HHS Public Access
Author manuscript
Psychol Addict Behav. Author manuscript; available in PMC 2024 February 01.

Published in final edited form as:
Psychol Addict Behav. 2023 February ; 37(1): 1–12. doi:10.1037/adb0000845.

Addictive Behavior as Molar Behavioral Allocation: Distinguishing Efficient and Final Causes in Translational Research and Practice

Jalie A. Tucker[1],
University of Florida and Center for Behavioral Economic Health Research, Gainesville, FL

Joanna Buscemi,
DePaul University, Chicago, IL

James G. Murphy,
University of Memphis, Memphis, TN

Derek D. Reed,
University of Kansas and Cofrin Logan Center for Addiction Research & Treatment, Lawrence, KS

Rudy E. Vuchinich
Center for Behavioral Economic Health Research, Gainesville, FL

Abstract

Objective.—Translational research on addictive behaviors viewed as molar behavioral allocation is critically reviewed. This work relates rates of behavior to rates of reinforcement over time and has been fruitfully applied to addictive behaviors, which involve excessive allocation to short-term rewards with longer-term costs.

Method.—Narrative critical review.

Results.—This approach distinguishes between final and efficient causes of discrete behaviors. The former refers to temporally extended behavior patterns into which the act fits. The latter refers to environmental stimuli or internal psychological mechanisms immediately preceding the act. Final causes are most clear when addictive behaviors are studied over time as a function of changing environmental circumstances. Discrete acts of addictive behavior are part of an extended/molar behavior pattern when immediate constraints on engagement are low and few rewarding alternatives are available. Research framed by efficient causes often use behavioral economic simulation tasks as individual difference variables that precede discrete acts. Such measures show higher demand for addictive commodities and steeper discounting in various risk groups, but whether they predict molar addictive behavior patterning is understudied.

Conclusions.—Although efficient cause analysis has dominated translational research, research supports viewing addictive behavior as molar behavioral allocation. Increasing concern with rate variables underpinning final cause analysis and considering how study methods and temporal units

[1]Correspondence concerning this article should be addressed to Jalie A. Tucker, Department of Health Education and Behavior, University of Florida, P.O. Box 118210, Gainesville, FL 32611-8210. jaliet@ufl.edu.

of analysis inform an efficient or final cause analysis may advance understanding of addictive behaviors that occur over time in dynamic environmental contexts. This approach provides linkages between behavioral science and disciplines that study social determinants of health.

Keywords

addictive behaviors; obesity; molar behaviorism; behavioral economics; social determinants of health

This special issue on addictive behavior as molar behavioral allocation is dedicated to Howard Rachlin, who pioneered and advanced the field conceptually and empirically from the 1970s until his death in 2021. The issue includes papers that focus on the scientific and applied fruits of molar behaviorism and behavioral economics as they pertain to understanding and changing addictive behavior. In this introduction, we first describe historical developments in basic behavioral science on behavioral allocation and articulate orienting assumptions of molar behaviorism that distinguish it from other theoretical approaches to understanding addictive behavior. Seminal applications to understanding addictive behavior are described.

After discussing measurement challenges in translational and applied human research, the present status of research guided by this framework is selectively reviewed and critiqued. This work is organized in two categories: (1) Studies of addictive behavior patterns as a function of changing environmental circumstances, with emphasis on the role of alternative reinforcers and substitute/complement relationships in understanding and changing addictive behavior; and (2) studies of individual difference variables in accounting for patterns of human behavioral allocation involving addictive behavior opportunities, with emphasis on the utility of analogue/simulation measures of behavioral economic variables (e.g., delay discounting, reward demand) to predict and perhaps mediate changes in addictive behavior.

In the final sections, we discuss important issues for advancing the field with emphasis on distinguishing among measurement approaches and temporal units of analysis. Focusing on rate variables and moving beyond cross-sectional investigation of individual difference variables and temporally contiguous stimulus-response relationships are recommended. We conclude with the usefulness of the framework to expand beyond an analysis of individual determinants of addictive behavior to investigate broader contextual features (e.g., community and social determinants of health) encompassed by the socioecological model of health behavior (Centers for Disease Control and Prevention [CDC], 2021; Institute of Medicine [IOM], 2003). This broadened analysis can inform intervention and policy approaches aimed at reducing the harm and prevalence of addictive behaviors.

Historical Context

Cognition and Behavior Therapy

Howard Rachlin completed his doctoral work in 1965 in the behavioral laboratory of Richard Herrnstein at Harvard University, and he became and would remain an ardent behaviorist throughout his career. That a behaviorist could have a dramatic impact on the applied field of addictive behavior is startling given that during the 1970s and 1980s, behavior therapy was striving to become free from the shackles many perceived as imposed on the field by the dominance of behaviorism. This complex cognitive-behavioral movement involved many clinician-scientists, but here we focus on the work of Michael Mahoney (1974; 1978), an influential representative.

A major perceived shackle concerned language. Behaviorists' scientific language (stimulus, response, reinforcer, etc.) developed for use in the behavioral laboratory was often too constraining and ill-suited for competent communication in a clinical situation. In his seminal 1974 book, Mahoney articulated this problem and argued convincingly for a focus on "private" events, or the myriad events thought to mediate between a stimulus and a response, which he called "mediational inferences." The effect of shedding this shackle was dramatic and legitimized consideration of private events as factors in human behavior, the exclusion of which "constituted a serious limitation in both comprehensiveness and clinical relevance of the then-current behavior theory" (p. 3).

Mahoney later (1978) focused on the causal force of "mediational inferences." Drawing on similar concerns in medicine regarding identification of causal links between the environment and disease (e.g., Hill, 1965), he formalized his analysis as a general template for identifying causal relations in psychological science: "1. relative temporal contiguity (togetherness in time); 2. priority (the cause must precede the effects); 3. noncontradiction (no observed instances of the cause without the effect); 4. factor isolation (the elimination or control of all possible influences other than the one being examined); and 5. replicability (the capacity to replicate the alleged relationship)" (p. 661). This template was later articulated further and became the current paradigm for identifying mediators and mechanisms of change in psychological treatments (Kazdin, 2007; Witkiewitz et al., 2022). The ideas of temporal contiguity and priority are crucial: If causes must precede and be temporally contiguous with their effects, and if there are no obvious candidates for causes of behavior in the observable situation, then pressure exists to hypothesize currently unobservable events typically inside the person to mediate between the two. Whether characterized as intervening variables or hypothetical constructs (MacCorquodale, & Meehl, 1948), their main conceptual function is to bridge the temporal gap between the situation (stimulus) and the behavior of interest (response). Mahoney's focus on "mediational inferences" soon dominated theory and research on addictive behavior, especially alcohol use disorder (Baker et al., 1988; Blane & Leonard, 1987; George & Marlatt, 1983; Marlatt & Gordon, 1985; Vuchinich, 1995).

Molar Behaviorism and Behavioral Economics

Contemporaneous with these developments in behavior therapy was a distinct evolution in basic psychological science regarding behavior allocation. Faithful to the Skinnerian tradition, this work was not concerned with what happens inside the organism between the stimulus and response. Instead, it was concerned with how rates of behavior over time may or may not entrain with rates of environmental events (especially reinforcement) over time. Operant laboratory research soon identified precise and robust relationships between rates of behavior and rates of reinforcement that Herrnstein (1970) formalized in the "Matching Law": $B_1/B_1+B_2 = R_1/R_1+R_2$; i.e., the relative frequency of behavior allocated to a response alternative equals the relative frequency of reinforcement obtained from that alternative. This development was theoretically important because it showed that any voluntary behavior can be studied as behavioral allocation arising out of a context of all possible behaviors and associated environment constraints. It was called “molar” because of the focus on rates of behavior and rates of environmental events over time (e.g., Baum, 1973). This work further showed that preference for a given activity or commodity depends on the constellation of available activities and environmental constraints in the choice context. Importantly, preference for a given commodity or activity can be changed by changing the choice context, e.g., by altering the direct constraints on the activity of interest or by altering the availability of other activities and the constraints on access to them.

The seminal Matching Law was soon shown to account for both animal (de Villiers, 1977) and human (Pierce & Epling, 1983) choice, positive and negative reinforcement (Herrnstein, 1969), and to apply to important human clinical situations, including choices between smaller sooner and larger delayed rewards (i.e., self-control; Ainslie, 1975; Rachlin, 1974; Rachlin & Green, 1972; Rachlin et al., 1986). This molar level of analysis relating rates of behavior to rates of consequences over time laid the foundation for the emergence of behavioral economics (e.g., Hursh, 1980; Lea, 1978; Rachlin et al., 1981), which merged operant methods on molar behavioral allocation with concepts from consumer demand theory in microeconomics.

