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Review

# Positive reinforcement is just the beginning: Associative learning principles for energy efficiency and climate sustainability

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ABSTRACT

A major cause of global climate change, human behavior has long been recognized as an essential part of the solution as well. Behavior change methods in turn rely in part on associative learning principles. Some learning principles, such as positive reinforcement and delay discounting, are already integrated into energy research and interventions. However, others remain underutilized. In this paper, we review selected learning principles, suggesting how they can enhance both our understanding of the behavioral challenges and our effectiveness in addressing them. We seek to interest and involve researchers and practitioners in a variety of energy and sustainability specializations.

## 1. Introduction

A major cause of global climate change, human behavior is an essential part of the solution as well. Indeed, given that humanity has possessed for some time the science and technology needed to achieve energy and environmental sustainability (e.g. [1,2]), climate change is very much a *behavioral and social science* challenge. In recognition, mitigation experts routinely include behavior change as a significant part of their policy recommendations (e.g. [1–4]).

Associative learning principles describe well-established and ubiquitous influences on behavior. From the incentives in cap-and-trade to public recognition for a firm's commuter cyclists, for example, the basic concept of positive reinforcement underlies many sustainability policies and interventions. Some learning principles, such as reinforcement, hyperbolic delay discounting, and generalization (i.e., spillover)[1], are already consciously integrated to some extent into energy and sustainability interventions (in this journal, see, for example, these articles [5–9]). That said, the nuances of these better-known principles extend beyond what is commonly employed, and other learning principles remain overlooked or underutilized. In this paper, we review a selection of these principles, suggesting how they can enhance both our understanding of the behavioral challenges and our effectiveness in addressing them.

We focus on a sample of associative learning topics that we consider particularly useful for those energy and sustainability professionals who deal in some fashion with behavior change. For each, we offer brief descriptions followed by real or potential examples of energy research and sustainability applications. We begin with a very brief outline of the history of research on associative learning.

## 2. Associative learning

B. F. Skinner and Ivan Pavlov, two of the top scientific psychologists of the 20th century (e.g. [10]),[2] discovered large sets of laboratory-based general principles for two distinctly different functional categories of behavior: operant learning and classical conditioning respectively - the two forms of associative learning.[3] Put very simply, operant learning centers on the selection of behavior by consequences, as in

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[1] Overlapping technical terms are problematic for many interdisciplinary areas, and sustainability is no exception. Use of “spillover” rather than the much older, established term “generalization” makes it harder to contact almost a century of experimental associative learning research. Both terms include behavioral as well as stimulus spillover (e.g. [121,122]). "Maintenance" and "persistence" are another such pair.

[2] Skinner won the US National Medal of Science; Pavlov won the Nobel Prize.

[3] Cognitive psychologist and psychology historian Thomas Leahey once called this area and sensation-perception the only advanced Kuhnian "normal science" parts of psychology: "The experimental analysis of behavior is without doubt the closest psychology has come to a normal science research program. It began with Skinner's first psychological book, *The Behavior of Organisms*" ([123], p. 317). Associative learning is considered a natural science, part of biology as well as psychology.

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positive reinforcement, while classical conditioning is based on reflexes, their eliciting stimuli, and stimulus pairing. Unsurprisingly, biology as well as behavior differentiates these processes, and scientists now understand much of the neurophysiology, genetics, and epigenetics involved (e.g. [11–15]).

Scientific discovery of the first associative learning principles dates back over a century (e.g. [16]), and thousands of subsequent experimental studies have built a well-replicated[4], well-quantified foundation of broad generality - across vertebrate and invertebrate animal species as well as humans [17,18]. The schedules of reinforcement discussed below are a good example: After reviewing their early history and Ferster and Skinner's "encyclopedia of schedules" [19], Zeiler went so far as to suggest that schedules be treated as biologically-founded empirical laws [20]. Likewise, thousands of studies documenting successful applications of learning principles can be found throughout the realm of human behavior, including education, the workplace, family life, and health and wellness (e.g. [18,21–23]). Endorsements of these applications come from a host of institutions such as the American Academy of Pediatrics, National Autism Center, National Research Council, US Surgeon General, and Veterans Administration [24–29].

