelley et al., 2018; Saini et al., 2018) or by providing other sources of alternative reinforcement (e.g., noncontingent reinforcement; Finch et al., 2022). The important message here is that I have learned to always include some form of alternative reinforcement on top of the extinction contingency for target responding in my human-operant research on relapse.

PERSPECTIVES FROM DR. SEAN SMITH

After I finished my undergraduate degree, I was introduced to applied behavior analysis while working at a residential program designed for the assessment and treatment of clients' severe destructive behaviors. I pursued a doctoral degree at the University of Nebraska Medical Center's Munroe-Meyer Institute to improve my clinical skills in this area of practice. During this time, I began working on human-operant and clinical research on treatment relapse. Early in my doctoral program, my advisor also informed me that he accepted a new position at another university, so it would be good to develop a dissertation project that could continue uninterrupted when the research lab moved. We decided to conduct a computer-based human-operant relapse research project using crowdsourcing methodology because (a) the research could be conducted without a physical space and without needing to establish new participant recruitment pools (e.g., undergraduate students, clinical patients) and (b) researchers had recently replicated relapse phenomena using crowdsourcing methodology (Robinson & Kelley, 2020). My experience conducting human-operant relapse research using this methodology is somewhat distinct from my co-authors and extends the breadth of our article, which is why I focus on discussing this aspect of my human-operant relapse research experience in this section. I am currently an Assistant Professor at SUNY Upstate Medical University, where I continue to conduct research in this area.

Crowdsourcing Methodology

The development and commercial availability of crowdsourcing platforms (e.g., Amazon MTurk, Prolific) on the Internet has created a new avenue for researchers to conduct experimental analyses of human behavior. Many relapse researchers have embraced this relatively new way of conducting human-operant research, leading to the publication of numerous experiments on relapse using this methodology (e.g., Kranak et al., 2022; Martinez-Perez et al., 2022; Podlesnik et al., 2020; Podlesnik et al., 2022; Ritchey et al., 2021; Ritchey et al., 2022; Ritchey et al., 2023; Robinson & Kelley, 2020; Smith & Greer 2022a; Smith & Greer, 2023). This section provides researchers with a broad overview of the advantages and disadvantages that may not be readily apparent in the empirical articles describing relapse research using this methodology.

Benefits

As noted in the introductory paragraph of this section, an important advantage of conducting computer-based human-operant research using crowdsourcing methodology is that it is relatively unaffected by events that may disrupt other research. This is because researchers do not need a physical space to conduct this research, nor do they need to work to establish recruitment pools. For example, my dissertation research was uninterrupted when I moved from Nebraska to New Jersey during my doctoral program, and my subsequent research using this methodology has been unaffected by additional recent moves (i.e., New Jersey to Florida, Florida to New York). My research was also unaffected by the global COVID-19 pandemic because the research was conducted remotely. These benefits may be advantageous for new researchers, who may be especially prone to disruptions to their research.

A second benefit of conducting research using crowdsourcing methodology is that it can hasten recruitment. A researcher can simply log onto a crowdsourcing platform and post their experiment, which will be seen and completed by a vast pool of workers almost immediately. Thus, using crowdsourcing methodology for research that does not require in-person participation tends to produce massive influxes of data, which relapse researchers have leveraged to facilitate rapid translation of relapse phenomena demonstrated with nonhuman animals to humans.

The third major benefit of conducting research using crowdsourcing methodology is that it usually costs a relatively small amount of money. Because there is such a large "supply"[2] of workers on crowdsourcing platforms and the "demand" for task completion is comparatively low, the compensation for workers tends to remain relatively low, as well. Thus, researchers can complete an entire study for a fraction of the cost associated with doing the same research without using crowdsourcing methodology. As a quick example, each relapse experiment conducted by Smith and Greer (2022a, 2023) cost less than $500.

2 Reference to "supply" and "demand" is to draw a helpful comparison to economic principles. It is not intended to suggest that humans are merely commodities.