Efficient Causes, Final Causes, and Teleological Behaviorism

In 1974 Rachlin published a paper on “Self-control” that contained a section entitled “What Can Cause Behavior?” (pp. 96–100). The behavior being caused in his example were rats’ bar presses in a Herrnstein and Hineline (1966) experiment on electric shock avoidance that programmed an inverse correlation over time between the rate of bar presses and the rate of irregularly timed shocks. Rats learned to press the bar even though no single bar press avoided any single shock, and the overall timeline of presses and shocks showed a clear inverse relation; i.e., the higher the rate of presses, the lower the rate of shocks, and vice versa. However, if the overall timeline was divided into more restricted observation periods and focused on individual presses or shocks, the inverse relation was no longer clear; sometimes a press occurred right after a shock, sometimes right before a shock, and sometimes there was no apparent relation. So, while the overall rates of bar presses and shocks were clearly inversely related, in truncated observation periods a co-occurrence or temporal priority of presses and shocks was absent, which violates conditions 1, 2, and 3 of Mahoney’s analysis of a causal relation. To pursue his analysis of causation would seem to require a finer-grained inspection of the processes that led to bar presses and the aftereffects of shock. In other words, it would require determining somehow what is happening inside the rat in the moments before and after a press or a shock.

Rachlin did not choose that path but instead proposed a broadened view of causation in psychological science (1992), one that includes final as well as efficient causes (following from Aristotle). Efficient causes, to which Mahoney’s analysis applies, include the cognitive, neural, physiological, or local environmental events that occur immediately before an act of interest. Final causes, as proposed by Rachlin, are the overall behavior pattern into which the act fits. In this way, a rat's single bar press can be caused by the overall rate of bar pressing, which in turn is caused by the reinforcement contingencies in effect over the study's duration. Rachlin did not argue that efficient causes are unimportant, because they obviously are important. Rather, in this situation, there are empirical regularities best characterized by an analysis of temporal relations that are much broader than the temporal contiguity lens of efficient causes. He termed a psychological science that focuses on final causes "teleological behaviorism" (1992) and later further articulated the distinction between efficient and final causes (Rachlin, 2013, 2014, 2017).

Molar Behaviorism as a Framework for Understanding Addictive Behavior in Context

Distinguishing Efficient and Final Causes in Translational Research and Practice

Two examples will highlight the conceptual issues involved in this broadened view of causation as applied to addictive behavior. First, imagine you are interviewing a client diagnosed with a substance use disorder, and he is describing his most recent episode of use. In order to identify the efficient causes of the episode, you want to know about the immediate environmental situation and what the client was thinking and feeling prior to and during the episode. In fact, from an efficient cause perspective, literally *everything* you need to know to account for the episode is present when it occurs, even if you do not know exactly how and where inside to look. Although you cannot directly observe all those efficient causes during the clinical interview, you assume that they are there and active, having been instantiated in the client's internal psychological mechanisms by his history.

In contrast, if you are interested in identifying the final causes of the episode, you want to know how this episode fits into his overall pattern of substance use over time and how that pattern fits into the more general behavior patterns of his life, including love, parenting, work, religion, friendships, finances, etc. In fact, from a final cause perspective, virtually *nothing* you need to know to account for the episode is present when it occurs (even though efficient causal factors are present and active), because those forces are spread out in time beyond the episode. You cannot directly observe all the components of those final causes during the interview, but you assume that they are there and active and were developed over extended periods of time by his interactions with the world.

Now consider another example: While napping, at that moment you are not working, exercising, or smoking cannabis. But, as the molar behavioral approach makes clear (e.g., Rachlin, 1992), it is also true that at that moment, you are engaging in each of those behaviors at certain rates over longer timeframes. Further consider over the last few weeks or months whether your behavior allocation patterns have been stable or altered by changing demands on your time or sudden events that changed your access to valuable activities. Exploring this kind of variability is at the core of a final cause analysis. Thus, for a particular act occurring at a particular moment, an efficient cause analysis looks deeper at that slice of time (e.g., what immediately precedes or follows your smoking cannabis at a certain time), often moving the cause inside the person. In contrast, a final cause analysis looks more broadly at different times (e.g., what variables reliably co-vary over time with your pattern of cannabis use and engagement in other behaviors). Although neglected in research, this molar level of analysis is similar to a functional analysis that has long been part of cognitive-behavioral treatments for addictive behaviors. Further, treatments in general place more emphasis on altering molar patterns than single acts of addictive behavior.

As discussed elsewhere (Acuff et al., 2022; Tucker & Vuchinich, 2015), the conceptual foundation of molar behaviorism and behavioral economics rests on Rachlin's (1992) distinction between efficient and final causes associated with any behavioral act. We are in no way gainsaying the significance of efficient causal variables of addictive behavior (e.g., negative affective states, craving, positive alcohol expectancies, environmental triggers, etc). Such variables have been reliably linked to risk for substance use escalation and resumption of substance use after a period of abstinence and have been productively applied in theoretical models of addictive behavior and treatment approaches, including efficacious cognitive and behavioral therapies that focus on avoiding or coping with these proximal high-risk events (Magill et al., 2019; Witkiewitz et al., 2022). Our point is that there is significant variability left unaccounted for, and we believe that variability can be addressed by accounting for patterns of addictive behavior over time.

Measurement Challenges in Translational and Applied Research

As in all translational research endeavors, extending these basic science concepts to translational and applied research has presented complications. Rates of behavioral and environmental events over long intervals under varied conditions are the primary empirical interpretations of relevant theoretical terms in basic behavioral economic science (Green & Freed, 1993; Hursh, 1980; Rachlin et al., 1981) and directly support an analysis of final causes. Some applied human behavioral economic measures assess patterns of behavior or monetary allocation (either retrospectively or prospectively) related to drug use and substance-free activities in order to connect these molar patterns of behavior with controlling variables (Murphy et al., 2015; Tucker et al., 2016, 2021).

But most behavioral economic studies with humans, however, do not measure *actual* rates of drug use, other behaviors, and contextual events over long time periods, for largely ethical and practical reasons. Instead, they rely on brief analogue (i.e., simulated) tasks that ask about hypothetical choices between immediate versus delayed monetary amounts (to estimate delayed reward discounting) or purchases of substances, food, and other commodities across escalating prices (to estimate reinforcer demand or value). This measurement approach, further described later, falls within the behavioral economic tradition because such measures represent a relevant reinforcement history that is related to patterns of behavior. It is consistent, at least in principle, with a final cause analysis, even though these tasks are often used to support efficient rather than final cause interpretations (Rachlin, 1992; 2013), wherein momentary changes in behavioral economic variables are investigated as causes of discrete behavioral acts.

For example, the applied alcohol field has sound measurement tools such as the Timeline Followback (TLFB) interview (Sobell & Sobell, 1992) that capture daily behavior and environmental characteristics over long intervals in the natural environment, commonly assessed using ratio scales that have meaning apart from a population distribution (e.g., frequency and quantity of drinking). Some research has used these data to model the temporal patterning of environment-behavior associations (e.g., Tucker et al., 2021), but most have reduced or eliminated concern with variability in rates of behavior over weeks, months, or years by computing summary indices of addictive behavior over intervals that vary from relatively long (1 year) to short (1 month). Clinically, the TLFB has been used both ways. At the individual client level of analysis, day-to-day TLFB drinking reports have been used in an ongoing functional analysis that identifies the contexts of problem alcohol use, identifies ways in which changes in client behavior are likely to change the environmental context, distinguishes among appropriate and inappropriate drinking for each occurrence based on drinking consequences within a certain context, and monitors progress (Sobell et al., 1976). At the group level of analysis, TLFB reports of heavy drinking days aggregated over months or longer have been used to calculate the percentage of participants in alcohol treatment clinical trials who report no heavy drinking days, which the Food and Drug Administration recommends as an efficacy endpoint indicative of treatment success (Falk et al., 2010).

Although such summary indices are useful for some research questions (e.g., evaluating treatment outcomes), they do not support a molar analysis of environment-behavior associations over time. Similarly, prospective ecological momentary assessment collects fine-grained daily data amenable to examining the temporal patterning of behavior and associations with changing environmental contexts as part of a final cause analysis. However, these data are commonly used to assess temporally contiguous associations with behavioral economic variables, typically assessed using simulation tasks, in service of an efficient cause analysis; e.g., momentary changes in discounting or demand are related to momentary changes in substance use at the individual episode level (e.g., Motschman et al., 2022; cf. Pearson et al., 2022).

Behavioral economic variables so derived can be used to support either an efficient or final causal analysis. From an efficient cause perspective, the measures are seen as reflecting the operation of a private mechanism (as one part within a representational system that includes other private mechanisms) that partly causes particular choices at a particular time (e.g., alcohol/ drug demand is viewed as causally related to drinking or drug use). From a final cause perspective, the measures are seen as reflecting molar behavioral-environmental relations (as one part of a representational system that includes other behavioral and environmental variables) that describes behavioral allocation patterns over time to activities. This approach seeks to estimate more general behavioral patterns (e.g., what will you drink across prices in the case of alcohol purchase tasks?) and may be used as a proximal outcome of a pattern of environmental events such as an intervention (e.g., alcohol/drug demand is viewed as a dynamic indicator of reward value that portents changes in substance use but one that is itself related to contextual variables such as limited alternative reinforcement or minimal constraints on substance use).