Behavior analysis, the discipline focused on basic and applied work on learning principles, can be viewed as a founding specialty of environmental psychology in the 1970s. Behavior analysts offered numerous empirical studies, culminating in two landmark books from leading experts [30,31]. Both books were recently described as "seminal" by social and environmental psychologist Richard Osbaldiston ([32], p. 260). However, behavior analysts subsequently focused more on other applications, and few currently work in environmental psychology.

Learning principles have also been represented from the start in the interdisciplinary area of behavioral economics, perhaps the predominant behavioral science approach to sustainability. They remain important elements of that field (see, e.g., [33–35]). Among other contemporary sustainability approaches, McKenzie-Mohr's eclectic, widely-used "community-based social marketing" includes learning principles [36]. And *The Guide to Greening Cities* [37], from big-city sustainability directors expert in energy conservation, also makes use of learning principles and behavior-analytic interventions such as "performance management" (see, e.g., [38]).

## 3. Reinforcement

It is not hard to see why: The consequences that are the basis of operant learning are ubiquitous. Turn to look out the window and spot an attractive view. Repeat later because of that experience and you've just demonstrated positive reinforcement (defined by function, not structure or intention[5]). Such common small-scale reinforcers include eye contact and other forms of attention, checks on checklists, and other low-cost, easily overlooked incentives critical in many sustainability interventions (e.g. [23,39]). Goal-setting, for example, automatically creates a reward if the goal is met or if sufficient progress is evident. Like any potent variable, positive reinforcement is effective whether used inadvertently or intentionally, but familiarity with the depth of these learning principles naturally brings the opportunity for improved program design.

Positive reinforcement approaches are the main focus in this paper. However, negative reinforcement is also relevant to many sustainability interventions. A standard example is the strengthening of green behavior through avoidance or escape of fines, social disapproval, or other aversives. Negative reinforcement is accordingly involved in the behavioral economics concept of loss aversion, the tendency in some cases for aversives to overpower otherwise comparable rewards. (For discussions of the relationship between loss aversion and negative reinforcement, see, e.g. [40,41].) Why might consumers avoid switching to a time-of-use electricity rate although it would likely save them money? As Nicolson et al.'s recent study found, "93% of bill payers are loss-averse (care more about avoiding financial losses than making savings) and loss-averse people are substantially less willing to switch" ([42], p. 82).

How to overcome this effect? Research on learning principles could potentially augment research on typical behavioral economics/cognitive variables such as changes in framing. Such research could also help inform programming decisions about the size and level of certainty of fines for wasteful behavior, such as breaking water restrictions. Yale behavioral economics expert Ian Ayres took advantage of behavior-analytic research to develop his popular self-control website stickK.com [43]. Its users make commitments to a longer-term goal, and can agree to lose something (typically money that they put up) if they fail to meet it – perhaps a last resort if more positive approaches failed. Sustainability goals such as bicycling more are included on this site that relies on both negative and positive reinforcement.

Learning necessarily takes place over time, and that can be a barrier to appreciating its presence, let alone its nuances. For example, repeatedly turning to enjoy a window view produces the consequence every time - a "continuous reinforcement schedule." Most behavior-consequence relationships are more complex, and intermittent schedules of a great variety of types are far more prevalent than continuous ones. All consequences are on such schedules, which describe the nature of the dependent relationship.[6] That includes details of the relations over time, plus associated variables like signals, delays, other consequences (context matters), and even history.[7] Researchers have identified dozens of different kinds of reinforcement schedules, each of which typically produces different and characteristic behavior patterns that apply across species as well as across individual humans [17]. Schedules are so powerful, they modify the very value of consequences [23].

[4] Replication has been built in from the start in both branches of associative learning because of their frequent reliance on single-case experimental research designs rather than, or in addition to, null hypothesis significance testing. Perone [124] suggested this approach "avoids the replication crisis plaguing psychology specifically because replication is an integral part of the method" (p. 94). A recent Replication feature of the journal *Perspectives on Behavior Science* provides detailed discussions of this methodology ([125]; also see [126–130]).