A fourth benefit of using crowdsourcing methodology to conduct relapse research is that it can mitigate risks associated with relapse procedures. Relapse research (e.g., resurgence, renewal) often includes procedures where participants are exposed to extinction for all behaviors at some point during the experiment (Kestner & Peterson, 2017; Podlesnik et al., 2023). Exposure to extinction can produce numerous potentially harmful side effects like emotional responding, response bursting, and aggression (Azrin et al., 1966; Fisher et al., 2023; Kelly & Hake, 1970; Lerman et al., 1999; Terrace, 1966). Using crowdsourcing methodology to conduct relapse research can mitigate these risks by recruiting participants less likely to experience these negative effects (i.e., adults without behavior disorders) and demonstrating effects with relatively brief exposures to extinction (e.g., 1 min of extinction during relapse testing in Robinson and Kelley, 2020). In fact, Smith and Greer (2023) explicitly state risk mitigation as a rationale for using their crowdsourcing methods when evaluating the effects of repeated exposures to extinction on resurgence mitigation. Thus, crowdsourcing methods may provide a safe avenue for increasing the initial empirical support for relapse phenomena with human participants. This additional support with human participants can help justify subsequent evaluations of relapse phenomena with participants more likely to experience the potentially harmful effects of extinction.

Drawbacks

Although conducting research using crowdsourcing methodology can be completed uninterruptedly, quickly, cheaply, and safely, there are also important drawbacks. Not only do the issues with human-operant research described by my coauthors (e.g., response persistence during extinction) continue to be present when this research is conducted over the internet, there are difficulties that are more unique to research conducted using crowdsourcing methodology. Some common concerns are outlined below, but this is not an exhaustive list of concerns. Rather, this list focuses on the concerns most relevant to completion of human-operant tasks related to relapse phenomena instead of concerns that may be more relevant for survey-based research.

An initial concern that relates specifically to conducting relapse research via crowdsourcing websites is that the researcher needs to create a computer interface for their experiment, which likely requires a basic understanding of software development. Unlike survey-based or delay-discounting research, which primarily involve answering a set of questions that can be organized according to a flow-chart, relapse research typically requires development of a user interface that participants will interact with dynamically. This often involves programming various (a) timing mechanisms for reinforcer deliveries and phase changes, (b) mechanisms for tracking participants' behavior, (c) response options (e.g., clickable buttons that move around the screen, keyboard buttons, text fields), (d) experimental stimuli (e.g., contextual backgrounds), and (e) interactions with each of the buttons that vary across the course of the experiment and which change based on participants' previous behavior (e.g., stimuli signaling reinforcer deliveries, point counters). Learning how to program such interfaces can be a complicated and daunting task. It can also be difficult to find a collaborator with the requisite skills or expensive to hire an expert. Thus, it may be particularly hard for relapse researchers to develop software to conduct research using crowdsourcing methodology.

Another set of concerns relates to who is actually completing the experiment. For example, it can be difficult for relapse researchers to ensure that the same participant does not complete an experiment multiple times because participants can always use other people's information (e.g., friends, family) to create a new log-in. This, in combination with a virtual private network (VPN, which can be used to hide one's identity on the internet; Kennedy et al., 2020), can make it extremely difficult for crowdsourcing platforms (and researchers using the platforms) to apply safeguards to prevent or detect repeated participation in a research project. This presents a clear problem for relapse researchers because repeated exposures to relapse testing may affect the likelihood or the magnitude of the relapse effect (e.g., Shahan et al., 2020; Smith & Greer, 2023). Similarly, researchers have documented that workers on crowdsourcing platforms have created simple software (i.e., bots) to automate the completion of tasks so the workers can complete tasks more rapidly and make more money (e.g., Dreyfuss et al., 2018; Stokel-Walker, 2018). Both repeated participants and bots present issues, especially if a researcher is unable to distinguish between responses submitted by novel human participants, repeated human participants, and/or bots.