These measurement challenges notwithstanding, as discussed next relevant empirical work on addictive behavior includes animal research that is decidedly molar in its level of analysis (e.g., Ainslie & Herrnstein, 1981; Carroll, 1996) and human research that is variously molar (e.g., Murphy et al., 2019a; Tucker et al., 2021; Vuchinich & Tucker, 1996) or uses concepts and measures from molar animal and human research applied within an efficient cause framework (e.g., Amlung et al., 2015; cf. Acuff et al., 2020). This work provides considerable support for concepts and relations from molar behaviorism and behavioral economics.

Present Status of Research on Addictive Behavior as Behavioral Allocation

Addictive Behavior Patterns as a Function of Changing Environmental Circumstances

Experimental laboratory studies and applied clinical and epidemiological research consistently show that high rates of substance use and other addictive behaviors are most likely in contexts characterized by few constraints on the addictive behavior and low availability of alternative reinforcers. Further, addictive behaviors will generally decrease if access to alternative reinforcers is increased, a relationship that is well established for substance use (Bickel et al., 2014; Higgins et al., 2004; Lamb & Ginsburg, 2018) and replicated in the obesity literature with food (Jacques-Tiura & Greenwald, 2016). For example, across an 18-month behavioral weight loss trial, Buscemi and colleagues (2014) found that food-related reinforcement decreased and food-free reinforcement increased, and greater reductions in body mass index were associated with greater relative increases over time the proportion of food-free to food-related reinforcement.

Numerous laboratory studies with human and non-human animals have found that experimental manipulations of the availability and magnitude of alternative reinforcers (e.g., substance-free activities, social companions, money) result in predictable changes in drug or food self-administration over time. For example, environmental enrichment is associated with lower levels of drug use initiation and with reductions in drug use among humans and animals who are regular users (Gage & Sumnall, 2018; Lamb & Ginsburg, 2018). In naturalistic human studies, reinforcement is variously measured by some combination of activity participation and enjoyment ratings, by the relative amount of time or money allocated to a given commodity or activity, or by questionnaires that ask directly about access to rewarding experiences (Acuff et al., 2019; Buscemi et al., 2014; Murphy et al., 2021). Reinforcement surveys, for example, measure the frequency of engagement in, and subjective pleasure associated, with a variety of activities (e.g., socializing, watching TV, using drugs), typically during the past month, and have been modified to differentiate substance-related and substance-free reinforcement (e.g., socializing with vs. without drug use; Correia et al., 2005; going to the movies with or without eating; Buscemi et al., 2014). Longitudinal research suggests that individual differences in access and responsiveness to alternative reinforcers prospectively predict smoking initiation (Audrain-McGovern et al., 2011), changes in drinking and alcohol use disorder symptoms following a brief alcohol intervention (Murphy et al., 2015, 2021), and heroin use during a 6-month follow-up of heroin users undergoing opioid-substitution therapy (Lubman et al., 2009).

Thus, both laboratory and naturalistic research supports molar behavioral theories of choice and reinforcement-based behavioral interventions that focus on increasing alternatives to substance use and other addictive behaviors (reviewed by Fazzino et al., 2019). This includes evidence-based intensive treatment approaches such as contingency management, community reinforcement, and behavioral activation, as well as brief motivational interventions that seek to reduce the relative reinforcing value of drugs by increasing engagement in future-oriented positive alternatives (e.g., Correia et al., 2005; Murphy et al., 2012, 2019). For example, in an evaluation of change processes associated with a brief alcohol intervention (Murphy et al., 2019), emerging adults who reduced their drinking showed increased reinforcement from substance-free activities at follow-up, and changes in proportionate reinforcement related to substance-free activities mediated the relation between the intervention and reductions in alcohol use. Further, having substance-free next-day responsibilities (e.g., employment, classes, volunteer work) has been linked to lower alcohol demand, as measured by a behavioral economic task, the Alcohol Purchase Task (Murphy & MacKillop, 2006), that quantifies hypothetical alcohol consumption and alcohol-related expenditures as a function of drink prices (Joyner et al., 2019). A review of clinical research on associations between social support and smoking (Fisher, 1996) supported conceptualizing both activities as commodities that could substitute for one another; specifically, social support is effective in reducing smoking while it is available but this salutary substitution relationship diminishes when access is constrained. This commodity model of social support has been successfully extended to other health behaviors including food choice, physical activity, and chronic disease management (Green & Fisher, 2000).

It is important to note that while many substance-free activities serve in this way as substitutes for substance use, other activities may co-occur with use and function as economic complements. For example, because alcohol is often consumed in social settings and is associated with social bonding, social reward may decrease following reductions in drinking (Murphy et al., 2005), and teens who experience more reward associated with substance-related activities report increased rates of substance use over time (Lee et al., 2018).

Research further suggests that increasing the salience of delayed outcomes of behavioral patterns can reduce impulsive response patterns and increase future orientation (Ashe & Wilson, 2020); e.g., focused thinking and writing about potential positive future events (“episodic future thinking”) can reduce delay discounting and alcohol demand and may promote positive behavior change (Patel & Amlung, 2020; Snider et al., 2016), especially if integrated in an approach focused on increasing substance-free activities (Meshesha et al., 2020). Episodic future thinking has also been found to reduce energy intake in adults (Daniel et al., 2013) and children (Daniel et al., 2015). Further, when future events were framed as part of a temporally extended behavior pattern leading to delayed rewards (“reward bundling”), their value was discounted less steeply than if presented as independent events or discrete choices (Rung & Madden, 2018).

Role of Reinforcer Discounting and Demand in Addictive Behaviors

In 1991, Rachlin et al. published a seminal paper translating concepts of delayed and probabilistic reinforcement to a new hypothetical discounting task. Human participants were instructed to make a series of hypothetical choices between either smaller immediate or larger delayed monetary rewards, as well as between smaller certain or larger uncertain rewards. Participants rendered discounting functions on this hypothetical task similar to those observed in experimental studies with nonhumans (Mazur, 1987), and the orderliness of the data and the quantitative models describing them were consistent with basic laboratory work that entailed temporally extended patterns of responding in concurrent choice arrangements. Rachlin (1995) later employed another laboratory preparation to explore behavioral patterning as a “soft commitment” procedure to increase self-control and noted that “[t]emporal patterning, such as the grouping of choice opportunities in threes or fours as in [operant laboratory tasks], tends to cause a series of momentary choices to be perceived as a unitary, temporally extended event” (p. 191). That these convenient laboratory tasks could be used to study temporal and probability discounting and behavioral patterning in humans had great translational promise.

The promise offered was soon extended to conceptualize and measure the relative reinforcing efficacy of substance use (e.g., Bickel et al., 1999; Bickel & Marsch, 2001). This inspired translations of operant demand procedures to hypothetical tasks to measure demand for opioids and cigarettes (Jacobs & Bickel, 1999), alcohol (Murphy & MacKillop, 2006), food (Epstein et al., 2007), cannabis (Collins et al., 2014), and non-medical prescription opioids (Strickland et al., 2020). Like the translational success of discounting tasks, hypothetical demand tasks yielded functions nearly identical to those observed in basic fixed-ratio demand assessments in the laboratory. That these brief hypothetical tools generated data indistinguishable from operant laboratory methods provided some confidence that they are a proxy to within-subject parametric studies examining operant responding for real rewards.

Responding on behavioral economic simulation tasks correlates well with measures of addictive behavior and appears to have discriminant validity in distinguishing participants who do and do not engage in addictive behavior (e.g., Amlung et al., 2017; MacKillop et al., 2011; Nighbor et al., 2019). However, their validity as proxies for the temporally extended choice profiles that characterize substance use disorders has yet to be directly evaluated. Moreover, an unfortunate byproduct of the convenience of brief hypothetical measures of demand and delayed reward discounting is that the number of studies using these approaches dwarfs the number that assessed molar behavioral patterns of substance use in relation to substance-free behavior and environmental events over time (Murphy et al., 2015; Tucker et al., 2021).

The robust measurement properties of brief demand curve and delay discounting measures has allowed numerous studies to evaluate various hypotheses associated with behavioral economic theories of addictive and other health risk behaviors. It is fitting that these tools—inspired by and evolved from Rachlin’s work translating economic principles to concurrent choice—are now employed to advance understanding of behavioral economic concepts. Several reviews have described the rich literature on ways in which contextual manipulations can alter responding on discounting and demand tasks (Acuff et al., 2020; Koffarnus et al., 2013; Rung & Madden, 2018). Notably, these hypothetical tasks are now being used to better understand scarcity effects and the openness of economies on choice responding in the context of demand (e.g., Amlung et al., 2019; Kaplan et al., 2017; Koffarnus et al., 2015; Skidmore & Murphy, 2011; Sze et al., 2017) and to evaluate the effects of framing probabilities (e.g., Yi & Bickel, 2005), delays (e.g., DeHart et al., 2018; Naudé et al., 2018), and unit prices (e.g., Kaplan & Reed, 2018) on choice responding in the context of discounting.