[5] Approaches like the behavior change wheel (e.g. [7]) are more structurally-based. In the functional approach of operant learning, consequences that lack effects are not reinforcers, regardless of their characteristics or intent. Likewise, signaled incentives in interventions are designed to motivate behavior change, but they do not always work, so they are not always reinforcers. In that case, they are best considered as failed attempts at reinforcement. Pilot testing and other methods of reinforcer preference assessment (e.g. [131]) can augment questionnaires and observation to help maximize the chance of success.

[6] Purchasing solar panels or adding attic insulation are behaviors that do not get repeated very often. They are still operant behaviors motivated by consequences and associated signals and rules, however. Buying that Energy Star appliance "on time" is different, for example, from putting it on a credit card and scheduling an immediate delivery. For more examples of how schedule dynamics apply to one-time behaviors, see ([23], p. 80).

[7] Any learning text will cover a variety of schedules. On a chained schedule, for example, signals distinguish schedules that follow each other, with reinforcement only at the completion of all. A tandem schedule is the same but without the signals. On a differential-reinforcement-of-low-rate schedule, for another example, a fixed delay in responding must pass before reinforcement is available. Again, each schedule produces characteristic behavior patterns, and plentiful real-life examples exist. Schedules running simultaneously have their own set of "schedules of schedules," and influence each other in ways that are also well researched – in this article see, for example, the generalized matching equation under Choice.

## 4. Variable schedules of reinforcement

### 4.1. Basics

The schedule types included under the broad category of variable schedules (e.g. [17]) are particularly prevalent and valuable in sustainability applications. Classic variable schedule examples include gambling and selling on commission: Not every behavior succeeds, but the very next roll of the dice or knock on the door might be a winner. That makes these schedules highly motivating. Although they require fewer resources than comparable continuous schedules, they can produce *more* behavior (e.g. [23]).

Accordingly, variable reinforcement schedules routinely help leverage incentives effectively in sustainability interventions: for example, via lotteries and competitions (e.g. [44–46]). As Vine and Jones [47] noted for competitions, they "have the ability to massively scale up interventions" and "can be very cost-effective" (p. 168); the same could be said for lotteries. Variable schedules have also long been explicitly employed in gamification for health and education as well as entertainment - and more recently for sustainability (e.g. [46,48–51]). Indeed, Zichermann and Cunningham's *Gamification by Design* [52] included a chapter on schedules of reinforcement. As one example, Ro et al's sustainability game Cool Choices successfully reduced participants' household electricity use, an effect that lasted 6 months after the intervention ended [51]. The game included small weekly cash prizes awarded randomly to participants who reported performing at least one sustainable behavior – a variable schedule. In a different sort of schedule application, Deslauriers and Everett [53] found statistically similar increases in bus ridership regardless of whether all received a discount token, or just every third person on average.

Utilizing the considerable knowledge base covering the finer points of schedules is well-documented to enhance intervention success. For example, variable schedules are more likely to sustain high behavior rates if they feature occasional short reinforcement intervals (e.g. [54]). Indeed, going too long without a success, whether it is a recipe from a vegan cookbook or a new lawn-replacement native plant, can disrupt or even completely end the behavior (see the literature on "ratio strain", e.g. [17]; these are real life examples from the authors).

Relatedly, some early reviews of household energy interventions suggested the benefits of frequent and more immediate eco-feedback (e.g. [55]; see Delay Discounting below on the benefits of immediacy). Why then has continuous feedback availability not consistently been found to be more effective (see, e.g., this meta-analysis [56], which did not find a clear relationship)? Furthermore, eco-feedback has a notorious novelty effect, starting strong but fading over time in its effectiveness (e.g. [6,57]). Analyzing the schedule of reinforcement might be helpful: A critical component may be the actual observing behavior required, and how frequently it is reinforced with useful or otherwise positively reinforcing (e.g., money-saving) information. After all, once the initial behavior changes they motivate have been made, in-home smart meters and other eco-feedback applications eventually fail to provide much useful new information.[8] That means the schedule of reinforcement, while still variable, can become too "thin" to be effective; that is, it offers too sparse an incentive rate. Eventually, the observing behavior falls off accordingly (see The Ostrich Effect and Feedback below). If new habits had not yet been established, the green target behaviors may fall off too.