An additional set of concerns relates to the behavior of research participants during an experiment. For example, a common concern is that participants may be inattentive throughout the experiment or completely disengage from the experiment during inopportune times (e.g., Goodman et al., 2013, Study 2). For example, in an experiment on relapse, disengaging from the experimental task during the critical relapse test could yield unusable data. There are also concerns about the overarching contingencies exerted by the crowdsourcing platform per se. For example, on crowdsourcing platforms, workers are often offered bonuses for good performance, and they also have their work rejected for poor performance. Further, as much as 25% of workers may rely on their earnings from crowdsourcing platforms as "all" or "most" of their income (Hitlin, 2016), so these overarching contingencies for "good" and "bad" performance may have a profound impact on how workers perform during tasks. These contingencies may not only affect the internal validity of an experiment: These types of contingencies do not typically exist in other research with human participants, so it may also be difficult to determine how findings on these experiments relate to other experimental findings on relapse.

A final concern pertains to the internet connectivity of the participants. Stated simply, if an experimental task requires a stable internet connection, the quality of the participants' internet connection could impact the integrity of the experimental procedures (e.g., the independent variable manipulations) or the integrity of the data collection (i.e., the dependent variables). For example, a faulty internet connection during relapse testing or data transfers (i.e., when data are being transferred to the server) could produce major confounds to an experiment.

Mitigating Drawbacks

Despite these drawbacks, there are ways researchers can mitigate these concerns. When it comes to addressing the hurdle of developing the software for an experimental interface, relapse researchers with previous experience have shared useful resources to help newer researchers. For example, Kuroda et al. (2021) provided a tutorial for developing software to conduct human-operant experiments on MTurk, and Smith and Greer (2022b) provided a framework for validating the functionality of such software. It may also be helpful for novice software developers to know that several relapse researchers have designed their experimental interfaces using Axure RP (e.g., Kranak et al., 2022; Robinson & Kelley, 2020; Smith & Greer, 2022a; Smith & Greer, 2023). Axure RP is a software with a relatively user-friendly interface intended for designing websites, which can be exported as HTML files that can be hosted on a server for users to interact with. Although researchers still need to supplement the HTML with a little bit of additional coding (e.g., JavaScript, PHP), Axure RP allows researchers to design most of their interfaces without needing to know how to write code. Axure RP also offers free licenses to students and faculty,[3] and there are an abundance of video tutorials and message boards that provide free instruction on how to use the software. I have also had success contacting other researchers[4] and the information and technology departments at multiple universities to help me develop my software and host it on a server for others to access.

To address many of the concerns related to participant verification and behavior during the experiment, researchers should use features built into the crowdsourcing platforms. For example, to address the concern that workers may be inattentive, researchers have recommended (and it has been generally accepted) that experimenters should use filters built into the crowdsourcing platform such that only workers who have completed at least 100 tasks with 95% approval ratings without prior completion of similar tasks posted by that research lab can participate (Berinsky et al., 2012; Goodman et al., 2013; Hauser & Schwarz, 2016; Paolacci et al., 2010; Peer et al., 2014). There is some empirical support for the success of this strategy, with experiments demonstrating that applying these filters to MTurk workers may produce a

3 True when this was written. For more information, visit https://www.axure.com.edu

4 Thank you, Théo Robsinon, for your guidance when I was developing my first experimental interface.

participant pool that is as attentive (e.g., Paolacci et al., 2010) or more attentive (e.g., Hauser & Schwarz, 2015) than college students completing the same tasks. This strategy may also help address the concern about "bots" completing experiments because bots notoriously produce bad data, so setting a threshold based on past performance may prevent people who use bots from completing an experiment. Notably, different crowdsourcing platforms offer different features for addressing these types of concerns (e.g., Prolific has a more rigorous vetting and verification process for workers, conducts ongoing performance checks on workers, and may produce better data on certain tasks, Douglas et al., 2023), so researchers should consider what built-in features are available on different platforms when selecting which platform to use for their research.