Although simulation tasks are typically one-shot (i.e., cross-sectional) measures of a "unitary temporally extended event," some emerging research has shown that they are helpful in examining health-related and addictive behavior over time. For example, they have been used as dependent variables to examine the effects of experimental treatments on steady-state responding in controlled translational studies using within-subject designs (e.g., Dixon & Holton, 2009; Kaplan et al., 2016). In the Kaplan et al. study, participants completed a simulated probability discounting task involving health outcomes at the start of each session. A multiple-baseline across participants design examined steady-state patterns of discount rates before and during implementation of an episodic future thinking intervention. Clear changes were observed in within-subject levels of discount rates in the presence of the intervention relative to baseline. Although promising, the numbers of such studies pale in comparison to the vast cross-sectional literature on hypothetical discounting and demand, and the longer term effectiveness of these episodic future interventions remains uninvestigated. Nevertheless, this line of research may be leading a new wave of empirical inquiry that includes a focus on measuring patterns of behavior over time in relation to environmental events—a paradigm shift we strongly recommend.

Unresolved Issues and Future Recommendations

The present literature often lacks clarity about whether a given study is pursuing an efficient or final cause analysis or some combination. A basic issue involves distinguishing among measurement approaches and temporal units of analysis in a given study and making clear the extent to which the design and methods address efficient or final causes, which lie on a continuum. Focusing on rate variables at a molar level is critical for the latter, and we think addictive behavior science would benefit from expanding beyond cross-sectional investigation of individual difference variables and temporally contiguous stimulus-response relationships.

Specifically, we recommend (1) maintaining a focus on molar addictive behavior patterning even if assessed retrospectively; (2) expanding the variable domains of interest beyond exclusive focus on a given addictive behavior to include investigation of valued activities and commodities that can compete with addictive behaviors; and (3) connecting behavioral economic simulation measures of individual difference variables, often generated with hypothetical drug demand and delayed-reward discounting tasks, with molar environment-behavior relationships that comprise addictive behavior patterns (e.g., McCarthy et al., 2018; Merrill & Aston, 2020; Schlienz et al., 2014; Xu et al., 2020). For example, daily self-monitoring studies could measure substance use over several months while also measuring the availability of and engagement in alternative drug-free activities and other contextual variables in order to evaluate potential molar functional associations that might not be evident with typical ecological momentary assessment approaches that include frequent assessments throughout the day but rarely cover more than a 2–4 week period.

It is possible that the challenges associated with measuring rates of substance use and other behavioral patterns over extended temporal intervals, and with quantifying elements of the environment such as the availability of alternative reinforcement and constraints on access to alcohol and drugs, have led to an underemphasis of these critical variables within applied research and theories of addictive behaviors relative to easily measured variables such as drug demand and delayed reward discounting. For example, whereas many older behavioral economic models of addictive behavior emphasized the critical role of alternative reinforcement as a risk factor and treatment target (Higgins et al., 2004; Rachlin, 1997; Vuchinich & Tucker, 1988; cf. Vuchinich & Heather, 2003), more recent behavioral economic models, including the influential "Reinforcer Pathology Model" (Bickel et al., 2014, 2020), place relatively greater emphasis on alcohol demand and delayed reward discounting as causal variables and on neurocognitive and narrative approaches to expanding the temporal horizon of decision-making as intervention elements. Given the abundance of experimental and clinical research supporting the role of environmental reward as a determinant of addictive behavior (Lamb & Ginsberg, 2018) and as a treatment mechanism (Fazzino et al., 2019; Murphy et al., 2019), the relative underemphasis on examining rates of addictive behavior over time in relation to features of the environment may be a case where the relative measurement convenience associated with simulated demand and delay discounting tasks has contributed to these variables exerting an outsized influence on applied research and theoretical models (cf. Tucker & Vuchinich, 2015).

Considering Addictive Behaviors in Broader Socioecological Context

Research guided by molar behaviorism and behavioral economics has yielded a rich body of work useful for understanding individual determinants of addictive behavior patterns and guiding interventions to change problem behavior at the individual person level. This work has shown the critical role of environmental contextual variables such as the availability of substances and substance-free alternatives over time. Given that the choices individuals make depend on the options available, this suggests broadening the scope of contextual variables to include upstream factors such as social, community, built environment, economic, and policy domains encompassed by the socioecological model of health behavior (CDC, 2021; IOM, 2003). For example, systemic racism and oppression limit many health promoting behaviors and increase health risk behaviors, thus perpetuating health inequities and the influence of social determinants of health (SDOH) on behavioral health disorders (CDC, 2021). Investigating such factors in addition to individual level determinants is an important next step that may inform prevention and treatment innovations and help address inequities in substance misuse, obesity, and other harmful health behaviors (Karriker-Jaffe et al., 2013; Roche et al., 2015). Indeed, Rachlin and his colleagues (2018) articulated how basic reinforcement principles and findings from behaviorism and behavioral economics can be used to address complex behavior patterns relevant to behavioral medicine and public health framed within an ecological model of health behavior.

Considering multiple levels of the socioecological model is consistent with behavioral economic models that emphasize enriching the environment with rewarding alternatives that can compete with drug use and other addictive behaviors (Murphy et al., 2019; Vuchinich &

Author Manuscript

Author Manuscript

Author Manuscript

Heather, 2003). This broadened focus occurred in the HIV area a decade ago in recognition of how community, social, and physical environmental features influence HIV risk and protective behaviors and outcomes of risk reduction interventions (Latkin et al., 2013). Considering individual and broader contextual factors beyond the treatment experience is firmly aligned with research from medical sociology, public health, and health economics that demonstrates the robust influence of SDOH on many health and behavioral health disorders. Understanding how SDOH operate within and across levels to influence health behaviors is considered essential to improve health status and reduce health disparities and inequities.

Although incipient, research on addictive and other health-compromising behaviors has found associations with community, built environment, and policy variables in addition to individual determinants. For example, communities with lower socioeconomic status (SES) experience more consequences from alcohol consumption (Roche et al., 2015; Grittner et al., 2012), even though higher SES communities consume more alcohol (Galea et al., 2007; Grittner et al., 2013). Lower SES communities have higher alcohol outlet densities, which is associated with greater consumption and negative consequences (Trangenstein, 2020). Further, deficits in alternative reinforcement are longitudinal mediators of the association between socioeconomic disparities and adolescent substance use (Lee et al., 2018), and diminished access to social, occupational, and economic rewards are predictors of U.S. drug-related deaths (Monnat, 2018). Similar neighborhood-level factors related to obesity have been found. Lower SES neighborhoods are less likely to have opportunities to engage in physical activity due to limited access to safe parks, sidewalks, and public transit and are more likely to be situated in a food desert, making it difficult to access healthy nutrient-dense foods (Beaulac et al., 2009).

SDOH have also been associated with recovery from addictive disorders. Participants receiving community-based alcohol treatment were less likely to achieve remission six months after treatment if they lived in areas with greater socioeconomic disadvantage and housing instability (Peacock et al., 2018). Both individual and community SDOH variables predicted alcohol recovery profiles 3-years post-treatment among participants in the multi-site COMBINE study (Swan et al., 2021). Individual SDOH, such as lower education and income, and community SDOH, such as lower rates of health insurance, lower income, and greater income inequality, predicted lower functioning profiles. Similarly, a meta-analysis (Bull et al., 2014) of evidence-based interventions for diet, physical activity, and smoking among individuals of lower income showed that while interventions had positive effects, the effect sizes were small and smaller than what is generally found among wealthier populations. Thus, there is a need to consider SDOH when developing interventions to promote long-term health behavior change.

Finally, policy applications support the utility of behavioral economics to guide prevention programs. The Icelandic Prevention Model, a policy initiative aligned with behavioral economic emphasis on enriching the environment with drug-free rewards, was implemented nationwide in Iceland over 20-years to reduce youth substance use (Kristjansson et al., 2020). Guided by sociology/criminology deviance theories that prioritize environments, primary prevention, and infrastructure building, the community-based Iceland Prevention

Model emphasizes long-term intervention and altering social environments at the neighborhood level in ways that reduce the likelihood that young people will initiate and subsequently maintain substance use. The approach has been highly effective based on population survey data collection within individual local schools: From 1998 to 2020, being drunk in the past month dropped from 42% to 6%, daily smoking dropped from 23% to 2%, and lifetime cannabis use dropped from 17% to 7% among 10th grade students.