### 4.2. Persistence

New sustainable behaviors are maintained indefinitely through a variety of processes: for example, social reinforcers from newly created social norms; naturally occurring reinforcers of any sort; naturally existing prompts and other cues; and ideally, establishment of new habits. Naturally occurring *extrinsic* reinforcers (those from outside) include the cost savings that automatically occur with improved energy efficiency. Naturally occurring *intrinsic* reinforcers include satisfaction of one's environmental conscience, or the endorphin rush from a bicycle commute. However, if an intervention brought about the initial behavior change, successful maintenance may require a carefully planned transition to these long-term supports. Otherwise, abruptly ending an intervention often ends the behavior change too (e.g. [58]). Skumatz [59] reviewed home energy report studies that offered follow-up data, noting that "retention studies of behavioral programs are still relatively scarce" (p. 28; also see the similar findings of Vine and Jones [47] for competitions). While the results were quite variable, a significant dropoff in energy savings was repeatedly noted (in addition to the novelty effect discussed above). Skumatz suggested "cycling" customers on and off the program to improve the benefit-cost ratio – a variable schedule, although that was not the reason given. We suggest that greater recognition and utilization of this learning principle could offer significant benefits. "Cycling" in this way is unusual: Feedback at fixed rather than variable intervals is the norm.

Variable schedules shine in fostering the critical transition to successful post-intervention maintenance. Indeed, they are known for enhancing perseverance[9] - problematic for gambling, but beneficial for sustainability. Gradually thinning a schedule naturally eases a transition from many to few rewards or none. Gradually reducing the value of any incentives can also help with the transition to successful persistence. Companies that set up energy conservation programs may need to provide extra attention and perks at first. Once the new habits develop sufficiently, the reinforcement schedule can be thinned (also see the xeriscaping example in Delay Discounting). Likewise, initially free charging from dealerships can help incentivize electric vehicle purchases, but can be decreased or discontinued as drivers install convenient home chargers or find other more convenient options (see [60] for a recent attempt at modeling the large-scale effects of providing temporary vs long-term free charging).

The general literature on maintenance in associative learning takes advantage of a number of methods like this (e.g. [61]). In many cases, extrinsic rewards can be entirely faded out. In others, they may be needed for long-term persistence - particularly if competing rewards are continuing to maintain the original, more wasteful behaviors.[10] Bicycling, carpooling, or taking public transit to work may be an apt example for some commuters if solo driving remains much easier and inexpensive.

### 4.3. Habit/Automaticity

Establishing a new green habit – a behavior that occurs with little or no conscious awareness – is the ultimate in sustainable behavior change that is itself sustained. During the process, continued reinforcement (often on a variable schedule) fosters the repetition that is an essential

[8] Karlin [132] described how energy feedback can support behavior change via two functions: tracking (i.e., monitoring one's performance) and learning (new information to support new behaviors). We suggest that the rewards associated with each of these types of information have different values and operate on different schedules. For example, tracking feedback initially offers a dense reinforcement schedule that declines markedly in value after the novelty effect ends. Information that supports learning something new may offer more valuable reinforcers, but much less often over time.

[9] Technically, "resistance to extinction," with extinction meaning the complete loss of the behavior. For example, those who spend longer on continuous reinforcement before switching to a variable schedule tend to be less resistant to extinction [133]. History matters.

[10] If an incentive system cannot be maintained, offering occasional incentives through methods like competitions still provides variable-schedule benefits and bolsters maintenance.

part of habit creation. It need not be recognized consciously: Scientists showed long ago that people are influenced by consequences without realizing (and learning without awareness continues to be a part of the associative learning literature, e.g. [62–64]). The fields of social psychology, cognitive science, and associative learning are all major contributors to this important interdisciplinary area.