Another strategy is to ask questions designed to exclude bots and inattentive participants. For example, Smith and Greer (2022a, 2023) required participants to complete quizzes (i.e., a quiz to obtain informed consent, a quiz to ensure understanding of the experimental task) with explicit correct and incorrect answers prior to completing their relapse experiments. Notably, Smith and Greer (2023) reported that 113 workers attempted to complete the consent quiz, but 56 participants failed the quiz and were excluded from the study even though they had passed the crowdsourcing platform's filter criteria. Researchers should also consider asking open ended questions because bots and poor performers often fail to respond appropriately to these questions. Although not explicitly described in Smith and Greer (2022a, 2023), inclusion of two open-ended questions and continuous monitoring of data as it was being collected allowed the researchers to identify that people were submitting identical responses within close temporal proximity during pilot testing, suggesting that some people were repeatedly completing the same pilot experiments. To address the concern that a worker could subvert the crowdsourcing platform's filter and complete an experiment multiple times, the experimenters posted their experiment such that only one person could complete the experiment at a time and evaluated each participants' data prior to posting another opportunity for someone to complete the experiment. Although this procedure slowed data collection considerably, the experimenters no longer observed identical responses to open-ended questions during their experiments like they had during pilot testing, suggesting that this procedure mitigated the concern that workers were completing the same experiment multiple times.

It is unclear whether researchers can address the concern regarding the overarching contingencies for "good" and "bad" performance on crowdsourcing platforms because it is directly related to how the platforms are designed. Rather than attempting to avoid this concern, researchers may consider "leaning in" to the concern by leveraging these contingencies within their relapse experiments. For example, several experiments on relapse have arranged their contingencies to align with other tasks on the crowdsourcing platform by informing participants that better performance on the experimental task will produce better compensation (e.g., Podlesnik et al. 2022; Smith & Greer 2022a; Smith & Greer, 2023). Although this may make it less clear which contingencies are truly operating on the participants' behavior, this sort of procedure may make it less likely that the contingencies of the platform would affect behavior in a way that opposes the contingencies programmed in the experiment.

To address the concern regarding internet connectivity, researchers should consider using methods similar to those described by Smith and Greer (2022b) to validate that their experimental procedures and data collection remain accurate across a range of internet connection speeds and qualities.

Collectively, relapse researchers should use multiple strategies to limit concerns related to the validity of conducting research using crowdsourcing methodology. Researchers should also refer to other recent sources like Goodrich et al. (2023), Griffin et al. (2022), Yarrish et al. (2019), and Zhang et al. (2022) that provide more comprehensive lists of mitigation strategies (e.g., adding "CAPTCHAs," duplicating questions, using redirection pages) and describe the relative effectiveness of such strategies (e.g., Simone et al. 2023), which could not be covered in this brief section. Notably, the aforementioned researchers have tended to identify strategies that are, in fact, effective for preventing or identifying bad respondents and yielding high-quality data. Although some of these researchers (e.g., Yarrish et al., 2019) caution against using too many mitigation strategies simultaneously because each additional strategy may also increase the likelihood of deterring good workers from completing experiments, in many cases decreasing the recruitment rate seems like a worthwhile trade-off for increasing the internal validity of the research.

Future Research

Although relapse and delay discounting researchers seem to have embraced crowdsourcing methodology to a greater extent than other behavior analytic researchers at this point in time,[5] crowdsourcing methodology could also facilitate behavior analytic research in new areas. For example, crowdsourcing methods could be leveraged to facilitate behavior analytic research on how people interact with technology per se. With the ubiquity of computers, smart phones, tablets, the Internet, and social media, an ever-increasing amount of human behavior is mediated through technology. In the United States in 2018, 92% of households had at least one type of computer and 85% had broadband internet (Martin, 2021). According to the Center for Disease Control and Prevention (2018), American children aged 8–10, 11–14, and 15–18 spend 6, 9, and 7.5 hours a day, respectively, consuming content on a screen. Although tracking screen time for American adults has been evaluated to a lesser extent, some research suggests the average American spends about seven hours looking at a screen each day (Moody, 2023). Aside from basic life-supporting behavior (e.g., breathing, sleeping), it is hard to think of a class of behaviors that occurs more than technology-mediated behavior.