Most U.S. policy initiatives to promote healthy eating are largely information-based and not guided by theory, although two methods are aligned with behavioral economics and choice architecture approaches (Thaler & Sunstein, 2009; Tucker et al., 2017): (1) incentives/price manipulation-based policies, and (2) offering healthful choice options as the default option (Cory et al., 2021). Enacting a sugary drink tax is an example of the former, and early data suggest that this decreases sugary beverage consumption and increases water consumption in low-income neighborhoods; e.g., Falbe et al. (2016) found that post-tax enactment, sugary beverage consumption decreased 21% and water consumption increased 63% in the target community, whereas sugary beverage consumption increased 4% and water consumption increased 19% in comparison control communities. Regulating what restaurants serve as their default beverages in children's meals is an example of the latter (e.g., serving water as the default rather than a sugary drink; Voices for Healthy Kids Action Center, 2019). Policy research suggests that these approaches increase purchases of healthful items and decrease purchases of less healthy items (e.g., soda, fries; Anzman-Frasca et al., 2015; Peters et al., 2016). For example, in 2006 Walt Disney World restaurants replaced the default options for a side and beverage in children's meals from french fries and a soda to vegetable and fruit selections and low-fat milk, water, and juice. Based on sales data over 3 years, the healthy defaults reduced calories (21.4%), fat (43.9%), and sodium (43.4%) for kids' meal sides and beverages compared to the original default condition, and 48% of side item and 66% of beverage purchases were healthy options (Peters et al., 2016).

These findings concerning broader community and policy effects highlight the value of expanding the scope of contextual variables to include consideration of multiple levels of the socioecological model. Disciplines other than psychology offer sound schemes to define and measure broader contextual variables, and behavioral economics offers conceptual and empirical guidance about their selection, organization, and implementation to promote positive change.

Conclusions

Efficient cause analysis grounded in the psychometric measurement tradition has dominated applied research, and concern with rate variables underpinning molar behaviorism and a final cause analysis are underdeveloped. Although both traditions have facilitated understanding of addictive behaviors, we argue that advances will come through systematic clarification in individual studies of how the methods and temporal units of analysis used serve an efficient or final cause analysis. Limiting research to identifying efficient causes either based on attributes within the person or the immediate context surrounding a discrete episode does not capture the broader temporal patterning that is a fundamental quality of addictive behaviors.

How such behaviors emerge from the totality of available activities and commodities, how they are maintained, and how they resolve over time as environmental circumstances change are essential questions posed by a molar behavioral analysis that contribute to the identification of final causes. Efficient cause analysis may be sufficient to account for individual occurrences of addictive behavior, but on its own cannot address these questions that are central to understanding and changing addictive behaviors. Broadening research and theory to include both kinds of analysis and clarifying the scope of research questions addressed hold promise for advancing understanding of addictive behaviors and are consistent with the socioecological model of health behavior that encompasses individual determinants of behavior and broader contextual features that often operate over longer temporal intervals.

Acknowledgments

Manuscript preparation was supported in part by NIH/NIAAA grants R01AA024930 and R01AA029031 (Murphy, PI) and R01AA028230 (Tucker, PI). The authors thank Samuel Acuff who provided comments on an earlier manuscript version.

References

Acuff SF, Amlung M, Dennhardt AA, MacKillop J, & Murphy JG (2020). Experimental manipulations of behavioral economic demand for addictive commodities: a meta-analysis. Addiction, 115, 817–831. 10.1111/add.14865 [PubMed: 31656048]

Acuff SF, Dennhardt AA, Correia C, & Murphy JG (2019). Measurement of substance-free reinforcement in addiction: A systematic review. Clinical Psychology Review, 70, 79–90. 10.1016/j.cpr.2019.04.003 [PubMed: 30991244]

Acuff SF, Tucker JA, Vuchinich RE, & Murphy JG (2022). Addiction is not (only) in the brain: Molar behavioral economic models of etiology and cessation of harmful substance use. In Heather N, Field M, Moss A, & Satel S (Eds.) on behalf of the Addiction Theory Network, Evaluating the brain disease model of addiction. Taylor & Francis.

Ainslie G (1975). Specious reward: A behavioral theory of impulsiveness and impulse control. Psychological Bulletin, 82(4), 463–496. https://psycnet.apa.org/doi/10.1037/h0076860 [PubMed: 1099599]

Ainslie G, & Herrnstein RJ (1981). Preference reversal and delayed reinforcement. Animal Learning & Behavior, 9(4), 476–482. 10.3758/BF03209777

Amlung MT, McCarty KN, Morris DH, Tsai CL, & McCarthy DM (2015). Increased behavioral economic demand and craving for alcohol following a laboratory alcohol challenge. Addiction, 110(9), 1421–1428. 10.1111/add.12897 [PubMed: 25732875]

Amlung MT, Vedelago L, Acker JD, Balodis I, & MacKillop J (2017). Steep delay discounting and addictive behavior: A meta-analysis of continuous associations. Addiction, 112(1), 51–62. 10.1111/add.13535

Anzman-Frasca S, Mueller MP, Sliwa S, Dolan PR, Harelick L, Roberts SB, Washburn K, & Economos CD (2015). Changes in children's meal orders following healthy menu modifications at a regional U.S. restaurant chain. Obesity, 23(5), 1055–1062. 10.1002/oby.21061 [PubMed: 25919925]

Ashe ML, & Wilson SJ (2020). A brief review of choice bundling: A strategy to reduce delay discounting and bolster self-control. Addictive Behaviors Reports, 11, 100262. 10.1016/j.abrep.2020.100262 [PubMed: 32467851]

Audrain-McGovern J, Rodriguez D, Rodgers K, & Cuevas J (2011). Declining alternative reinforcers link depression to young adult smoking, Addiction, 106(1), 178–187. 10.1111/j.1360-0443.2010.03113.x [PubMed: 20840206]

Baum WM (1973). The correlation based law of effect. Journal of the Experimental Analysis of Behavior, 20(1), 137–153. https://dx.doi.org/10.1901%2Fjeab.1973.20-137 [PubMed: 16811687]

Baker TB (1988). Models of addiction: Introduction to the special issue. Journal of Abnormal Psychology, 97(2), 115–117. 10.1037/h0092431

Beaulac J, Kristjansson E, & Cummins S (2009). A systematic review of food deserts: 1966–2007. Preventing Chronic Disease, 6(3), A105. [PubMed: 19527577]

Bickel WK, Athamneh LN, Snider SE, Craft WH, DeHart WB, Kaplan BA, & Basso JC (2020). Reinforcer pathology: Implications for substance abuse intervention. Current Topics in Behavioral Neurosciences, 47, 139–162. 10.1007/7854_2020_145 [PubMed: 32462615]

Bickel WK, Johnson MW, Koffarnus MN, MacKillop J, & Murphy JG (2014). The behavioral economics of substance use disorders: Reinforcement pathologies and their repair. Annual Review of Clinical Psychology, 10, 641–677. 10.1146/annurev-clinpsy-032813-153724

Bickel WK, & Marsch LA (2001). Toward a behavioral economic understanding of drug dependence: Delay counting processes. Addiction, 96 (February 2000), 73–86. 10.1080/09652140020016978 [PubMed: 11177521]

Bickel WK, Odum AL, & Madden GJ (1999). Impulsivity and cigarette smoking: Delay discounting in current, never, and ex-smokers. Psychopharmacology, 146(4), 447–454. 10.1007/Pl00005490 [PubMed: 10550495]

Blane HT, & Leonard KE (Eds.) (1987). Psychological theories of drinking and alcoholism. Guilford Press.

Bull ER, Dombrowski SU, McCleary N, & Johnston M (2014). Are interventions for low-income groups effective in changing healthy eating, physical activity and smoking behaviours? A systematic review and meta-analysis. BMJ Open, 4(11). 10.1136/bmjopen-2014-006046

Buscemi J, Murphy JG, Berlin KS, & Raynor HA (2014). A behavioral economic analysis of changes in food-related and food-free reinforcement during weight loss treatment. Journal of Consulting and Clinical Psychology, 82(4), 659–69. 10.1037/a0036376 [PubMed: 24660672]

Carroll ME (1996). Reducing drug abuse by enriching the environment with alternative nondrug reinforcers. In Green L & Kagel JH (Eds.), Advances in behavioral economics: Substance use and abuse (Vol. 3, pp. 37–68). Ablex Publishing.