## 5. Shaping, delays, and other principles

### 5.1. Shaping

Behavior change interventions can often be more effective when the existing green behavior levels are taken into account: Meet people where they're at. Progress can be systematically built into a program through *shaping*, a widely established method in areas such as education and health (e.g. [65]).

Technically, shaping is the reinforcement over time of successive approximations to a target behavior [66]. While a variety of associated factors typically assist, including signals and rules, the focus is simply on incentivizing progress. Hence, shaping is an inherent part of classic gamification, with its advancement to different achievement levels, plus social recognition and badges for increased proficiency. But it can be a lot simpler. Encouraging carpooling? Offer appreciation for *the very first try* and build from there.

Seattle's In Motion initiative supporting alternatives to solo driving made good use of shaping principles, providing free public transit passes to help get people started, then reinforcing gradual progress via weekly emails tailored to each individual [67]. While approximating a shaping approach to a large group simultaneously can succeed - and is sometimes the only practicable alternative - individualized interventions like Seattle's clearly allow more effective tailoring, just as in gamification. That can also happen automatically: Real-time fuel economy feedback from modern dashboards naturally reinforces - shapes - incremental improvements in eco-driving (to sometimes dangerous levels for "hypermilers," who gamify fuel efficiency, e.g. [68]). Another area of eco-feedback research is the use of in-shower devices to promote shorter showers, conserving water and energy for water heating (e.g. [69]). Smart home technology could take this kind of feedback to the next level by learning consumer habits, such as baseline shower length, and gradually shaping individual progress. The same approach could work for supporting decreases in hot water temperature settings or incremental changes in home heating and air conditioning settings via smart thermostat algorithms. Just as for variable schedules, maintaining a sufficiently high reinforcement rate during the shaping process is one of a number of useful shaping principles (see, e.g. [70,71]). We suggest that this is another learning principle that frequently flies under the radar.

### 5.2. Signals

These ubiquitous features indicate whether rewards are available. Sunny days bring out more commuter cyclists than rainy ones, for example. Sadly, sustainable behavior reminders alone (like other information-alone approaches) often fail to bring significant lasting behavior change (e.g. [36,72]; classically [30,31]; with exceptions as in [73]). Making signals more effective is an interdisciplinary specialty, involving in this case the arts as well as scientific methods like framing and stimulus generalization/spillover (e.g. [36]).

Among the applications of this research domain is a routine sustainability campaign challenge: the choice between signals showing progress toward a goal vs. the distance remaining. These signals often function as consequences as well. The classic "goal gradient" finding corresponds to a similar result for many schedules of reinforcement: Fundraising drives that are close to their targets attract more donations by emphasizing the small remaining gap. If the gap is large, highlighting existing progress is usually more effective ([74], but see [75,76] for sample exceptions and nuances; also see Fantino's delay reduction theory from associative learning, e.g. [77]). In some cases, providing *no* signals of progress is best, because they can actually decrease the target behavior rate if the news is bad enough. Individual learning history is one of a number of contributing variables (e.g. [23]). Application to community power use or greenhouse gas emissions targets would appear to be straightforward.

### 5.3. Incentive contingency basis

A frequent question is whether to make incentives depend on – "contingent" on - general *outcomes*, such as a target reduction in electricity usage, or on specific *behaviors*, such as turning off unnecessary lights and electronics (again, classically discussed in [31]). A Minnesota school district achieved Energy Star status through focusing on specifics [78], and McKenzie-Mohr [36] recommended identifying specific end-state behaviors as a routine part of sustainability intervention design. In a different area, Pryor [79] noted the greater success of a specific-behavior focus in pay-for-performance programs in K-12 education. However, tracking specific behaviors can be more difficult than tracking outcomes; indeed, changes in overall electricity usage are often easier to measure than the relevant individual behaviors.