Although there is some behavior analytic research evaluating interventions to decrease technology and social media usage (e.g., Stanley et al., 2022; Stinson & Dallery, 2023, Williams-Buttari et al., 2023), there does not appear to be appreciable behavior analytic research evaluating the *basic principles* by which humans interact with technology. On the other hand, private corporations have been researching how humans interact with technology prolifically. For example, Google Research has publicly shared over 792 of their own studies on "human-computer interaction and visualization."[6]

Behavior analytic researchers should consider broadening their horizons. Rather than focusing on humans' behavior on computers as an analogue for other socially relevant behaviors or as a behavior that should be decreased, perhaps they should begin studying the basic principles that govern technology-mediated behavior. Given the ubiquity of these behaviors, understanding the principles guiding these behaviors could have profound impacts on both human behavior and the development of computer-based technologies (including, but not limited to, developing more effective ways to decrease screentime and social media usage). Given the advantages of crowdsourcing methodology and its inherent connection to technology-mediated behavior (i.e., workers have to use technology to access the crowdsourcing platforms), crowdsourcing methodology may be an ideal avenue for behavior analytic researchers to begin these socially important research endeavors.

DISCUSSION

This project started with the goal in mind of sharing the perspectives of four researchers who have extensive experience with human-laboratory analyses of relapse with readers who may be interested in undertaking research in this area. In doing so, we hoped to provide insights into laboratory work that may be helpful to readers and to emphasize benefits of, and barriers to, research in this setting. In this section, I will summarize some themes that emerged from the researchers' earlier sections.

Drs. Kimball, Saini, and Smith introduced readers to the breadth of settings and procedures that are used to study human behavior based on work from their respective laboratories. They also provided important insights into the specific barriers that they have faced in their work. Specifics of the populations with which researchers' work often play a role in directing their research programs. Researchers'

5 Based on a cursory Google Scholar keyword search of "MTurk" or "Prolific" in the "Journal of the Experimental Analysis of Behavior" or the "Journal of Applied Behavior Analysis" conducted in January of 2024

6 As of January 2024; available at https://research.google/pubs/?area=human-computer-interaction-and-visualization

procedures often are carefully designed to reduce the impact of extraneous factors that may complicate data interpretation like participant fatigue or inattention. Moreover, the setting in which research is conducted introduces idiosyncratic considerations, like taking steps to reduce the influence of the presence of observers on participant behavior during laboratory visits, introducing measures to prevent individuals from participating in online research multiple times, and reducing the influence of bots in remotely delivered operant tasks. Thus, considerable attention to such factors may be required when designing novel lines of human-laboratory research on relapse.

Unlike laboratory rats or pigeons, who have comparatively homogenous behavioral histories when entering the operant chamber for the first time, humans enter the human-operant chamber with complex and uncontrolled behavioral histories that may complicate data interpretation. Issues derived from participants' histories of reinforcement for rule following featured prominently in Dr. Sullivan's section, but Drs. Kimball and Saini also wrote on this topic. It is well established that rules may supersede operant contingencies in terms of behavioral control, provided the individual has an adequate history of reinforcement for rule following (e.g., Baron & Galizio, 1983; Galizio, 1979). Given that most human-laboratory visits begin with presentation of some set of rules for the task at hand, researchers may put a good deal of thought into the structure of those rules to avoid inadvertently guiding behavior in one direction or the other. To complicate matters further, participants may self-impose rules that are not ever formally presented as a part of the laboratory task (Peláez & Moreno, 1998). I have seen this outcome in my own work, where participants sometimes report in post-experimental debriefings that they developed patterned, paced, or persistent responding because they thought they were meant to respond accordingly. Controlling for the effects of participant-imposed rules may be more difficult than controlling for those of experimenter-imposed rules, but collecting data on such rules may be illuminating and may present future targets for research.