Centers for Disease Control and Prevention (CDC). Social determinants of health. Published 2021. Accessed September 6, 2021. https://www.cdc.gov/socialdeterminants/index.htm

Collins RL, Vincent PC, Yu J, Liu L, & Epstein LH (2014). A behavioral economic approach to assessing demand for marijuana. Experimental and Clinical Psychopharmacology, 22(3), 211–221. 10.1037/a0035318 [PubMed: 24467370]

Cory M, Loiacono B, Clark Withington M, Herman A, Jagpal A, & Buscemi J (2021). Behavioral economic approaches to childhood obesity prevention nutrition policies: A social ecological perspective. Perspectives on Behavior Science, 44, 317–332. [PubMed: 34632280]

Correia CJ, Benson TA, & Carey KB (2005). Decreased substance use following increases in alternative behaviors: A preliminary investigation. Addictive behaviors, 30(1), 19–27. 10.1016/j.addbeh.2004.04.006 [PubMed: 15561446]

Daniel TO, Stanton CM, & Epstein LH (2013). The future is now: Reducing impulsivity and energy intake using episodic future thinking. Psychological Science, 24, 2339–2342. 10.1177/0956797613488780 [PubMed: 24022653]

Daniel TO, Said M, Stanton CM, & Epstein LH (2015). Episodic future thinking reduces delay discounting and energy intake in children. Eating Behaviors, 18, 20–24. 10.1016/j.eatbeh.2015.03.006 [PubMed: 25863227]

DeHart WB, Friedel JE, Frye CCJ, Galizio A, & Odum AL (2018). The effects of outcome unit framing on delay discounting. Journal of the Experimental Analysis of Behavior, 110(3), 412–429. 10.1002/jeab.469 [PubMed: 30203525]

de Villiers P (1977). Choice in concurrent schedules and a quantitative formulation of the law of effect. In Honig WH & Staddon JER (Eds.), Handbook of operant behavior (pp. 233–287). Prentice-Hall.

Dixon MR, & Holton B (2009). Altering the magnitude of delay discounting by pathological gamblers. Journal of Applied Behavior Analysis, 42(2), 269–275. 10.1901/jaba.2009.42-269 [PubMed: 19949514]

Epstein LH, Leddy JJ, Temple JL, & Faith MS (2007). Food reinforcement and eating: A multilevel analysis. Psychological Bulletin, 133(5), 884–906. 10.1037/0033-2909.133.5.884 [PubMed: 17723034]

Falbe J, Thompson HR, Becker CM, Rojas N, McCulloch CE, & Madsen KA (2016). Impact of the Berkeley excise tax on sugar-sweetened beverage consumption. American Journal of Public Health, 106(10), 1865–1871. 10.2105/AJPH.2016.303362 [PubMed: 27552267]

Fazzino TL, Bjorlie K, & Lejuez CW (2019). A systematic review of reinforcement-based interventions for substance use: Efficacy, mechanisms of action, and moderators of treatment effects. Journal of Substance Abuse Treatment, 104, 83–96. 10.1016/j.jsat.2019.06.016 [PubMed: 31370989]

Fisher EB Jr. (1996). A behavioral-economic perspective on the influence of social support on cigarette smoking. In Green L, & Kagel JH (Eds.), Advances in behavioral economics, Vol 3: Substance use and abuse (pp. 207–236). Norwood, NJ: Ablex.

Gage SH, & Sumnall HR (2019). Rat Park: How a rat paradise changed the narrative of addiction. Addiction (Abingdon, England), 114(5), 917–922. 10.1111/add.14481 [PubMed: 30367729]

Gainsbury SM, Tobias-Webb J, & Slonim R (2018). Behavioral economics and gambling: A new paradigm for approaching harm minimization. Gaming Law Review, 22(10), 608–617. 10.1089/glr2.2018.22106

Galea S, Ahern J, Tracy M, & Vlahov D (2007). Neighborhood income and income distribution and the use of cigarettes, alcohol, and marijuana. American Journal of Preventive Medicine, 32(6 Suppl), S195–S202. https://dx.doi.org/10.1016%2Fj.amepre.2007.04.003 [PubMed: 17543711]

George WH, & Marlatt GA (1983). Alcoholism: The evolution of a behavioral perspective. In Galanter M (Ed.), Recent developments in alcoholism (pp. 105–138). Plenum Press.

Grittner U, Kuntsche S, Gme G, & Bloomfield K (2013). Alcohol consumption and social inequality at the individual and country levels - Results from an international study. European Journal of Public Health, 23(2), 332–339. 10.1093/eurpub/cks044 [PubMed: 22562712]

Green L, & Fisher EB Jr. (2000). Economic substitutability: Some implications for health behavior. In Bickel WK & Vuchinich RE (Eds.), Reframing health behavior change with behavioral economics (pp. 115–144). Mahwah, NJ: Erlbaum.

Green L, & Freed DE (1993). The substitutability of reinforcers. Journal of the Experimental Analysis of Behavior, 60(1), 141–158. 10.1901/jeab.1993.60-141 [PubMed: 16812696]

Grittner U, Kuntsche S, Graham K, & Bloomfield K (2012). Social inequalities and gender differences in the experience of alcohol-related problems. Alcohol and Alcoholism, 47(5), 597–605. 10.1093/alcalc/ags040 [PubMed: 22542707]

Herrnstein RJ, (1969). Method and theory in the study of avoidance. Psychological Review, 76(1), 49–69. https://psycnet.apa.org/doi/10.1037/h0026786 [PubMed: 5353378]

Herrnstein RJ (1970). On the law of effect. Journal of the Experimental Analysis of Behavior, 13(2), 243–266. https://dx.doi.org/10.1901%2Fjeab.1970.13-243 [PubMed: 16811440]

Herrnstein RJ, & Hineline PN (1966). Negative reinforcement as shock-frequency reduction. Journal of the Experimental Analysis of Behavior, 9(4), 421–430. 10.1901/jeab.1966.9-421 [PubMed: 5961510]

Higgins ST, Heil SH, & Lussier JP (2004). Clinical implications of reinforcement as a determinant of substance use disorders. Annual Review of Psychology, 55, 431–461. 10.1146/annurev.psych.55.090902.142033

Hill AB (1965). The environment and disease: Association or causation? Journal of the Royal Society of Medicine, 58(5), 295–300. https://doi.org/10.1177%2F003591576505800503

Hursh S (1980). Economic concepts for the analysis of behavior. Journal of the Experimental Analysis of Behavior, 34(2), 219–238. 10.1901/jeab.1980.34-219 [PubMed: 16812188]

Institute of Medicine (2003). Who will keep the public healthy? Educating public health professionals for the 21st century. National Academies Press.

Jacobs EA, & Bickel WK (1999). Modeling drug consumption in the clinic using simulation procedures: demand for heroin and cigarettes in opioid-dependent outpatients. Experimental and Clinical Psychopharmacology, 7(4), 412–426. 10.1037/1064-1297.7.4.412 [PubMed: 10609976]

Jacques-Tiura AJ & Greenwald MK (2016). Behavioral economic factors related to pediatric obesity. Pediatric Clinics of North America, 63(3), 425–446. 10.1016/j.pcl.2016.02.001 [PubMed: 27261543]

Joyner KJ, Meshesha LZ, Dennhardt AA, Borsari B, Martens MP, & Murphy JG (2019). High opportunity cost demand as an indicator of weekday drinking and distinctly severe alcohol problems: A behavioral economic analysis. Alcoholism: Clinical and Experimental Research, 43(12), 2607–2619. 10.1111/acer.14206 [PubMed: 31661166]

Kaplan BA, & Reed DD (2018). Happy hour drink specials in the alcohol purchase task. Experimental and Clinical Psychopharmacology. 10.1037/pha0000174

Kaplan BA, Reed DD, & Jarmolowicz DP (2016). Effects of episodic future thinking on discounting: Personalized age-progressed pictures improve risky long-term health decisions. Journal of Applied Behavior Analysis, 49(1), 148–169. 10.1002/jaba.277 [PubMed: 26679531]

Kaplan BA, Reed DD, Murphy JG, Henley AJ, DiGennaro Reed FD, Roma PG, & Hursh SR (2017). Time constraints in the alcohol purchase task. Experimental and Clinical Psychopharmacology, 25(3), 186–197. 10.1037/pha0000110 [PubMed: 28240924]

Karriker-Jaffe KJ, Roberts SCM, & Bond J (2013). Income inequality, alcohol use, and alcohol-related problems. American Journal of Public Health, 103(4), 649–656. https://dx.doi.org/10.2105%2FAJPH.2012.300882 [PubMed: 23237183]

Kazdin A (2007). Mediators and mechanisms of change in psychotherapy research. Annual Review of Clinical Psychology, 3, 1–27. 10.1146/annurev.clinpsy.3.022806.091432

Koffarnus MN, Franck CT, Stein JS, & Bickel WK (2015). A modified exponential behavioral economic demand model to better describe consumption data. Experimental and Clinical Psychopharmacology, 23(6), 504–512. https://psycnet.apa.org/doi/10.1037/pha0000045 [PubMed: 26280591]

Koffarnus MN, Jarmolowicz DP, Mueller ET, & Bickel WK (2013). Changing delay discounting in the light of the competing neurobehavioral decision systems theory: A review. Journal of the Experimental Analysis of Behavior, 99(1), 32–57. 10.1002/jeab.2 [PubMed: 23344987]