As usual, the choice of strategy depends on a number of other variables as well. From a different application area, a review of behavior-analytic safety studies [80] found an outcome basis to be generally preferable for persistence - in part because of an enhancement of the desirable maintenance feature of "indiscriminability." Variable schedules can serve as an example, because when they are in effect, people usually cannot predict which particular actions will be rewarded and/or at what times. More behavior can be fostered as a result. Heward and Kimball [44] offered a range of sustainability examples for indiscriminability. On the negative side, an outcome contingency basis can also leave more room for methods that "sabotage the contingency," also known as "gaming" - acquiring the reinforcer without doing the desired behavior (again, see [44]). In his book on climate policy, Harvey [1] noted that Europe's system for establishing vehicle fuel economy was flawed and susceptible to gaming, which accordingly had taken place. Likewise, new amount-based trash pickup charges ("pay as you throw") can be circumvented not by waste reduction, recycling, and composting as intended, but by the surreptitious transfer of garbage to public bins [81].

### 5.4. Delay discounting

Delay discounting describes the tendency among all animals, including humans, to choose a smaller-but-sooner reward over a larger-later benefit. Indeed, the fact that delayed consequences are consistently discounted in value is a major force behind anthropogenic climate change itself. It exemplifies the "social dilemma": rampant greenhouse gas emissions bringing short-term rewards for the few, while externalizing and delaying mammoth aversive consequences for all, for generations. Indeed, the largest challenge to the speedy achievement of sustainability may be the malign effects of delay on consequence value (aka "present bias"). Delays discount value, often steeply, thus decreasing the likelihood of the target behavior change. The mathematical model that provides the best account, hyperbolic delay discounting, came from associative learning research [82,83], and an extensive human and nonhuman literature exists (e.g. [84,85]; delay discounting is one of many contributions of associative learning to behavioral economics[11]). People who discount more steeply in questionnaires or lab assessments often tend in real life to choose smaller-sooner incentives, as shown recently for energy-efficient lighting choices ([86]; also see, e.g., [87]).

How to surmount the temptation of these smaller-sooner incentives?

[11] Laboratory analogues of demand curves through schedules of reinforcement are well established, with price as a schedule parameter [134,135].

We saw above how reinforcing feedback can effectively bridge the delays to savings on an electric bill, supporting cuts in heating, cooling, and other energy use. Another common challenge, starting a new project, is often particularly difficult because of the long delay to the reinforcing completion. Extra incentives at the start can help surmount this barrier, and sustainability experts routinely provide them. Transitioning to a money-saving eco-friendly yard with no-mow xeriscaping, for example, is easier when initial cash incentives for drought-tolerant plants and support are provided. Among the many municipalities that have successfully adopted this approach are Sacramento and Las Vegas. Learning researchers have developed a number of additional intervention approaches for self-control (see, e.g., climate action recommendations for behavior analysts [88]), which can readily be combined with research from other disciplines.

### 5.5. *Choice*

Choices track consequences: The consequence that is higher quality, bigger, easier to get, more immediate, or more frequent is more attractive than a lesser alternative. Basic learning researchers have provided a sophisticated understanding of the relationships. Laboratory-based quantitative analysis of choice produced the "generalized matching equation," tested and applied for 50 years now (e.g. [89–91]). One of the most widely applicable mathematical relations in the behavioral sciences, it covers an immense range of different behaviors, consequences, and species, and incorporates signals and delays.[12] Perhaps its two parameters might one day be useful for sustainability in the ways seen for the sole parameter in the hyperbolic delay discounting equation [84].

We *always* have choices – so energy experts should ensure that a green behavior of some sort is always available, as easily performed and richly reinforced as possible, while simultaneously making existing, more wasteful behaviors harder and less rewarding. When using gasoline-powered lawn equipment becomes less attractive, greener options are automatically more appealing, and behavioral economics "nudges" accomplish just this. Indeed, the "choice architecture" of Thaler and Sunstein's *Nudge* [92] is built on such learning principles.

Providing an array of green choices automatically offers the benefits of control because of the ability to make a selection. Choice is usually a demonstrable reinforcer [23,93]; unsurprisingly, then, the opportunity to have a choice tends to be reinforcing in itself (e.g. [94]).[13] Successful sustainability gamification frequently relies on choice: As Ro et al [51] noted about their successful app Cool Choices, "by presenting the intervention in a game-like format, participants are provided with a choice about which energy-saving and sustainable behaviors they want to perform and which ones they want to adopt first" (p. 22) – enhancing motivation.