Behavioral-history effects may also contaminate data collected in the human laboratory depending on the apparatus used to collect those data. Dr. Saini described one such potential effect as it relates to persistence of human behavior using high-tech apparatuses: Participants may persist in engaging with such apparatuses during extinction because they have a long history of reinforcement for persistent technology use in the natural environment. The possibility of such effects underscores the importance of systematic replication in the human laboratory (e.g., Saini et al., 2021). If replications using different apparatuses produce similar outcomes, the origin of behavior control may rest someplace other than the apparatus. Evidence for procedural artifact may be provided if such replications produce different outcomes.

Each researcher discussed the degree to which the same behavior processes engender outcomes derived from the human laboratory and those derived from other research settings. Preservation of behavior process across research settings is an important consideration, especially when the human laboratory is used as a proxy for the animal laboratory or clinic or as an intermediary step in the research process when transitioning research questions between the two. Unfortunately, the degree to which researchers achieve conservation of process between research settings often is unclear. One may infer conservation of process if research conducted in two different settings demonstrates similar functional relations between independent and dependent variables. Inasmuch, we encourage a bidirectional approach to translational research where findings from the animal laboratory or clinic are replicated and extended in the human laboratory, and vice versa. In that manner, we may be more confident that each component of the research enterprise contributes meaningfully to our understanding of relapse and other important behavioral outcomes.

Baron and Perone (1982) identified complexities associated with human-laboratory research similar to those described throughout this paper (i.e., the influence of demand characteristics and deep and uncontrolled behavior histories on participant performance). Ultimately, they concluded that those complexities should not be seen as limitations to studies conducted in this research setting but instead simply as variables that should (and could) be brought under experimental control. We firmly agree with their position. It is important to acknowledge, too, that behavior in the natural environment does not occur in a vacuum. Individuals who engage in clinically significant problem behavior are likely to have deep and uncontrolled behavior histories similarly to human-laboratory participants. The human laboratory might provide unique insights into how historical variables and independent variables under investigation jointly influence behavioral outcomes. Moreover, if a human-laboratory study aims to take a step away from the stillness of the laboratory and toward the noise of the natural environment, it may not be beneficial or even appropriate to evaluate the meaningfulness of the data it produces relative to data from more tightly controlled settings. Thus, the *goal* of research conducted in the human laboratory is another important factor to consider when evaluating study outcomes.

The perspectives shared above offer insights into the complexities of human-laboratory research on relapse, but they may only represent the tip of the proverbial iceberg. Many others conduct research in this area, and their input may offer unique, complementary, or competing perspectives. Inasmuch, we encourage readers who are interested in developing lines of human-operant research on relapse to develop a community filled with researchers who are conducting similar work. We are able to learn from others' successes in the published literature. It is often more difficult to learn from others' failures, as those may be less accessible due to issues with publication bias. Both of these sources of information are important when developing procedures to explore novel questions, especially given the complexities of human-laboratory research described above. An additional benefit to developing community in this context is that researchers may take steps toward reducing the between-group variability in the procedures that are used to study relapse of human behavior or at least toward better understanding the effects of procedural variability between groups on empirical outcomes. Thus, developing community among human-operant relapse researchers may have benefits not only for researchers who hope to join the fray but also for the experimental analysis of human behavior, more generally. We (the authors) developed a community amongst ourselves because we shared mutual interests and had the good fortune of professionally crossing paths. We certainly invite others to join us and would be excited to help develop a thriving contingent of researchers who experimentally analyze relapse using human participants.

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