Kristjansson AL, Mann MJ, Sigfusson J, Thorisdottir IE, Allegrante JP, & Sigfusdottir ID (2019). Implementing the Icelandic Model for preventing adolescent substance use. Health Promotion Practice, 21(1), 70–79. 10.1177/1524839919849033 [PubMed: 31162979]

Latkin CA, German D, Vlahov D, & Galea S (2013). Neighborhoods and HIV: A social ecological approach to prevention and care. American Psychologist, 68(4), 210–224. https://dx.doi.org/10.1037%2Fa0032704 [PubMed: 23688089]

Lamb RJ, & Ginsburg BC (2018). Addiction as a BAD, a Behavioral Allocation Disorder. Pharmacology, Biochemistry, and Behavior, 164, 62–70. 10.1016/j.pbb.2017.05.002 [PubMed: 28476485]

Lea SEG (1978). The psychology and economics of demand. Psychological Bulletin, 85, 441–466. 10.1037/0033-2909.85.3.441

Lee JO, Cho J, Yoon Y, Bello MS, Khoddam R, & Leventhal AM (2018). Developmental pathways from parental socioeconomic status to adolescent substance use: Alternative and complementary reinforcement. Journal of Youth and Adolescence, 47(2), 334–348. 10.1007/s10964-017-0790-5 [PubMed: 29188410]

Lubman D, Yücel M, Kettle JWK, Scaffidi A, Mackenzie T, Simmons GJ, & Allen NB (2009). Responsiveness to drug cues and natural rewards in opiate addiction: Associations with later heroin use. Archives of General Psychiatry, 66(2), 205–212. 10.1001/archgenpsychiatry.2008.522 [PubMed: 19188543]

MacCorquodale K, & Meehl PE (1948). On a distinction between hypothetical constructs and intervening variables. Psychological Review, 55(2), 95–107. https://psycnet.apa.org/doi/10.1037/h0056029 [PubMed: 18910284]

MacKillop J, Amlung MT, & Acker JD (2010). Further validation of an alcohol purchase task: Equivalence of versions for hypothetical and actual rewards. Alcoholism: Clinical and Experimental Research, 34(6), 48A. 10.1111/j.1530-0277.2010.01210.x

MacKillop J, Amlung MT, Few LR, Ray LA, Sweet LH, & Munafò MR (2011). Delayed reward discounting and addictive behavior: A meta-analysis. Psychopharmacology, 216(3), 305–321. 10.1007/s00213-011-2229-0 [PubMed: 21373791]

Magill M, Ray L, Kiluk B, Hoadley A, Bernstein M, Tonigan JS, & Carroll K (2019). A meta-analysis of cognitive-behavioral therapy for alcohol or other drug use disorders: Treatment efficacy by contrast condition. Journal of Consulting and Clinical Psychology. 87(12), 1093–1105. 10.1037/ccp0000447 [PubMed: 31599606]

Mahoney MJ (1974). Cognition and behavior modification. Ballinger.

Mahoney MJ (1978). Experimental methods and outcome evaluation. Journal of Consulting and Clinical Psychology, 46(4), 660–672. https://psycnet.apa.org/doi/10.1037/0022-006X.46.4.660

Marlatt GA, & Gordon JR (Eds.) (1985). Relapse prevention. Guilford Press.

Mazur JE (1987). An adjusting procedure for studying delayed reinforcement. In Commons ML, Mazur JE, Nevin JA, & Rachlin H (Eds.), The effect of delay and of intervening events on reinforcement value (pp. 55–73). Lawrence Erlbaum Associates.

McCarthy DE, Minami H, Bold KW, Yeh VM, & Chapman G (2018). Momentary assessment of impulsive choice and impulsive action: Reliability, stability, and correlates. Addictive Behaviors, 83, 130–135. 10.1016/j.addbeh.2017.11.031 [PubMed: 29221928]

Merrill JE, & Aston ER (2020). Alcohol demand assessed daily: Validity, variability, and the influence of drinking-related consequences. Drug and Alcohol Dependence, 208, 107838. 10.1016/j.drugalcdep.2020.107838 [PubMed: 31954948]

Meshesha LZ, Soltis KE, Wise EA, Rohsenow DJ, Witkiewitz K, & Murphy JG (2020). Pilot trial investigating a brief behavioral economic intervention as an adjunctive treatment for alcohol use disorder. Journal of Substance Abuse Treatment, 113, 108002. 10.1016/j.jsat.2020.108002 [PubMed: 32359674]

Monnat SM (2018). Factors associated with county-level differences in U.S. drug-related mortality rates. American Journal of Preventive Medicine, 54(5), 611–619. 10.1016/j.amepre.2018.01.040 [PubMed: 29598858]

Motschman CA, Amlung M, & McCarthy DM (2022). Alcohol demand as a predictor of drinking behavior in the natural environment. Addiction. Online ahead of print. 10.1111/add.15822

Murphy JG, Campbell KW, Joyner KJ, Dennhardt AA, Martens MP, & Borsari B (2021). Trajectories of reward availability moderate the impact of brief alcohol interventions on alcohol severity in heavy-drinking young adults. Alcoholism: Clinical and Experimental Research, 45(10), 2147–2159. 10.1111/acer.14681 [PubMed: 34342015]

Murphy JG, Correia CJ, Colby SM, & Vuchinich RE (2005). Using behavioral theories of choice to predict drinking outcomes following a brief intervention. Experimental and Clinical Psychopharmacology, 13(2), 93–101. 10.1037/1064-1297.13.2.93 [PubMed: 15943542]

Murphy J, Dennhardt A, Martens M, Borsari B, Witkiewitz K &, Meshesha L (2019). A randomized clinical trial evaluating the efficacy of a brief alcohol intervention supplemented with a substance-free activity session or relaxation training. Journal of Consulting and Clinical Psychology, 87(7), 657–669. 10.1037/ccp0000412 [PubMed: 31070386]

Murphy JG, Dennhardt AA, Skidmore JR, Borsari B, Barnett NP, Colby SM, & Martens MP (2012). A randomized controlled trial of a behavioral economic supplement to brief motivational interventions for college drinking. Journal of Consulting and Clinical Psychology, 80(5), 876–886. 10.1037/a0028763 [PubMed: 22663899]

Murphy JG, Dennhardt AA, Yurasek AM, Skidmore JR, Martens MP, MacKillop J, & McDevitt-Murphy ME (2015). Behavioral economic predictors of brief alcohol intervention outcomes. Journal of Consulting and Clinical Psychology, 83(6), 1033–1043. 10.1037/ccp0000032 [PubMed: 26167945]

Murphy JG, & MacKillop J (2006). Relative reinforcing efficacy of alcohol among college student drinkers. Experimental and Clinical Psychopharmacology, 14(2), 219–227. 10.1037/1064-1297.14.2.219 [PubMed: 16756426]

Naudé GP, Kaplan BA, Reed DD, Henley AJ, & DiGennaro Reed FD (2018). Temporal framing and the hidden-zero effect: rate-dependent outcomes on delay discounting. Journal of the Experimental Analysis of Behavior, 109(3), 506–519. 10.1002/jeab.328 [PubMed: 29663440]

Nighbor TD, Zvorsky I, Kurti AN, Skelly JM, Bickel WK, Reed DD, Naudé GP, & Higgins ST (2019). Examining interrelationships between the Cigarette Purchase Task and delay discounting among pregnant women. Journal of the Experimental Analysis of Behavior, 111(3), 405–415. 10.1002/jeab.499 [PubMed: 30681144]

Peacock A, Eastwood B, Jones A, & Millar T (2018). Effectiveness of community psychosocial and pharmacological treatments for alcohol use disorder: A national observational cohort study in England. Drug and Alcohol Dependence, 186, 60–67. 10.1016/j.drugalcdep.2018.01.019 [PubMed: 29550623]

Pearson MR, Emery NN, & Schwebel FJ (2022). Use of mobile technology to understand and improve recovery from alcohol use disorder. In Tucker JA & Witkiewitz K (Eds.), Dynamic pathways to recovery from alcohol use disorder: Meaning and methods (pp. 239–259). Cambridge University Press.

Peters J, Beck J, Lande J, Pan Z, Cardel M, Ayoob K, & Hill J0 (2016). Using healthy defaults in Walt Disney World restaurants to improve nutritional choices. Journal of the Association for Consumer Research, 1(1), 92–103. 10.1086/684364 [PubMed: 30417105]

Pierce WD, & Epling WF (1983). Choice, matching, and human behavior: A review of the literature. The Behavior Analyst, 57–76. 10.1007/BF03391874 [PubMed: 22478577]

Rachlin H (1974). Self-control. Behaviorism, 2(1), 94–108.