### 5.6. *Classical conditioning*

Pavlovian processes routinely interact with these pervasive operant principles. In sustainability, their role in emotions and emotional behavior is particularly important. Heart-tugging images include suffering climate refugees – particularly children – or animals victimized by climate change-facilitated fires or droughts. These motivate action by simultaneously eliciting emotions (Pavlovian) and changing the value of the relevant consequences (operant). They offer negative reinforcement, in effect, since taking action can alleviate both the suffering and the painful emotions it inspires in onlookers. Taking advantage of what is known about Pavlovian processes (e.g., principles like "second-order conditioning" [17]) could help inspire more empathy and behavior change.

Unobtrusive Pavlovian emotional conditioning plays a role in the social marketing that is commonly used to promote energy efficiency and sustainability. For example, words with emotional connotations like "sunshine" or "lost" were shown long ago to serve as effective reinforcers or punishers, in some cases without participants' awareness ([95]; also see [96,97]). This is not news to marketing experts, of course. The World Resources Institute's Better Buying Lab demonstrated that sustainable food labels like "vegetarian" are often turn-offs for non-vegetarians, and best replaced by terms with more generally positive emotional associations such as those highlighting flavor (e.g., "smoky soul chili" [98,99]). The Lab offered a list of principles, successful descriptors, and behavior change outcomes.

### 5.7. *The Ostrich Effect*

Pavlovian as well as operant processes are also present in the Ostrich Effect. People sometimes avoid seeking potentially discouraging information even when the ultimate, delayed consequences are quite important (e.g., testing HIV status [100]; see [101]). In the context of sustainability, denial provides the classic example. If climate change is real, then many aversives follow, so better not to investigate too closely (also illustrating the learning principle of avoidance). Many years ago, the development of the "observing response" methodology in associative learning operationalized attention and information-seeking - that is, made them possible to investigate objectively, even with nonhumans. An extensive experimental literature was created (see, e.g. [102]). In this methodology, an extra signal-revealing behavior is required to indicate the nature of the schedule of reinforcement for the target behavior – a schedule that can change without other notice. Is the current schedule sufficiently reinforcing for effective motivation? Richly reinforced schedules are (obviously) preferable to schedules offering few rewards or worse. Classically conditioned associations with aversives – the bad news, such as a bleak schedule of reinforcement, or one with some significant penalties – help shut down all observing despite the overall benefits gained from keeping track of the information. Once again, the phenomenon proved to apply to a large range of animal species as well as to humans (e.g. [102]). Ultimately, incorporating this research literature might help scientists better understand and circumvent climate change denial.

### 5.8. *Feedback*

Learning-based component analyses have parsed "feedback" into several more basic behavioral functions [103].[14] For example, it can serve as reinforcement (or punishment), as a motivating operation that creates other reinforcers, as a signal indicating that consequences are available, and as a rule.[15] Careful analysis and design can optimize these combinations. Eco-feedback interventions, however, sometimes focus mostly on the consequence function. According to several researchers, these interventions could do better to leverage motivational design strategies (e.g. [104,105]; see [6] for an inventory of eco-feedback design dimensions in the context of behavioral processes). One such strategy is the use of Pavlovian-style eliciting signals for empathy [106]. In a successful gamification app, for example, energy researchers incorporated healthy-looking or ailing cartoon chickens as part of their office energy consumption feedback [107]. These empathetic signals were intended to make the energy consumption data more engaging, effectively motivating app use as well as reinforcing specific energy-

[12] Indeed, it was successfully incorporated into signal detection theory long ago [136].

[13] With the caveat of avoiding too many paralyzing choices (e.g. [137]).

[14] The authors of [104] also noted that variable training schedules produced better results than continuous ones, for feedback as well as for other operant functions.

[15] Rules in associative learning are contingency-specifying statements (if-then behavior-consequences; see, e.g., [138]).

saving behaviors. A 13% reduction in average energy consumption was achieved. The effectiveness of progress markers (Signals section) is also influenced by this mix of functions.