Rachlin H (1992). Teleological behaviorism. American Psychologist, 47(11), 1371–1382. 10.1037/0003-066X.47.11.1371 [PubMed: 1482004]

Rachlin H. (1995). The value of temporal patterns in behavior. Current Directions in Psychological Science, 4(6), 188–192. 10.1111/1467-8721.ep10772634

Rachlin H (1997). Four teleological theories of addiction. Psychonomic Bulletin & Review, 4, 462–473. 10.3758/BF03214335

Rachlin H (2013). About teleological behaviorism. The Behavior Analyst, 36, 209–222. 10.1007/BF03392307 [PubMed: 28018032]

Rachlin H (2014). The escape of the mind. Oxford University Press.

Rachlin H (2017). In defense of teleological behaviorism. Journal of Theoretical and Philosophical Psychology, 37(2), 65–76. https://psycnet.apa.org/doi/10.1037/teo0000060

Rachlin H, Battalio R, Kagel J, & Green L (1981). Maximization theory in behavioral psychology. Behavioral & Brain Sciences, 4(3), 371–388. 10.1017/S0140525X00009407

Rachlin H, & Green L (1972). Commitment, choice and self-control. Journal of the Experimental Analysis of Behavior, 17(1), 15–22. 10.1901/jeab.1972.17-15 [PubMed: 16811561]

Rachlin H, Green L, Vanderveldt A, & Fisher EB (2018). Behavioral medicine's roots in behaviorism: Concepts and applications. In Fisher EB (Ed.), Principles and concepts of behavioral medicine (pp. 241–275). Springer Science+Business Media LLC.

Rachlin H, Logue AW, Gibbon J, & Frankel M (1986). Cognition and behavior in studies of choice. Psychological Review, 93(1), 33–45. https://psycnet.apa.org/doi/10.1037/0033-295X.93.1.33

Rachlin H, Raineri A, & Cross D (1991). Subjective-probability and delay. Journal of the Experimental Analysis of Behavior, 55(2), 233–244. 10.1901/jeab.1991.55-233 [PubMed: 2037827]

Roche A, Kostadinov V, Fischer J, Nichols R, O'Rourke K, Pidd K, & Trifonoff A (2015). Addressing inequities in alcohol consumption and related harms. Health Promotion International, 30(Suppl. 2), ii20–ii35. 10.1093/heapro/dav030 [PubMed: 26420810]

Rung JM, & Madden GJ (2018). Experimental reductions of delay discounting and impulsive choice: A systematic review and meta-analysis. Journal of Experimental Psychology. General, 147(9), 1349–1381. 10.1037/xge0000462 [PubMed: 30148386]

Schlienz NJ, Hawk LW, Tiffany ST, O'Connor RJ, & Mahoney MC (2014). The impact of pre-cessation varenicline on behavioral economic indices of smoking reinforcement. Addictive Behaviors, 39(10), 1484–1490. 10.1016/j.addbeh.2014.05.008 [PubMed: 24949949]

Snider SE, LaConte SM, & Bickel WK (2016). Episodic future thinking: Expansion of the temporal window in individuals with alcohol dependence. Alcoholism: Clinical and Experimental Research, 40(7), 1558–66. 10.1111/acer.13112 [PubMed: 27246691]

Skidmore JR, & Murphy JG (2011). The effect of drink price and next-day responsibilities on college student drinking: A behavioral economic analysis. Psychology of Addictive Behaviors, 25(1), 57–68. 10.1037/a0021118 [PubMed: 21142332]

Sobell LC, & Sobell MB (1992). Timeline followback: A technique for assessing self-reported alcohol consumption. In Litten RZ & Allen JP (Eds.), Measuring alcohol consumption: Psychosocial and biochemical methods (pp. 41–72). Humana Press. 10.1007/978-1-4612-0357-5_3

Sobell MB, Sobell LC, & Sheahan DB (1976). Functional analysis of drinking problems as an aid in developing individual treatment strategies. Addictive Behaviors, 1(2), 127–132. 10.1016/0306-4603(76)90005-8

Strickland JC, Campbell EM, Lile JA, & Stoops WW (2020). Utilizing the commodity purchase task to evaluate behavioral economic demand for illicit substances: A review and meta-analysis. Addiction, 115(3), 393–406. 10.1111/add.14792 [PubMed: 31454109]

Swan JE, Aldridge A, Joseph V, Tucker JA, & Witkiewitz K (2021). Individual and community social determinants of health and recovery from Alcohol Use Disorder three years following treatment. Journal of Psychoactive Drugs, 53(5), Published online: 02 Nov 2021. 10.1080/02791072.2021.1986243

Sze YY, Stein JS, Bickel WK, Paluch RA, & Epstein LH (2017). Bleak present, bright future: Online episodic future thinking, scarcity, delay discounting, and food demand. Clinical Psychological Science, 5(4), 683–697. 10.1177/2167702617696511 [PubMed: 28966885]

Trangenstein PJ, Gray C, Rossheim ME, Sadler R, & Jernigan DH (2020). Alcohol outlet clusters and population disparities. Journal of Urban Health, 97(1), 123–136. 10.1007/s11524-019-00372-2 [PubMed: 31264024]

Thaler RH, & Sunstein CR (2009). Nudge: Improving decisions about health, wealth, and happiness (Revised & Expanded edition). Penguin Books.

Tucker JA, Chandler SD, & Cheong J (2017). Role of choice biases and choice architecture in behavioral economic strategies to reduce addictive behaviors. In Heather N & Segal G (Eds.), Addiction and choice: Rethinking the relationship. (pp. 346–364). Oxford University Press.

Tucker JA, Cheong J, & Chandler SD (2021). Shifts in behavioral allocation patterns as a natural recovery mechanism: Post-resolution expenditure patterns. Alcoholism: Clinical and Experimental Research, 45(6), 1304–1316. 10.1111/acer.14620 [PubMed: 33885166]

Tucker JA, Cheong J, Chandler SD, Lambert BH, Pietrzak B, Kwok H, & Davies SL (2016). Prospective analysis of behavioral economic predictors of stable moderation drinking among problem drinkers attempting natural recovery. Alcoholism: Clinical and Experimental Research, 40(12), 2676–2684. https://psycnet.apa.org/doi/10.1111/acer.13245 [PubMed: 27775161]

Tucker JA, & Vuchinich RE (2015). Efficient and final causes of alcohol consumption. Addiction, 110(9), 1429–1430. 10.1111/add.12983 [PubMed: 26223172]

Voices for Healthy Kids Action Center (2019). California becomes first state to require healthy drinks on kids' restaurant menus. American Heart Association. https://voicesforhealthykids.org/impact/success-stories/cakidsmeals#:~:text=On%20Jan.,with%20kids'%20meals%20at%20restaurants.

Vuchinich RE (1995). Alcohol abuse as molar choice: An update of a 1982 proposal. Psychology of Addictive Behaviors, 9(4), 223–235. 10.1037/0893-164X.9.4.223

Vuchinich RE, & Heather N (Eds.) (2003). Choice, behavioural economics and addiction. Pergamon/Elsevier Science Inc. 10.1016/B978-0-08-044056-9.X5040-4

Vuchinich RE, & Tucker JA (1988). Contributions from behavioral theories of choice to an analysis of alcohol abuse. Journal of Abnormal Psychology, 97(2), 181–195. 10.1037//0021-843X.97.2.181 [PubMed: 3133403]

Vuchinich RE, & Tucker JA (1996). Alcoholic relapse, life events, and behavioral theories of choice: A prospective analysis. Experimental & Clinical Psychopharmacology, 4(1), 19–28. 10.1037//1064-1297.4.1.19

Witkiewitz K, Pfund RA, & Tucker JA (2022). Mechanisms of behavior change in substance abuse disorder with and without formal treatment. Annual Review of Clinical Psychology, 18, 13.1–13.29. 10.1146/annurev-clinpsy-072720-014802

Xu Y, Towe SL, Causey ST, Dennis PA, & Meade CS (2020). Effects of substance use on monetary delay discounting among people who use stimulants with and without HIV: An

Author Manuscript
Author Manuscript
Author Manuscript

ecological momentary assessment study. Experimental and Clinical Psychopharmacology. 10.1037/pha0000423

Yi R, & Bickel WK (2005). Representation of odds in terms of frequencies reduces probability discounting. Psychological Record, 55(4), 577–593. 10.1007/BF03395528

Author Manuscript

Author Manuscript

Author Manuscript

Public Health Statement

Addictive behaviors are dynamic patterns spread over time and occur within broader dynamic environmental contexts. Research to date, however, has tended to focus on identifying the causes of addictive behavior either based on attributes within the person or the immediate context surrounding a discrete episode, in contrast to investigating how addictive behavior patterns emerge, are maintained, and remit over time as environmental circumstances change. Broadening research and theory to include both kinds of analysis holds promise for advancing understanding of the controlling variables of addictive behavior and is consistent with a socioecological model of health behavior that encompasses analysis of individual determinants of behavior and considers broader contextual features (e.g., social determinants of health) that often operate over longer temporal intervals.