### 5.9. Social motivation

Focusing on large groups rather than individuals can amplify sustainability successes, and establishing green social norms as widely as possible is the ultimate goal. How to take more advantage of inexpensive social reinforcers to bring about these changes? The relationships between social reinforcers, social norms, and group contingencies are complex just from a learning principles-based viewpoint. For example, an "interdependent" group contingency provides incentives only if all members of the group jointly meet a requirement. On a "dependent" group contingency, in contrast, the whole group benefits if just a few who are the focus make the improvement [108]. Both approaches obviously entail social reinforcers and ideally establish new social norms. An interdependent group contingency in one Pennsylvania town successfully increased recycling. As summarized by Heward and Kimball [44], "Residents earn points, dispensed and redeemable on line, on the basis of the quantity of recycling collected ***in their respective neighborhoods*** [emphasis added]; the more that households participate and the more material they recycle, the more points each participating household earns" (p. 8; also see [46]). Similarly, a Vermont utility that had failed to keep heat-wave peak demand below a limit with time-of-use financial incentives for individuals succeeded with a very different group-based approach: a donation to a local charity ([109]; for the current version, see [110]).

## 6. Coda

We have introduced a range of sample learning principles that play a role in energy and sustainability research and interventions. We suggest that many are influential, a number get overlooked, and all could potentially offer significant value if more researchers and practitioners were able to incorporate them along with the other scientific principles that apply.

In this last section, no discussion of associative learning and sustainability would be complete without mention of how they are involved in some common intervention pitfalls. We briefly introduce a methodology that can assist with analyzing the consequences influencing the target behaviors we seek to modify. Finally, we note that effective interdisciplinary scientific progress toward climate sustainability requires all of us to work at overcoming barriers to collaboration and mutual understanding (for a view from behavior analysis, see, e.g., [111,112]).

### 6.1. Pitfalls

The problem already discussed of "gaming" the contingencies is well known, highlighting the value of analyzing behavior-consequence relationships in detail. Relatedly, negative unintended consequences – due, for example, to perverse incentives that result in the opposite of the planned environmental impact - are a well-known plague. In-depth analysis from specialists in different disciplines can be required to ferret out and forestall or amend this problematic effect. As a prominent example, decoupling utility profits from power usage has been an effective strategy for driving energy use decline (for a recent summary, see [113]). Less obviously, providing group comparison energy use feedback – descriptive norms – is intended to motivate behavior change in high-use households and reward the energy-conserving. Unfortunately, it can also serve as a signal to the latter that consuming more is an acceptable social norm. Rewarding smiley faces can counteract this "boomerang" effect (e.g. [114]). In general, conducting an effective analysis of variable and shifting target audience motivations – and over a delayed as well as immediate time horizon - can be challenging to say the least. All the more reason to employ all available tools.

### 6.2. Mapping the incentives

All too often, environmentally unfriendly behaviors offer easier, more potent reinforcers than conscientious actions, and they're well learned and habitual to boot. A learning-based "functional analysis" deciphers these causal relations: What consequences are actually maintaining the behavior? Under what circumstances? Established experimental methods to assess the answers might usefully augment related approaches such as "barrier analysis" (e.g. [115]) and adoption studies, and suggest effective, targeted interventions. For a range of functional analysis methods and applications, see [36,116–119]. They can also be a useful part of intervention component analyses. We repeat that the immense challenge of multiple competing consequences, for many different people, small and large scales, and both immediate and delayed time horizons, deserves all the science we can throw at it.

### 6.3. Working together

Addressing climate change effectively and expeditiously requires all the relevant sciences; time is running out according to the recent report from the Intergovernmental Panel on Climate Change [120]. Energy experts perform many top-down, aggregate-data, correlationally-based analyses and interventions. This paper advocates for the value of incorporating in addition a more bottom-up approach, based on the long-established, scientifically rigorous operant and Pavlovian research bases. Ubiquitous as they are, we suggest that increased incorporation of associative learning principles can help move us forward.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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